

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Vehicles and equipment are subject to deterioration due to their use and exposure to environmental conditions as a result of wear and tear of parts in relative motion and improper lubrication of the sliding parts and should be fully utilized with minimum cost of maintenance. Dodge(2003) reported that vehicle's breakdown due to unplanned maintenance (sudden failure) would increase the repair cost and machine downtime. However, Nakagawa and Osaki(1974) were of the view that if the deterioration and breakdown are not checked, the vehicles may become unserviceable. To avoid this, it therefore becomes necessary to attend to the vehicles from time to time, repair and recondition them so as to enhance their life economically, and protect them from failure. This has made the role of maintenance and replacement an important activity in the transportation industries. Maintenance, according to Duffuaa, Ben-Daya, Al-Sultan and Andijani(2001) is defined as the combination of activities to restore the component or equipment to a state in which it can perform its designated functions, as supported by Dillon(2002). In a similar manner, Godwin and Nsobundu(2013) defined maintenance as the activity directed towards the upkeep and repair of plant facilities/equipment.

Every vehicle requires maintenance. Even if it is best designed, the maintenance must be done, at such a period when it will have least disruptions of service. This is why Cassidy and Kutanoglu(2005) and buttressed by the declaration made by Panagiotidou and Tagaras(2007), opined that vehicles or machines should undergo maintenance when not in use or their use may be postponed without affecting service and operation. However, in reality, most of the equipment failures are influenced, not only by the internal factor (age-time usage) but also by the external factor as observed by Latham(2008). These

external factors would be the effects of the environment such as dust, humidity, precipitation, temperature, condition of the road and heat, human skills, product types and maintenance activities. The timely maintenance of vehicles in the fleet is one of the fundamental programs that serve as a backbone of a successful transport system as upheld by El-Ferik and Ben-Daya(2006). Vehicles are transit system's most valuable assets because good customer service is dependent on the condition of the fleet.

The total cost of the fleet is usually the most expensive asset, even more so than the facilities that house the operation. An aging fleet presents a poor image to the system customers and the general public. Vehicle maintenance expenses usually increase as the age of a vehicle advances, thereby triggering replacement as reasoned by Taboada, Espiritu and Coit(2008). Vehicles are subject to breakdown and deterioration, therefore, maintenance policy can be beneficial in order to prevent failures during operation. In this regard, Beaumont(2007) was of the opinion that checking of vehicles should be done when they are not in operation so that the defect, if any, can be immediately rectified. Maintenance of vehicles and equipment in good working condition is necessary in order to achieve specified level of quality, reliability and efficient operation. Besides, vehicle maintenance is an important service function of an efficient productive system. Zeqing and Shin(2006) concurred that adequate maintenance would increase the operational efficiency of the transport facilities and thus contributes to revenue by reducing the operating costs thereby enhance the effectiveness of production. It also reduces costs, since we can legitimately assess that a repair upon failure costs more than a preventive repair.

All transport service providers in Nigeria maintain large fleets of equipment. This equipment represents a substantial investment and is a vital set of resources that is used to maintain roads and highways as buttressed by Martorell, Sanchez

and Serradell(1999).Chee(2012) maintained that managing such a large amount of equipment is an important and difficult challenge when deciding the appropriate maintenance decisions that should have a clearly documented economic impact. This was supported by David (1995) who opined that the ability of the fleet to provide required equipment when needed is dependent on the degree of prevailing maintenance policy. In the same vein, Daniel and Ellis (2007) further noted that effective maintenance extends vehicles life, improves availability and retains vehicles in proper condition. Conversely, Panagiotidou et al (2007) was of the view that poorly maintained vehicles may lead to more frequent equipment failures, poor utilization and delayed operation schedules.

However, high cost of procuring spare parts , inability to keep the vehicles till its life span and failure to state when a vehicle is due to be replaced are some of the maintenance challenges experienced in Anambra State Transport Service. Furthermore, maintenance activity with emphasis on the transportation industries is therefore a formal activity directed towards vehicles, equipment and facilities to ensure upkeep and repair, as well as their good working condition carried out by the maintenance department with a view to improving and increasing the operational efficiency. In conclusion, this research work is geared towards solving the maintenance challenges of Anambra State Transport Service using recursive Dynamic Programming model, Forecasting models, Main and Cause effect tool and Response Surface model.

1.2 Problem Statement

The need for maintenance is predicated on actual or impending failure as reported by Mahmut (2000). The design life of most vehicles requires periodic maintenance. In this regard, Latham(2008) was of the opinion that failure to perform maintenance activities intended by the vehicle's designer shortens the operating life of the vehicles. For decades, transport operators and other organizations pay more attention to service and material production, generally

ignoring the maintenance functions, which are considered unimportant. However, Duffuaa, Ben-Daya, Al-Sultan and Andijani (2001) maintained that one of the most important factors causing this was that maintenance departments become cost centers within these organizations. For many asset-intensive industries the maintenance costs are a significant portion of the operational costs. With respect to this, Pongpech, Murthy and Boondis (2006) observed that the maintenance expenditure accounts for 20-50% of the service cost for the industry, depending on the level of the equipment.

Prior to this study, Anambra State Transport Service (ATS) was challenged with high cost of maintaining its vehicles, high costs of procuring spare parts, inability to keep the vehicles till its life span, and failure to state when a vehicle is due to be replaced and how these vehicles could be rated for replacement purposes, but to a large extent, based on any such decision on the vehicles' expected useful life (economic life span). These decisions are meant to ensure that vehicles purchased with Anambra Transport Sector's funds are maintained and remained in transit use for a minimum of normal service life. If the right kind of maintenance strategy is rightly implemented, there should be a commensurate positive effect on the vehicles efficiency and reliability.

1.3 Aim and Objectives

1.3.1 Aim:

The aim of this research work is to develop vehicles preventive maintenance and replacement schemes for Anambra State transport Service.

1.3.2 Objectives:

To achieve the above aim, the following objectives are pursued:

1. To model the operational costs of Anambra State Transport Service vehicles, using dynamics programming to determine the optimal replacement policy.

2. To apply some selected forecasting techniques in estimating the operational costs of Anambra State Transport Service vehicles.
3. To Analyze the influence of environmental factors on the operational costs of Anambra State Transport Service vehicles, using main cause and effect tool.
4. To optimize the operational costs of Anambra State Transport Service Vehicles, using response surface method.

1.4 Justification

The accomplishment of the dynamic programming based automobile replacement policy stated would assist Anambra State Transport Service in particular and perhaps other Transport Service Providers nationwide to better access and manage vehicle need, particularly maintenance and replacement. The creation of a more effective vehicles replacement system would be of tremendous benefit in money savings. Furthermore, the study would provide specific maintenance and replacement action indices for determining, monitoring and evaluating the effectiveness of maintenance and replacement activities. Finally, the study would be used as a guide for organizations to improve or promote their maintenance strategies, and the result would benefit future researchers in this field on how to adopt maintenance measures.

1.5 Scope of Study

This research work is concerned with the application of maintenance and replacement models at Anambra State Transport Service. However, for the past years the company has experienced a lot of maintenance challenges such as high cost of maintaining its vehicles, high costs of procuring spare parts, inability to keep the vehicles till its life span, and failure to state when a vehicle is due to be replaced and how these challenges can be overcome remains a problem. In fact, the work, though generalized, is mainly an attempt at solving the maintenance and replacement problems at Anambra State Transport Service.

Thus, the maintenance management problems presented and solved in this work are particularly those that exist at Anambra State Transport Service.

CHAPTER TWO

LITERATURE REVIEW

The literature for the study was reviewed under the following headings; conceptual framework(maintenance, components of maintenance, maintenance policies), dynamic programming, maintenance models for a fleet of vehicles, replacement problems,algorithms(exact, heuristics and meta-heuristics, hybrid, multi-objective),simulation models(Monte Carlos, discreteevent, continuous), age reduction and improvement factor model, applications of dynamic programming technique(production and inventory control problem, manufacturing and production problem, equipment replacement problem), and summary of the review.

2.1 Conceptual Framework

2.1.1 Maintenance

The key objective of maintenance is to identify potential failures with sufficient lead time to plan and schedule the corrective work before actual failures as supported by Redmer(2005). Maintenance is also geared towards identifying potential vehicle component defects for replacement or repair before the vehicle experiences a failure. Maintenance provides extensive knowledge of the vehicle fleet as well as analysis of maintenance activities and failure trends. In this regard, Quansong and Steele(2006) reported that maintenance provides and promotes vehicle safety and extends vehicle life, reliability and longevity. Reiterating, Kelly and Harris(1998) upheld that optimum maintenance strategy entails ensuring the equipment functions (availability, reliability, product quality etc.); ensuring the equipment reaches its design life; ensuring equipment and environmental safety; ensuring cost effectiveness in maintenance and the efficient use of resources.

The maintenance of production machinery, equipment and assurance of availability of spare parts are becoming increasingly important as seen in Ramdeen(2005).The challenges of intense international competition and market globalization have placed enormous pressure on maintenance system to improve efficiency and reduce operational costs as upheld by Godwin and Achara(2013). These challenges have forced maintenance managers to adopt tools, models, methods, and concepts that could stimulate performance growth and minimize errors, and to utilize resources effectively. Maintenance management according to Kamran (2008) is the art of keeping the machineries and their operators in good working condition. Poor maintenance management causes frustration in business because the machineries fail erratically and sometimes, when it is most needed. It is necessary that one knows everything about the equipment he is operating. To this end, Ezechukwu(2012) opined that staff training is extremely important in keeping the machineries in good working condition. The maintenance of complex equipment often accounts for a large portion of the costs associated with that equipment. It has been estimated, for example, that the maintenance costs of military equipment comprise almost one third of all the operating costs incurred as opined by Pongpech et al(2006).

One of the goals of a successful and efficient public transportation provider according to Joe, Levers and Ferris(1997)is to promote vehicle safety and extend vehicle life. Vehicle reliability and longevity can only be accomplished by implementing various maintenance practices. This practice as supported by Kuo and Chang(2007)requires extensive knowledge of the vehicle fleet as well as analysis of maintenance activities and failure trends. Proactive maintenance is preferable to reactive maintenance when managing a fleet of vehicles as reported byLeng, Ren and Gao(2006) . Responding to failures after they happen, instead of anticipating them as buttressed byLim and Park(2007)limits the ability of the agency to plan and schedule their maintenance. This creates a continual failures and making emergency repairs to get vehicles back in service,

thus creating an unmanageable and costly situation. Bottazzi, Dubi, Gandini, Goldfeld, Righini and Simonot(1992) reported that poor maintenance management causes frustration in business because the machineries fail erratically and sometimes, when it is most needed. There are different approaches to how maintenance can be performed to ensure vehicles reach or exceed its design life. In all sectors of engineering, every effort is put on maintenance schedule. Some need daily attention, others weekly or monthly while some require annual maintenance, etc.

2.1.2 Components of Maintenance

Maintenance can be classified into two scheduled and unscheduled maintenance as under listed:

(1)**Scheduled Maintenance:** This is otherwise called Planned Maintenance. Scheduled maintenance according to Malik(1979) entails that every item in the system is put into the maintenance schedule and a well-planned schedule will provide for alternative supply when an important item is taken out for maintenance. This planned component repair or replacement is often triggered by preventive maintenance inspections, pre-trip and post trip inspections, regular oil changes and grease jobs, etc., all of which are also scheduled activities as supported by Martorell, Sanchez and Serradell(1999). Scheduled maintenance has preventive maintenance as its component.

(a)**Preventive Maintenance:** The equipment here according to Panagiotidou and Tagaras(2007) is periodically taken out of service for scheduled maintenance including replacement of worn components, inspection and cleaning, etc. The frequency of machine maintenance may be based on hours of usage, number of machines cycles, calendar time, etc., as reported by Shalaby, Gomaa and Mohib(2004). Hopefully, the preventive maintenance makes failures less likely. Normal preventive tasks include the following: state inspection, as required by the law; oil changes, tune-up, as stated by the manufacturer of the

vehicle; the vehicles service life can be prolonged by doing preventive maintenance. It is further divided into periodic maintenance, predictive maintenance, routine maintenance and proactive maintenance.

(ai)**Periodic Maintenance:** This is otherwise known as Time based maintenance (TBM). Time based maintenance according to Shum and Gong(2007) consists of periodically inspecting, servicing and cleaning vehicles and replacing parts to prevent sudden failures and process problems.

(aii)**Predictive Maintenance:** This is a method in which the service life of important part is predicted based on inspection or diagnosis as reported by Limbourg and Kochs(2006). Here the vehicle is continually monitored or frequently inspected by manual or automated means. Required maintenance is identified and performed upon inspection.

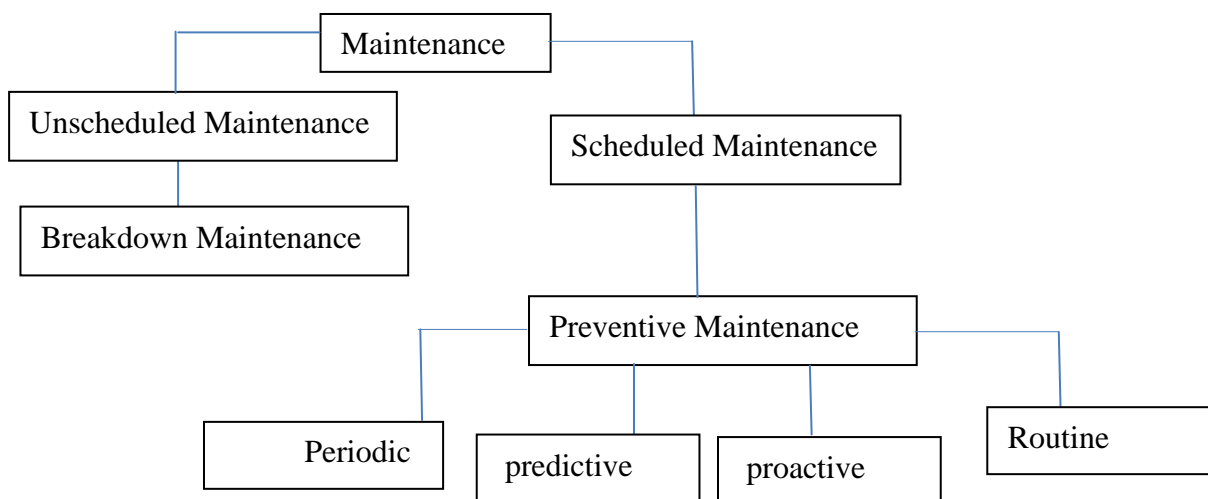
(aiii)**Routine Maintenance:** This is otherwise known as Regular Maintenance. Routine maintenance, as reported by Fard and Nukala(2004) encompasses that each vehicle has a regular oil changes as specified by the manufacturer and annual state inspection. The regular maintenance contributes to the efficiency of vehicle serviceability. Oil changes and minor repairs are carried out in a timely fashion at the specified vehicle maintenance facility.

(aiv)**Proactive Maintenance:** This begins with preventive maintenance inspections. These inspections as supported by Billiton and Pan(2000) can include pre-trip and post-trip checks, oil changes and other related services, and preventative intervals for vehicle components identified. Drivers are the first line of defense against unexpected failures. Mechanics rely on the observations of the driver, while operating the vehicle to identify potential failures. Mechanics must also be skilled and familiar with the vehicles they are inspecting and follow guidelines regarding how preventive maintenance should be carried out. A mechanic must have this knowledge and experience to identify the correct repair to be made. Without proper work identification, maintenance

resources will be wasted and incorrect work will be planned as upheld by Alfare(2002).

(2)**Unscheduled Maintenance:** This is called an unplanned maintenance or emergency maintenance. This, according to Rezg, Chelbi and Xie(2005) results from errors that were not detected during the planned maintenance. Accident can also trigger this off. In this case, the equipment has broken down. An emergency arrangement has to be provided to put it back to service(at all costs).For example, in power supply, as supported by Sherwin(1999),consumers may not have prior knowledge of the outage and that can cause a lot of disorganization of plans and frustrations etc.Unplanned maintenance includes break down maintenance.

(i)**Break down maintenance:** This is otherwise known as reactive Maintenance. The vehicle here is put in service and operated until it fails as maintained by Tam, Chan and Price(2006).Maintenance forces then repair the vehicle and attempt to restore it as closely as possible to a like-new condition, where upon the vehicle is put back in operation. Maintenance is confined to repair following failures.



(Source :Ezechukwu,2012)

Figure 2.1:Components of Maintenance.

2.1.3 Maintenance Policies

Six maintenance policies are identified as itemized below:

(i)**Operate Until Failure:** This type of maintenance policy implies that all repairs will be corrective as upheld by Tsai,Wang andTeng(2001).In this situation, work flow cannot be effective, making it the least preferred strategy. However,Tsitsiklis and Van(2009) were of the view that this maintenance policy could be the most cost effective under two conditions, if the item cannot be monitored or if it is just as cost effective to replace the item after failure as it is before.Examples are fuses, light bulbs, etc.

(ii)**Condition Based Maintenance:** This is the maintenance resulting from observed change(s) in the monitored parameter. Such parameters according, to Wang and Hwang(2004) could be one or more of temperature,sound,acoustic,corrosion,color,vibration,etc. Condition based maintenance as supported by Wang and Handschin(2000),can predict approaching failures when monitoring a component is possible, for examples brake shoe wear and oil consumption. The component is used until nearly the end of its life, with respect to this, Zhou, Jiang, Wang,Wu, and Xi(2007) opined that such component should be replaced before an in-service failure causes significant additional maintenance costs. Unpredictable failures are also nearly eliminated. These are monitored through regularly scheduled preventive maintenance inspections and data analysis.

(iii)**Fixed Mileage Maintenance:** Fixed mileage maintenance can be carried out where there is a known relationship between miles travelled and failures as reported by Suresh and Kumarappan(2006).This type of maintenance as concurred bySortrakul, Nachtmann and Cassidy(2005)has a degree of chance variation unlike condition based maintenance. For example, a specific transmission model has shown a history of 150,000 miles as developed by Savsar(1997) in which a manager initiates a campaign to overhaul the transmission before the vehicle reaches 150,000 miles. The maintenance manager can schedule work flow more efficiently, and reduce road calls, while increasing service reliability.

(iv)**Design Out Maintenance:** Design out maintenance is a procedure being developed by Rees, Clayton and Taylor(1982)that attempts to remove the maintenance problem on occasion where manufacturing designs appear feasible but do not work in an actual operating environment. If maintenance costs are excessive the manufacturer may need to redesign the component or the transit agency may have to purchase an alternate component or system as reported by Paz, Leigh and Rogers(1994).

(v)**Time Based Maintenance:** This is the type of scheduled maintenance as observed by Lin, Eamonn and Chiu(2003)which is carried out at stipulated time intervals, sometimes recommended by the manufacturer. The time interval recommended for maintenance of a system could change as the vehicle gets older and requires more frequent maintenance. Besides, maintenance interval could be determined by other factors such as: distance covered, environment, duty cycle etc.

(vi)**Condition Monitored Maintenance:** In this method statistical approach is adopted and probability theory is used in determining where and how to replace an item as explained by Marseguerra, Zio and Podofillini(2002).This is in line with Lisnianski and Levetin(2003) observation that the trend detection through data analysis exposes failure cause and preventive actions that can be taken to avoid such failures in the future. Statistical approach is most effective where there are large numbers of similar items.

2.2 Dynamic Programming Review

Dynamic programming works on the principle of finding an overall solution by operating on an intermediate point that lies between where we are now and where we want to go. They do not have to be written even in a computer programming language, David(1995) as concurred by Cheng, Chen & Guo(2007).It is basically a stage wise search method of optimization problems whose solutions may be viewed as the result of a sequence of decisions as

elaborated in Bhowmik(2010). Unlike the case in divide-and-conquer algorithms, immediate implementation of the recurrence results in identical recursive calls that are executed more than once, Alsuwaiyelh(2002) explained. The structure of dynamic programming is similar to divide-and-conquer, except that the sub problems to be solved are overlapping in nature which makes as a consequence different recursive paths to the same sub problems, Chow et al(1989) indicated. Thus, for solving a problem, divide-and-conquers is independent sub-problems, solve sub-problems independently and recursively. Conversely, in dynamic programming sub problems are dependent. Greedy method is also a powerful technique for optimizations but not much like dynamic programming approach. In greedy method, we solve a problem making greedy choices. After the choice is made the sub problem arises. These choices may depend on previous choices. However, the choice is independent of the solutions to sub problems as seen in Chan(2001) with respect to Vijay(2006). Top-down convention is normally used towards the feasible solution decreasing current problem size. Unlike greedy, choice is made at each step and bottom up approach is employed increasing problem size from smaller to larger sub problems answering optimal solutions.

In identifying an optimal strategy for finding a solution to a contract bridge tournament, Beaumont(2007) used dynamic programming to accomplish this task. The contract bridge tournament comprises several rounds of matches in which players compete as pairs for, master points, awarded for each match won or drawn and for being highly placed at the end of the tournament. In the second and subsequent rounds, pairs are matched against other pairs that have been approximately equally successful so far. The optimal strategy is a function of pair's ability. The best-scoring set of beat times that reflects the tempo as well as corresponding to moments of a high ,onset strength, in a function derived from audio was found using dynamic programming as seen in Daniel andEllis(2007).This very simple and computationally efficient procedure is

shown to perform well on the MIREX-06 beat tracking training data, achieving an average beat accuracy of just fewer than 60% on the data development, but was not able to arrange data properly. Nicole and Quenez(1995) also used to determine a solution for the problem of pricing contingent claims or options from the price financial market. In this situation, there is a price range for the actual market price of the contingent claim. The maximum and minimum prices are studied using stochastic control methods.

The main result of this work is the determination that the maximum price is the smallest price that allows the seller to hedge completely by a controlled portfolio of the basic securities. Billiton and Pan(2000) described a compile-time analyzer that detects dynamic errors in large, real - world programs. The analyzer traces execution paths through the source code, modeling memory and the reporting experienced a lot of inconsistencies. Zeqing et al(2006) introduced and studied properties of solutions for functional equations arising in dynamic programming of multistage decision processes but was inconclusive. Quansong and Steele(2006) in their studies identified the microbial community composition and its variations in environmental ecology using dynamic programming. Clustering analysis of the Automated Ribosomal Interagency Spacer Analysis (ARISA) from different times based on the dynamic programming algorithm binned data revealed important features of the biodiversity of the microbial communities but was inaccurate. Stochastic dynamic programming model was used by Norman et al(2004) to examine the appropriateness of sending a lower order batsman into, hold the fort, “on sticky wickets”. In cricket, a rain-affected pitch can make batting more difficult than normal. Several other conditions such as poor light or an initially lively pitch may also result in difficulties for the batsman. All these are referred to as “sticky wickets”. Dynamic programming (DP) was used to get an optimal price for a car of a professor who had limited number of days to leave a country after his sabbatical leave. Mahmut(2000) detailed this classical dynamic

programming application. DP approach is by far the most powerful optimization paradigm over the others. But its popularity stems from the comparative study with other two popular techniques Divide-and-Conquer and Greedy Method carried out in Hagmark and Virtanen(2007) as upheld by Bhowmik(2010). Like divide-and-conquer, dynamic programming results in optimal solutions by combining the partial best possible solutions to sub-problems.

2.3 Review of Maintenance Models for a Fleet of Vehicles

Here the maintenance models for a fleet of vehicles are being reviewed.

The first works done in this direction were some attempts to apply classical methods to determine optimal replacement policies of a vehicle. The "economic life approach". Which consists of replacing a vehicle after a fixed interval of time was applied widely at the beginning as opined by Eilon, King and Hutchinson(1966). But this approach was not very effective since it did not take into account the specificity of each vehicle. Hasting(1969) presented the "repair limit method", which was at that time used by the British Army, and which consists of comparing the eventual repair cost of a failed unit upon failure with a repair limit. If the estimated cost is less than the limit, the repair is carried out, otherwise a replacement is made. Westman and Hanson(2000) developed a model to determine the mean time to failure (MTTF) as a function of the uptime for a workstation in a multi-stage manufacturing system. The authors assumed that the uptime of the workstation has an increasing failure rate and would be reduced if preventive maintenance actions were performed. They mentioned that this methodology did not capture the flexibility and multi-stage properties of manufacturing systems. Westman and Hanson(2000) formulated a mathematical model to find the optimal production scheduling via linear quadratic Gaussian Poisson function with state dependent Poisson process. They considered the total cost of production and maintenance

policies as the objective function and demonstrated the application of the model by a numerical example. Burton, Banerjee and Sylla(1989)proposed an improved replacement policy based on this repair limit method.

The age of the vehicle was discretized in m states. Each state was associated two stochastic processes: one described the number of failures in that state and the other the cost of repairing the vehicle upon failure. The cumulative cost of repairing a vehicle was the stochastic process under study. It was not a Markov process (except if all failure counting processes are Poisson), but the sequence of visited states formed a Markovian chain and this made the analysis tractable. In each state, the cost of a repair was considered to be Weibull distributed and the number of failures formed a Nyman distribution. The different parameters were set from the data, and then using a dynamic programming method, the optimum set of repair limits was obtained. Besides, the authors investigated the case of the existence of a constraint on the number of available repair hours, and a penalty cost of having a vehicle off. But as in any replacement policy which uses repair limit based on age or mileage, this model assumed that all the mentioned processes were independent. Another drawback was that decisions were all taken upon failure so there was no planned schedule of the maintenance. Dedopoulos and Smeers(1998)used the approach of an Annual Maintenance Cost Limit (AMCL) to set replacement decisions. Each year the decision to replace or not a vehicle was made by comparing the estimated maintenance bill for the next year with the AMCL. The maintenance cost of a vehicle of a specific age was considered to be Weibull distributed and the optimal maintenance cost limit which minimizes the expected total cost of maintaining and replacing a vehicle over a fixed planning horizon was determined. Jabayalan and Chaudhuri(1992) presented two different preventive maintenance models for maintaining bus engines in a public transit network based on minimization of the total cost over a finite planning horizon. They constructed the models based on the concept of mean time between failure

(MTBF) of the engines and assumed the upper bound for the failure rates. The first model was based on different Weibull failure functions between preventive maintenance activities and the second assumed that each preventive maintenance action reduced the effective age of the system. Besides, the authors showed how to take into account the effect of allowances on replacement decisions. But once again, the suggested policy only set when it was preferable to replace than continue to maintain a vehicle, no schedule of the preventive maintenance was considered and the assumption of a fixed, finite planning horizon was contentious. Savsar (1997) conducted a case study about the maintenance of tramcars for Hong Kong Trams way Company. The vehicle was subject to regular overhauls and failures.

The general maintenance policy was to make the best use of opportunities provided by failed components and essential overhauls. In this goal, preventive replacement age limits for the different components must be determined. The difficulty here was that the cost of a component preventive replacement depended on what else was being repaired at that time. No failure cost was added, and the times between overhauls were assumed to be identically distributed. The authors stressed on the fact that for a system of more than two components. The optimum age limits would not be constant but would depend on the age of the non-failed components. They proposed two suboptimal policies which are pairwise control policies. Fischer (2010) reported a model of maintenance planning for transit vehicles, which has been implemented under the features of a computer software package called MASSTRAM. They modeled each component failure time with a Weibull distribution and determined for each of them the best replacement mileage. With inflation taken into consideration, this age replacement strategy was found to be more cost-effective than the "repair upon failure" policy, "provided that a set of real failure data was available and the assessment of cost was accurate. "After these first surveys on the fleet vehicle problem, the attention was brought to the importance

of maintenance schedules. So, the subsequent research focused on the determination of optimal inspection and maintenance schedules. Whitley(1989) advanced a methodology for modeling planned preventive maintenance for a vehicle fleet. Merediscussion on what should be on the maintenance schedule (recommending snap-shot modeling for this stage), he investigated the scheduled inspection, re-scheduled repairs (when some defects noticed during the inspection, have been re-scheduled because of insufficient resource) and unscheduled repairs (which correspond to breakdown repairs). The author reduced the problem to an inspection system. He used the concept of delay-time analysis, whereby the percentage of defects arising at breakdowns could be expressed as a function of the inspection period, then they could evaluate the optimal inspection period. However, this approach assumed that the delay-time density probability function was accessible, which is not realistic and that the occurrence of defects was not uniformly distributed over the interval between PM services. John(2006) analyzed a vehicle-fleet system where the vehicles were subject to periodic inspections (every N kilometers), and defined an optimal inspection schedule which maximizes the vehicle availability. Breakdowns occurrence, repair time and inspection time were assumed to be exponentially distributed. But the major point of this model was the assumption that vehicle breakdowns could be influenced by the inspection frequency, thus the mean distance to failure varies with the value of the periodic inspection distance. The authors demonstrated how this relation could be estimated in practice and then showed how the total downtime of the vehicles due to inspection and repair was related to the inspection frequency. Javadan (2006) considered another approach. Preventive maintenance (PM) was not performed at periodic inspections any longer but when the failure rate of the system reached a critical predetermined level. The post-maintenance condition lies between "as good as new" and "as bad as old". Two cases were considered: when the system had a different Weibull time to failure distribution between

PMs, and when it was just considered that the age of the system was reduced after each PM. In both cases, the number of PM interventions before scrap were determined such that the expected average cost per unit time over an infinite horizon was minimized.

Other works have been developed which dealt with the maintenance of a fleet of vehicle but their focus were on different topics. So Goel, Nanda and DSa(1973) suggested applying multiple criteria decision making in the field of transit vehicles maintenance in order to take greater account, when determining optimal policies, of the different criteria such as minimum cost rate, maximum availability, bottom-line component reliability etc. Canfield(1986) tackled the problem of equipment replacement in an unsteady economy. Indeed, the replacement of units in a fleet of fork lift trucks, for instance during a period of inflation and uncertain economy has to be considered differently than in the traditional case. All these considerations have obviously been taken into account while elaborating a maintenance model. Besides, we want to mention here the existence of two studies, conducted by Limbourg and Kochs(2006) devoted to the comparison of popular models subjected to real data. The objective of the first one was to find optimal bus replacement times, and of the second one the optimal maintenance epochs for components of transit buses. To conclude on this particular system of a vehicle fleet, we could say that many approaches have been considered which dealt with the maintenance problems. Some and especially those focusing on optimal inspection schedule were of a real interest but they have never considered the fleet as a whole. However, this approach needs to be conceived in some cases such as when the maintenance capacities are limited, or when the work load was shared so that a vehicle breakdown has a non-negligible impact on the failure rate of the other vehicles.

2.4 Review of Replacement Problems

Various approaches and models have been deployed towards addressing the problems of replacement by researchers. In order to complete a comprehensive and a thorough overview of developed approaches, published models and studies were reviewed and a survey was carried out to answer how replacement problems were managed in practice at various Transport service providers as upheld by Cheng et al(2007). This approach revealed among other things a difference between theory and practice. This assessment focused on equipment replacement studies and research that were applicable or motivated by replacement for bus fleets. It is worth noting, however, that equipment replacement dates back from two early works of Taylor(1923) as strengthened by Hotelling(1925). Taylor in his paper developed by means of a discrete period analysis, a formula relating the average unit cost of the output of a machine over L years (the years of machine life) to the cost of a new machine, the scrap value of the machine after L periods of service, the operating costs of the machine in each period of service up to the L period, the output of the machine in each period, and the rate of interest.

The manufacturer's desire to make his unit cost a minimum or that consideration of profit led him to scrap the machine at some different point in time from what makes the unit cost a minimum remained the key challenge that propelled Hotelling's different dimension to Taylor's preposition. He advanced the view point that the owner of the machine wished to maximize the present value of machine's output minus its operating costs. Preinreich(1940) explained that the economic life of a single machine could not be determined in isolation from the economic life of other machines in the chain of future replacements extending as far as into the future as the firm's profit horizon. He argued that the firm should maximize the present value of the "aggregate goodwill" of all replacement, where the goodwill was the present value of earnings of the future machine, replacements minus the present value of costs of all such machines. An intuitive method for identifying replacement candidates was to define a

replacement standard such as an equipment age standard. Assets that exceed the age standard were candidates for replacement. A ranking can then be implemented that sorts equipment units by how much they exceed the standard. One of the most popular approaches to estimate an optimum replacement point that results in the lowest total overall cost over the vehicle's economic life was the application life cycle cost analysis (LCCA) of single asset replacement to compute an "economic life," as supported by Adams(2015). But this approach was flexible and needed extensive amounts of data and could be complicated to implement. Elion et al(1966), considered acquisition cost, resale value and maintenance cost in order to derive the minimum average costs per equipment year and the corresponding optimal equipment age policy for a fleet of fork lift trucks. Chee(2012) analyzed the fleet of Ontario Hydro using LCCA and generated optimal equipment age policies for different equipment classes. Chee proposed also to consider repair costs for individual equipment units given that LCCA gives only one replacement criterion— namely the economic life — for a single equipment class.

As a result, repair cost limits were computed in addition to an economic life. If a fleet member stays within the repair cost limits for each year, it was replaced only after reaching the economic life of its class. Weismann and Gona(2003) applied LCCA to individual pieces of equipment in the Texas DOT fleet. Their results indicated that this approach combined with a multi-attribute ranking was more cost efficient than utilizing a single age standard. This multi-attribute ranking considers economic life, operation costs, repair costs and usage in order to assign replacement priorities to equipment units. Love, Rodger and Blazenko(1982) came out with similar results having worked with fleet data from Postal Canada and compared economic age policies with repair cost limit policies. They derived economic ages analytically and repair cost limits were generated in a Markov simulation. Applied to the Postal Canada fleet, the repair cost limit policy was superior to the economic age policy. Instead of using

repair cost limits for repairs that have occurred. Hastings(1969) derived repair cost limits for estimates of future repair costs. He assumed that before any repair measure was conducted, fleet members were run through an inspection and repair costs were estimated. The actual repair was only undertaken if estimated costs were smaller than the derived repair cost limit. Nakagawa(1974) in a much more different approach did not focus on repair costs, but on repair time. Their policy was characterized by defining a limit for the time a broken unit of equipment spends in repair measures. Minimizing expected costs per unit time over an infinite time span yielded the repair time limit as per its derivation. The problem of optimal replacement to the problem of optimal buy, operate and sell policies has been expanded by other approaches, Simms, Lamarre and Jardine(1984)detailed data from an urban transit bus fleet. Equipment units in this fleet were operated at different levels and performed different tasks as a function of age or cumulative mileage, subject to varying capacity constraints.

Consequently, newer equipment units had different acquisition and operating cost structures than older less sophisticated fleet members. By applying a combination of dynamic programming and linear optimization, an optimal buy, operate and sell policy was derived for the investigated fleet. Hartman in a similar fashion as Simms et al looked for the minimum cost replacement schedule and associated utilization levels for a multi-asset case – emphasizing that utilization is a decision variable and not a parameter. The author examined the problem of simultaneous determination of asset utilization levels as well as replacement schedules, while the total costs of assets that operated in parallel were minimized. A linear program that considered dependency of operating costs on utilization levels and dependency of utilization levels on a deterministic demand solved the problem. In later works, Hartman was encountered with the same challenge, but asset utilization levels had to meet a stochastic demand as posited by Hartman(2004). With two equipment units and

parallel operation of both assets in a much more simplified case, the author determined the optimal replacement schedules and utilization levels for both individual buses by applying dynamic programming. Both Simms and Hartman faced complex equipment replacement, and operating problems in bus fleets. They did not promote particular replacement criteria but presented optimization methodologies that led to cost efficient results for a specific fleet. Previous works reviewed specifically did not consider decreasing utilization levels of assets as they age. At some transport Sectors, equipment utilization has been decreasing with equipment age, but constant utilization has been a widely spread assumption made in the replacement models literature.

Simms et al(1984) derived an optimal buy, operate and sell policy for an urban transit bus fleet whose members operated at different levels depending on equipment age. They reduced the problem to two levels of utilization: young buses were operated at a constantly high level meeting the base demand, while utilization was constantly low for buses older than ten years because they were only used when needed to meet peak demand. Unlike the replacement decision at other transport service providers however, they assumed utilization was controllable. Redmer(2005) derived the optimal lifetime limit or economic life for freight transportation fleet, which showed decreasing utilization as equipment grew older and constant utilization levels within age classes. The basis of his model was the LCCA approach from Elion et al(1966), which assumed constant utilization, and thus, was not directly applicable to the fleet considered. Redmer concluded that Elion's model provided lifetime limits approaching infinity when the fleet data showed decreasing utilization with age. Instead of using costs per unit time, Redmer modified Elion's LCCA approach so that costs were given per kilometer. As a result, discounted costs of ownership per kilometer were minimized over replacement age and a feasible, cost minimizing economic life was provided. Problems related to equipment replacement in fleets were analyzed by Khasnabis, Bartus

&Ellis(2003).Davenport, Anderson and Farrington(2005) made a replacement demand forecast by simulating the steady process of deterioration and equipment breakdown within a Markov type network.

They created a fleet condition forecast model for a fleet of cutaway passenger vans by using a regression model they found out that, the parameters equipment age, total mileage, miles per year on unpaved roads, lift equipment, and percentage of population older than age 65 were the best equipment condition predictors. With the assumption that future demand for fleet services and the expected costs of replacement, rehabilitation and remanufacturing were known. Khasnabis et al(2003) showed that the optimal capital allocation for the dual purpose of purchasing new equipment units and rebuilding existing ones within the constraint of a fixed budget could be obtained with linear programming, but could not consider the historical trend of these equipment.

Zhou and Lee(2006) presented a dynamic opportunistic condition-based predictive maintenance policy for a continuously monitored multi-unit series system that was proposed based on short-term optimization with the integration of imperfect effect into maintenance actions. In their research, it was assumed that a unit's hazard rate distribution in the current maintenance cycle could be directly derived in which case when one of the units fails or reaches its reliability threshold, the whole system has to stop. Gupta and Lawsirirat(2006) presented a simulation based optimization method for strategically optimum maintenance of monitoring-enabled multi-component systems using continuous-time jump deterioration models. Sherwin(1999) with the concept of opportunity maintenance suggested new ways to construct and update preventive schedules for a complex system by making better use of system failure down time to do preventive work. Moreover, the time scale assumed discrete and the „true' state of the system (excellent, medium and bad) was not directly observable. The

observation was the performance of the system measured in terms of number of defectives ‘per time period.

2.5 Algorithms

Many useful algorithms are recursive in structure. In solving a given problem the algorithm calls a subroutine recursively one or more times to deal with closely related sub-problems. These algorithms typically follow a divide-and-conquer approach in the sense that they break the problem into several sub-problems that are similar to the original problem but smaller in size. The sub-problems that are similar to the original problem but smaller in size are solved recursively, and then these solutions are combined to create a solution to the original problem. Some of these algorithms are reviewed as listed below:

2.5.1 Exact Algorithm

Exact algorithm has been applied in numerous ways by researchers to tackle maintenance and replacement challenges. Yin, Wen, Qian, and Yang(2007)presented a two-layer hierarchical model that optimizes the preventivemaintenance in semiconductor manufacturing operations and optimized this model via a mixed integer linearprogramming model. They defined profit of cluster tools production as the objectives and limitation of resources as the constraint, which were nonlinear functions. In order to achieve a global optimum, they transferred the nonlinearfunctions into linear ones and use EasyModeler and OSL as the optimization software.Jayakumar and Asagarpoor(2004)applied a linear programming model in orderto optimize the maintenance policy for a component with deterioration and random activefunction to bemaximized and considered time window for preventive maintenance to optimize the maintenance policy for a component with deterioration and random failure rate. They determine optimal mean times of minor and major preventive maintenance actions based on maximizing the availability of the component. They utilize MAPLE and LINGO for solving the

linear programming model of Markov decision process. Dwaikat(2009) presented a model and algorithm for maintenance optimization of a system with series components.

In this research, they assumed that all components have linearly increasing failure rate with a constant improvement factor for imperfect maintenance. In addition, they considered the total cost as the objective function and the total downtime as the main constraint. In terms of maintenance activities, they defined preventive and corrective maintenance for each component. Finally, their algorithm optimized the interval of time between maintenance actions for each component over a planning horizon. Canfield(1986) presented an optimization model to schedule a preventive maintenance of a real power plant over a planning horizon. He considered the total cost of various operations as the objective function and uses Bender's decomposition to solve a mixed-integer linear programming model. Brown(1984) presented two mixed-integer linear programming models for preventive maintenance problems. The author assumed the total cost including possession costs, maintenance costs, and the penalty costs of early consecutive maintenance activities as the objective function for both models. He presented and proved a theorem about the NP-hard structure of the preventive maintenance problem and use GAMS to implement the optimization models. He used CPLEX as the optimization software to find the optimal preventive maintenance schedule. He applied their model to a case study of railway maintenance scheduling. In addition, he developed four heuristic optimization algorithms, two for each model, and compared the computational results obtained from exact algorithms in CPLEX with the results achieved from heuristic algorithms and mentioned the advantages of each solution methodology.

Another excellent study in this area was by Lapa, Pereira and De Barros(2006) who developed three nonlinear optimization models: one that minimizes total cost subject to satisfying required reliability, one that

maximizes reliability at a given budget, and one that minimizes the expected total cost including expected breakdown outages cost and maintenance cost. They utilized MS-Excel Solver as the optimization software that used a generalized reduced gradient (GRG) algorithm to solve the nonlinear optimization models. Using these models, they determined the optimal maintenance intervals for a multi-component system but their models considered only maintenance actions for components and did not consider replacement actions. Panagiotidou et al(2007) developed an optimization model that optimizes the preventive maintenance schedules in a transportation process. The authors considered two different states for components, in-control or out-of-control, before complete failure. They treated the time to shift and the time to failure as random variables and expressed them with Weibull and Gamma distributions. Shirmohammadi, Zhang and Love(2007) presented an age based nonlinear optimization model to determine the optimal preventive maintenance schedule for a single component system. They defined two types of decision variables, the time between preventive replacements and the cut-off age, and assumed an expected cost of failures, maintenance, replacement costs, and total cycle cost the preventive maintenance schedules in a manufacturing process for a single component system. They defined two types of decision variables, the time between preventive replacements and the cut-off age, and assume an expected cost of failures, maintenance, replacement costs, and total cycle cost in the cost function and considered cost per unit time as the objective function. In order to solve the optimization model and show the effectiveness of the proposed approach, they utilized MAPLE and run the program for a numerical example by setting different values for an improvement factor, which was assumed as a constant in the model.

Dynamic programming has been broadly used as a standard optimization technique to achieve the optimal maintenance and replacement actions in engineering problems. Canfield(1986), studied preventive maintenance

optimization models via focusing on different aspects of failure function on systems reliability. He mentioned that preventive maintenance actions did not change or affect deterioration behavior of failure rate, so the developed failure function was constant with maintenance actions. He considered increasing failure rate based on the Weibull distribution for his study and determined the optimal cost of maintenance policies by defining the average cost-rate of system operation and applying dynamic programming as the solution approach. Robelin and Madanat(2006)developed a maintenance optimization model for bridge decks via a Markov chain process.

2.5.2 Heuristics and Meta-Heuristics Algorithms

One of the approaches that had been used to address the maintenance and replacement problems is Genetic algorithm. This was based on the heuristic and meta heuristic algorithm.Tsai,Wang and Teng (2001)considered two activities, imperfectmaintenance, and replacement, in their preventive maintenance optimization model. They modeled imperfect maintenance activities based on the concept of an improvement factor, which was determined by aquantitative assessment procedure. They used a genetic algorithm to find the optimal preventive maintenance activities while the system unit-cost life was considered as the objective function.Usher, Kamal and Hashmi(1998) in the same vein, presented an optimization maintenance and replacement model for a single-component system. They determined an optimal maintenance and replacement action for a new system subject to deterioration, by considering the time value of money in all future costs, increasing rate of occurrence of failure over time and the use of the improvement factor to provide for the case of imperfect maintenance actions.Leng, Renand Gao(2006)presented notable studies in the area of reliability and maintenance optimization for multi-state multi-component systems .They defined a multi-state system as a system in which all or some of components have different performance levels, from proper

functioning to complete failure and the reliability of the system as its ability of satisfying the demand levels.

They formulated an optimization model to determine maintenance actions that affect the effective age of components. Their model was based on minimization of cost subject to required level of reliability. They applied a universal generating function technique and use a genetic algorithm to determine the best maintenance strategy. Cassidy et al (2005) presented an optimization model to schedule the best preventive maintenance tasks of all machines in a single product manufacturing production line. They assumed that each machine should be assigned to each operator and considered the total throughput of the line as the objective function to be maximized. At the first step, they formulated the optimization model and analyzed it via analytical approach. Then, the researchers used C++ as a programming environment and applied genetic algorithm in order to find the best combination of preventive maintenance tasks. In addition, they constructed an experimental design to set and analyze the parameters of genetic algorithm and utilized the Taguchi method and statistical analysis to validate the results. Finally, an application of the approach was performed in an actual production line of car engines. Lin, Eamonn and Chiu (2003) presented an optimization model to find the optimal preventive maintenance schedule for a multi-component system. He considered total cost of operations and maintenance activities along with reliability as the criteria of the system and transfers them into the objective function by defining degree of violation from required reliability. In addition, he defined maintenance crew and duration of maintenance as the system's constraints. He applied his optimization model in a case study with six electric generators and utilized genetic algorithm as the optimization methodology to determine the best preventive maintenance schedule. Han, Fan, Ma and Jin (2003) considered the recursive nature of failure rate between preventive maintenance cycles and developed a nonlinear optimization model based on repair cost, preventive maintenance cost, and

production loss cost in a production system. They applied a genetic algorithm as the optimization technique and mentioned that their model can be considered in decision support systems for maintenance and job shop scheduling. Billiton et al(2000) considered cost and availability as the systems criteria in their research. They optimized a model including cost in the objective function and availability as the constraint by using a genetic algorithm to find the best preventive maintenance schedule. They used a time-dependent Birnbaum importance factor to generate the ordered sequence of first inspection times and utilize MATLAB to calculate the system availability via a Monte Carlo simulation approach. Limbourg and Kochs(2006) proposed several techniques to represent the decision variables in maintenance and replacement models that used heuristics and meta-heuristics optimization algorithms.

They tested various non-standard approaches and compared them to binary representations by a heuristic algorithm, and the computational results showed the effectiveness of their approaches. In addition, they applied some modified crossover and mutation procedures in a genetic algorithm and showed the improvement in performance of their algorithm in terms of computational time and accuracy. Other research on the application of genetic algorithms to maintenance optimization has been recently done by Lapaet et al(2006). They considered flexible intervals between maintenance actions and mentioned the advantage of this assumption over the common methodologies of continuous fitting of the schedules. They developed a model that included preventive and corrective maintenance actions and the associated cost with them, outage times, reliability of the system, and probability of imperfect maintenance. Vijaya(2006) group systems and sub-systems of a large engineering plant into higher modular assemblies (HMA) and applied a multi-objective preventive maintenance scheduling method. They modeled this problem as a constrained nonlinear multi-objective mathematical program with reliability, cost, and non-concurrence of maintenance periods and maintenance start time

factor as elements of the objective functions and used a genetic algorithm to solve the model. They examined the effect of these costs on the optimal maintenance schedule in numerical example. Other meta-heuristics have been used as the combinatorial optimization techniques to solve maintenance scheduling problems. Samrout, Benouhiba, Chatelet and Yalaoui(2006) used an ant colony algorithm to optimize the problem that was previously optimized via genetic algorithm.

2.5.3 Hybrid Algorithms

In this approach, Kamran(2008) combined genetic algorithm with simulated annealing in order to optimize a large-scale and long-term preventive maintenance and replacement scheduling problem. In their research, the acceptance probability of a simulated annealing method was considered as a measure for individual survival in the genetic algorithm. Tam, Chan and Price(2006) developed a general framework for preventive maintenance optimization in chemical process operations. They assumed a Weibull model for failure rate and considered different maintenance activities that can be performed. By using this approach, they achieved a near optimal solution in a short period of time compared to the computational time of simple genetic algorithm. As a case study, they optimized a long-term maintenance scheduling problem of a thermal system. They developed a methodology that combines Monte Carlo simulation with a genetic algorithm to solve opportunistic maintenance problems with a non-deterministic objective function. In addition, they considered system reliability, minimum intervals between maintenance actions, and crew availability as the constraints of their model. Finally, a combination of genetic algorithm and simulation was utilized to optimize the model. Allaoui and Artiba(2004) presented a combination of simulation and optimization models in order to solve the NP-hard hybrid flow shop scheduling problem with maintenance constraints and multiple objective functions based on

flow time and due date. In addition, they considered setup times, cleaning times, and transportation times performed. They developed a methodology that combined Monte Carlo simulation with a genetic algorithm to solve opportunistic maintenance problems with a non-deterministic objective function. They applied their approach to two case studies to compare the results obtained from the proposed model with the results achieved from analytic approach, and Monte Carlo simulation with a neural network.

Besides, they mentioned the advantages of their approach over other approaches. Marseguerra, Zio and Podofillini (2002) developed a condition-based maintenance (CBM) model for multi-component systems and used a Monte Carlo simulation model to predict the degradation level in a continuously monitored system. They applied a genetic algorithm to optimize the degradation level after maintenance actions in a multi-objective optimization model with profit and availability as the objective functions. Based on the computational results, they mentioned that the combination of a genetic algorithm with Monte Carlo simulation is an effective approach to solve the combinatorial optimization problems. Sortrakul, Nachtmann and Cassidy (2005) developed an optimization model for preventive maintenance scheduling of multi-component and multi-state systems. They defined sequence of preventive maintenance activities as the decision variables and the summation of preventive maintenance, minimal repair, and downtime costs as the objective function. In addition, they considered system reliability, minimum intervals between maintenance actions, and crew availability as the constraints of their model. In this case, a combination of simulation and optimization models was presented in order to solve the NP-hard hybrid flow shop scheduling problem with maintenance constraints and multiple objective functions based on flow time and due date. In addition, they considered setup times, cleaning times, and transportation times in the model and mentioned that the performance of the algorithm can be affected by the number of the breakdown times. They

mentioned that using hybrid algorithm in a large-scale problem is more efficient than the simple algorithm.

Finally, they proved that the effectiveness of the simulated annealing algorithm is better than other heuristic algorithms with the same conditions. They also mentioned that the method could produce better solutions if some changes and modification are made to the solution procedure. As a case study, they tested the method on 62-unit state electrical system of Victoria. Sam routet al(2006) presented another paper on the combination of an ant colony algorithm and genetic algorithm to optimize a large-scale preventive maintenance problem. They divided the objective function of their problem into two sections and then utilized each algorithm to improve the sections separately.

2.5.4 Multi-Objective Algorithms

Pongpech, Murthy and Boondis (2006) developed a multi-criteria preventive maintenance optimization model to find the optimal preventive maintenance intervals of components in a production system using multi-objective algorithms. The authors considered an age-based failure rate for components by fitting a Weibull distribution to the data and defined expected total cost per unit time and the reliability of the production system as the main criterium. A novel approach in preventive maintenance scheduling of thermal generating systems was developed by Drinkwater and Hastings(1967). The authors developed a large-scale multi-objective combinatorial optimization model with three objective functions and a set of the constraints. They considered minimization of total fuel costs, maximization of reliability in term of expected unsaved energy, and minimization of technological concerns as the objective functions. In addition, they defined maintenanceduration, technological concerns as the objective functions and limitation on simultaneous maintenance of thermal units, total capacity on maintenance due to labor and resources as the constraints.

They developed a multi-objective preventive maintenance scheduling software based on a multi-objective branch and bound algorithm implemented in FORTRAN. As a case study, they applied their methodology in a paper factory and used PROMCALC as the optimization software. Finally, they mentioned the advantage of their approach in which decision makers and managers can input various criteria into the model and do sensitivity analysis on the optimal solutions. Konak, Coit and Smith (2006) presented a comprehensive study on multi-objective genetic algorithms and their applications in reliability optimization problems. They defined the problem as a multi-objective optimization problem by considering the minimization of workforce idle time and the minimization of maintenance time and mentioned that there was a tradeoff between the objective functions. As the solution procedure, they used utility theory instead of dominance-based Pareto search to determine the non-inferior solutions and showed the advantage of this method via numerical example.

Taboada, Espiritu and Coit (2008) presented a recent study in this area. They developed a multi-objective genetic algorithm in order to solve multi-state reliability design problems. The authors utilized the universal moment generating function to measure the reliability and availability criteria in the system. They applied their approach into two examples; the first one is a system of five units connected in series in which each component has two states, functioning properly, or failure, and the second one is a system of three units connected in series. In this system, each component has multi states with different levels of performance, which range from maximum capacity to total failure. They utilized MATLAB as the programming environment, and showed the effectiveness of their approach in terms of computational times and obtained non-inferior solution.

2.6 Simulation Models

Numerous simulation softwares have been used in the past to evaluate the performance of the optimization models as regards maintenance activities, some of which are discussed below.

2.6.1 Monte Carlo Simulation

The researchers used a Monte Carlo continuous time simulation to model the age of equipment, availability of equipment, maintenance activity backlog, and preventive maintenance policies and considered different wafer production scenarios. They analyzed and compared the different maintenance strategies on the status of manufacturing equipment and operating conditions of the wafer production flow. They further described how the combination of age and availability-based models increased the throughput and provided better results than the simple age-based models. In the same capacity, Bottaziet al(1992) presented the results of a systematic collection of actual failure times and preventive and corrective maintenance activities of 900 buses over a period of five years. They created an updatable database to estimate the failure distributions and to evaluate the influence of systematic preventive and corrective maintenance actions. They considered the total cost and availability as the objective functions, applied Monte Carlo simulation approach to evaluate and compare different maintenance policies, and presented the computational results. Billiton et al(2000), developed a model, which was based on the use of Monte Carlo simulation, to determine the total failure frequency and the optimum maintenance interval for a parallel-redundant system. The authors presented a modified distribution function assuming an exponential distribution for component useful life period and the Weibull distribution for the wear out period.

The procedure included construction of a mathematical model and definition of the stopping rule in simulation for a parallel-redundant system. They stated that if the shape parameter β of the Weibull distribution increases, the optimum

maintenance interval could not be determined. Zhou et al(2005) developed an approach for sequential preventive maintenance scheduling based on the concept of age reduction due to imperfect maintenance actions. They considered an assumption for the time of imperfect maintenance actions based on required reliability of the system. They utilized a hybrid recursive method based on an assumed improvement factor and increasing failure rate and developed an optimization model with a maintenance cost rate in the life cycle of the system as the objective function. Finally, they applied Monte Carlo simulation and described how their computational results can be used in decision support systems for maintenance scheduling. Marquez et al(2006) developed a simulation model to find the best preventive maintenance strategy in semiconductor manufacturing plants.

2.6.2 Discrete-Event and Continuous Simulation

The researchers had in various ways considered various subsystems such as preventive maintenance subsystem, defects subsystem, condition-based subsystem, failure subsystem, corrective maintenance subsystem, and performance subsystem applying discrete event and continuous simulation models and utilized SIMULINK to build up the model. They analyzed the structure of components and the relation of their constraints in a maintenance system and present the advantages of the model over classical stochastic process methods in a numerical example. In addition, they mentioned that obtained simulation results expressed the dynamic nature of maintenance systems. Burton et al(1989) developed a simulation model to evaluate the performance of a job shop while Goelet al(1973) presented a simulation model and developed a statistical analysis that considered three different types of preventive maintenance activities for components by defining stochastic and deterministic decision variables as well as unavailability and cost as the objectives. In addition, they made a 2-level sequential fractional factorial design in order to

facilitate their simulation. By designing the simulation model based on experimental design approach, their model produced the preventive maintenance schedule for ground electronics systems.

In this research, the effectiveness of the preventive maintenance scheduling under different conditions such as shop load, job sequencing rule, maintenance capacity, and strategy was not displayed. Krishnan(1992)developed a simulation model to determine the maintenance schedule for an automated production line in a steel rolling mill plant. He considered three different maintenance policies as opportunistic, failure, and block with the percent of availability as the objective function. He showed that the existing maintenanc policy only included the failure and block maintenance actions. By using the historical data of maintenance activities in the simulation model, the optimal preventive maintenance schedule was obtained in the form of checklist. Martorell and Serradell(1999)presented a simulation model in order to determine the frequency of the shutdown for periodic system overhaul, preventive and corrective maintenance, and inspections in a sugar manufacturing plant. They utilized a time dependent simulation model to minimize the total cost including maintenance costs and downtime losses.

One of the most recent studies on application of simulation in preventive maintenance scheduling was presented by Hag mark et al(2007). They developed a simulation model to determine the level of reliability, availability and corrective and preventive maintenance at the early stage of design. After running the simulation model and analyzing the computational results, they mentioned that preventive maintenance and corrective maintenance policies have a high impact on the performance measures of just-in-time production systems and by combining the maintenance activities and just-in-time operations one can improve the effectiveness of the this kind of systems. Greasley(2000)presented a simulation model to find the optimal maintenance

planning in train maintenance depot for an underground transportation facility in UK.

He developed a simulation based on two different situations. The first situation assumed there is no random arrival and the second one considered random arrivals and investigated the effect of the arrival on service level performance measures. He utilized ARENA as the simulation software and showed the effectiveness of the maintenance policies obtained by the simulation model. Chan(2001) developed a simulation model to analyze the effects of preventive maintenance policies on buffer size, inventory sorting rules, and process interruptions in a flow line of a push production system. He presented the performance of the production system under different operational conditions and preventive maintenance policies. Duffuaa et al(2001) presented a generic conceptual simulation model for maintenance systems. They defined this simulation model by constructing seven modules including an input module, maintenance load module, planning and scheduling module, materials and spares module, tools and equipment module, quality module and finally, a performance measure module. The authors mentioned that this model could be used to develop a discrete event simulation models in one of the commercial simulation software. In addition, they suggested that by using this model one can evaluate the need for contract maintenance and effect of availability of spare parts on performance measures in the system. Han et al(2004) developed a finite time horizon model to achieve preventive maintenance scheduling of manufacturing equipment based on setback based residual factors, and used simulation to solve the model. They mentioned the consistency of computational results and showed that simulation is a useful and effective method to solve such finite time problems. Jaturonnate, Murthy and Boondiskulchok(2006) developed a preventive maintenance optimization model for a multi-component production process. They defined a combination of mechanical service, repair, and replacement activities for each component and

use Markov decision process to present the transition function of probability for maintenance activities. In addition, they considered required reliability of the system as the constraint and total preventive maintenance cost as the objective function of the model.

A simulation approach was utilized to find the optimal schedule as the solution procedure. The authors described that considering the combination of preventive maintenance activities could reduce more cost in comparison with the situation that different activities are considered separately. Their method only considered repair time delays and effect of preventive maintenance on the system's failure observed by condition monitoring and diagnostic resources.

2.7 Age Reduction and Improvement Factor Models

One of the recent works on methods for estimating age reduction factor is by Éva and Kleinberg (2005), where they considered an optimal preventive maintenance for a deteriorating one-component system via minimizing the expected cost over a finite planning horizon. They developed a model for estimating improvement factor to measure the restoration of component under the minimal repair. The proposed improvement factor was only a function of effective age of the component, the number of preventive maintenance actions, and the cost ratio of each maintenance action to the replacement action.

Nakagawa and Osaki (1974) presented a basic and notable approach for models that utilized improvement factor. The work has been referenced by many researchers. They developed two analytical models in order to find the optimal preventive maintenance schedule based on an assumption of increasing failure rate over time. The first model, called a preventive maintenance hazard rate model, calculated the average failure cost of minimal repairs along with costs of preventive maintenance and replacement under the assumption that preventive maintenance actions reduced the next effective age to zero, the failure rate was assumed to increase with increasing the frequency of preventive maintenance

actions. But, this model assumed that maintenance activities took place at fixed intervals between each predetermined replacement. The second model, called an age reduction preventive maintenance model, considered the average failure cost of minimal repairs as well as costs of preventive maintenance and replacement by assuming the age reduction after each minimal repair. In order to find the optimal schedule, both models were optimized by calculus methods. He applied the models in a numerical example and described that based on obtained computational results the second model was more practical than the first model. Fard and Nukala(2004)proposed another referenced work on age reduction and improvement factors models. They developed an optimization model and branching algorithm that minimized the total cost of preventive maintenance and replacement activities. They assumed a constant improvement factor and defined a required failure rate. In addition, they assumed a zero failure cost and did not consider time value of money for future costs. Their algorithm determined the optimal schedule of maintenance actions before each replacement action in order to minimize the total cost in a planning horizon. They utilized FORTRAN to implement the algorithm and proved the effectiveness of the algorithm via several numerical examples.Dedopoulos and Smeers(1998)developed a nonlinear optimization model to find the best preventive maintenance schedule by considering the degree of age reduction as the variable in the model. The researchers defined improvement factor, time and duration of preventive maintenance activities as the decision variables, considered fixed cost and variable cost for maintenance actions, and defined the variable cost as a function of the degree of age reduction, the duration of the action and the effective age of the component. Moreover, they presented the failure rate in each period as a recursive function of age reduction from a previous period and considered the net profit as the objective function of the model. They implemented the model in GAMS and use GAMS/MINOS optimization software, but did not consider other factors.Martorellet al(1999)

presented an age-dependent preventive maintenance model based on the surveillance parameters, improvement factor, and environmental and operational conditions of the equipment in a nuclear power plant. They considered risk and cost as the criteria of the model based on the age of the system and made the sensitivity analysis to show the effect of the parameters on the preventive maintenance policies.

They expressed that the results obtained from their model were different from those resulted from the models that did not consider the improvement factor and working conditions. Lin, Zuo and Yam(2001)combined the models developed by Nakagawa et al(1974) and presented hybrid models in which effects of each preventive maintenance action were considered by two aspects; one for its immediate effects and the other one for the lasting effects when the equipment was put to use again. The authors constructed two models that reflected the concept of maintainable and non-maintainable failure modes. In the first model, they assumed that preventive maintenance and replacement time were independent decision variables and considered the mean cost rate as the objective function to be minimized. Jaturonnateet al(2006)developed an analytical model in order to find the optimal preventive maintenance of leased equipment by minimizing a total cost function. They defined maintenance actions as preventive and corrective, each with associated costs, and then considered the concept of reduction in failure intensity function along with penalty costs due to violation of leased contract issues. They presented a numerical example for a system with Weibull failure rate, solved the model analytically, and examined the effect of penalty terms on the optimal preventive maintenance policies. Bartholomew-Biggs, Christianson and Zuo(2006) presented several preventive maintenance scheduling models that considered the effect of imperfect maintenance on effective age of component. The researchers developed optimization models that minimized the total cost of preventive maintenance and replacement activities. In this study, they assumed a known

failure rate to express the expected failures as a function of age and considered age reduction in the effective age, based on the concept of an improvement factor.

They developed a new mathematical programming formulation to achieve the optimal maintenance schedule and utilized automatic differentiation as the numerical approach, instead of analytical approach, to compute the gradients in the optimization procedure, which was the global minimization of non-smooth performance function. Cheng et al(2007) in their research on models for estimating the degradation rate of the age reduction factor came out with two optimization models, which minimized the cost subject to required reliability. The first model has a periodic preventive maintenance time interval for every replacement and the second one contains the maintenance schedule where the time interval between the final maintenance and replacement was not constant. Lim and Park(2007) presented three analytical preventive maintenance models that considered the expected cost rate per unit time as the objective function. In this research, they assumed that each preventive maintenance activity reduced the starting effective age but did not change the failure rate and considered the improvement factor as the function of number of preventive maintenance activities. They also assumed that the failure function was based on a Weibull distribution and developed mathematical formulation for three different situations; preventive maintenance period was known, number of preventive maintenance was known, and number and period of preventive maintenance was unknown. They derived the optimal preventive maintenance and replacement schedules by taking an analytical approach and applied them to a numerical example to show an application of their models. In same capacity, various applications have been developed by various other institutions in Nigeria and across the globe to model maintenance and replacement in automobile industries but all are still embedded with one problem or the other.

2.8 Applications

The versatility of the dynamic programming method is really appreciated by exposure to a wide variety of applications. These include:

2.8.1 Production and inventory control problem

Here minimization problem was considered according to Limbourg & Kochs (2006) where the sum of the production cost and inventory holding cost was minimized over a three – month period subject to demand, production capacity, warehouse capacity and inventory holding capacity. At any period, the ending inventory would be calculated as: $Ending\ inventory = beginning\ inventory + production - demand$. During the period the total cost for each period was the sums of production cost and inventory holding cost for the month and was to be minimized for each period and over the entire duration. The ending inventory which served as the first constraint must be less than or equal to the warehouse capacity. The second constraint was that the production level in each period must not exceed the production capacity and the third constraint remained that the beginning inventory plus production must be greater than or equal to demand. Supposed that the developed forecasts of the demand for cars over three months would decide upon a production quantity for each of the periods so that demand could be satisfied at a minimum cost. There are two costs to be considered: production costs and inventory holding costs. It was assumed that production setup costs made each period would be constant. As a result other costs were not considered in the analysis. This made the model more limited as buttressed by David et al (1988).

2.8.2 Manufacturing and production problem

Here maximizing benefit (total value rating) subjected to the number of days available (10) for processing of a job and the number of jobs available was considered. The stage transformation functions were then defined as:

x_{n-1} = the number of days available at stage n – the product of the number of days needed to complete one job by the number of jobs to process. The return functions at each stage were based on the value rating of a job times the number of jobs selected for processing. The first constraint was that the number of days needed to process a job must be less than or equal to the number of days available (10). Secondly, the number of jobs selected must be less than or equal to the number of jobs available. Each item has a certain weight associated with it as well as a value. The problem was to determine how many units of each item is to be placed in the knapsack in order to maximum total value as upheld by Kralj and Petrovic(1995). Here a constraint was placed on the maximum weight permissible. In this direction, manager of a manufacturing operation who has selection of jobs to process during the following 10 – day period was considered. The estimated time required for completion and the value rating associated with each category of job were also calculated. The main aim of the manager was to find out how many jobs to choose from each category to process in order to maximize performance value as upheld by McClymonds and Winge(1987).

2.8.3 Equipment replacement problem.

Here replacement policy which is a specification of a sequence of “keep” or “replace” actions, one for each period was considered. Two simple examples are the policy of replacing the car every year and the policy of keeping the first car until the end of period N . In this case a car which has to be operated throughout a planning horizon of N periods, and when it reached a specific age would be more economical to replace was considered. Given that each period corresponds to one year; and that it was required to make a decision as to whether or not to replace the car at the beginning of every year. The problem of interest was to determine an optimal replacement policy. In this regard, optimal policy for solving this problem using dynamic programming was derived by organizing

the solution procedure into four steps:(i)Definition of appropriate stages and states (ii)Definition of the optimal-value function.(iii)Construction of a recurrence relation(iv)Recursive Computation as proposed by Abdul(2011).

2.9 Summary of the Review

In this chapter, recent work pertaining to methods and applications of maintenance and replacement models and approaches were reviewed. They are categorized as optimization models, simulation models, age reduction and improvement factor, and applications in production and inventory, network, manufacturing, replacement, service and power systems. Although, many approaches and models have been applied in the past to analyze the operational costs of transportation industries but could not be used widely to fit second order model to the response surface and were not able to display the extent of the significance of the control factors on the yield. Also, many approaches and models being used in the past havenot been used to predict the operational costs of the case study. In addition, the influence of environmental factors on the operational costs of ATS were analyzed. Hence, the development models that would help to identify replacement candidates among fleet members so that total fleet costs are minimized in the long run and net profit maximized is being proposed. Also mathematical models to estimate the influence of environmental factors on operational costs of the vehicles of the case company were developed. These were the research contributions pursued and they can be customized to solve a wide range of problems.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

The study, after data collection, employed backward dynamic programming using the recursive equation to model the operational costs of ATS and to find the best sequence of maintenance or replacement action, the optimal replacement policy of each vehicle over the planned period; the maximum net profit in operation. Replace and keep analysis and plots were made. Thereafter, a forecast was carried out between (2015-2019) years on these data using selected forecasting models with their accompanying equations to determine the future impact of the maintenance costs, replacement costs and income generation on the aforementioned company vehicles over the planned period. Plots were made and considerations were based on the forecasting models with least errors. Besides, analysis of the influence of environmental factors on the operational costs using main cause and effect tool was carried out and plots were made. Finally, response surface method (RSM) via Box – Behnken design was employed to optimize the operational costs of the vehicles under investigation, analysis of variance was made to justify the significance of each control factor on the response and plots were made.

3.2 Data Collection

Data for the study were collected from two sources namely: the primary source and the secondary source. The primary data source on the types of vehicles, replacement costs, maintenance costs, income generated each year by each

vehicle, and distance (km) covered by each vehicle were obtained from the workshop manager and the statistical office of the company and environmental factors were obtained from Metrological Institute of Nigeria respectively. While the information obtained from company journals, magazines, maintenance manuals and records, the internet, books from the main Library at Nnamdi Azikiwe University and Industrial/Production Engineering department's library were consulted and thoroughly read in the course of the research work and this formed the secondary source.

Primary data were also collected through interviews and interactions with the maintenance personnel of the case company.

3.3 Data Presentation

Anambra State Transport Service(ATS) is a passenger transport company with enviable track record. This company has a fleet size of more than 185 vehicles with Awka depot having 90 vehicles of seven distinct types. The company aims at operating an effective and affordable transport service system in an economical and sustainable way to the public. This study was carried out on seven vehicle types, namely; Ten Nissan Urvan, nine Sienna, eight Peugeot Expert, fifteen J5 bus, twelve Ford bus, ten Toyota Hiace and eight Taxi cab. The studied planned period is 10 years, which covered the years 2005 to 2014.

The actual maintenance costs data collected for the vehicles were based on the costs incurred by (regular oil change, alignment, removing and replacing vehicles spare parts, vulcanizing work, panel beating work, electrical works, servicing of air condition, and general engine servicing etc.), and all the costs incurred in procuring or purchasing any replaceable or serviceable parts (tyres, oil filters, fuel filters, fan belts, wipers, pumps, bulbs etc.) of the vehicles formed the replacement costs, while the net income generated includes (total income generated minus total expenditure). The selected forecasting models were used to predict the future values for the rest of the planned period (2015-2019). Tables

3.3(a, b, c, d, e,f) represent the case study data collected. The data include: the types of vehicles, maintenance costs of vehicles, replacement costs of vehicles, income generated by each vehicle, environmental factors and distance travelled(km) by each vehicle for the planned years.

Table 3.3(a): Vehicle Types and their Capacities

Vehicle Types	No of Vehicles	Capacity(No. of Passengers)
Nissan Urvan	10	14
Peugeot Expert	8	7
Sienna bus	9	7
J5 Bus	15	14
Ford Bus	12	14
Toyota Hiace Bus	10	14
Taxi cab	8	4

(cf ANIDS annual report 2010)

Table 3.3(a) summarized the selected fleet size of each vehicle types with their corresponding numbers and capacities.

Table 3.3(b): Maintenance Costs of ATS Vehicles in Naira(×1000)

VEHICLE TYPES/YEAR	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
NISSAN URVAN	1,969	2,250	2,520	2,815	3,030	3,240	3,360	3,590	3,995	4,005
SIENNA	1,900	2,440	2,905	3,230	3,700	3,920	4,405	4,610	4,880	4,881.5
PEUGEOT EXPERT	2,090	2,130	2,590	2,900	3,050	3,310	3,505	3,790	3,890	3,980
J5	2,337	2,410.8	3,665.4	3,811	3,990	4,050	4,410	4,600	4,250	4,820
FORD BUS	2,165.4	2,297.7	3,115.8	3,488.7	3,590	3,690	3,780	3,905	4,1600	4,145
TOYOTA HIACE	2,205	2,400	2,510	2,790	3,020	3,330	3,515	3,640	3,713.2	3,802.1
TAXI CAB	1,890	2,080	2,160	2,310	2,500	2,910	3,012	3,220	3,370	3,405

(Source: ATS maintenance Workshop)

Table 3.3(b) specified the maintenance costs of Anambra State Transport Sector's vehicles as collected from the maintenance workshop department of the case company over the given period. The trend of the data showed that as the

age increases, the maintenance cost increases. From Table 3.3(b), it is observed that the costs incurred for the maintenance of Nissan Urvan vehicles as shown in Table 3.3(a) is ₦1,969,000 which means that the sum of ₦196,900 was used to maintain each Nissan Urvan vehicle for the year 2005. In a similar way, the maintenance cost for each other vehicle type was done, also applicable to other operational costs (replacement costs and income generation).

Table 3.3(c): Replacement Costs of ATS Vehicles in Naira (× 1000)

VEHICLE TYPES/YEAR	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
NISSAN URVAN	1,992	2,240	2,400	2,500	2,568	2,681	2,705	2,805	2,856	2,943
SIENNA	1,100	1,150	1,200	1,250	1,280	1,309	1,329	1,336	1,352.4	1,370
PEUGEOT EXPERT	1,500	1,520	1,550	1,650	1,665	1,685	1,700.5	1,733	1,772	1,781
J5	1,803.0	1,809	1,817	1,830	1,852	1,866	1,884	1,901	1,920	1,935
FORD BUS	1,803.5	1,812	1,813	1,825	1,828	1,836	1,840	1,862	1,876	1,889
TOYOTA HIACE	1,892.4	1,897.5	1,900	1,912.5	1,932.8	1,944	1,950	1,966	1,967	1,970
TAXI CAB	1,000	1,011	1,102	1,152	1,164	1,170	1,195	1,201.5	1,209	1,215

(Source: ATS maintenance Workshop)

Table 3.3(c) is the replacement costs of Anambra State Transport Sector's vehicles as obtained from the maintenance workshop department of the case company. From the data collected, it is observed that replacement costs increase, with increase in age of the vehicles.

Table 3.3(d): Income Generated by ATS Vehicles in Naira (× 1000)

VEHICLE TYPES/YEAR	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
NISSAN URVAN	9,807.3	9,782.4	9,600	9,515	9,020	8,850	8,610	8,489.7	8,340	8,300
SIENNA	9,000	8,710	8,420	8,205	8,150	8,040	7,800	7,710	7,140	7,015
PEUGEOT EXPERT	8,830	8,600	8,420	7,990	7,755	7,605	7,415	7,050	6,805	6,760
J5	8,910	8,540	8,330	8,150	7,920	7,760	7,606	7,500	7,450	6,980
FORD BUS	9,200	9,020	8,713	8,614	8,290	7,880	7,740	7,550	7,195	6,875

TOYOTA	10,012	9,706	9,550	9,220	9,019	8,812	8,600	8,330	7,911	7,880
HIACE										
TAXI CAB	7,890	7,721.5	7,500	7,119	6,830	6,615	6,309	5,880	5,690	5,405

(Source: ATS maintenance Workshop)

Table 3.3(d) displayed the income generated for ten years by Anambra State Transport Sector's vehicles as procured from the maintenance workshop department of the company under investigation. It is observed from the data that there is a decrease in income generated as the age of the vehicles increases.

Table 3.3(e): Environmental Factors

TIME	Year	Precipitation (cubic centimeters)	Temperature(° C)	Relative Humidity
1	2005	1620	29.2	148
2	2006	1500	28.5	156.9
3	2007	1650.3	28.96	176.98
4	2008	1507	28.15	159.56
5	2009	1579.1	28.3	126.2
6	2010	1506.6	27.8	122.65
7	2011	1695.4	28.85	129.7
8	2012	1662	27.9	148.0
9	2013	2294.7	28.3	122.65
10	2014	1695	28.4	129.68

(Source: Metrological Institute of Nigeria)

Table 3.3(e) is the environmental factors affecting the operational costs of Anambra State Transport Sector's vehicles over the given period as obtained from the Metrological Institute of Nigeria. From the data collected, it was observed that there is a fluctuations in the afore mentioned factors, a pointer to the fact that these environmental factors vary with a particular season.

Table 3.3(f): Anambra State Transport Sector's Vehicles Designated Routes (km).

Route Years	Lagos Route Nissan Urvan	Abuja Route Sienna	PH Route J5	ABAKILI KI Route Taxi Cab	Sokoto Route Toyota Hiace	Jos Route Peugeot Expert	Owerri Route Ford Bus
	Nissan Urvan (km)	Sienna (km)	J5 (km)	Taxi Cab (km)	Toyota Hiace (km)	Peugeot Expert (km)	Ford Bus (km)
2005	101616	79042.98	73647.24	45359.64	161059.2	93849.14	32632.6
2006	102784	79951.52	74493.76	48977.28	173774.4	99943.24	34751.6
2007	105120	81768.6	76610.06	50368.68	185430	102380.9	35599.2
2008	113296	88128.38	82112.44	52038.36	186489.6	107256.2	37294.4
2009	116800	90854	84652	52316.64	187549.2	107256.2	39837.2

2010	117384	91308.27	85075.26	52594.92	188608.8	108475	40049.1
2011	117968	91762.54	85498.52	53429.76	190728	111522	42777.7
2012	118552	92216.81	85921.78	56490.84	191787.6	118225.5	43015.7
2013	119720	93125.35	86768.3	54264.6	194966.4	115178.5	44320.5
2014	120304	93579.62	87191.56	53708.04	201324	117616.1	44896.7

(Source: ATS maintenance Workshop)

Table 3.3(f) showed Anambra State Transport Sector's Vehicles designated routes as travelled by each vehicle measured in km. The trend of the data collected indicated that the distance(km)travelled depends on the age of the vehicles.

3.4 Method of Data Analysis

The methods employed for the data analysis in this study are:

a. Dynamic Programming (Recursive) Model

Dynamic programming works on the principle of finding an overall solution by operating on an intermediate point that lies between where we are now and where we want to go. Since the intermediate point is a function of the point already visited, the procedure is said to be recursive. Dynamic programming and many useful algorithms are recursive in structure. In solving a given problem the algorithm calls a subroutine recursively one or more times to deal with closely related sub-problems.

Dynamic programming is an optimization tool, its recursive equation of an automobile replacement problem for either keep or replace decision with the aim of determining the appropriate life span of the vehicles under investigation, according to Abdul(2011) is of the form:

$$V_k(i) = \min \begin{cases} C_k(i) - I_k(i) + V_{k+1}(i+1) \text{Keep} \\ C_k(0) - I_k(0) + R_k(i) + V_{k+1}(1) \text{Re place} \end{cases} \quad (1)$$

where:

$C_k(i)$ = Represent total cost at each stage (k) of an old vehicle.

$C_k(0)$ = Represent total cost at each stage (k) of a new vehicle.

$I_k(i)$ = Represent the old vehicle income at stage (k).

$I_k(0)$ = Represent the new vehicle income at stage (k).

$R_k(i)$ = Represent the vehicle replacement cost at stage (k).

$V_k(i)$ = Represent the total recursive cost for a vehicle of age (i) at stage (k).

$V_{k+1}(i + 1)$ = Represent the total recursive cost for a vehicle of age ($i+1$) at stage ($k+1$).

$V_{k+1}(1)$ = Represent the total recursive cost for a vehicle of age (1) at stage ($k+1$)

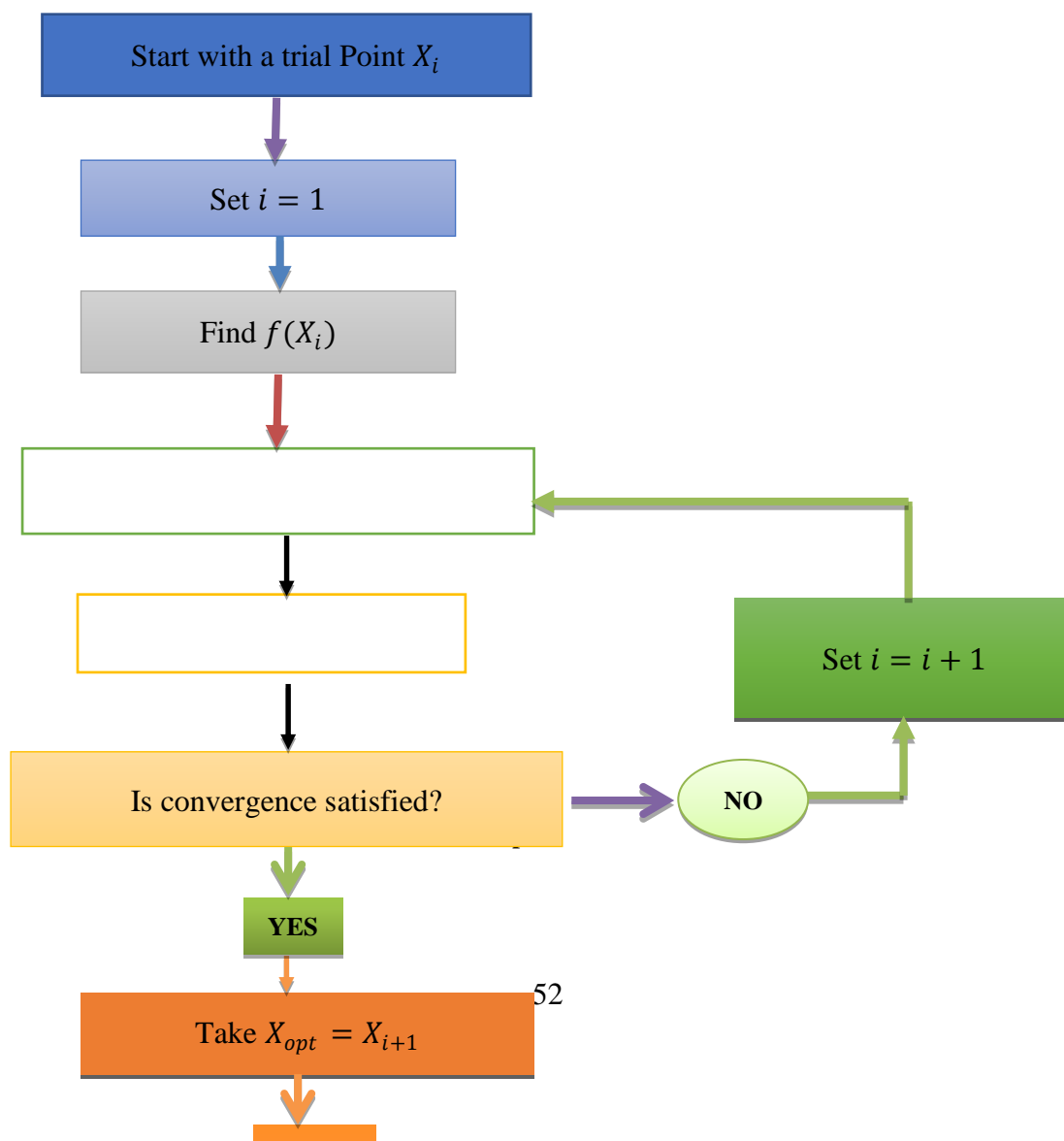
i = Represent the vehicle age at stage k , (the state variable)

D_k = Represent the decision at stage k .

k = Represent the stage.

Equation(1) was employed to determine the minimum total net recursive cost of the vehicles under investigation.

3.4.1 Flow Chart for Dynamic Programming Model



Replace

Figure 3.1: Flow Chart Analysis for Dynamic Programming Model

Figure 3.1 presents a flow chart analysis of an optimization method in the system. The model starts with an optimal recursive dynamic programming model $f(X_i)$ which starts with the backward dynamic function at an initial trial point X_i (that is the future) to recur backward to the past i.e. $f(X_{i+1})$. However, the model has the capacity to trace from the future to the past of an event. In a state where the model converge to be the optimal is the point of optimal satisfaction but if the state is not satisfied, the system X_{i+1} would generate a new point $f(X_{i+1})$ of convergence to satisfy the optimal function in the system. If the converged point is not satisfied, then continue to keep and $X_{opt} \leq X_{i+1}$. However, if the converged point is satisfied, replace and $X_{opt} = X_{i+1}$ and end generating new point.

b. Forecasting Models

The company may choose from a wide range of forecasting techniques. There are basically two approaches: qualitative approach (forecast based on judgment and opinion) and quantitative approach (forecast based on historical data and causal effect). Based on the literature review in forecasting models, the researcher made use of quantitative forecasting models which include:

i ARIMA (AUTOREGRESSIVE INTEGRATED MOVING AVERAGE)

In statistics and econometrics, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of

an autoregressive moving average (ARMA) model. These models are fitted to time series data either to better understand the data or to predict future points in the series (forecasting). They are applied in some cases where data show evidence of non-stationary, where an initial difference step (corresponding to the "integrated" part of the model) can be applied to reduce the non-stationary. Non-seasonal ARIMA models are generally denoted $ARIMA(p, d, q)$ where parameters p , d , and q are non-negative integers, p is the order of the Autoregressive model, d is the degree of differencing, and q is the order of the Moving-average model. Seasonal ARIMA models are usually denoted $ARIMA(p, d, q)(P, D, Q)_m$, where m refers to the number of periods in each season, and the uppercase P, D, Q refer to the autoregressive, differencing, and moving average terms for the seasonal part of the ARIMA model. ARIMA models form an important part of the Box-Jenkins approach to time-series modeling. When two out of the three terms are zeros, the model may be referred to base on the non-zero parameter, dropping "AR", "I" or "MA" from the acronym describing the model. For example, ARIMA (1,0,0) is AR(1), ARIMA(0,1,0) is I(1), and ARIMA(0,0,1) is MA(1). Given a time series of data X_t where t is an integer index and the X_t are real numbers, then an ARMA(p' , q) model is given by:

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) X_t = \left(1 + \sum_{i=1}^q \theta_i L^i\right) \varepsilon_t \quad (2)$$

where L is the lag operator, the α_i are the parameters of the autoregressive part of the model, the θ_i are the parameters of the moving average part and the ε_t are error terms. The error terms ε_t are generally assumed to be independent, identically distributed variables sampled from a normal distribution with zero

mean. Assume now that the polynomial $\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right)$ has a unitary root of multiplicity d .

Then it can be rewritten as:

$$\left(1 - \sum_{i=1}^{p'} \alpha_i L^i\right) = \left(1 - \sum_{i=1}^{p'-d} \phi_i L^i\right) (1-L)^d \quad (3)$$

An ARIMA (p, d, q) process expresses this polynomial factorization property with $p=p'-d$, and is given by:

$$\left(1 - \sum_{i=1}^p \phi_i L^i\right) (1-L)^d X_t = \left(1 + \sum_{i=1}^q \theta_i L^i\right) \varepsilon_t \quad (4)$$

and thus can be thought as a particular case of an ARMA $(p+d, q)$ process having the autoregressive polynomial with d unit roots. (For this reason, every ARIMA model with $d>0$ is not wide sense stationary.)

The above can be generalized as follows.

$$\left(1 - \sum_{i=1}^p \phi_i L^i\right) (1-L)^d X_t = \delta + \left(1 + \sum_{i=1}^q \theta_i L^i\right) \varepsilon_t \quad (5)$$

This defines an ARIMA (p, d, q) process with **drift** $\delta/(1-\sum\phi_i)$.

ARIMA shows the measuring accuracy of the data using box-pierce (ljung-box) chi-square statistic. The techniques measure the errors as chi-square, Significance value, degree of freedom, lagging and correlation matrix.

ii Moving Average Methods

One weakness of the naive method is that the forecast just traces the actual data, with a lag of one period; it does not smooth at all. But by expanding the amount of the historical data a forecast is based on, this difficulty can be overcome. A moving average forecast uses a number of the most recent actual data values in generating a forecast. The moving average forecast can be computed using the following equation:

$$F_t = MA_n = \frac{\sum_{i=1}^n A_{t-i}}{n} \quad (6)$$

where, i = an index that corresponds to time periods

n = Number of periods (data points) in the moving average

A_i = Actual value in period $t - i$

MA = Moving average

F_t = Forecast for time period t

iii **Weighted Moving Average Method**

A weighted average is similar to a moving average, except that it assigns more weight to the most recent values in a time series.

$$\text{In general, } F_t = W_n A_{t-n} + W_{n-1} A_{t-(n-1)} + \dots + w_1 A_{t-1} \quad (7) W_1$$

= Weighted value

Fischer(2010) observed that for instance, the most recent value might be assigned a weight of .40, the next most recent value a weight of .30, the next after that a weight of .20, and the next after that a weight of .10. Note that the weights sum of 1.00 and that the heaviest weights are assigned to the most recent values.

iv **Winter Modeling**

Seetharama (1997) reported that winter developed a very popular model for handling trends and seasons. For explanatory purposes, we will demonstrate his trend calculations first and then add his seasonal factors in the next section. Winters used the Holt trend model, which begins with the usual trend average trend estimation.

$$T_t = \beta(F_t - F_{t-1}) + (1 - \beta)T_{t-1} \quad (8)$$

T_t = Trend estimate at time t

F_t =Exponential average at time t

β =fractions,

$$f_t = (F_{t-1} - T_{t-1}) \quad (9) F_t = \alpha D_t +$$

$$(1 - \alpha)(F_{t-1} - T_{t-1}) \quad (10)$$

where F_t = Forecast for period t

F_{t-1} = Forecast for the previous period

α = Smoothing constant (represents the percentage of the forecast error)

D_t =Demand

$$f_{t+1} = (F_t - T_t) \quad (11)$$

f_{t+1} = Winter Forecast

v **Double Exponential Smoothing**

Delurgio(1986) observed that it is appropriate when data varies around an average or have step or gradual changes. If a series exhibits trend, and simple smoothing is used on it, the forecast will all lag the trend: if the data are increasing, each forecast will be too low; if decreasing, each forecast will be too high. Double Exponential Smoothing forecast (DEF) is composed of two elements: a smoothed error and a trend factor.

$$DEF_{t-1} = S_t + T_t \quad (12)$$

Where S_t = Previous forecast plus smoothed error

T_t = Current trend estimate

$$\text{And } S_t = DEF_t + \alpha(A_t - DEF_t) \quad (13)$$

$$T_t = T_{t-1} + \beta(DEF_t - DEF_{t-1} - T_{t-1}) \quad (14)$$

where α and β = smoothing constants.

In order to use this method, one must select values of α and β which are usually done through trial and error and make a starting forecast and an estimate of trend.

vi. Time Series Decomposition Model

The decomposition of time series is a statistical method that deconstructs a time series into notional components. There are two principal types of decomposition which are decomposition based on rates of change and decomposition based on predictability (deterministic or non-deterministic). Decomposition based on rates of change is an important technique for all types of time series analysis, especially for seasonal adjustment as supported by Dodge (2003). It seeks to construct, from an observed time series, a number of component series (that could be used to reconstruct the original by additions or multiplications) where each of these has a certain characteristic or type of behavior. For example, time series as proposed by Shumway (1988) are usually decomposed into:

The Trend Component that reflects the long term progression of the series (secular variation: occurring once in the course of age or century).

The Cyclical Component that describes repeated but non-periodic fluctuations.

The seasonal component reflecting seasonality (seasonal variation).

The irregular component (or "noise") that describes random, irregular influences. It represents the residuals of the time series after the other components have been removed. Decomposition procedures are used in time series to describe the trend and seasonal factors in a time series. More extensive decompositions might also include long-run cycles, holiday effects, day of week

effects and so on. Here, we'll only consider trend and seasonal decompositions. One of the main objectives for decomposition is to estimate seasonal effects that can be used to create and present seasonally adjusted values. A seasonally adjusted value removes the seasonal effect from a value so that trends can be seen more clearly. For instance, in many regions of the U.S. unemployment tends to decrease in the summer due to increased employment in agricultural areas. Thus a drop in the unemployment rate in June compared to May doesn't necessarily indicate that there's a trend toward lower unemployment in the country. To see whether there is a real trend, we should adjust for the fact that unemployment is always lower in June than in May.

The additive model is useful when the seasonal variation is relatively constant over time.

The multiplicative model is useful when the seasonal variation increases over time.

Basic Steps in Decomposition include:

1. The first step is to estimate the trend. Two different approaches could be used for this (with many variations of each).

One approach is to estimate the trend with a smoothing procedure such as moving averages. With this approach no equation is used to describe trend.

The second approach is to model the trend with a regression equation.

2. The second step is to "de-trend" the series. For an additive decomposition, this is done by subtracting the trend estimates from the series. For a multiplicative decomposition, this is done by dividing the series by the trend values.

3. Next, seasonal factors are estimated using the de-trended series. For monthly data, this entails estimating an effect for each month of the year. For quarterly data, this entails estimating an effect for each quarter. The simplest method for estimating these effects is to average the de-trended values for a specific season. For instance, to get a seasonal effect for January, we average the de-trended values for all Januarys in the series, and so on. (Minitab uses medians rather than means, by the way.)The seasonal effects are usually adjusted so that they average to 0 for an additive decomposition or they average to 1 for a multiplicative decomposition.

4. The final step is to determine the random (irregular) component.

For the additive model, random = series – trend – seasonal.
 For the multiplicative model, random = series / (trend*seasonal).The random component could be analyzed for such things as mean absolute size, or mean squared size (variance), or possibly even for whether the component is actually random or might be modeled with an ARIMA model.

vii Trend Analysis Model:

Analysis of trend involves developing an equation that will suitably describe trend (assuming that trend is present in the data)as upheld by Godwin & Okafor (2012). The trend component may be linear or nontrend.

$$F_t = bt + a \tag{15}$$

Where t = Specified number of time periods from t= 0

F_t =Forecast for period t or the dependent variable

a =Value of F_t at t = 0

b = Slope of the line

$$b = \frac{n \sum ty - \sum t \sum y}{n \sum t^2 - (\sum t)^2} \quad (16)$$

$$a = \frac{\sum y - b \sum t}{n} \quad (17)$$

Where, n = Number of periods

y = Value of the time series

\bar{y} = mean value of the time series

\bar{t} = mean values of the period t

Forecasting accuracy measures are the terms used to measure the accuracy of any forecast. The terms are Mean Absolute Deviation (MAD), Mean Square Deviation (MSD), Standard Deviation (SD), Mean Absolute Percentage Error (MAPE), Forecasting Errors (FE), Root Mean squared error (RMSE), Forecast skill (SS), Actual Forecast (AF) and Sum of Errors (SE). The forecasting measuring accuracy are being calculated from the collected data. The forecasting errors are the difference between the actual data and the predicted data. It is also called the absolute deviation. The actual forecast are the forecasting results developed using analytical means or by the use of a software. The sum of errors is the summation of all the errors in the data having in mind that errors are the difference between the actual and the predicted results. Mean absolute deviation is the average error in the data. It can be expressed as the mean of the errors in the data. Mean square deviation is mean of the squared errors in the data. When the errors in each of the data are squared, the mean of the squared errors are expressed as the Mean Square Deviation. Root Mean Squared error is simply expressed as the square root of mean square deviation. Root mean square errors is also called root mean square deviation and it is also known as standard deviation. The root mean square deviation is used to checkmate the errors in the forecasting and to measure the rate of accuracy in the forecast. $E_t = Y_t - F_t$ (18)

where E is the forecast error at period t, Y is the actual value at period t, and F is the forecast for period t.

Measures of aggregate error:

Mean Absolute Percentage Error

$$MAPE = \frac{\sum_{t=1}^N \frac{E_t}{Y_t}}{N} \quad (19)$$

Mean Absolute Deviation (MAD)

$$MAD = \frac{\sum_{t=1}^N E_t}{N} \quad (20)$$

Mean Squared Error (MSE)

$$MSE = \frac{\sum_{t=1}^N E_t^2}{N} \quad (21)$$

Root Mean Square Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{t=1}^N E_t^2}{N}} \quad (22)$$

Forecast Skill (SS)

$$SS = 1 - \frac{MSE_{forecast}}{MSE_{ref}} \quad (23)$$

Average Error (\bar{E})

$$\bar{E} = \frac{\sum_{t=1}^N e_i}{N} \quad (24)$$

c. Main Cause and Effect tool

Cause and Effect Analysis was devised by Professor Kaoru Ishikawa in 1960s, a pioneer of quality management. Main cause and effect tool is a tool in Design Expert software. It is an experimental tool used for process or experimental design. It shows the effect of the variables in the process or system design. It is used to analyze the influence of variables in the system. The technique uses a diagram-based approach for thinking through all of the possible causes of a problem. The diagrams that you create with are known as Ishikawa Diagrams or Fishbone Diagrams (because a completed diagram can look like the skeleton of a fish). The main aim of cause and effect analysis is to identify the likely causes of problems and its effect on the output. Although it was originally developed as a quality control tool, yet the tool can be used as well in other areas as proposed by Gregory (1992). For instance, you can use it to:

Discover the root cause of a problem.

Uncover bottlenecks in your processes.

Identify where and why a process isn't working.

How to Use the Tool

With Cause and Effect Analysis the following steps can be taken to solve a problem:

Step 1: Identify the Problem

First, write down the exact problem you face. Where appropriate, identify who is involved, what the problem is, and when and where it occurs. Then, write the problem in a box on the left-hand side of a large sheet of paper, and draw a line across the paper horizontally from the box. This arrangement, looking like the head and spine of a fish, gives you space to develop ideas.

Step 2: Work Out the Major Factors Involved

Next, identify the factors that may be part of the problem. These may be systems, equipment, materials, external forces, people involved with the problem, and so on.

Try to draw out as many of these as possible. As a starting point, you can use models such as the McKinsey 7S Framework (which offers you Strategy, Structure, Systems, Shared values, Skills, Style and Staff as factors that you can consider) or the 4Ps of Marketing (which offers Product, Place, Price, and Promotion as possible factors). Brainstorm any other factors that may affect the situation. Then draw a line off the "spine" of the diagram for each factor, and label each line.

Step 3: Identify Possible Causes

Now, for each of the factors you considered in step 2, brainstorm possible causes of the problem that may be related to the factor. Show these possible causes as shorter lines coming off the "bones" of the diagram. Where a cause is large or complex, then it may be best to break it down into sub-causes. Show these as lines coming off each cause line.

Step 4: Analyze Your Diagram

By this stage you should have a diagram showing all of the possible causes of the problem that you can think of. Depending on the complexity and importance of the problem, you can now investigate the most likely causes further. This may involve setting up investigations, carrying out surveys, and so on. These will be designed to test which of these possible causes is actually contributing to the problem.

d. Response Surface Optimization of the Operational costs of ATS Vehicles.

The response surface models are second order regression models with $\{(n+1)(n+2)/2\}$ numbers of regression parameters, with n being the number of

factors. Response Surface Method (RSM) is a modeling approach in which polynomials are used as local approximations to the true input/output relationship. It is also used for the optimization of multivariable. Most of the RSM fits to a process or an experimental data belong to either linear (first order) model or quadratic (second order) formulation as expressed by Hillier & Gerald (2005). Cubic and higher order models are also becoming popular with the recent implementation of RSM algorithm on commercially available statistical analysis software and other computer applications. Response surface method was used as a second order function for approximating the response of factors with interaction effects, Amponsah (2006). For purposes of analyzing response surface, the special design used to fit a second order model to the response was Box – Behnken design. Box – Behnken design is a three level factor design that is widely used in response surface method to fit second order model to the response.

i. Fitting a second order model to the data of maintenance costs.

The response function of a second order model is best characterized by multivariate power equation. The data obtained from the statistical office of Anambra State Transport Sector (ATS) is linearized on the assumption that the sample results follow a power law model of the form:

$$Y = a_0 A^{a1} B^{a2} C^{a3} \dots N^{an} \tag{25}$$

and that the response surface is optimized by a second order polynomial equation stated as:

$$Y = \beta_0 + \sum_{i=1}^q \beta_i x_i + \sum_{i=1}^q \beta_{ii} x_i^2 + \sum_{i=1}^{q-1} \sum_{j=2}^q \beta_{ij} + \varepsilon \tag{26}$$

For four factors, three level design equation (25) reduces to:

$$Y = a_0 A^{a1} B^{a2} C^{a3} D^{a4} \tag{27}$$

And equation (26) expanded to:

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{44} x_4^2 + \beta_{12} x_1 x_2 + \beta_{13} x_1 x_3 + \beta_{14} x_1 x_4 + \beta_{23} x_2 x_3 + \beta_{24} x_2 x_4 + \beta_{34} x_3 x_4 \quad (28)$$

The power equation (27) is transformed into multiple linear regression by taking the logarithm of the terms to give:

$$\text{Log} Y_{m\text{cost}} = \text{Log} a_0 + a_1 \text{Log} A + a_2 \text{Log} B + a_3 \text{Log} C + a_4 \text{Log} D \quad (29)$$

The values of the coefficients are calibrated by setting up the sum of squares of the residuals of the equation according to Chapra and Canale (2006) as:

$$S_r = \sum_{i=1}^n (Y_i - \text{Log} a_0 - a_1 \text{Log} A - a_2 \text{Log} B - a_3 \text{Log} C - a_4 \text{Log} D)^2 \quad (30)$$

Differentiating equation (30) with respect to each of the unknown coefficients as partial derivatives, we have:

$$\frac{\partial S_r}{\partial \text{Log} a_0} = -2 \sum (y_i - \text{Log} a_0 - a_1 \text{Log} A_i - a_2 \text{Log} B_i - a_3 \text{Log} C_i - a_4 \text{Log} D_i) \quad (31)$$

$$\frac{\partial S_r}{\partial a_1} = -2 \sum (y_i - \text{Log} a_0 - a_1 \text{Log} A_i - a_2 \text{Log} B_i - a_3 \text{Log} C_i - a_4 \text{Log} D_i) \text{Log} A_i \quad (32)$$

$$\frac{\partial S_r}{\partial a_2} = -2 \sum (y_i - \text{Log} a_0 - a_1 \text{Log} A_i - a_2 \text{Log} B_i - a_3 \text{Log} C_i - a_4 \text{Log} D_i) \text{Log} B_i \quad (33)$$

$$\frac{\partial S_r}{\partial a_3} = -2 \sum (y_i - \text{Log} a_0 - a_1 \text{Log} A_i - a_2 \text{Log} B_i - a_3 \text{Log} C_i - a_4 \text{Log} D_i) \text{Log} C_i \quad (34)$$

$$\frac{\partial S_r}{\partial a_4} = -2 \sum (y_i - \text{Log} a_0 - a_1 \text{Log} A_i - a_2 \text{Log} B_i - a_3 \text{Log} C_i - a_4 \text{Log} D_i) \text{Log} D_i \quad (35)$$

The coefficients yielding the minimum sum of squares of the residuals are obtained by setting the partial derivatives equal to zero and expressed in matrix form as:

$$n \text{Log} a_0 + a_1 \sum \text{Log} A_i + a_2 \sum \text{Log} B_i + a_3 \sum \text{Log} C_i + a_4 \sum \text{Log} D_i = \sum y_i \quad (36)$$

$$\begin{aligned} & \text{Log} a_0 \sum \text{Log} A_i + a_1 \sum \text{Log} A_i^2 + a_2 \sum \text{Log} A_i \text{Log} B_i + a_3 \sum \text{Log} A_i \text{Log} C_i + a_4 \sum \text{Log} A_i \text{Log} D_i \\ & = \sum \text{Log} A_i y_i \end{aligned} \quad (37)$$

$$\begin{aligned} &Loga_0 \sum LogB_i + a_1 \sum LogA_i LogB_i + a_2 \sum LogB_i^2 + a_3 \sum LogB_i LogC_i + a_4 \sum LogB_i LogD_i \\ &= \sum LogB_i y_i \end{aligned} \quad (38)$$

$$\begin{aligned} &Loga_0 \sum LogC_i + a_1 \sum LogA_i LogC_i + a_2 \sum LogB_i LogC_i + a_3 \sum LogC_i^2 + a_4 \sum LogC_i LogD_i \\ &= \sum LogC_i y_i \end{aligned} \quad (39)$$

$$\begin{aligned} &Loga_0 \sum LogD_i + a_1 \sum LogA_i LogD_i + a_2 \sum LogB_i LogD_i + a_3 \sum LogC_i LogD_i + a_4 \sum LogD_i^2 \\ &= \sum LogD_i y_i \end{aligned} \quad (40)$$

Expressing equations (36) – (40) in matrix form gives:

$$\begin{bmatrix} n & \sum LogA_i & \sum LogB_i & \sum LogC_i & \sum LogD_i \\ \sum LogA_i & \sum LogA_i^2 & \sum LogA_i LogB_i & \sum LogA_i LogC_i & \sum LogA_i LogD_i \\ \sum LogB_i & \sum LogA_i LogB_i & \sum LogB_i^2 & \sum LogB_i LogC_i & \sum LogB_i LogD_i \\ \sum LogC_i & \sum LogA_i LogC_i & \sum LogB_i LogC_i & \sum LogC_i^2 & \sum LogC_i LogD_i \\ \sum LogD_i & \sum LogA_i LogD_i & \sum LogB_i LogD_i & \sum LogC_i LogD_i & \sum LogD_i^2 \end{bmatrix} \begin{bmatrix} Loga_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} \sum y_i \\ \sum LogA_i y_i \\ \sum LogB_i y_i \\ \sum LogC_i y_i \\ \sum LogD_i y_i \end{bmatrix} \quad (41)$$

Table 3.4(b) is obtained by using the logarithm (base 10) of the data in Table 3.4(a).

Table 3.4(a): Operational Parameters for Nissan Urvan Maintenance Costs.

<i>Year</i>	<i>Factor A Dis tan ce, Km</i>	<i>Factor B Pr eci pita tio n, Cubic</i>	<i>Factor C Tempe rature, ° C</i>	<i>Factor D Re lative Hu midity</i>	<i>Re sponse Y Ma int enance Cost (#x1000)</i>
2005	101616	1620	29.2	148	1969
2006	102784	1500	28.5	156.9	2250
2007	105120	1650.3	28.96	176.98	2520
2008	113296	1507	28.15	159.56	2815
2009	116800	1579.1	28.3	126.2	3030
2010	117384	1506.6	27.8	122.65	3240
2011	117968	1695.4	28.85	129.7	3360
2012	118552	1662	27.9	148	3590
2013	119720	2294.7	28.3	122.65	3995
2014	120304	1695	24.4	129.68	4005

Table 3.4(b): Log transformed data for maintenance costs.

<i>Factor A</i>	<i>Factor B</i>	<i>Factor C</i>	<i>Factor D</i>	<i>Re sponse Y</i>	<i>Log A</i>	<i>Log B</i>	<i>Log C</i>	<i>Log D</i>	<i>Log Y</i>
101616	1620	29.2	148	1969	5.007	3.2095	1.4654	2.1703	3.2942
102784	1500	28.5	156.9	2250	5.012	3.1761	1.4548	2.1956	3.3522
105120	1650.3	28.96	176.98	2520	5.0217	3.2176	1.4618	2.2479	3.4014
113296	1507	28.15	159.56	2815	5.0542	3.1781	1.4495	2.2029	3.4495
116800	1579.1	28.3	126.2	3030	5.0674	3.1984	1.4518	2.1011	3.4814
117384	1506.6	27.8	122.65	3240	5.0696	3.1780	1.4440	2.089	3.5105
117968	1695.4	28.85	129.7	3360	5.0718	3.2293	1.4601	2.1129	3.5263
118552	1662	27.9	148	3590	5.0739	3.2206	1.4456	2.1703	3.5551
119720	2294.7	28.3	122.65	3995	5.0782	3.3607	1.4518	2.0887	3.6015
120304	1695	24.4	129.68	4005	5.0803	3.2292	1.3874	2.1129	3.6026

The computation required to develop the normal equation expressed in matrix

form (Table 3.4(c)) is presented in Table 3 in the appendix A₃.

Table 3.4(c): Normal equation expressed in matrix form.

$$\begin{bmatrix} 10 & 50.536 & 32.198 & 14.472 & 21.492 \\ 50.536 & 255.397 & 162.719 & 73.134 & 108.600 \\ 32.198 & 162.719 & 103.694 & 46.596 & 69.187 \\ 14.472 & 73.134 & 46.596 & 20.949 & 31.107 \\ 21.492 & 108.600 & 69.187 & 31.107 & 46.217 \end{bmatrix} \begin{bmatrix} \text{Log}a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} 34.775 \\ 175.76337 \\ 111.99225 \\ 50.314685 \\ 74.7033466 \end{bmatrix}$$

The system of normal equation can be solved using regression as analysis tool for evaluating log transformed data of input parameters for:

$$\text{Log}a_0 = -13.532598$$

$$a_1 = 3.183453789$$

$$a_2 = 0.465364202$$

$$a_3 = -0.80574072$$

$$a_4 = 0.274461545$$

The multiple linear equation of the transformed power equation expressed in equation (29) becomes:

$$\text{Log } Y_{\text{mcost.}} = -13.532598 + 3.183453789\text{Log}A + 0.465364202\text{Log}B - 0.80574072\text{Log}C + 0.274461545\text{Log}D. \quad (42)$$

Since $\text{Log}a_0 = -13.532598$

$$a_0 = \text{Inv. Log } -13.532598$$

$$= 2.933607451\text{E-}14$$

Expressing equation (42) as a power equation of the form of equation (27).

$$Y_{\text{mcost}} = 2.933607451\text{E-}14 * (A^{3.183453789}) * (B^{0.4665364202}) * (C^{-0.80574072}) * (D^{0.274461545}) \quad (43)$$

ii. Fitting a second order model to the Data of Replacement Costs.

Following the linearization process employed for the data of maintenance costs,

the data of replacement cost shown in Table 3.4(d) is linearized to give the log transformed data of Table 3.4(e). With Table 3.4(e), we generated the normal equation that was expressed in matrix form. The computation required to develop the normal equation is presented in Table 9 in the appendix A₃.

Table 3.4(d): Operational Parameters for Nissan Urvan Replacement Costs.

<i>Year</i>	<i>Factor A Distance, Km</i>	<i>Factor B Precipitation, Cubic</i>	<i>Factor C Temperature, °C</i>	<i>Factor D Relative Humidity</i>	<i>Response Y Replacement Cost (x1000)</i>
2005	101616	1620	29.2	148	1992
2006	102784	1500	28.5	156.9	2240
2007	105120	1650.3	28.96	176.98	2400
2008	113296	1507	28.15	159.56	2500
2009	116800	1579.1	28.3	126.2	2568
2010	117384	1506.6	27.8	122.65	2681
2011	117968	1695.4	28.85	129.7	2705
2012	118552	1662	27.9	148	2805
2013	119720	2294.7	28.3	122.65	2856
2014	120304	1695	24.4	129.68	2943

Table 3.4(e): Log transformed data for replacement costs.

<i>Factor A</i>	<i>Factor B</i>	<i>Factor C</i>	<i>Factor D</i>	<i>Response Y</i>	<i>Log A</i>	<i>Log B</i>	<i>Log C</i>	<i>Log D</i>	<i>Log Y</i>
101616	1620	29.2	148	1992	5.007	3.2095	1.4654	2.1703	3.2993
102784	1500	28.5	156.9	2240	5.012	3.1761	1.4548	2.1956	3.3502
105120	1650.3	28.96	176.98	2400	5.0217	3.2176	1.4618	2.2479	3.3802
113296	1507	28.15	159.56	2500	5.0542	3.1781	1.4495	2.2029	3.3979
116800	1579.1	28.3	126.2	2568	5.0674	3.1984	1.4518	2.1011	3.4096
117384	1506.6	27.8	122.65	2681	5.0696	3.1780	1.4440	2.089	3.4283
117968	1695.4	28.85	129.7	2705	5.0718	3.2293	1.4601	2.1129	3.4322
118552	1662	27.9	148	2805	5.0739	3.2206	1.4456	2.1703	3.4479
119720	2294.7	28.3	122.65	2856	5.0782	3.3607	1.4518	2.0887	3.4558
120304	1695	24.4	129.68	2943	5.0803	3.2292	1.3874	2.1129	3.4688

Table 3.4(e) is obtained by using the logarithm (base 10) of the data in Table 3.4(d). With Table 3.4(e), we generated the normal equation that was expressed in matrix form. The computation required to develop the normal equation is presented in Table 9 in the appendix A₃. The normal equation is presented in Table 3.4(f).

Table 3.4(f): Normal equation expressed in matrix form.

$$\begin{bmatrix} 10 & 50.536 & 32.198 & 14.472 & 21.492 \\ 50.536 & 255.397 & 162.719 & 73.134 & 108.600 \\ 32.198 & 162.719 & 103.694 & 46.596 & 69.187 \\ 14.472 & 73.134 & 46.596 & 20.949 & 31.107 \\ 21.492 & 108.600 & 69.187 & 31.107 & 46.217 \end{bmatrix} \begin{bmatrix} \text{Log} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} 34.07 \\ 172.19025 \\ 109.70834 \\ 49.30100 \\ 73.20761 \end{bmatrix}$$

The system of normal equation can be solved using regression as analysis tool for evaluating log transformed data of input parameters for:

$$\text{Log} a_0 = -6.192542669$$

$$a_1 = 1.813623751$$

$$a_2 = 0.139777175$$

$$a_3 = -0.378185139$$

$$a_4 = 0.247298984$$

The multiple linear equation of the transformed power equation expressed in equation (29) becomes:

$$\text{Log } Y_{\text{rcost}} = -6.192542669 + 1.813623751 \text{Log} A + 0.139777175 \text{Log} B - 0.378185139 \text{Log} C + 0.247298984 \text{Log} D. \quad (45)$$

$$\text{Since } \text{Log} a_0 = -6.192542669$$

$$a_0 = \text{Inv. Log } -6.192542669 = 6.418851538\text{E-}07$$

Expressing equation (45) as a power equation of the form of equation (27).

$$Y_{\text{rcost}} = 6.418851538\text{E-}07 * (A^{1.813623751}) * (B^{0.139777175}) * (C^{-0.378185139}) * (D^{0.247298984}) \quad (46)$$

iii. Fitting a second order model to the data of income generated.

Following the linearization process of equations (25) to (40), the data of income generated as illustrated in Table 3.4(g) is linearized to give the transformed data using logarithm (base 10) presented in Table 3.4(h) with detail in appendix A₃.

Table 3.4(g): Operational Parameters for Nissan Urvan with Income Generated.

<i>Year</i>	<i>Factor A Dis tan ce, Km</i>	<i>Factor B Pr ecipitatio n, Cubic</i>	<i>Factor C Temperat ure, ° C</i>	<i>Factor D Re lative Humidity</i>	<i>Re sponse Y In come Gene rated Cost (x1000)</i>
2005	101616	1620	29.2	148	9807.30
2006	102784	1500	28.5	156.9	9782.40
2007	105120	1650.3	28.96	176.98	9660.00
2008	113296	1507	28.15	159.56	9515.00
2009	116800	1579.1	28.3	126.2	9020.00
2010	117384	1506.6	27.8	122.65	8850.00
2011	117968	1695.4	28.85	129.7	8610.00
2012	118552	1662	27.9	148	8489.70
2013	119720	2294.7	28.3	122.65	8340.00
2014	120304	1695	24.4	129.68	8300.00

Table 3.4(h): Log transformed data for income generated

<i>Factor A</i>	<i>Factor B</i>	<i>Factor C</i>	<i>Factor D</i>	<i>Response Y</i>	<i>Log A</i>	<i>Log B</i>	<i>Log C</i>	<i>Log D</i>	<i>Log Y</i>
101616	1620	29.2	148	1992	5.007	3.2095	1.4654	2.1703	3.9915
102784	1500	28.5	156.9	2240	5.012	3.1761	1.4548	2.1956	3.9904
105120	1650.3	28.96	176.98	2400	5.0217	3.2176	1.4618	2.2479	3.9850
113296	1507	28.15	159.56	2500	5.0542	3.1781	1.4495	2.2029	3.9784
116800	1579.1	28.3	126.2	2568	5.0674	3.1984	1.4518	2.1011	3.9552
117384	1506.6	27.8	122.65	2681	5.0696	3.1780	1.4440	2.089	3.9469
117968	1695.4	28.85	129.7	2705	5.0718	3.2293	1.4601	2.1129	3.9350
118552	1662	27.9	148	2805	5.0739	3.2206	1.4456	2.1703	3.9289
119720	2294.7	28.3	122.65	2856	5.0782	3.3607	1.4518	2.0887	3.9212
120304	1695	24.4	129.68	2943	5.0803	3.2292	1.3874	2.1129	3.9191

With Table 3.4(h), the normal equation was developed as shown in Table 3.4(i)

and the normal equation is expressed in matrix form as:

Table 3.4(i): Normal equation expressed in matrix form

$$\begin{bmatrix} 10 & 50.536 & 32.198 & 14.472 & 21.492 \\ 50.536 & 255.397 & 162.719 & 73.134 & 108.600 \\ 32.198 & 162.719 & 103.694 & 46.596 & 69.187 \\ 14.472 & 73.134 & 46.596 & 20.949 & 31.107 \\ 21.492 & 108.600 & 69.187 & 31.107 & 46.217 \end{bmatrix} \begin{bmatrix} \text{Log} a_0 \\ a_1 \\ a_2 \\ a_3 \\ a_4 \end{bmatrix} = \begin{bmatrix} 39.552 \\ 199.871434 \\ 127.338323 \\ 57.2430936 \\ 85.0133484 \end{bmatrix}$$

The system of normal equation can be solved using regression as analysis tool for evaluating log transformed data of input parameters for:

$$\text{Log} a_0 = 7.361286894$$

$$a_1 = -0.668996929$$

$$a_2 = -0.147041359$$

$$a_3 = 0.240003793$$

$$a_4 = 0.046911726$$

The multiple linear equation of the transformed power equation as expressed equation (29) is:

$$\text{Log } Y_{\text{income gen.}} = 7.361286894 - 0.668996929\text{Log}A - 0.147041359\text{Log}B + 0.240003793\text{Log}C + 0.046911726\text{Log}D. \quad (48)$$

Since $\text{Log} a_0 = 7.361286894$

$$\begin{aligned} a_0 &= \text{Inv. Log } 7.361286894 \\ &= 22976659.8 \end{aligned}$$

Expressing equation (48) as a power equation of the form of equation (27), we have:

$$Y_{\text{income gen.}} = 22976659.8 * (A^{-0.668996929}) * (B^{-0.147041359}) * (C^{0.240003793}) * (D^{0.046911726}) \quad (49)$$

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Data Analysis

4.1.1 Modeling the operational costs of Anambra State Transport Sector's vehicles using dynamic recursive programming model.

This was done by employing equation (1) shown in chapter three.

The stage and state variables are shown in Table 4.1.1(a) with columns 1 and 2 representing various years (stages) and their corresponding age(states) variables respectively.

Table 4.1.1(a): Stage and State Variables for Anambra State Transport Sector's Vehicles (ATS).

K(Stage Variables)	i(State Variables)
1	0,2
2	1,3
3	1,2,4
4	1,2,3,5
5	1,2,3,4,6
6	1,2,3,4,5,7
7	1,2,3,4,5,6,8
8	1,2,3,4,5,6,7,9
9	1,2,3,4,5,6,7,8,10
10	1,2,3,4,5,6,7,8,9,11
11	1,2,3,4,5,6,7,8,9,10,12
12	1,2,3,4,5,6,7,8,9,10,11,13
13	1,2,3,4,5,6,7,8,9,10,11,12,14
14	1,2,3,4,5,6,7,8,9,10,11,12,13,15

The problem is solved by backward dynamic programming using the recursive equations (1) shown in chapter three, with the assumption that a vehicle can only be kept or replaced at the beginning of each year and vehicles of relatively the same age are considered. The vehicles are again not subjected to catastrophic failure. The model operates on the principle of finding an overall solution based on intermediate points. Every stage has more than one state in which a decision is taken at each state either to keep or replace, which forms a sub decision to the next state and continues till the final state in a stage is reached.

Subsequently, the following are the summary outcome of the computational analyses.

Nissan Urvan Vehicles

Table 4.1.1(b) is the obtained mean optimal keep and replace action of Nissan Urvan vehicles over the given period.

Table 4.1.1(b): Mean Optimal Keep and Replace Action of Nissan Urvan Vehicles(× 1000)

Stages(Years)	$V_k(\text{₦})$	$V_r(\text{₦})$	$V_k(i)$	D_k
14	20100.37	20214.00	20100.37	Keep
13	20141.00	21808.00	20141.00	Keep
12	21894.50	18613.40	18613.40	Replace
11	25462.33	30855.80	25462.33	Keep
10	30273.11	31933.12	30273.11	Keep
9	34019.80	39443.50	34019.80	Keep
8	35868.28	44633.30	35868.28	Keep
7	39748.09	50040.70	39748.09	Keep
6	41839.80	52663.00	41839.80	Keep
5	54195.42	56815.06	54195.42	Keep
4	59643.40	63327.70	59643.40	Keep
3	63273.00	65785.80	63273.00	Keep
2	69201.60	72674.70	69201.60	Keep
1	72423.60	74343.30	72423.60	Keep

Table 4.1.1(b) is the average optimal keep and replace action of Nissan Urvan vehicles over the given period. The keep actions are observed at stages(14,13,11,10,9,8,7,6,5,4,3,2,1) and replace action displayed at stage 12. This showed that Nissan Urvan vehicles could be used and replaced after twelve years of service to enhance the profitability of the case study company. Detailed computations of states/stages of operational costs of Nissan Urvan vehicles are in Appendix A₁.

Sienna Vehicles

Table 4.1.1(c) represented the optimal keep and replace action of Sienna vehicles over the given period.

Table 4.1.1(c): Mean Optimal Keep and Replace Action of Sienna Vehicles ($\times 1000$).

Stages(Years)	$V_k(\text{₹})$	$V_r(\text{₹})$	$V_k(i)$	D_k
14	2015.17	2026.46	2015.17	Keep
13	2387.77	3330.56	2387.77	Keep
12	3957.42	4646.46	3957.42	Keep
11	5018.03	5705.68	5018.03	Keep
10	5689.19	5782.16	5689.19	Keep
9	6896.76	6911.25	6896.76	Keep
8	7674.01	7833.66	7674.01	Keep
7	8750.85	7264.02	7264.02	Replace
6	1254.37	1396.67	1254.37	Keep
5	1691.43	1808.03	1691.43	Keep
4	2715.58	3638.58	2715.58	Keep
3	2297.37	2624.74	2297.37	Keep
2	3494.05	3768.67	3494.05	Keep
1	4020.02	4251.32	4020.02	Keep

Table 4.1.1(c) displayed the average optimal keep and replace actions of Sienna vehicles over the given years or stages. The keep actions are observed at stages(14,13,12,11,10,9,8,6,5,4,3,2,1) and replace action displayed at stage 7. The trend showed that the operational (maintenance and replacement) costs increase up to the seventh year where replace action is taken and vice versa. Detailed computations of states/stages of operational costs of Sienna vehicles are in Appendix A₁.

Peugeot Expert Vehicles

Table 4.1.1(d) clarified the optimal keep and replace action of Peugeot Expert vehicles over the given period.

Table 4.1.1(d): Optimal Keep and Replace Action of Peugeot Expert Vehicles ($\times 1000$)

Stages(Years)	$V_k(\text{₹})$	$V_r(\text{₹})$	$V_k(i)$	D_k
14	1903.94	8719.02	1903.94	Keep
13	3975.73	6180.11	3975.73	Keep
12	7070.97	7347.89	7070.97	Keep
11	7469.09	7681.88	7469.09	Keep
10	8417.60	8498.61	8417.60	Keep
9	8580.23	8598.61	8580.23	Keep
8	8616.18	5862.29	5862.29	Replace
7	8506.28	8978.12	8506.28	Keep
6	1524.98	2155.88	1524.98	Keep
5	1629.57	2243.73	1629.57	Keep
4	1708.32	2343.73	1708.32	Keep
3	1757.50	2373.78	1757.50	Keep
2	1840.83	2383.08	1840.83	keep
1	1889.46	2530.33	1889.46	Keep

Table 4.1.1(d) show the average optimal keep and replace actions of Peugeot Expert vehicles over the given years. The keep and replace actions are observed at stages (14,13,12,11,10,9,7,6,5,4,3,2,1) and stage 8 respectively. In this regard, it is observed that the operational costs of Peugeot Expert vehicle increase with increase in age. Detailed computations of states/stages of operational costs of Peugeot Expert vehicles are in Appendix A₁.

J5 Vehicles

Table 4.1.1(e) displayed the mean optimal keep and replace action of J5 vehicles over the given period.

Table 4.1.1(e): Optimal Keep and Replace Action of J5 Vehicles($\times 1000$)

Stages(Years)	$V_k(\text{₹})$	$V_r(\text{₹})$	$V_k(i)$	D_k
14	22390.53	84755.30	22390.53	Keep
13	54961.28	69817.45	54961.28	Keep
12	85365.50	85779.35	85365.50	Keep
11	12802.50	12829.57	12802.50	Keep
10	13453.07	15131.72	13453.76	Keep
9	20730.30	16329.73	16329.73	Replace
8	17253.07	19015.92	17253.07	Keep
7	19066.72	19473.50	19066.72	Keep
6	20796.86	21473.75	20796.86	Keep
5	24036.56	25872.96	24036.56	Keep
4	25377.55	25928.02	25377.55	Keep
3	26489.43	26586.52	26489.43	Keep
2	27003.80	27105.40	27003.80	Keep
1	28240.50	28585.10	28240.50	Keep

Table 4.1.1(e) explained the average optimal keep and replace actions of J5 vehicles over the given periods. The keep actions are noticed at stages(14,13,12,11,10,8,7,6,5,4,3,2,1) and replace action at stage 9. The trend revealed that there is an increase in the operational costs of J5 vehicles with a corresponding increase in age. This showed that J5 vehicles can be used and replaced after nine years of usage. Detailed computations of states/stages of operational costs of J5 vehicles are in Appendix A₁

Ford Bus Vehicles

Table 4.1.1(f) clarified the mean optimal keep and replace actions of Ford bus vehicles over the given period.

Table 4.1.1(f): Mean Optimal Keep and Replace Action of Ford Bus Vehicles($\times 1000$)

Stages(Years)	$V_k(\text{₦})$	$V_r(\text{₦})$	$V_k(i)$	D_k
14	30947.37	40770.53	30947.37	Keep
13	49735.62	52856.04	49735.62	Keep
12	72699.35	86034.40	72699.35	Keep
11	92387.35	95217.49	92387.35	Keep
10	11041.80	12432.55	11041.80	Keep
9	12132.56	12364.88	12132.56	Keep
8	23295.74	18190.40	18190.40	Replace
7	22777.80	26248.56	22777.80	Keep
6	23680.51	25655.73	23680.51	Keep
5	24089.09	27997.24	24089.09	Keep
4	24195.88	25080.38	24195.88	Keep
3	25272.33	26326.56	25272.33	Keep
2	30814.90	30914.90	30814.90	Keep
1	31315.70	31555.90	31315.70	Keep

Table 4.1.1(f) displayed the mean optimal keep and replace actions of all the states and stages of Ford bus vehicles. The keep actions are observed at stages(14,13,12,11,10,9,7,6,5,4,3,2,1) and replace action at stage 8. This showed that Ford bus vehicles can be used and replaced after eight years of service. Detailed computations of states/stages of operational costs of Ford vehicles are in Appendix A₁.

Toyota Hiace Vehicles

Table 4.1.1(g) represented the mean operational costs of Toyota Hiace vehicles over the given years.

Table 4.1.1(g): Mean Optimal Keep and Replace Action of Toyota Hiace Vehicles ($\times 1000$)

Stages(Years)	$V_k(\text{₹})$	$V_r(\text{₹})$	$V_k(i)$	D_k
14	29137.59	71159.80	29137.59	Keep
13	82064.95	89595.39	82064.95	Keep
12	10792.20	15798.40	10792.20	Keep
11	21496.67	23054.00	21496.67	Keep
10	28909.10	29841.31	28909.10	Keep
9	36565.90	33837.70	33837.70	Replace
8	38736.53	42271.10	38736.53	Keep
7	42961.70	45602.70	42961.70	Keep
6	47690.02	47840.06	47690.02	Keep
5	51657.98	52767.40	51657.98	Keep
4	56966.28	57181.88	56966.28	Keep
3	62371.13	62523.20	62371.13	Keep
2	68739.00	68965.55	68739.00	Keep
1	74122.10	74131.00	74122.10	Keep

Table 4.1.1(g) depicted the average optimal keep and replace actions of Toyota Hiace vehicles over the given periods. The keep actions are observed at stages (14,13,12,11,10,8,7,6,5,4,3,2,1) and replace action at stage 9. This showed that Toyota Hiace vehicles can be used and replaced after nine years of service. Detailed computations of states/stages of operational costs of Toyota Hiace vehicles are in Appendix A₁.

Taxi Cab Vehicles

Table 4.1.1(h) revealed the average optimal keep and replace actions of Taxi cab vehicles over the given years or stages.

Table 4.1.1(h): Mean Optimal Keep and Replace Action of Taxi Cab Vehicles($\times 1000$)

Stages(Years)	$V_k(\text{₦})$	$V_r(\text{₦})$	$V_k(i)$	D_k
14	33628.23	47612.58	33628.23	Keep
13	43663.82	48544.48	43663.82	Keep
12	76418.42	93122.49	76418.42	Keep
11	11500.64	12790.86	11500.64	Keep
10	15964.27	16112.71	15964.27	Keep
9	18438.29	15482.40	15482.40	Replace
8	16685.48	18307.70	16685.48	Keep
7	17858.82	20583.94	17858.82	Keep
6	18722.03	22019.02	18722.03	Keep
5	20040.30	24711.45	20040.30	Keep
4	23244.09	26069.05	23244.09	Keep
3	26818.93	27253.43	26818.93	Keep
2	42074.25	42517.90	42074.25	Keep
1	46791.20	46018.30	46791.20	Keep

Table 4.1.1(h) showed the average optimal keep and replace actions of Taxi cab vehicles over the given years. The keep actions are observed at stages(14,13,12,11,10,8,7,6,5,4,3,2,1) and replace action at stage 9. This revealed that Taxi Cab vehicles can be used and replaced after nine years of service. Detailed computations of states/stages of operational costs of Taxi Cab vehicles are in Appendix A₁.

4.1.2 Selected forecasting techniques for modeling the operational costs of ATS Vehicles.

The selection was done using multi-regression analysis to show the significance of each factor utilized as shown in Appendices (D_{11} - D_{17} , D_{21} - D_{27} , D_{31} - D_{37}).

Maintenance Cost

The trend forecast model was employed for the analysis of Sienna, Peugeot Expert and Taxi Cab vehicles for the five years forecast(2015-2019) as shown

in Table 4.1.2(a).The analysis was done using “Eq. (15)” as established in chapter threewith details in Appendix A₂.

Table 4.1.2(a): Summary of trend forecast for maintenance costs of Sienna, Peugeot Expert and Taxi Cab vehicles (×1000).

Periods	Years	Sienna	Peugeot Expert	Taxi Cab
11	2015	5559.93	4205.75	3875.31
12	2016	5900.44	4328.73	4158.07
13	2017	6240.95	4433.73	4461.46
14	2018	6581.45	4520.73	4786.99
15	2019	6921.96	4709.23	5136.27

Table 4.1.2(a) showed the summary of trend forecast of maintenance costs of Sienna, Peugeot Expert and Taxi Cab vehicles for five years (2015-2019). The trend indicated that the maintenance costs increase as the years increase.

The double exponential smoothing forecast was employed for the analysis of J5, Ford bus, Toyota Hiace vehicles for the five years forecast (2015-2019) as presented in Table 4.1.2(b). The analysis was done using “Eq. (12)” as established in chapter threewith details in Appendix A₂.

Table 4.1.2(b): Summary of double exponential smoothing forecast for maintenance costs of J5, Ford, Toyota Hiace vehicles (×1000).

Period	Years	J5	Ford Bus	Toyota Hiace
11	2015	5007.42	4266.03	3872.78
12	2016	5237.31	4432.78	3894.21
13	2017	5467.20	4599.53	3915.64
14	2018	5697.08	4766.29	3937.08
15	2019	5926.97	4933.04	3958.51

Table 4.1.2(b) is the summary of double exponential smoothing forecast of maintenance costs for J5, Ford, Toyota Hiace vehicles. It is observed that the maintenance costs increase with an increase in age of the said vehicles.

Replacement Cost

The double exponential smoothing forecast model was used for the analysis of Nissan Urvan, J5, and Taxi Cab vehicles for the five years forecast (2015-2019) as shown in Table 4.1.2(c). The analysis was carried out with “Eq. (12)” as established in chapter three details in Appendix A₂.

Table 4.1.2(c): Summary of double exponential smoothing forecast for Replacement costs of Nissan Urvan, J5, Taxi Cab vehicles ($\times 1000$).

Period	Years	Nissan Urvan	J5	Taxi Cab
11	2015	2396.04	1951.26	1220.06
12	2016	2427.51	1967.14	1235.12
13	2017	2476.13	1983.02	1250.19
14	2018	2507.32	1998.89	1265.26
15	2019	2556.22	2014.77	1280.32

Table 4.1.2(c) is the summary of double exponential smoothing forecast analysis of Nissan Urvan, J5, Taxi Cab replacement costs. The observation is that the replacement costs increase as the age of the said vehicles increase.

The trend forecast model was deployed for the analysis of replacement costs of Sienna, Peugeot Expert, Toyota Hiace vehicles for the five years forecast as illustrated in Table 4.1.2(d). The analysis was carried out with “Eq. (15)” as established in chapter three with details in Appendix A₂.

Table 4.1.2(d): Summary of trend analysis forecast for Replacement costs of Sienna, Peugeot Expert, Toyota Hiace over the given period ($\times 1000$).

Period	Years	Sienna	Peugeot Expert	Toyota Hiace
11	2015	1370.30	1808.99	1983.07
12	2016	1476.05	1929.37	2090.39
13	2017	1580.54	2048.04	2197.28
14	2018	1684.03	2165.10	2203.74
15	2019	1696.75	2280.68	2309.77

Table 4.1.2(d) revealed the selected forecasting models for the replacement costs of Sienna, Peugeot Expert, and Toyota Hiace. The trend indicated that the

replacement costs of the said vehicles increase with increase in the age of the vehicles.

The winters forecast model was employed for the analysis of replacement costs of Ford Bus vehicles for the five years forecast as shown in Table 4.1.2(e). The analysis was done with “Eq. (8)” as established in chapter three with details in Appendix A₂.

Table 4.1.2(e): Summary of winters forecast for Replacement costs of Ford Bus over the given period ($\times 1000$).

Period	Years	Ford Bus
11	2015	1878.46
12	2016	1891.78
13	2017	1904.30
14	2018	2007.67
15	2019	2110.14

Table 4.1.2(e) exemplified the selected winters forecasting model for the replacement costs of Ford bus vehicles over the given period. The outcome revealed that the replacement costs increase with increase in age of the said vehicles.

Income Generation Cost

The time series decomposition forecast model was employed for the analysis of income generation of Nissan Urvan and Ford Bus vehicles for the period of five years as presented in Table 4.1.2(f) with details in Appendix A₂.

Table 4.1.2(f): Summary of time series analysis decomposition forecast for income generation of Nissan Urvan, Ford Bus over the given period ($\times 1000$).

Period	Years	Nissan Urvan	Ford Bus
11	2015	7926.74	6669.67
12	2016	7780.58	6438.97
13	2017	7535.42	6152.99
14	2018	7386.77	5920.06
15	2019	7144.11	5636.30

Table 4.1.2(f) showed the selected time series analysis decomposition forecasting model for the income generation of Nissan Urvan and Ford bus vehicles over the given period. The observation is that as the income generated decreases the age of the vehicles increases.

The trend forecast model was employed for the analysis of income generation of Sienna, Peugeot Expert, J5, Toyota Hiace vehicles for the five years forecast as shown in Table 4.1.2(g). The analysis was done using “Eq. (15)” as established in chapter three with details in Appendix A₂.

Table 4.1.2(g): Summary of Trend Analysis forecast for income generation of Sienna, Peugeot expert, J5, Toyota Hiace over the given period ($\times 1000$).

Periods	Years	Sienna	Peugeot Expert	J5	Toyota Hiace
11	2015	6792.66	6494.42	6914.65	7573.33
12	2016	6568.34	6308.16	6750.99	7331.39
13	2017	6344.01	6131.18	6591.20	7089.45
14	2018	6119.69	5963.48	6435.19	6847.52
15	2019	5895.36	5805.07	6282.87	6605.58

Table 4.1.2(g) is the summary of trend analysis forecast for income generation of Sienna, Peugeot expert, J5, Toyota Hiace vehicles over the given period. The trend showed that the income generated for the said vehicles decreases, as the age of the vehicle increases.

The winters forecast model was used for the analysis of income generation of Taxi Cab vehicles over the given forecasting period as presented in Table 4.1.2(h). The analysis was carried out with “Eq. (8)” as established in chapter three with details in Appendix A₂.

Table 4.1.2(h) represented the winter forecast for the income generation of Taxi Cab over the given period ($\times 1000$).

Period	Years	Taxi Cab
11	2015	5226.23
12	2016	4873.95
13	2017	4676.90
14	2018	4333.24
15	2019	4127.57

Table 4.1.2(h) is the summary of winter's forecast for the income generation of Taxi cab vehicles over the given period. The trend showed that the income generated for the said vehicles decreases, as the age of the vehicle increases.

4.1.3 Optimization of the operational costs of Nissan Urvan vehicles, using response surface method.

i. Evaluation of maintenance costs of Nissan Urvan vehicles using power equation. The power equation (43) was used to develop the design matrix of Box – Behnken as displayed in Table 4.1.3(a).

Table 4.1.3(a): Design matrix of Box-Behnken for optimization of maintenance costs.

Std. Order	Run order	Distance	Precipitation	Temp.	Relative Humidity	Response Maintenance cost
23	1	110960	1500.00	26.8	176.980	2970.01
14	2	110960	2294.70	24.4	149.815	3729.47
3	3	101616	2294.70	26.8	149.815	2613.34
2	4	120304	1500.00	26.8	149.815	3670.10
8	5	110960	1897.35	29.2	176.980	3092.00
18	6	120304	1897.35	24.4	149.815	4415.72
26	7	110960	1897.35	26.8	149.815	3165.11
22	8	110960	2294.70	26.8	122.650	3273.18
11	9	101616	1897.35	26.8	176.980	2503.97
13	10	110960	1500.00	24.4	149.815	3060.03
27	11	110960	1897.35	26.8	149.815	3165.11
15	12	110960	1500.00	29.2	149.815	2647.79
10	13	120304	1897.35	26.8	122.650	3875.47
1	14	101616	1500.00	26.8	149.815	2144.24
21	15	110960	1500.00	26.8	122.650	2685.64
16	16	110960	2294.70	29.2	149.815	3227.05
25	17	110960	1897.35	26.8	149.815	3165.11
5	18	110960	1897.35	24.4	122.650	3231.25
9	19	101616	1897.35	26.8	122.650	2264.22
24	20	110960	2294.70	26.8	176.980	3619.76
19	21	101616	1897.35	29.2	149.815	2232.31
12	22	120304	1897.35	26.8	176.980	4285.82
20	23	120304	1897.35	29.2	149.815	3820.84
6	24	110960	1897.35	29.2	122.650	2795.95
17	25	101616	1897.35	24.4	149.815	2579.86
7	26	110960	1897.35	24.4	176.980	3573.39
4	27	120304	2294.70	26.8	149.815	4473.01

The regression model resulting from the evaluation of the design matrix of Box-Behnken for maintenance costs shown in Table 4.1.3(a) is stated as equation (44) for uncoded factors respectively.

ii. Evaluation of replacement cost of Nissan Urvan vehicles using power equation. The power equation (46) was used to develop the design matrix of Box – Behnken as presented in Table 4.1.3(b).

Table 4.1.3(b): Design matrix of Box-Behnken for optimization of replacement costs.

Std. Order	Run order	Distance	Precipitation	Temp.	Relative Humidity	Response Maintenance cost
23	1	110960	1500.00	26.8	176.980	2613.64
14	2	110960	2294.70	24.4	149.815	2757.82
3	3	101616	2294.70	26.8	149.815	2269.18
2	4	120304	1500.00	26.8	149.815	2904.24
8	5	110960	1897.35	29.2	176.980	2614.72
18	6	120304	1897.35	24.4	149.815	3109.61
26	7	110960	1897.35	26.8	149.815	2591.88
22	8	110960	2294.70	26.8	122.650	2533.20
11	9	101616	1897.35	26.8	176.980	2302.62
13	10	110960	1500.00	24.4	149.815	2598.71
27	11	110960	1897.35	26.8	149.815	2591.88
15	12	110960	1500.00	29.2	149.815	2428.08
10	13	120304	1897.35	26.8	122.650	2856.34
1	14	101616	1500.00	26.8	149.815	2138.26
21	15	110960	1500.00	26.8	122.650	2387.05
16	16	110960	2294.70	29.2	149.815	2576.74
25	17	110960	1897.35	26.8	149.815	2591.88
5	18	110960	1897.35	24.4	122.650	2555.86
9	19	101616	1897.35	26.8	122.650	2103.00
24	20	110960	2294.70	26.8	176.980	2773.66
19	21	101616	1897.35	29.2	149.815	2139.14
12	22	120304	1897.35	26.8	176.980	3127.48
20	23	120304	1897.35	29.2	149.815	2905.43
6	24	110960	1897.35	29.2	122.650	2388.03
17	25	101616	1897.35	24.4	149.815	2289.47
7	26	110960	1897.35	24.4	176.980	2798.47
4	27	120304	2294.70	26.8	149.815	3082.05

The Design matrix of Box-Behnken for optimization of replacement costs is shown in Table 4.1.3(b). The regression model resulting from the evaluation of the design matrix of Box-Behnken for replacement costs is stated as equation (47) for uncoded factors.

iii .Evaluation of income generated by the Nissan Urvan vehicles using power equation. The power equation (48) shown in chapter three was used to develop the design matrix of Box – Behnken as presented in Table 4.1.3(c).

Table 4.1.3c: Design matrix of Box-Behnken design for optimization of income generated.

Std. Order	Run order	Distance	Precipitation	Temp.	Relative Humidity	Response Income Generated
27	1	110960	1897.35	26.8	149.815	8889.55
4	2	120304	2294.70	26.8	149.815	8189.29
19	3	101616	1897.35	29.2	149.815	9624.49
15	4	110960	1500.00	29.2	149.815	9393.46
24	5	110960	2294.70	26.8	176.980	8712.29
11	6	101616	1897.35	26.8	176.980	9502.40
21	7	110960	1500.00	26.8	122.650	9116.12
1	8	101616	1500.00	26.8	149.815	9759.88
16	9	110960	2294.70	29.2	149.815	8824.23
13	10	110960	1500.00	24.4	149.815	8997.20
22	11	110960	2294.70	26.8	122.650	8563.69
6	12	110960	1897.35	29.2	122.650	8989.66
14	13	110960	2294.70	24.4	149.815	8451.97
7	14	110960	1897.35	24.4	176.980	8759.83
2	15	120304	1500.00	26.8	149.815	8717.56
8	16	110960	1897.35	29.2	176.980	9145.64
25	17	110960	1897.35	26.8	149.815	8889.55
23	18	110960	1500.00	26.8	176.980	9274.30
20	19	120304	1897.35	29.2	149.815	8596.63
26	20	110960	1897.35	26.8	149.815	8889.55
3	21	101616	2294.70	26.8	149.815	9168.45
9	22	101616	1897.35	26.8	122.650	9340.33
5	23	110960	1897.35	24.4	122.650	8610.43
10	24	120304	1897.35	26.8	122.650	8342.82
18	25	120304	1897.35	24.4	149.815	8233.98
12	26	120304	1897.35	26.8	176.980	8487.58
17	27	101616	1897.35	24.4	149.815	9218.48

The design matrix of Box-Behnken for optimization of income generated is presented in Table 4.1.3(c) which clearly displayed the standard order, run order, control factors and the level of response.

4.2 Results of Dynamic Programming(Recursive)Model.

The results of the Dynamic Programming(recursive)model arising from the analysis are represented in Tables[4.1.1(b,c,d,e,f,g,h)]and plotted in Figures 4.2(a,b,c,d,e,f,g) for the said vehicles andTable 4.2.2displayed the summary of the optimal decision variable sequence for the studied vehicles as deduced fromthe analysis shown in Appendix A₁.

Figure 4.2(a)is the chart of Nissan Urvan Vehicles over the given period.

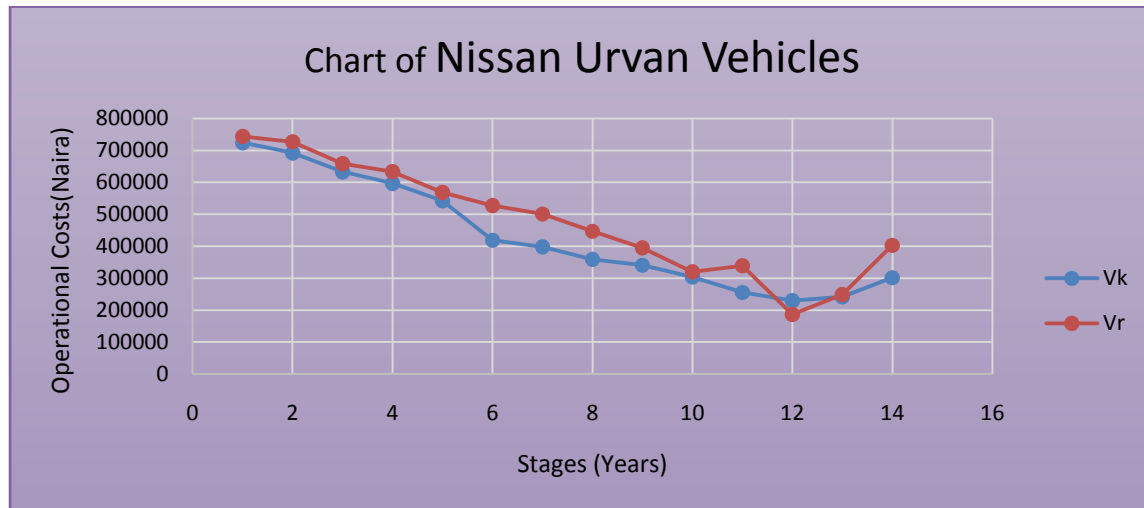


Figure 4.2(a): Optimum Replacement Time for Nissan Urvan Vehicles.

The optimum replacement time for the average operational costs of Nissan Urvan vehicles over the given period is represented in figure 4.2(a).From the plot it is observed that as the total net recursive costs for keep(V_k) decrease, the vehicles service optimal years increase up to stage 12 where the total net recursive costs (V_r)forreplace action becomes less than the total net recursive keep action. At this stage the company would make a net profit of ₦18,613,400, if replace action is adhered to and a loss of ₦21,894,482 for non-adherence to the optimum replacement policy. At the beginning of the 12th year, therefore, the company is advised to replace all its Nissan Urvan vehicles. It should be noted here that salvage value was not considered because the vehicles in question were not subjected to a catastrophic failure.

Figure 4.2(b) is the chart of Sienna Vehicles over the given years or stages.

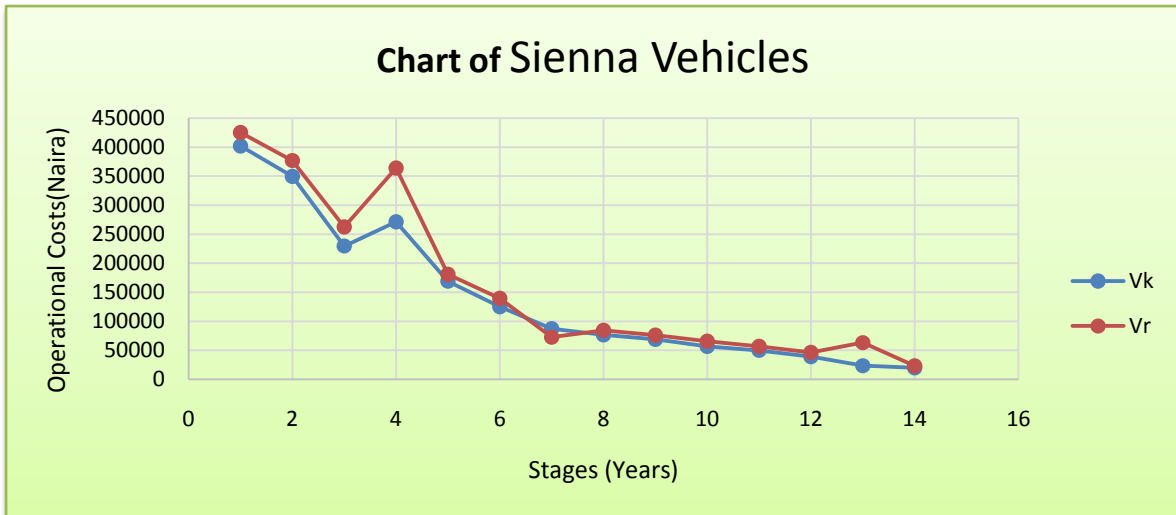


Figure 4.2(b): Optimum Replacement Time for Sienna Vehicles

Figure 4.2(b) exhibited the operational costs of Sienna vehicles over the given period. From the chart, it is observed that as the total net recursive costs (V_k) for keep decrease, the vehicles optimal service years increase up to stage 7 where the total net recursive costs (V_r) replace action becomes less than the total net recursive keep action. At this stage the company would make a net profit of ₦7,264,015 if replace action is adhered to and a loss of ₦8,750,759 for non-adherence to the optimum replacement policy. At this time the company is advised to replace all its Sienna vehicles.

Figure 4.2(c) provided the operational costs of Peugeot Expert Vehicles over the given years or stages.

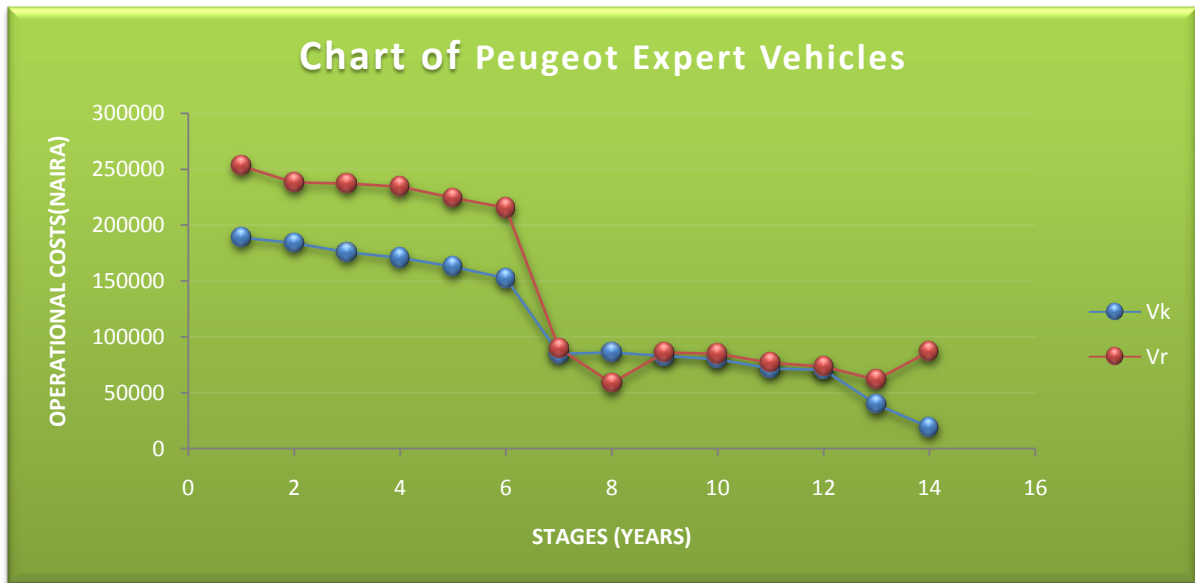


Figure 4.2(c): Optimum Replacement Time for Peugeot Expert Vehicles.

Figure 4.2(c) is the optimum replacement time of the average operational costs of Peugeot Expert vehicles over the given years. From the plot, it is observed that as the total net recursive costs decrease, the number of optimal service years increase up to stage 8 where the total net recursive cost for replace action becomes less than the total net recursive keep action. At this stage the company makes a net profit of ₦5,862,286 if replace action is adhered to and a loss of ₦8,616,168 for non-adherence to the optimum replacement policy. At this instance the company is advised to replace all its Peugeot expert vehicles.

Figure 4.2(d) clarified the operational costs of J5 vehicles over the given years or stages.

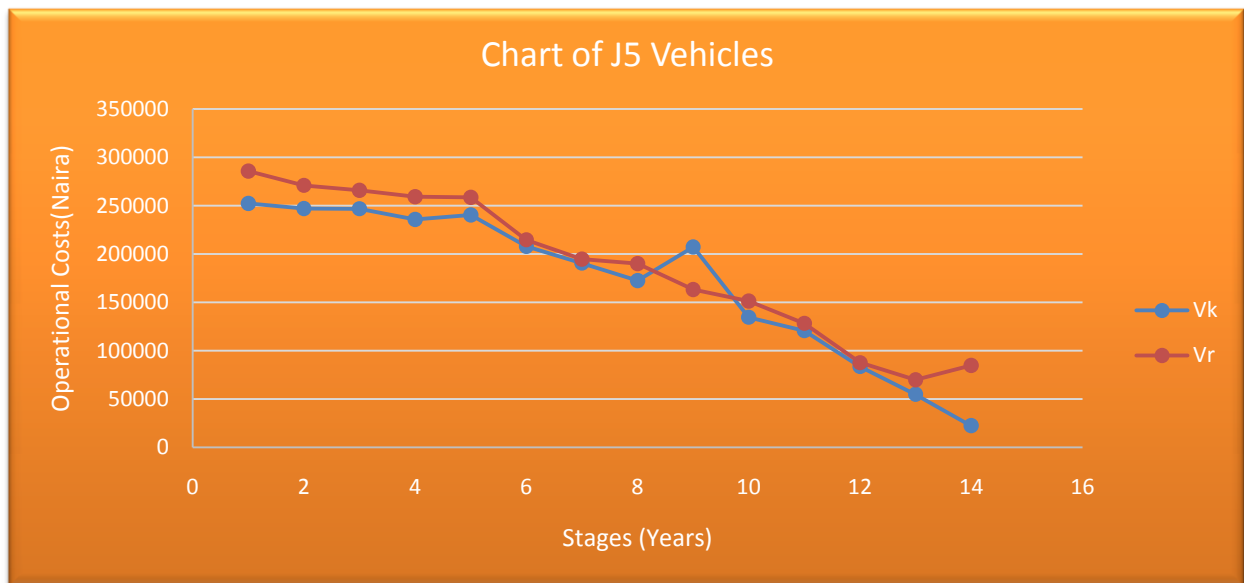


Figure 4.2(d): Optimum Replacement Time for J5 Vehicles.

The optimum replacement time of the mean operational costs of J5 vehicles over the given period is shown in figure 4.2(d). From the chart it is noticed that as the total net recursive operational costs (V_k) for keep decrease, the number of optimal service years increase up to stage 9 where the total net recursive cost (V_r) for replace action becomes less than the total net recursive keep action. During this period the company makes a net profit of ₦16,329,730 for adhering to replace action and a loss of ₦20,730,290 for non-adherence to the optimum replacement policy. In this regard, the company is advised to replace all its J5 vehicles at beginning of the 9th year.

Figure 4.2(e) displayed the operational costs of Ford bus vehicles over the given years or stages.

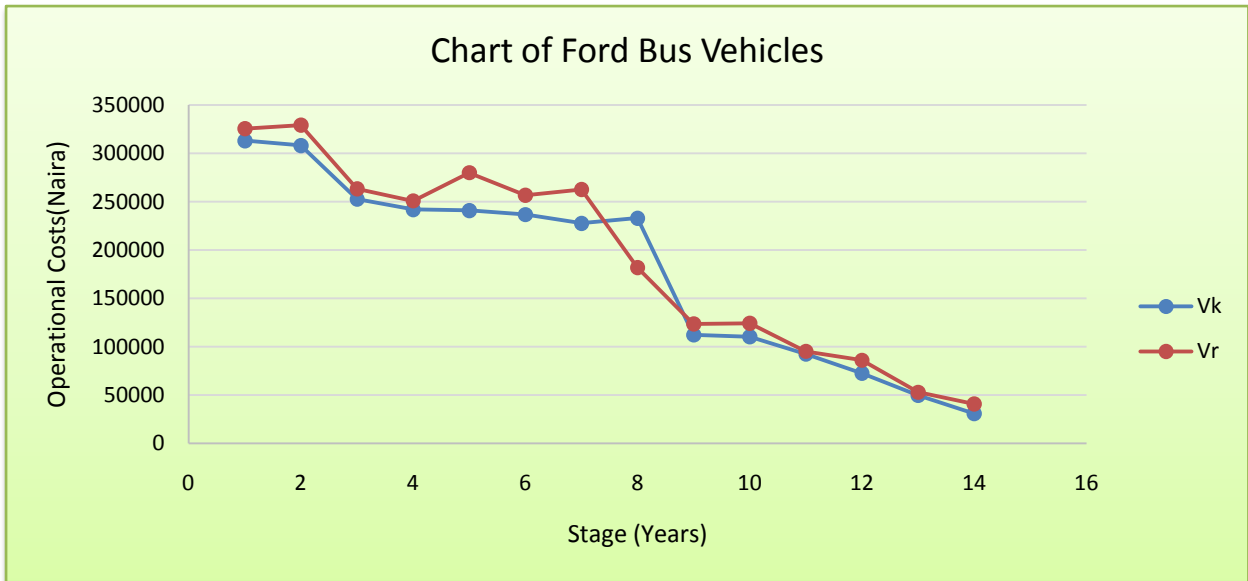


Figure 4.2(e): Optimum Replacement Time for Ford Bus Vehicles.

Figure 4.2(e) simplified the optimum replacement point for the mean operational costs of Ford bus vehicles over the given period. From the graph it is observed that as the total net recursive operational costs for keep (V_k) decrease the number of years increase up to the 8th year where the total net recursive operational costs for replace action (V_r) becomes less than the total net recursive cost for keep action. At this stage the company makes a net profit of ₦18,190,395 if replace action is taken and a loss of ₦23,295,735 incurred for not obeying the optimum replacement policy. At this point the company is advised to replace all its Ford bus vehicles.

Figure 4.2(f) show cased the operational costs of Toyota Hiace vehicles over the given years or stages.

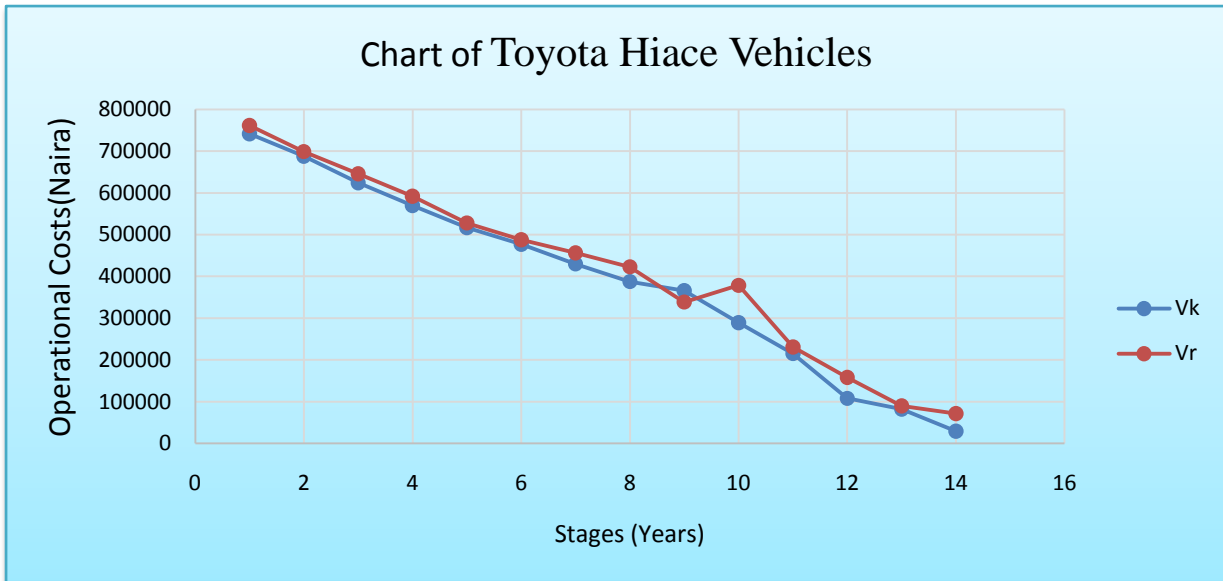


Figure 4.2(f): Optimum Replacement Time for Toyota Hiace Vehicles.

Figure 4.2(f) is a display of the optimum replacement time for the mean operational costs of Toyota Hiace vehicles over the given period. From the chart, it is observed that as the total net recursive operational costs for keep (V_k) decrease, the vehicles optimal years of service increase up to stage 9 where the total net recursive operational costs for replace action (V_r) becomes less than the total net recursive cost for keep action. At this instance the company is expected to make a net profit of ₦ 33,837,700 for adherence to the optimum replacement policy and a loss of ₦ 36,565,887 for non-adherence. The company is therefore advised to replace all its Toyota Hiace vehicles at the beginning of the 9th year.

Figure 4.2(g) is the operational costs of Taxi Cab vehicles over the given years or stages.

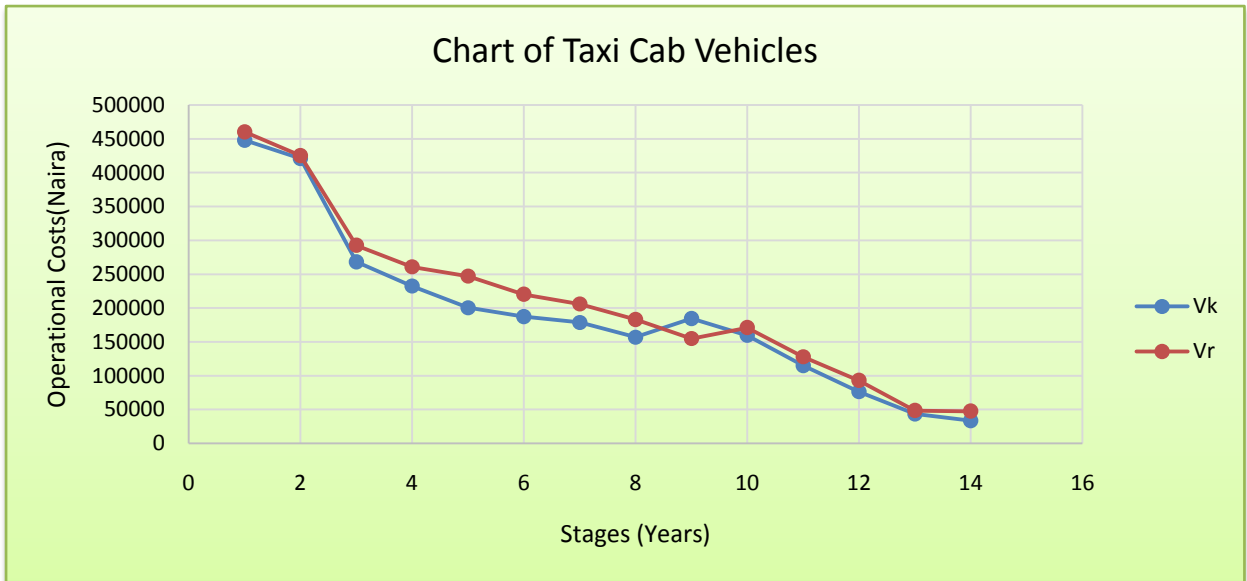


Figure 4.2(g): Optimum Replacement Time for Taxi Cab Vehicles.

The optimum replacement time for the average operational costs of Taxi cab vehicles over the given period is presented in figure 4.2(g). The plot showed that as the total net recursive operational costs for keep (V_k) decreases, the vehicles optimal service years increase up to stage 9 (nine), where the total net recursive cost (V_r) for replace action is less than the total net recursive cost for keep action. At this point the company makes a net profit of ₦15,482,395 if replace action is adhered to and a loss of ₦18,438,288 for non-adherence to the optimum replacement policy. At this time a replacement action of the Taxi cab vehicles is needful.

4.2.1 Validation of Dynamic Programming Model

The dynamic programming recursive model applied was validated using Microsoft Excel Solver as summarized in Table 4.2.1(a) and plotted in Figures 4.2.1(i,ii,iii,iv,v,vi,vii) with details in Appendix (B₁ to B₇).

Table 4.2.1(a): Summary of the average operational costs of vehicles types from Excel Output.

Vehicles	Loss obtained from Keep(#)	Profit obtained from Replace(#)	policy Year
Nissan Urvan	21,875,300	18,612,210	12
Sienna	8,751,710	7,263,000	7
Peugeot Expert	8,614,150	5,861,260	8
J5	20,720,100	16,328,510	9
Ford Bus	23,290,850	18,187,200	8
Toyota Hiace	36,560,750	33,836,600	9
Taxi Cab	18,437,180	15,480,980	9

Table 4.2.1(a) is the Summary of the average operational costs of vehicles types from Excel Output at the policy year as derived from Microsoft Excel Solver shown in Appendix B₁ – B₇.

Figure 4.2.1(i) explained the chart of Nissan Urvan Vehicles over the given period.

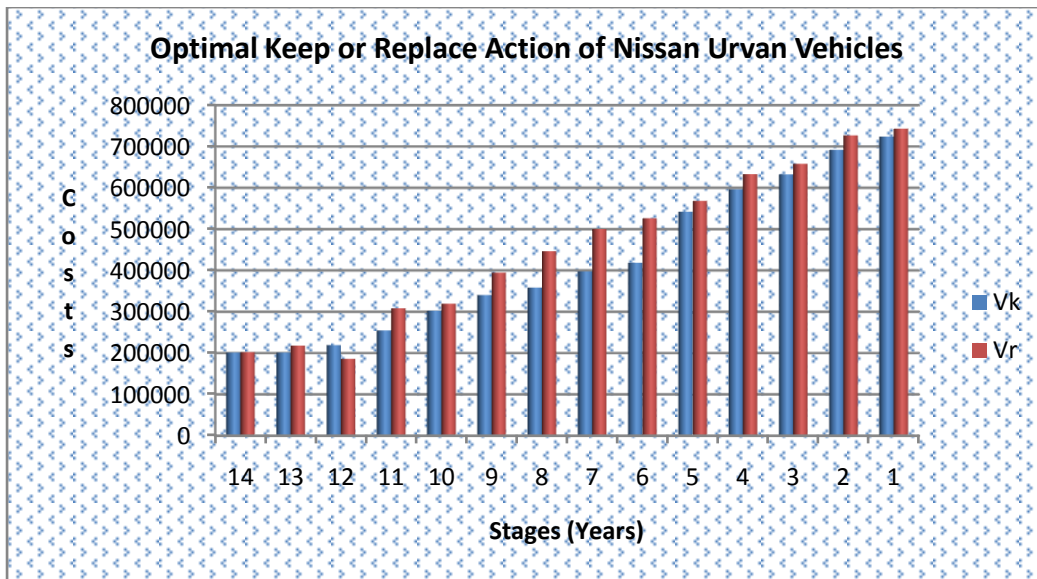


Figure 4.2.1(i):Plot of Nissan Urvan Vehicles versus Stages(years)

From the chart shown in Figure 4.2.1(i),it was observed that the appropriate time to replace the vehicles under investigation is at the 12th year which validates the manual computation earlier carried out for Nissan Urvan vehicles employing dynamic programming model.

Figure 4.2.1(ii)exemplified the chart of Sienna Vehicles over the given years or stages.

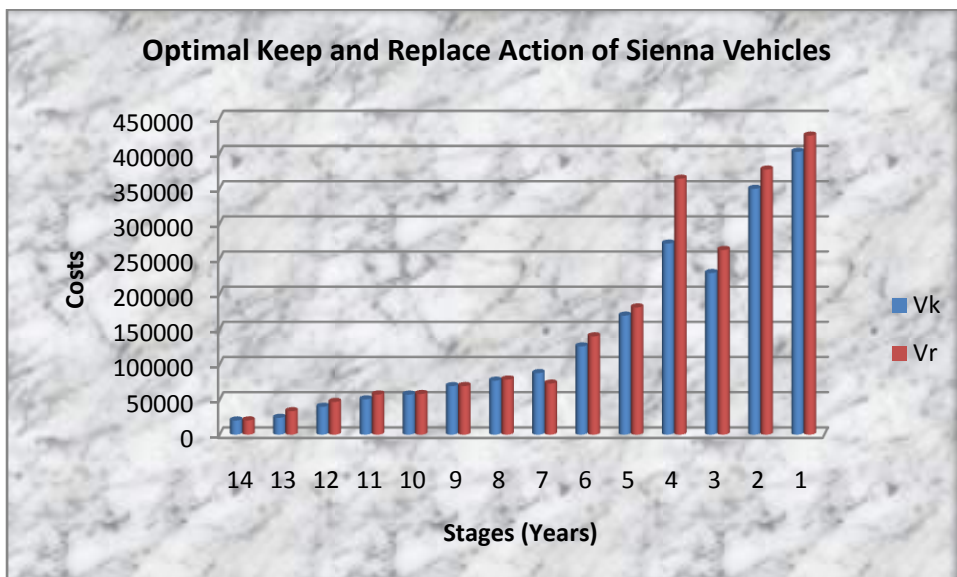


Figure 4.2.1(ii):Chart of Sienna vehicles versus Years(stages)

The Chart of Sienna vehicles under the reviewed period is presented in Figure 4.2.1(ii).The plot indicated that the optimum replacement time for Sienna

vehicles occurred at the seventh year which ascertained the earlier manual results established for Sienna vehicles from dynamic programming model.

Figure 4.2.1(iii) verified the operational costs of Peugeot Expert Vehicles over the given years.

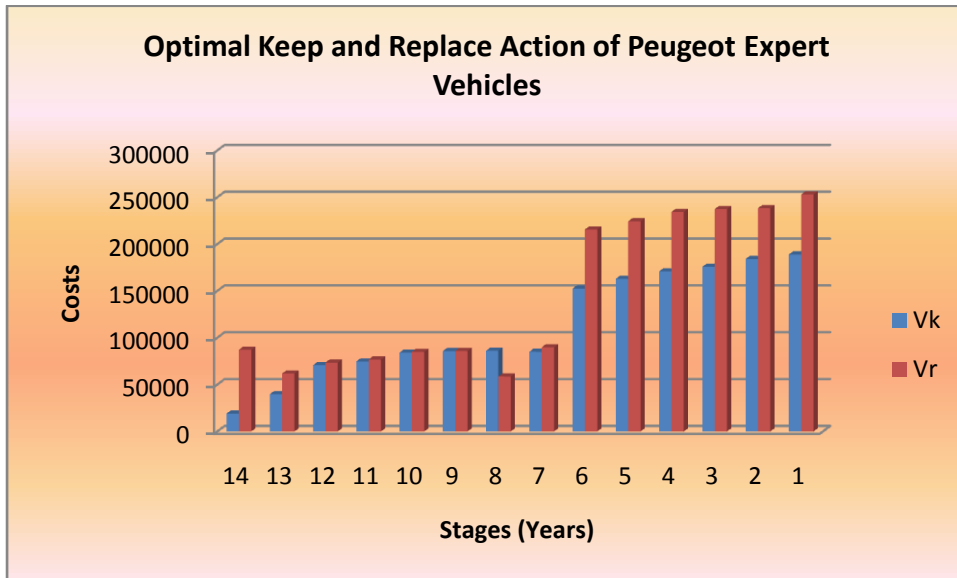


Figure 4.2.1(iii): Plot of Peugeot Expert vs. Years

The chart of mean optimal keep and replacement action of Peugeot expert vehicles is shown in Figure 4.2.1(iii). The plot revealed that the Peugeot Expert vehicles have to be used and replaced on the 8th year which proved the earlier manual results established for Peugeot Expert vehicles from dynamic programming model.

Figure 4.2.1(iv) clarified the mean operational costs of J5 vehicles over the given years.

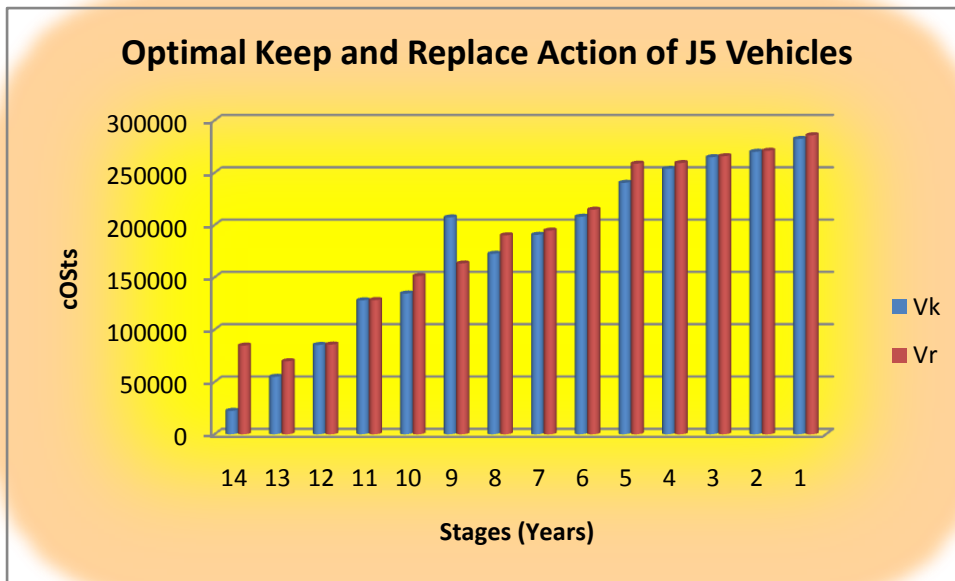


Figure 4.2.1(iv): Plot of operational costs of J5 vehicle against Year

The optimum replacement time of the mean operational costs of J5 vehicles over the given period is shown in figure 4.2.1(iv). During this period the company makes a net profit of ₦16,328,510 for adhering to replace action and a loss of ₦20,720,100 for non-adherence to the optimum replacement policy which confirmed the result of dynamic programming earlier obtained for J5 vehicles. In this regard, the company is advised to replace all its J5 vehicles at beginning of the 9th year.

Figure 4.2.1(v) showed the operational costs of Ford bus vehicles over the given period.

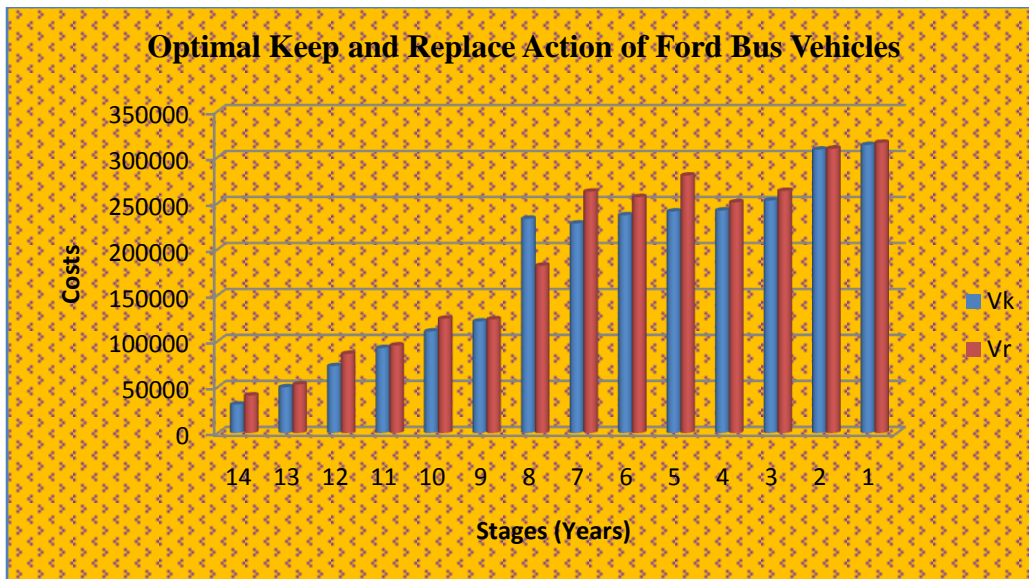


Figure 4.2.1(v):Chart of operational costs of Ford bus vs. Years

From the chart, it is noticed that as the total net recursive operational costs (V_k) for keep decrease, the number of optimal service years increase up to stage 8 where the total net recursive cost (V_r) for replace action becomes less than the total net recursive keep action, thereby triggering off replacement action which confirmed the result of dynamic programming model earlier applied for Ford vehicles.

Figure 4.2.1(vi) explained the operational costs of Toyota Hiace vehicles over the given years.

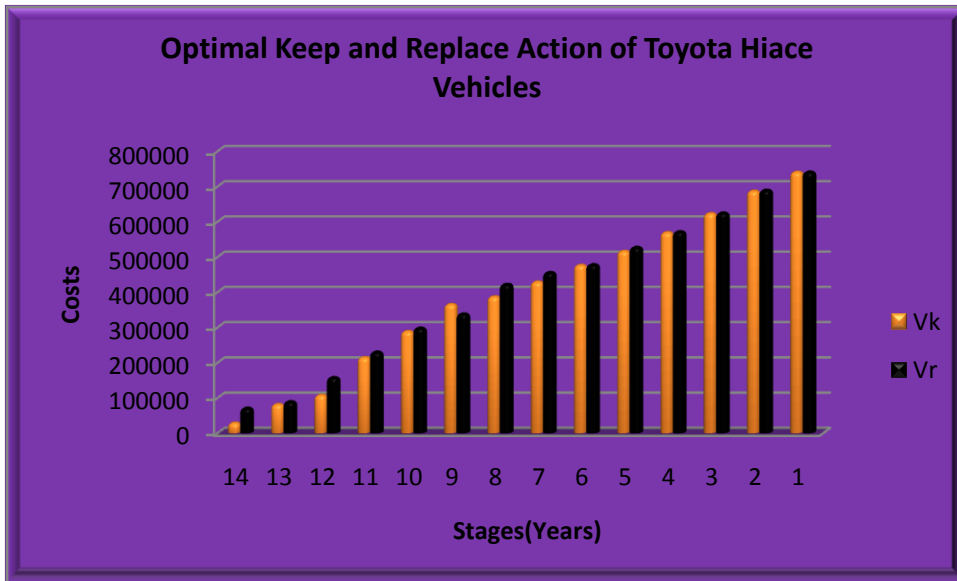


Figure 4.2.1(vi): Plot of Operational costs of Toyota Hiace Vehicles vs. Years

Figure 4.2.1(vi) is a display of the optimum replacement time for the average operational costs of Toyota Hiace vehicles over the given period. From the plot, it is observed that while the total net recursive operational costs for keep (V_k) decrease, the vehicles optimal years of service increase up to stage 9 where the total net recursive operational costs for replace action (V_r) becomes less than the total net recursive cost for keep action. At this point the company is expected to make a net profit of ₦ 33,836,600 for adherence to the optimum replacement policy and a loss of ₦ 36,560,750 for non-adherence which validates the dynamic programming model earlier applied in the work for Toyota Hiace vehicles .

Figure 4.2.1(vii) is the operational costs of Taxi Cab vehicles over the given period.

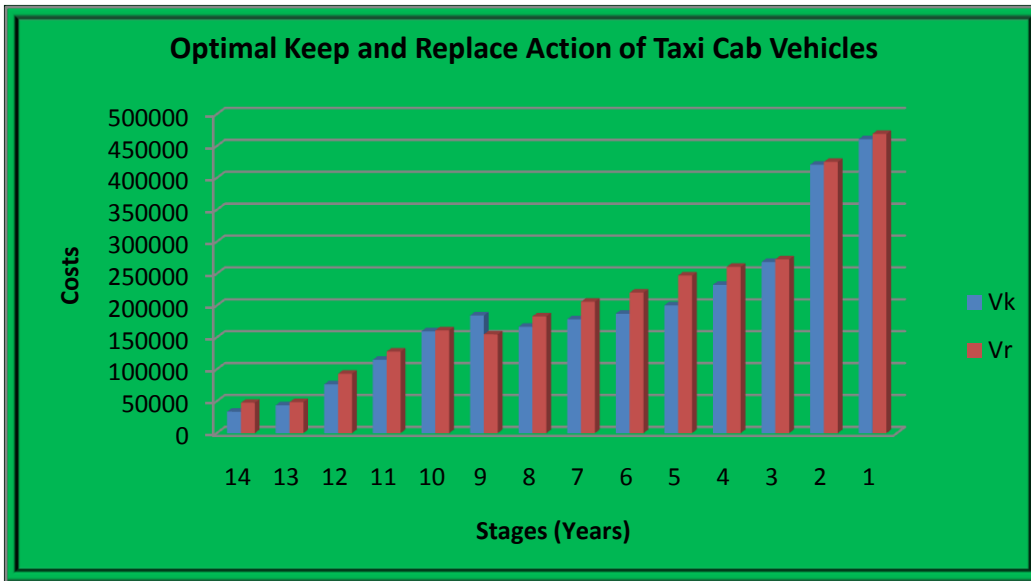


Figure 4.2.1(vii): Operational costs of Taxi Cab vehicles over the given years or stages.

The plot showed the operational costs of Taxi Cab Vehicles over the given period. The observation is that the total net recursive operational costs for keep (V_k) decreases as the vehicles optimal service years increase up to stage 9 (nine), where the total net recursive cost (V_r) for replace action is less than the total net recursive cost for keep action. At this point the company makes a net profit of ₦15,480,980 if replace action is adhered to and a loss of ₦18,437,180 for non-adherence to the optimum replacement policy which validates the dynamic programming model earlier applied in the work for Taxi cab vehicles .

4.2.2 Summary of the vehicles Optimal Decision Variable Sequence

The optimal decisions sequence for vehicle types of ATS are presented in Table 4.2.2(a).

Table 4.2.2(a): Summary of Vehicles Optimal Decision Variable Sequence

Vehicles	Stage 14	Stage 13	Stage 12	Stage 11	Stage 10	Stage 9	Stage 8	Stage 7	Stage 6	Stage 5	Stage 4	Stage 3	Stage 2	Stage 1
Nissan Urvan	K	K	R	K	K	K	K	K	K	K	K	K	K	K
Sienna	K	K	K	K	K	K	K	R	K	K	K	K	K	K
Peugeot Expert	K	K	K	K	K	K	R	K	K	K	K	K	K	K
J5	K	K	K	K	K	R	K	K	K	K	K	K	K	K
Ford Bus	K	K	K	K	K	K	R	K	K	K	K	K	K	K
Toyota Hiace	K	K	K	K	K	R	K	K	K	K	K	K	K	K
Taxi Cab	K	K	K	K	K	R	K	K	K	K	K	K	K	K

where, K = Keep, R = Replace

This means that Nissan Urvan Vehicle comes with the optimal policy (K,K,K,K,K,K,K,K,K,K,K,R,K,K) with a corresponding total net profit of ₦18,613,400. The implication is that ATS should keep the vehicle for first eleven years of service and replace at the beginning of the twelfth year and then follows with the keep decision till the end of the planned horizon. On the other hand, Sienna bus is characterized with the optimal policy (K,K,K,K,K,K,R,K,K,K,K,K,K) with a corresponding net profit of ₦7,264,015, which means that keep action is initiated in the first six years then followed by replace decisions at the start of seventh year and then keep action up till the end of the planned horizon. In the same capacity, Peugeot Expert comes with the optimal policy (K,K,K,K,K,K,K,R,K,K,K,K,K) with a corresponding total net profit of ₦5,862,286, which means the company should keep the vehicle for seven years and replace at the start of the eighth year and keep again at the beginning of the ninth year till the end of the planned horizon. In the same vein, the optimal policy for the J5 bus is (K,K,K,K,K,K,K,K,R,K,K,K,K) with a corresponding total net profit of ₦16,329,730, in which case the company keeps the vehicle for eight years, replace at the beginning of the ninth year and keep again throughout the planned period. For the Ford bus, the optimal policy is (K,K,K,K,K,K,K,R,K,K,K,K,K) with the net profit of ₦18,190,395, which

means that the company should keep the vehicle for seven years ,start replacing at the beginning of the eighth year and start keeping again till the end of the planned horizon. More so, Toyota Hiace comes with the optimal policy of (K,K,K,K,K,K,K,K,R,K,K,K,K,K)with the net profit of ₦33,837,700, a pointer to the fact that the company should keep the vehicle for eight years and start replacing it from the beginning of the ninth year, then keep again till the end of the planned period. Finally, Taxi Cab comes with an optimal policy of (K,K,K,K,K,K,K,K,R,K,K,K,K,K) and a corresponding net profit of ₦15,482,395, an indicator that the company should keep the vehicle for eight years and start replacing at the beginning of the ninth year ,keep again till the end of the planned horizon. Salvage value was not considered because the vehicles in question were not subjected to catastrophic failure.

4.3 Resultsof the Selected Forecasting Models Applied

The results of selected forecasting models arising from the analysis are shown in Tables [4.1.2(a-h)] andplotted in Figures [(4.3.1a(i-vi),4.3.1b(i-vi),4.3.1c(i-v)] for the maintenance costs, replacement costs and income generation of the said vehicles respectively.

4.3.1a Results of the Forecasting models for Maintenance Costs of Vehicle types.

Tables[4.3.1a(i-vi)] show cased the actual data and forecasted results for maintenance costs of vehicle types over the given periodand are plotted in Figures [(4.3.1a(i-vi)].

Table 4.3.1a(i): The actual data collected and forecasted results of maintenance costs of Sienna over the given period × 1000

Sienna	1900	2440	2905	3230	3700	3920	4405	4610	4880	4882	5559.93	5900.44	6240.95	6581.45	6921.96
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(i) is the actual data collected and forecasted results of the maintenance costs of Sienna over the given period. The trend showed that the maintenance costs of sienna vehicles increase as the age of the said vehicles increases.

Figure 4.3.1a(i) represented the Trend analysis plot of maintenance cost for Sienna Vehicle over the given period.

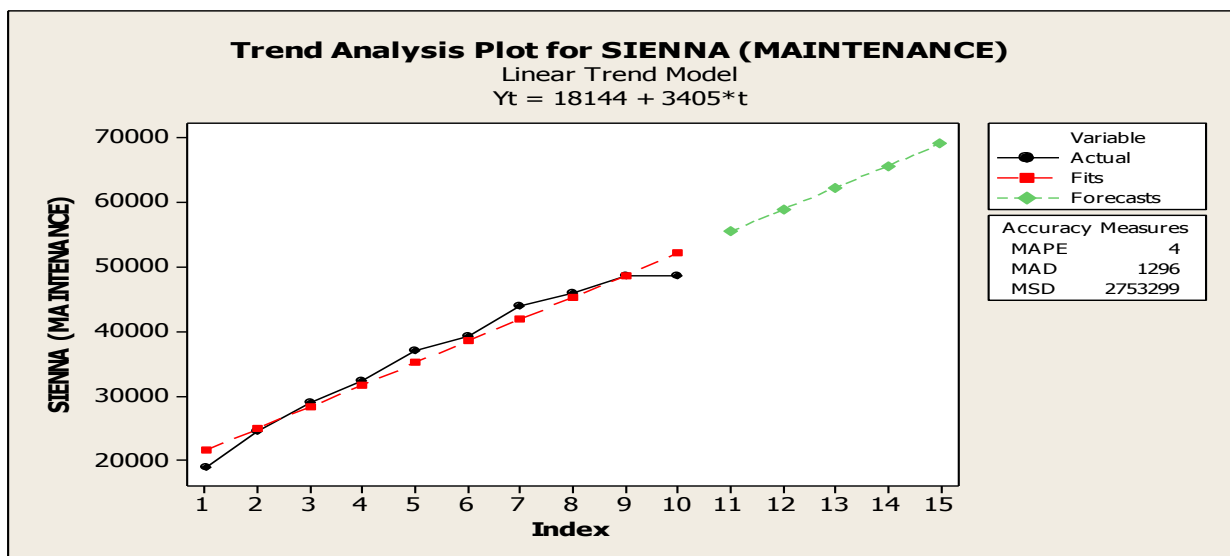


Figure 4.3.1a(i): Trend Analysis Plot for Sienna (Maintenance costs)

Figure 4.3.1a(i) showed the trend forecast of the Sienna maintenance costs of the vehicle over a given period. From the plot it is observed that the maintenance cost of Sienna vehicles increase as the age of the said vehicles increases.

Table 4.3.1a(ii):The actual data collected and forecasted results of maintenance costs of Peugeot Expert over the given period ×1000.

Peugeot	2090	2130	2590	2900	3050	3310	3505	3790	3900	3980	4205.75	4328.73	4433.73	4520.73	4709.23
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(ii) is the actual data and forecasted results of maintenance costs of Peugeot Expert vehicles over the given periods. The trend revealed that the maintenance costs increase as the Peugeot expert vehicles age

Figure 4.3.1a(ii)clarified the Trend forecast analysis plot of maintenance costs for Peugeot Expert Vehicle over the given periods.

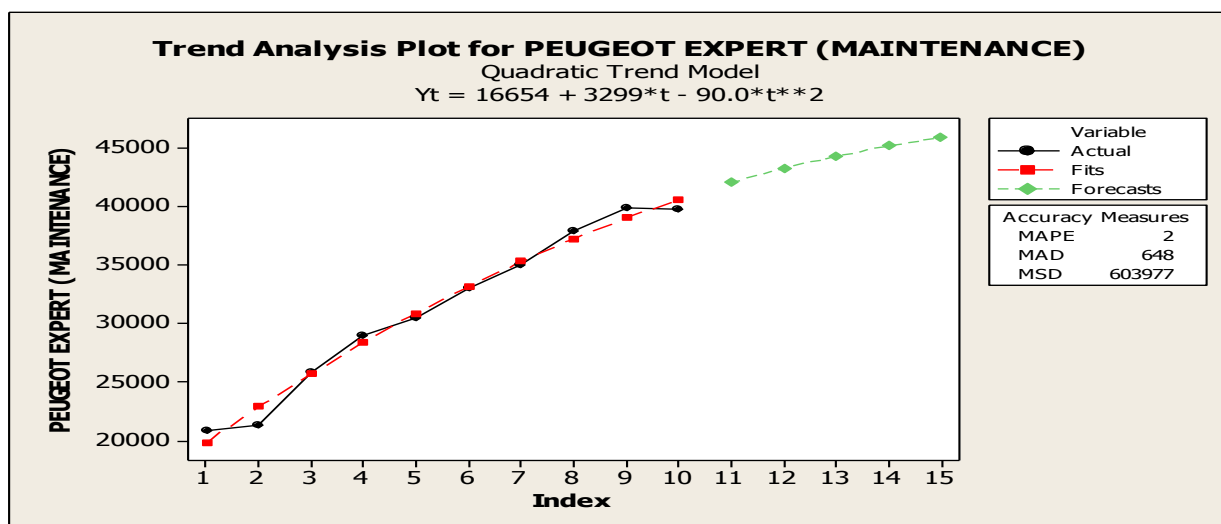


Figure 4.3.1a(ii): Trend Analysis Plot for Peugeot Expert (Maintenance)vs.Yrs

Figure 4.3.1a(ii)is the trend forecast of the maintenance costs ofPeugeot Expert vehicles over the given period. The chart also showed a continuous increase in future maintenance cost of Peugeot vehicles with age, which goes a long way to show that as the vehicle is aging it costs more to maintain it.

Table 4.3.1a(iii) :The actual data and forecasted results of maintenance costs of J5 over the given period ×1000.

J5	2337	2411	3665.4	3811	3990	4050	4410	4600	4750	4820	5007.42	5237.31	5467.26	5697.08	5738.34
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(iii)disclosed the actual data and forecasted results of the maintenance costs of J5 vehicles over the given period.The trend revealed that the maintenance costs of Peugeot expert vehicles is directly proportional to the age of the said vehicles.

Figure 4.3.1a(iii)showed the double exponentialsmoothing plot of maintenance cost for J5Vehicle over the given period.

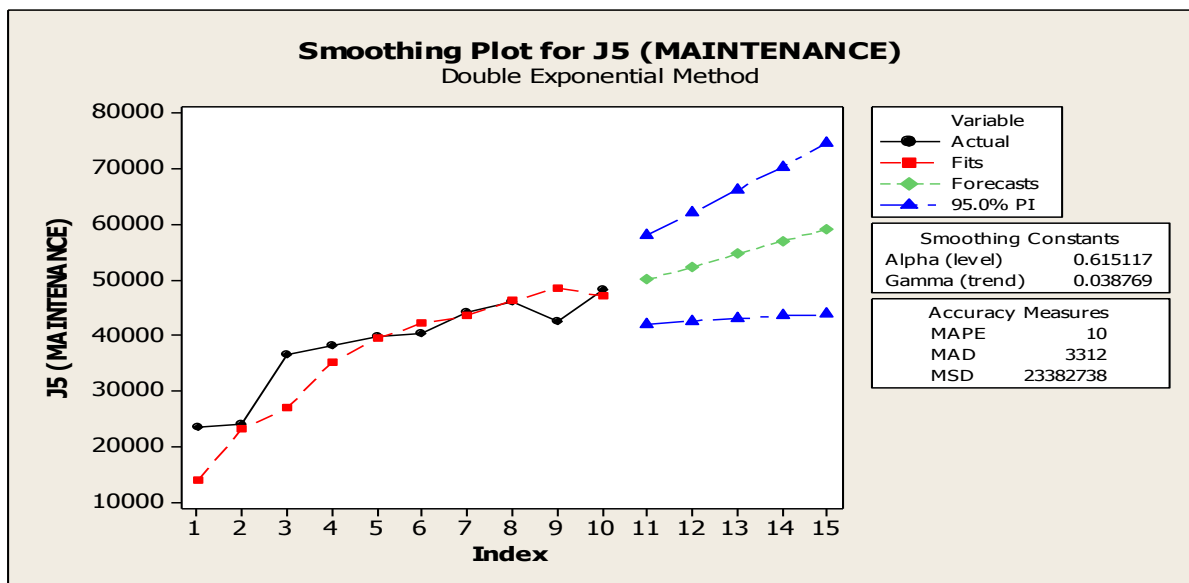


Figure 4.3.1a(iii): Double Exponential Smoothing Plot for J5 (Maintenance) vs.Yrs.

The double exponential smoothingplot of the maintenance costs of J5 vehicles under the reviewed period is presented in Figure 4.3.1a(iii) . It is observed, from the chart that the maintenance costs of J5 increase with an increase in the age of the vehicles under investigation.

Table 4.3.1a(iv) :The actual data and forecasted results of maintenance costs of Ford Bus vehicles over the given period ×1000 .

Ford	2165.4	2297.7	3115.8	3488.7	3600	3690	3780	3905	4160	4195	4266.03	4432.78	4599.53	4766.29	4932.3
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(iv)showedthe actual data and forecasted results of the maintenance costs of Ford Bus vehicles over the given period. The outcome points to the fact that it takes more to maintain a vehicle as it ages.

Figure 4.3.1a(iv) is the Double Exponential Smoothing plot of maintenance cost for Ford Bus Vehicle over the given period.

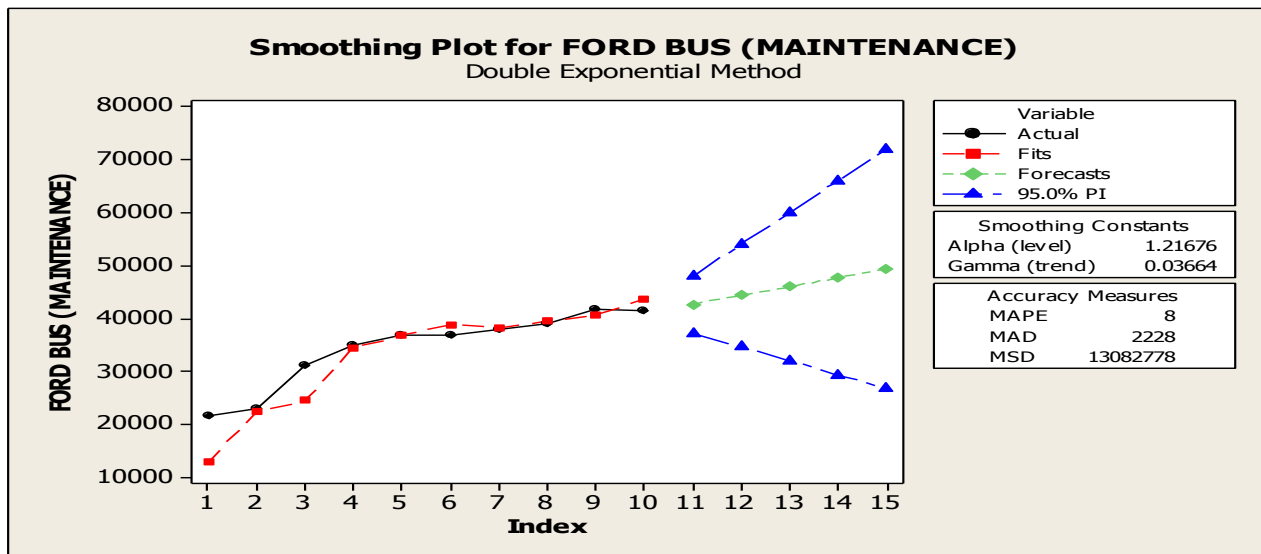


Figure 4.3.1a(iv): Double Exponential Smoothing Plot for FORD BUS (MAINTENANCE)

Figure 4.3.1a(iv) exhibited double exponential smoothing forecast of the maintenance costs of Ford bus vehicles over the given periods.. From the result, it is observed that there is a continuous increase in future maintenance cost of Ford bus vehicle with increase in time.

Table 4.3.1a(v): The actual data and forecasted results of maintenance costs of Toyota Hiace over the given period $\times 1000$.

Toyota	2205	2400	2510	2790	3020	3330	3515	3640	3713.2	3802.1	3872.78	3894.21	3915.64	3937.0	4113.3
a														8	6
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(v) unveiled the actual data and forecasted results of the maintenance costs of Toyota Hiace vehicles over the given periods. The trend points to the fact that the maintenance costs of Toyota Hiace vehicles increase as years increase, which means that it takes more to sustain a vehicle as it ages.

Figure 4.3.1a(v) depicted the Double Exponential Smoothing plot of maintenance costs for Toyota Hiace vehicles over the given period.

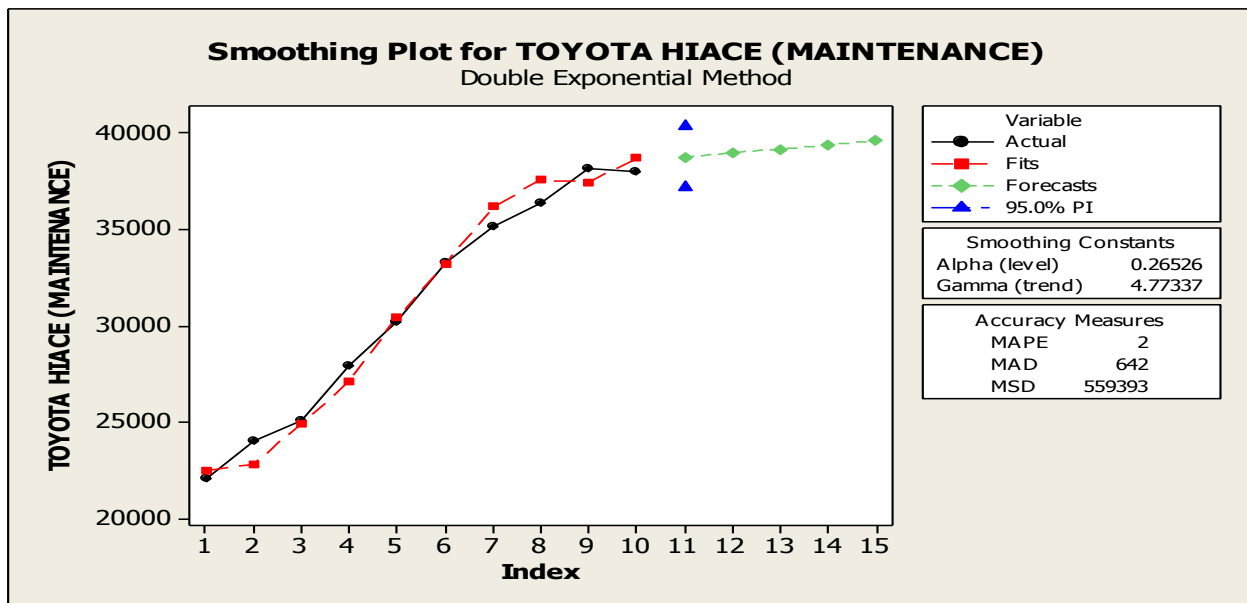


Figure 4.3.1a(v): Double Exponential Smoothing Plot for Toyota Hiace (Maintenance).

Figure 4.3.1a(v) represented the plot of Maintenance costs of Toyota Hiace vehicles against the year counts using the double exponential smoothing model. The result showed that the cost of maintenance increases as the year increases. This is a pointer to the fact that as the vehicles age increase, the more maintenance costs incurred.

Table 4.3.1a(vi): The actual data and forecasted results of maintenance costs of Taxi cab vehicles over the given periods $\times 1000$.

Taxi Cab	1890	2080	2160	2310	2500	2910	3012	3220	3370	3405	3875.31	4158.07	4461.46	4786.99	5136.27
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1a(vi) displayed the actual data and forecasted results of the maintenance costs of Taxi Cab vehicles over the given periods. It is observed that the maintenance costs directly affect the age of the vehicles.

Figure 4.3.1a(vi) is the Trend analysis plot of maintenance cost for Taxi cab vehicle over the given periods.

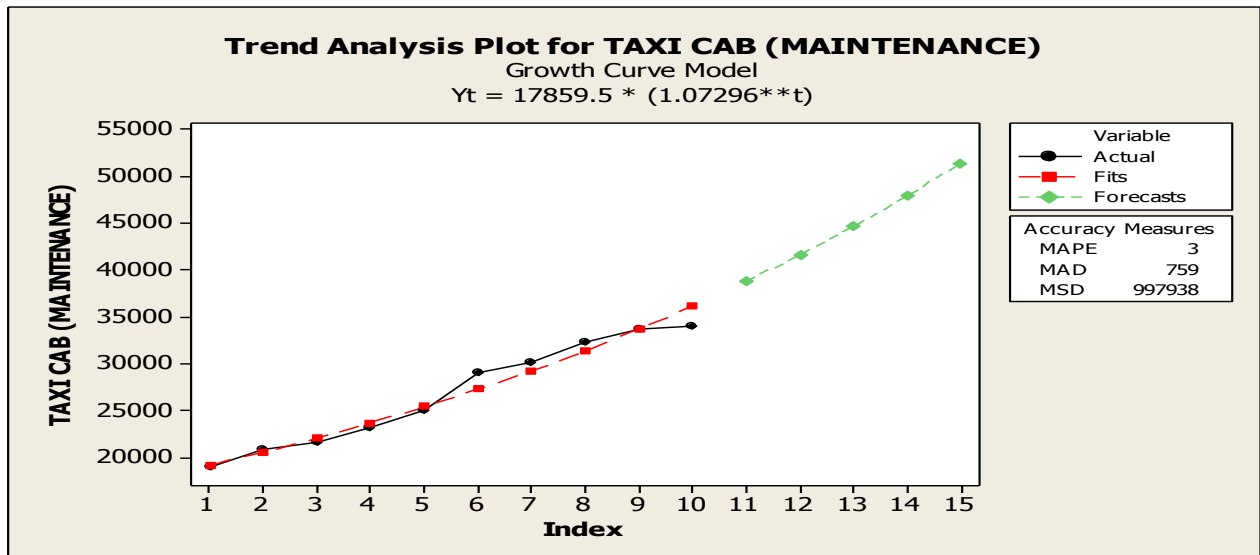


Figure 4.3.1a(vi): Trend Analysis Plot for TAXI CAB (MAINTENANCE)

The figure 4.3.1a(vi) is a display of the plot of Maintenance cost of Taxi Cab against the year counts using Trend analysis model. The output showed that the cost of maintenance increases as the years increase, a pointer to the fact that more would be used to maintain taxi cab vehicles as they age.

4.3.1b: Results of the Forecasting models for Replacement Costs of Vehicle Types.

The actual data and forecasted results for replacement costs of vehicle types over the given period are presented in Tables [4.3.1b(i-vi)] and plotted in Figures {4.3.1b(i-vi)}.

Table 4.3.1b(i): The actual data and forecasted results of Replacement Costs of Nissan Urvan vehicles over the given periods $\times 1000$.

Nissan	1992	2024	2100	2130	2156.8	2181	2201.5	2305	2316	2343	2396.04	2427.51	2476.13	2507.32	2556.22
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(i) clarified the actual data and forecasted results of the replacement costs of Nissan Urvan vehicles over the given period. The trend revealed that the replacement costs of Nissan Urvan vehicles increase with increase in the age of the said vehicles.

Figure 4.3.1b(i) represented the time series decomposition forecast of Nissan Urvan cost of the vehicle over the given periods.

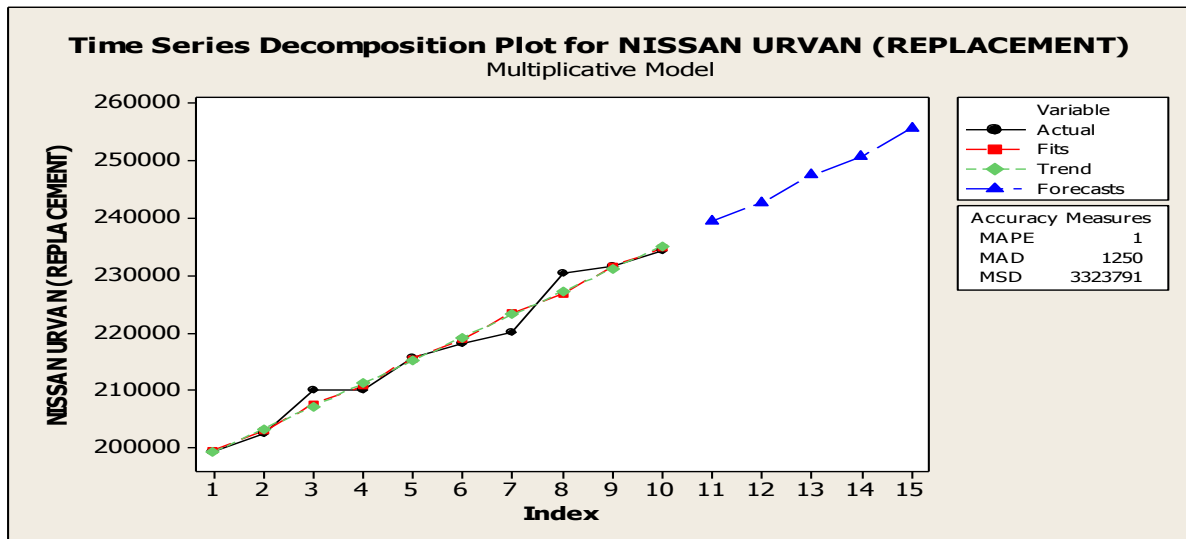


Figure 4.3.1b(i): Time Series Decomposition Plot for NISSAN URVAN (Replacement costs) over the given period.

The time series decomposition forecast of Nissan Urvan replacement cost over the given period is shown in Figure 4.3.1b(i). The result revealed that replacement costs increase with a corresponding increase in the age of vehicles under review.

Table 4.3.1b(ii): The actual data and forecasted results of replacement costs of Sienna vehicles over the given periods $\times 1000$.

Sienna	1100	1150	1250	1260	1280	1309	1329	1336	1352.4	1370	1435.60	1476.05	1580.54	1684.03	1696.75
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(ii) showed the actual data and forecasted results of the replacement costs of Sienna vehicles over the given periods. The trend shows that the replacement costs of Sienna vehicles increase as age of the vehicles increases

Figure 4.3.1b(ii) is the Trend Analysis plot of replacement cost for Sienna vehicles over the given periods.

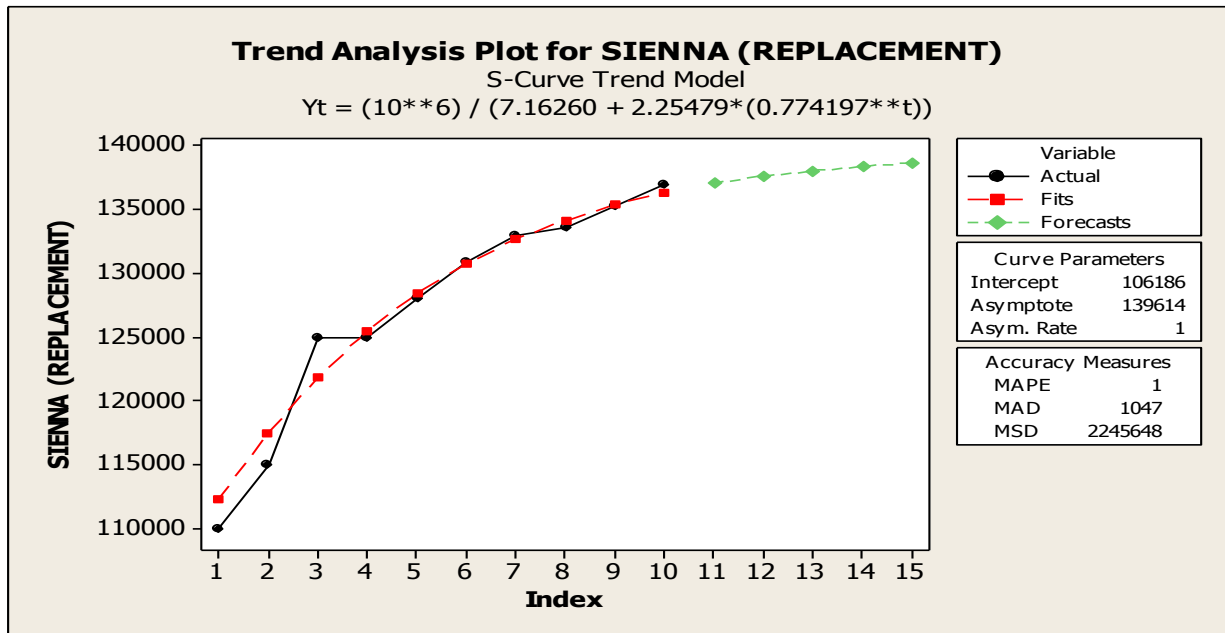


Figure 4.3.1b(ii): Trend Analysis plot for Sienna Replacement Costs vs. Years

Figure 4.3.1b(ii) show cased the Trend Analysis plot of replacement cost for Sienna vehicles. The outcome reveals an increase in future replacement costs of Sienna vehicles as they age.

Table 4.3.1b(iii) :The actual data and forecasted results of replacement cost of Peugeot Expert vehicles over the given periods $\times 1000$.

Peugeot	1500	1520	1550	1650	1665	1685	1700.5	1733	1772	1781	1808.99	1929.37	2048.04	2165.10	2280.61
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(iii) showed the actual data collected and forecasted results of the maintenance costs of Peugeot Expert vehicles over the given period.

Figure 4.3.1b(iii) is the Trend Analysis plot of replacement cost for Peugeot Expert vehicles over the given period.

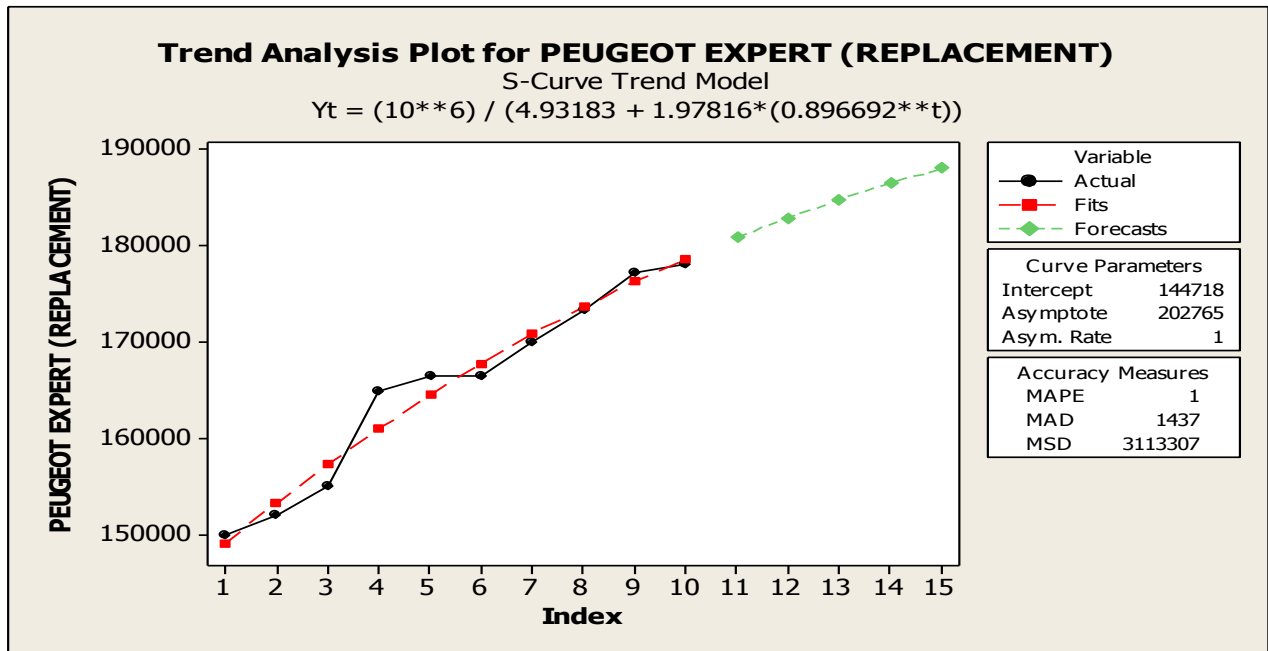


Figure 4.3.1b(iii): Trend Analysis Plot for Peugeot Expert (Replacement costs) over the given period.

Figure 4.3.1b(iii) revealed the plot of replacement cost of Peugeot Expert over the years using Trend Analysis model. The outcome of the plot displayed an increase in future replacement cost of Peugeot Expert vehicles with age.

Table 4.3.1b(iv): The actual data and forecasted results of replacement cost of Ford Bus vehicles over the given periods $\times 1000$.

Ford	1804	1812	1813	1825	1829	1836	1840	1862	1876	1879	1888.46	1891.78	1904.30	2007.67	2110.14
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(iv) is the actual data and forecasted results of the replacement costs of Ford Bus vehicles over the given periods. It is observed from the data obtained that the cost of replacing a vehicle progressively increases as the age of the said vehicle increases.

Figure 4.3.1b(iv) explained the winters' plot of replacement cost for Ford vehicles over the given period.

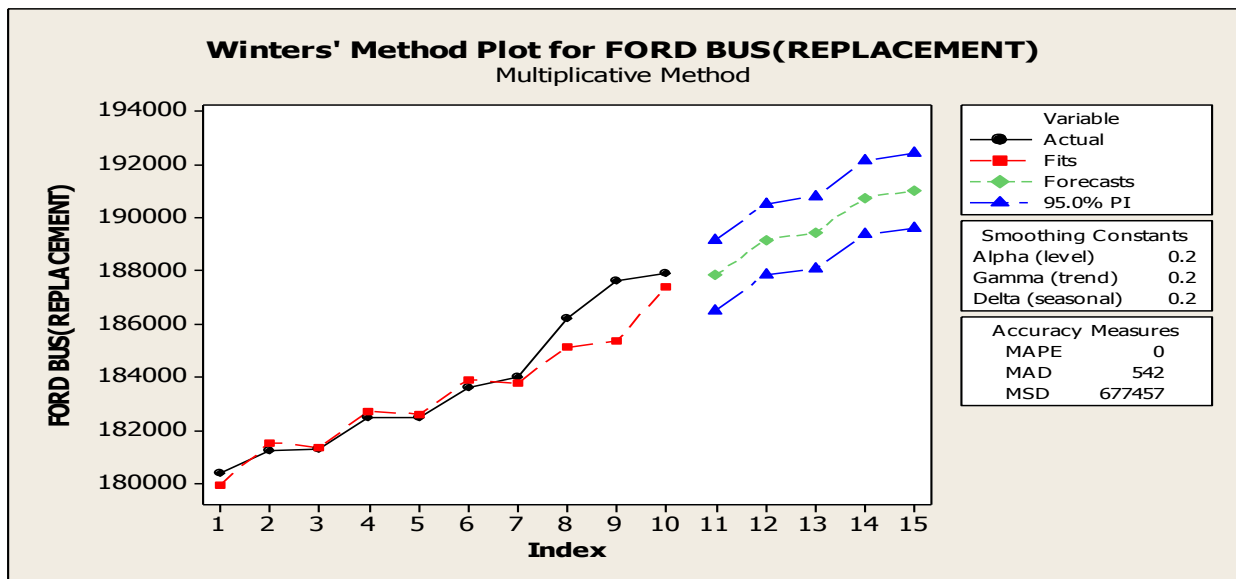


Figure 4.3.1b(iv): Winters' method Plot for Ford Bus (Replacement) vs. Years Counts.

Figure 4.3.1b(iv) is the plot of replacement cost of Ford vehicles against the stated years using winters' model. The result shows a case of an increase in future replacement costs of Ford bus vehicle with an increase in the age of the vehicles. A pointer to the fact that it costs more to replace a vehicle as it ages.

Table 4.3.1b(v): The actual data collected and forecasting results of replacement cost of Toyota Hiace vehicles over the given period $\times 1000$.

Toyota	1893	1898	1900	1913	1932.8	1944	1950	1966	1967	1970	1983.07	2090.39	2197.28	2203.74	2309.77
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(v) represented the actual data and forecasted results of the replacement costs of Toyota Hiace vehicles over the given period. The trend revealed that the replacement cost is directly proportional to the age of the vehicle.

Figure 4.3.1b(v) clarified the Trend Analysis plot of replacement cost for Toyota Hiace vehicle over the given period.

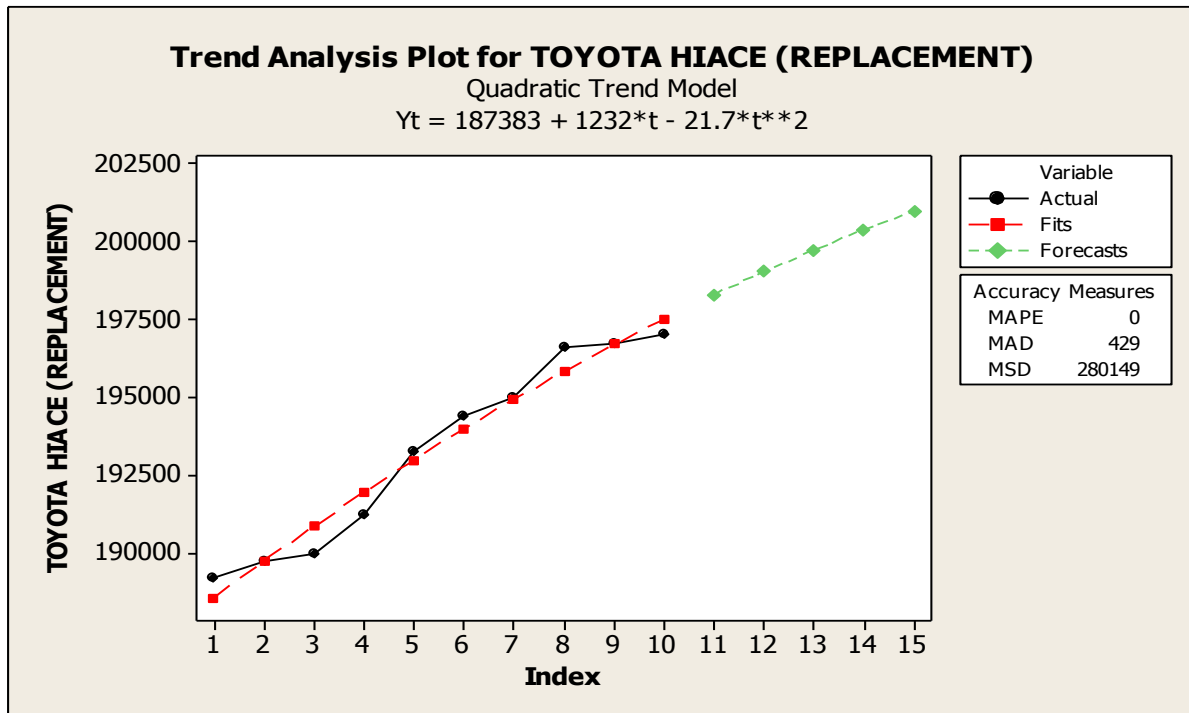


Figure 4.3.1b(v): Trend Analysis Plot for Toyota Hiace (Replacement)

Figure 4.3.1b(v) disclosed the plot of replacement cost of Toyota Hiace over the given period applying Trend Analysis model. The outcome of the plot showcased an increase in future replacement cost of the said vehicle as it ages.

Table 4.3.1b(vi): The actual data and forecasted results of replacement cost of Taxi Cab vehicle over the given periods × 1000.

Taxi	1000	1011	1102	1152	1164	1170	1195	1202	1206	1210	1220.06	1235.12	1250.19	1265.26	1280.32
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1b(vi) represented the actual data and forecasted results of the replacement costs of Taxi Cab vehicle over the given period.

Figure 4.3.1b(vi) displayed the Double Exponential Smoothing plot of Replacement cost for Taxi Cab vehicle over the given period.

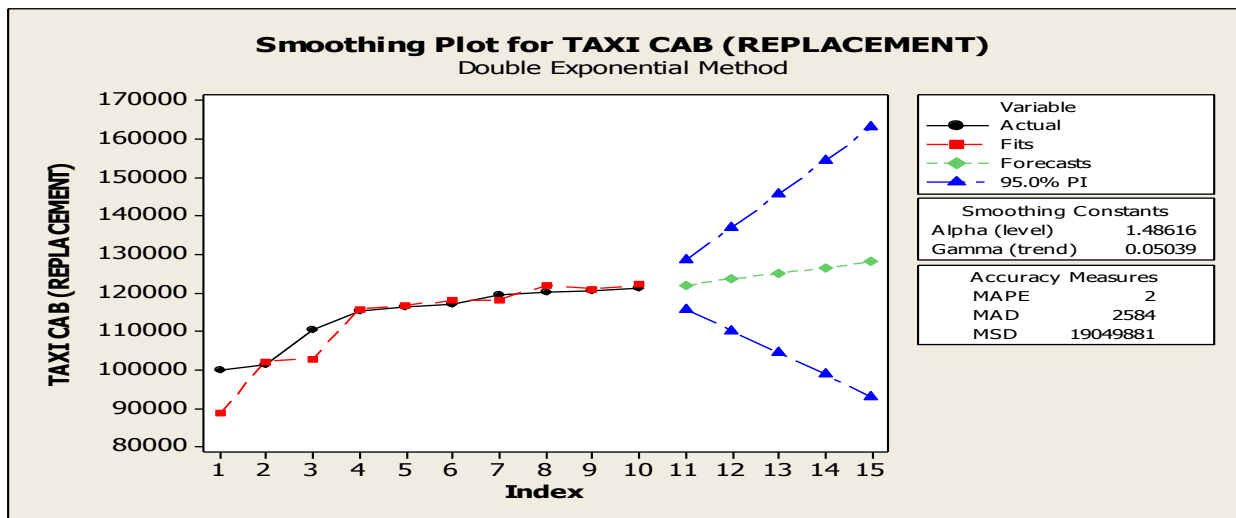


Figure 4.3.1b(vi): Double Exponential Smoothing Plot for Taxi Cab (Replacement costs) vs. year counts.

Figure 4.3.1b(vi) showed the plot of replacement cost of Taxi Cab against the year count using double exponential smoothing model. The output of the plot reflected an increase in future replacement costs as the age of Taxi Cab vehicles

4.3.1c: Results of Forecasting models for Income Generation of Vehicle Types.

The actual data and forecasted results for income generation of the vehicle types over the given period are shown in Tables [4.3.1c(i-v)] and plotted in Figures {4.3.1c(i-vi)}.

Table 4.3.1c(i): The Actual data collected and Forecasted Results of the Income generated for the Sienna vehicle over the given periods $\times 1000$.

Sienna	9000	8710	8420	8205	8150	8040	7800	7710	7140	7015	6792.66	6568.34	6344.01	6119.69	5895.36
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1c(i) disclosed the actual data collected and forecasted results of the income generation of Sienna vehicle over the given period. The trend showed

that the income generated by Sienna vehicle decreases as the age of the said vehicle increases.

Figure 4.3.1c(i) represented the time series decomposition plot of income generated for Sienna vehicle over the given periods .

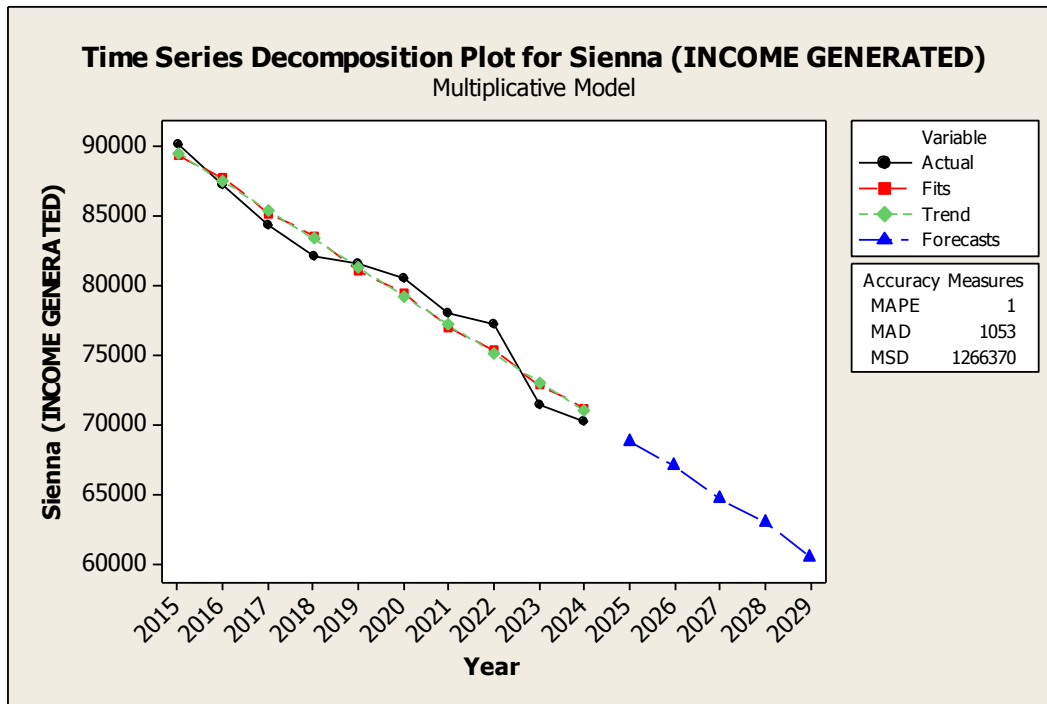


Figure 4.3.1c(i): Time series Analysis Plot for Sienna (Income Generated) vs. year counts.

Figure 4.3.1c(i) clarified the plot of income generation of Sienna vehicles over the given years using time series decomposition model. The plot further revealed that an increase in the age of the vehicle decreases the income generation of the said vehicles.

Table 4.3.1c(ii): The Actual data and Forecasted Results of the Income generation of Peugeot Expert vehicle over the given periods $\times 1000$.

Peugeot	8830	8600	8420	7990	7755	7605	7415	7050	6805	6760	6494.42	6308.16	6131.18	5963.48	5805.07
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1c(ii) show the actual data and forecasted results of the income generation of Peugeot Expert vehicle over the given periods. It is observed from

the above information that the income generation of the said vehicle is affected by the age of the vehicle.

Figure 4.3.1c(ii) demonstrated the Trend Analysis plot of Income Generated for Peugeot Expert vehicle over the given periods.

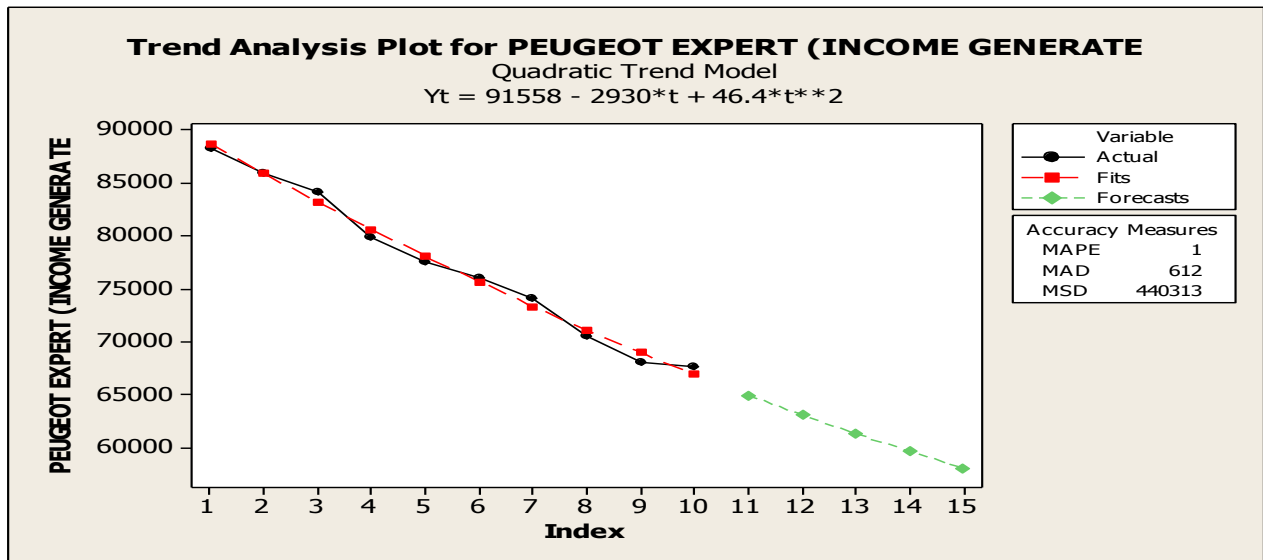


Figure 4.3.1c(ii): Trend Analysis Plot for Peugeot Expert (Income Generated) vs. Year counts.

Figure 4.3.1c(ii) revealed the plot of income generation of Peugeot Expert vehicle against the year counts using trend analysis model. The outcome showed a continuous decrease in future income generation of Peugeot Expert vehicle with increase in the age of the said vehicle.

Table 4.3.1c(iii): The actual data and Forecasted results of the Income generated for the J5 vehicle over the given periods × 1000.

J5	8910	8540	8330	8150	7920	7760	7606	7500	7450	6980	6914.65	6750.99	6591.20	6435.19	6282.88
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1c(iii) is a display of the actual data and forecasted results of the income generation of J5 vehicle over the given periods. The trend showed that the income generation of J5 vehicle decrease with increase in the age of the said vehicles.

Figure 4.3.1c(iii) depicted the Trend Analysis plot of Income Generated for J5 vehicle over the given period.

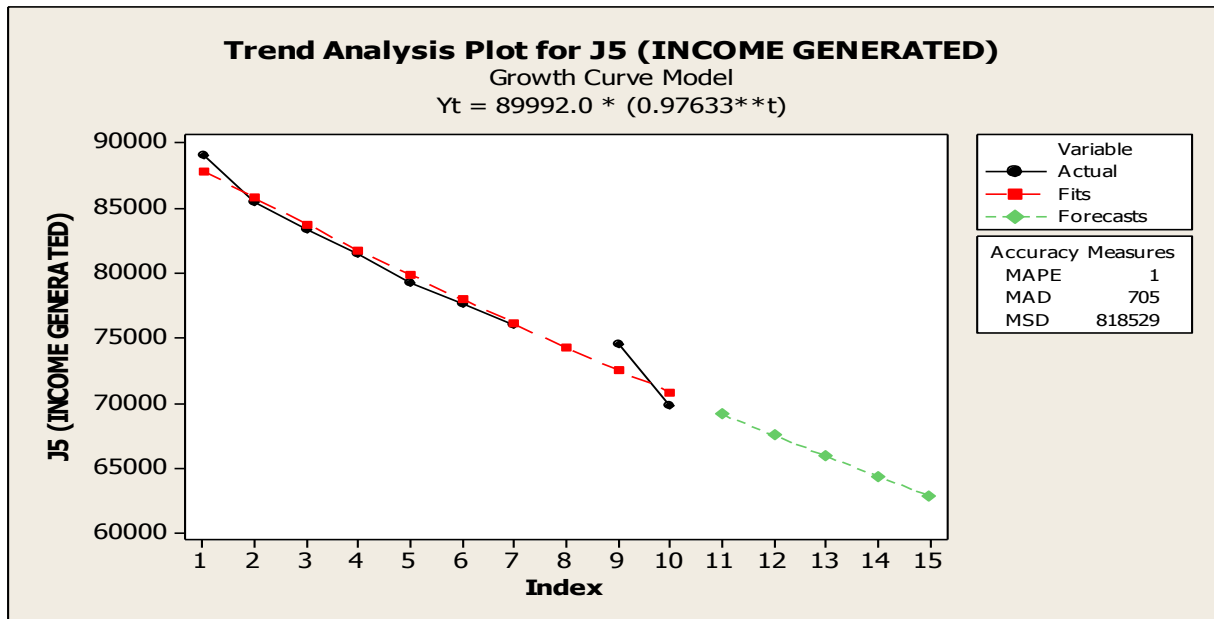


Figure 4.3.1c(iii): Trend Analysis Plot for J5 (Income Generated) vs. Year counts.

Figure 4.3.1c(iii) showed the plot of income generation of J5 over the given years using the trend analysis model. The result revealed a continuous decrease in future income generated cost of J5 vehicle with increase in the age of the vehicle in question.

Table 4.3.1c(iv): The Actual data collected and Forecasting Results of the Income generated for the Ford bus vehicle over the given period $\times 1000$.

Ford	9200	9020	8713	8614	8290	7880	7740	7550	7195	6875	6669.67	6438.97	6152.99	5920.06	5636.30
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1c(iv) described the actual data and forecasted results of the income generation of Ford bus vehicles over the given periods. The trend shows that the income generation of Ford vehicle decreases with increase in the age of the said vehicle.

Figure 4.3.1c(iv) portrayed the Time Series Decomposition plot of Income generation of Ford vehicles over the given period.

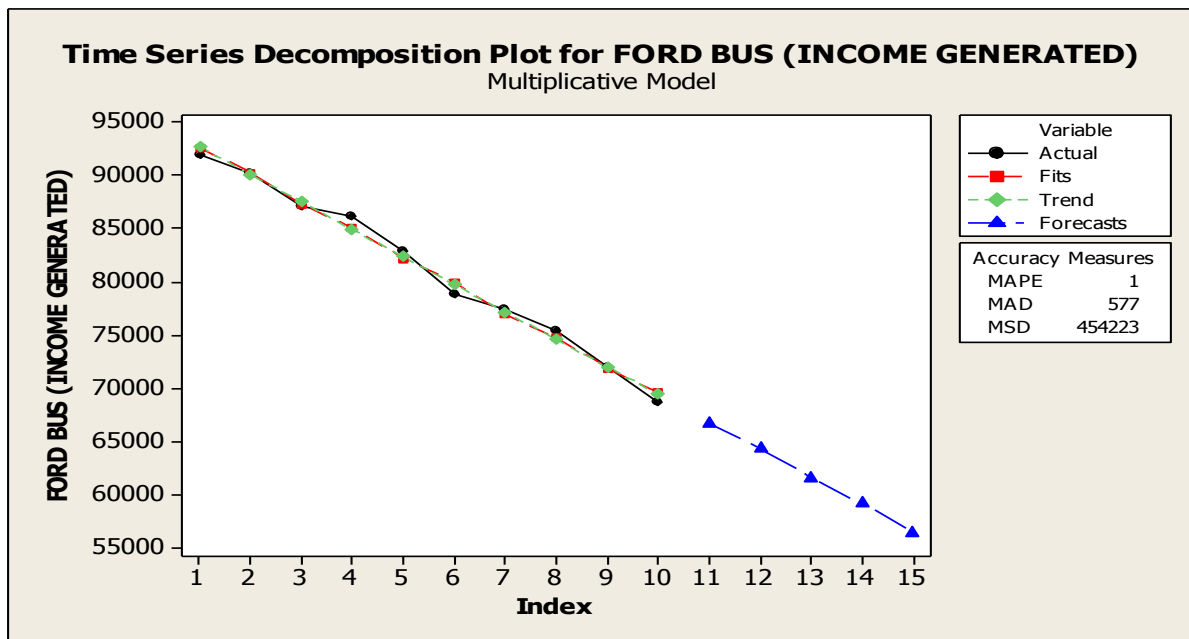


Figure 4.3.1c(iv): Time Series Decomposition Plot for Ford Bus (Income Generated) .

Figure 4.3.1c(iv) is the time series decomposition plot of income generated for Ford Bus over the given period. The output revealed a continuous decrease in future income generation of Ford bus vehicles. The result also showed that the income generation of the said vehicles decreases as the age of the vehicle increases.

Table 4.3.1c(v): The Actual data collected and Forecasted Results of the Income generated for Toyota Hiace vehicle over the given period $\times 1000$.

Toyota	10012	9706	9550	9220	9019	8812	8600	8330	7911	7880	7573.33	7089.45	7089.45	6847.52	6605.58
Years	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15

Table 4.3.1c(v) represented the actual data and forecasted outcome of the income generation of Toyota Hiace vehicle over the given periods. The trend shows that the income generation of Toyota Hiace vehicle decreases with increase in the age of the said vehicle.

Figure 4.3.1c(v) displayed the trend analysis smoothing plot of income generated for the Toyota Hiace vehicle over the given period.

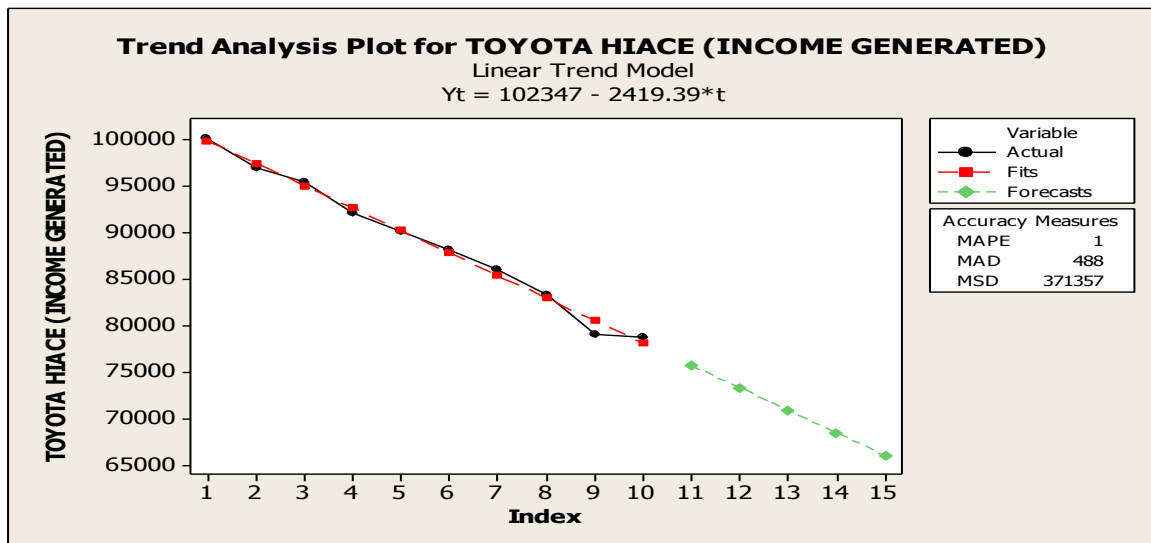


Figure 4.3.1c(v): Trend Analysis Plot for Toyota Hiace (Income Generated) vs. Year counts

Figure 4.3.1c(v) is the plot of income generation of Toyota Hiace against the year counts using trend analysis model. The outcome reflected a continuous decrease in future income generation of Toyota Hiace vehicle with increase in time. The result also revealed that the income generation of the said vehicle decreases as the age of the vehicles increases.

4.4 Results of the Analysis of the Influence of Environmental Factors on the Operational Costs of ATS Vehicles using Main cause and Effect tool.

The data collected on the environmental factors, distance covered (km), maintenance costs, replacement costs and income generated by ATS vehicles are represented in Tables [4.4.1a(i-vii), 4.4.1b(i-vii), 4.4.1c(i-vii)] and plotted in Figures [4.4.1a(i-vii), 4.4.1b(i-vii), 4.4.1c(i-vii)].

4.4.1a: Results of Effect of Environmental Factors on the Maintenance Costs of Vehicle Types.

The data on the environmental factors and maintenance costs of the vehicle types are shown in Tables[4.4.1a(i-vii)] and plotted in Figures[4.4.1a(i-vii)].

Table 4.4.1a(i): The Actual environmental factors and Maintenance Cost of Nissan Urvan vehicles over the given period.

Time	Year	Precipitation(cm ³)	Temperature (°C)	Relative Humidity	Nissan Urvan(Km)	NISSAN URVAN (Maint .Cost,₹) ×1000
1	2005	1620	29.2	148	101616	1969
2	2006	1500	28.5	156.9	102784	2250
3	2007	1650.3	28.96	176.98	105120	2520
4	2008	1507	28.15	159.56	113296	2815
5	2009	1579.1	28.3	126.2	116800	3030
6	2010	1506.6	27.8	122.65	117384	3240
7	2011	1695.4	28.85	129.7	117968	3360
8	2012	1662	27.9	148.0	118552	3590
9	2013	2294.7	28.3	122.65	119720	3995
10	2014	1695	28.4	129.68	120304	4005

Table 4.4.1a(i) demonstrated the selected environmental factors, the distance travelled by Nissan Urvan as measured in kilometers and the maintenance cost of the Nissan Urvan over the given period.

Figure 4.4.1a(i) showed the main effect of the environmental factors on the maintenance costs of Nissan Urvan vehicles over the given period.

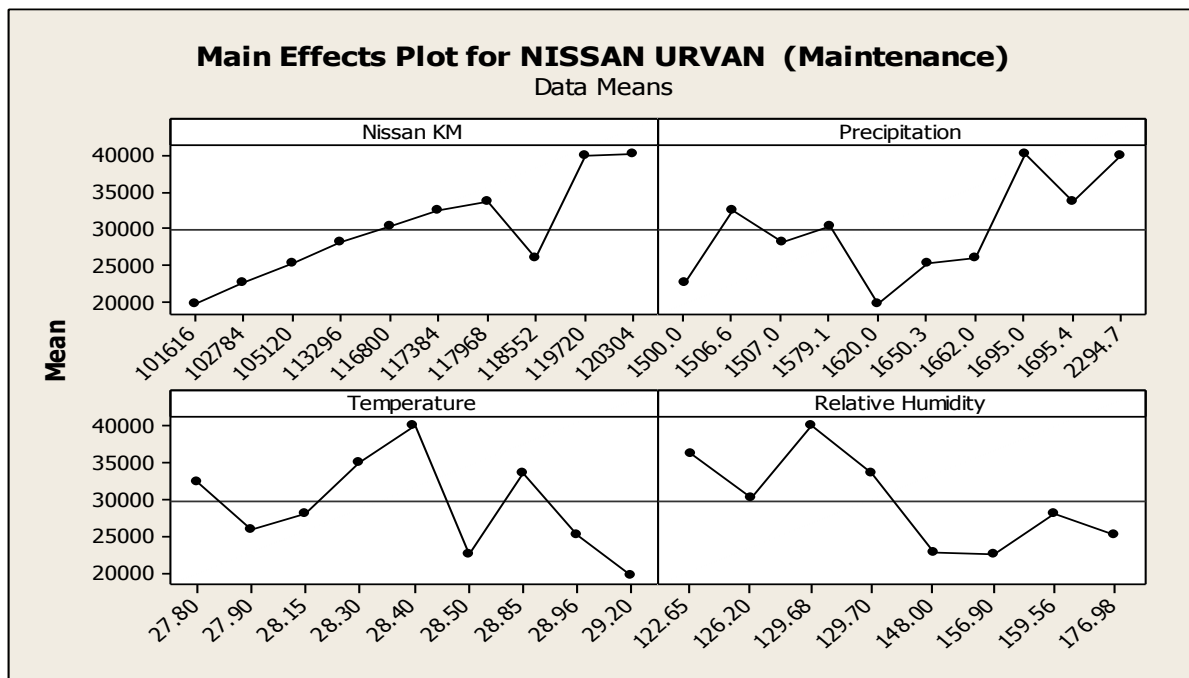


Figure 4.4.1a(i): Main Effects Plot for NISSAN URVAN (Maintenance Cost) vs Env. Factors.

Figure 4.4.1a(i) showed the main effect of the measurable environmental factors on the maintenance costs of Nissan Urvan vehicles over the given periods. From the plot, it is observed that the maintenance cost increases as the (km) increases, but at the distance of 11852(km), there is a decrease in maintenance cost a pointer to the fact that there is a possibility of having a less maintenance by virtue of good road and better management. Precipitation, Temperature and Relative Humidity had the highest effect at 1696.4, 28.40 and 129.68 respectively while the lowest environmental influences were at 1620.0, 29.20 and 156.90 respectively on maintenance costs of Nissan Urvan vehicles. The plots also showed that at the maximum environmental effect, the company would spend more on the maintenance of its vehicles and less income would be generated.

Table 4.4.1a(ii):The Actual environmental factors and Maintenance Cost of Sienna vehicle over the given period.

Time	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	Sienna (Km)	Sienna (Maint .Cost,₦)×1000
1	2005	1620	29.2	148	79042.98	1900
2	2006	1500	28.5	156.9	79951.52	2440
3	2007	1650.3	28.96	176.98	81768.6	2905
4	2008	1507	28.15	159.56	88128.38	3230
5	2009	1579.1	28.3	126.2	90854	3700
6	2010	1506.6	27.8	122.65	91308.27	3920
7	2011	1695.4	28.85	129.7	91762.54	4405
8	2012	1662	27.9	148.0	92216.81	4610
9	2013	2294.7	28.3	122.65	93125.35	4880
10	2014	1695	28.4	129.68	93579.62	4882

Table 4.4.1a(ii) represented the selected environmental factors, the distance travelled by Sienna vehicles as measured in kilometers and its maintenance cost over the given periods.

Figure 4.4.1a(ii) is the effect of environmental factors on the maintenance cost of Sienna vehicle over the given periods.

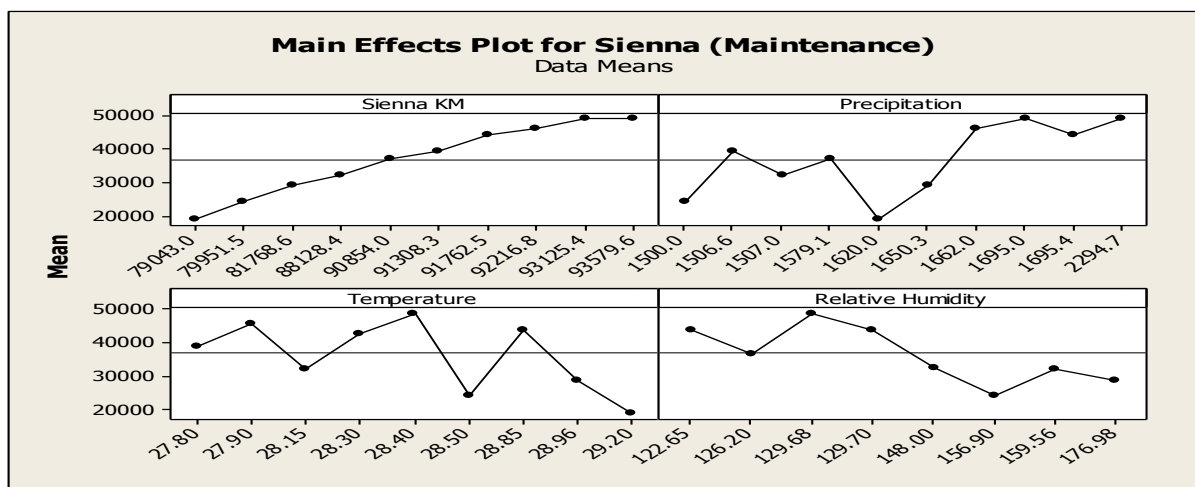


Figure 4.4.1a(ii): Main Effects Plot for SIENNA (Maintenance Cost) vs Env.factors

Figure 4.4.1a(ii) established the effect of the measurable environmental factors on the maintenance cost of Sienna vehicles. The outcome showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.70 respectively while the lowest environmental influences were at 1620.0, 29.20 and 156.90 respectively for the maintenance cost of Sienna vehicles. The outcome also showed that at the maximum environmental effect, the company would spend more on the maintenance of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the maintainability of its vehicles, thereby making more profit.

Table 4.4.1a(iii): The Actual environmental factors and Maintenance Cost of Peugeot Expert vehicle over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	Peugeot Expert(km)	Peugeot Expert(maint.cost, ₦)×1000
1	2005	1620	29.2	148	93849.14	2090
2	2006	1500	28.5	156.9	99943.24	2130
3	2007	1650.3	28.96	176.98	102380.9	2590
4	2008	1507	28.15	159.56	107256.2	2900
5	2009	1579.1	28.3	126.2	107256.2	3050
6	2010	1506.6	27.8	122.65	108475	3310
7	2011	1695.4	28.85	129.7	111522	3505
8	2012	1662	27.9	148.0	118225.5	3790
9	2013	2294.7	28.3	122.65	115178.5	3900
10	2014	1695	28.4	129.68	117616.1	3980

Table 4.4.1a(iii) is the effect of Environmental factors on the Maintenance Cost of Peugeot Expert vehicles over the given period. The table also shows the distance travelled by the said vehicle as measured in kilometers. The trend is that the maintenance costs increase with the age of vehicles.

The Figure 4.4.1a(iii) signified the effect of environmental factors on the maintenance costs of Peugeot Expert vehicles over the given period.

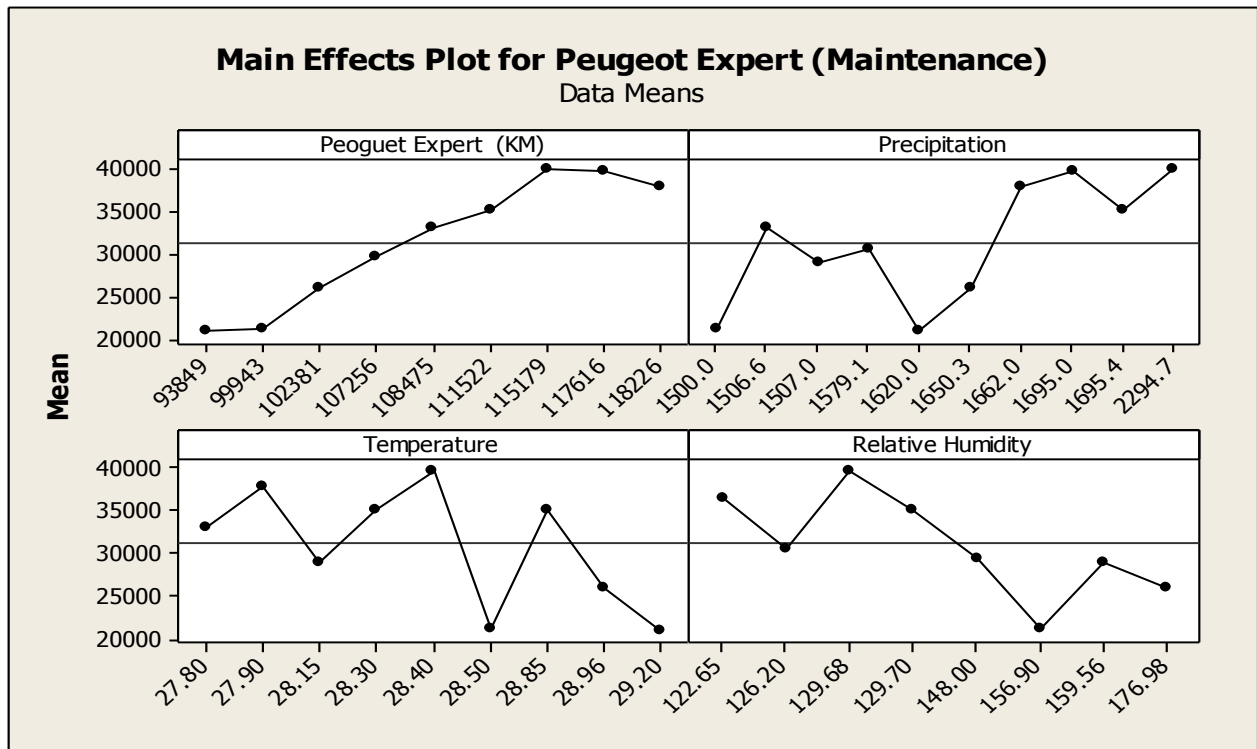


Figure 4.4.1a(iii): Main Effects Plot for Peugeot Expert (Maintenance Cost)

Figure 4.4.1a(iii) showed the effect of the measurable environmental factors on the maintenance cost of Peugeot Expert vehicles. The output showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68 respectively while the lowest environmental influences were at points of 1500.0 and 1620.0 for precipitation, points of 28.50 and 29.20 for temperature and at 156.90 for relative humidity for the maintenance cost of Peugeot Expert vehicles. More so, the result revealed that the maintenance costs increase as the distance travelled increases as measured in kilometers.

Table 4.4.1a(iv):The Actual environmental factors and Maintenance Costs of J5 vehicles over the given period.

Time	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	J5(km)	J5 (Maint. Cost,₦)×1000
1	2005	1620	29.2	148	73647.24	2337
2	2006	1500	28.5	156.9	74493.76	2410
3	2007	1650.3	28.96	176.98	76610.06	3665
4	2008	1507	28.15	159.56	82112.44	3811
5	2009	1579.1	28.3	126.2	84652	3990
6	2010	1506.6	27.8	122.65	85075.26	4050
7	2011	1695.4	28.85	129.7	85498.52	4410
8	2012	1662	27.9	148.0	85921.78	4600
9	2013	2294.7	28.3	122.65	86768.3	4750
10	2014	1695	28.4	129.68	87191.56	4820

Table 4.4.1a(iv) is the effect of Environmental factors on the maintenance cost of J5 vehicles over the given period. The trend revealed that the maintenance costs increase with increase in the distance travelled by the said vehicle as measured in kilometers.

Figure 4.4.1a(iv) clarified the effect of environmental factors on the maintenance cost of J5 vehicle over the given period.

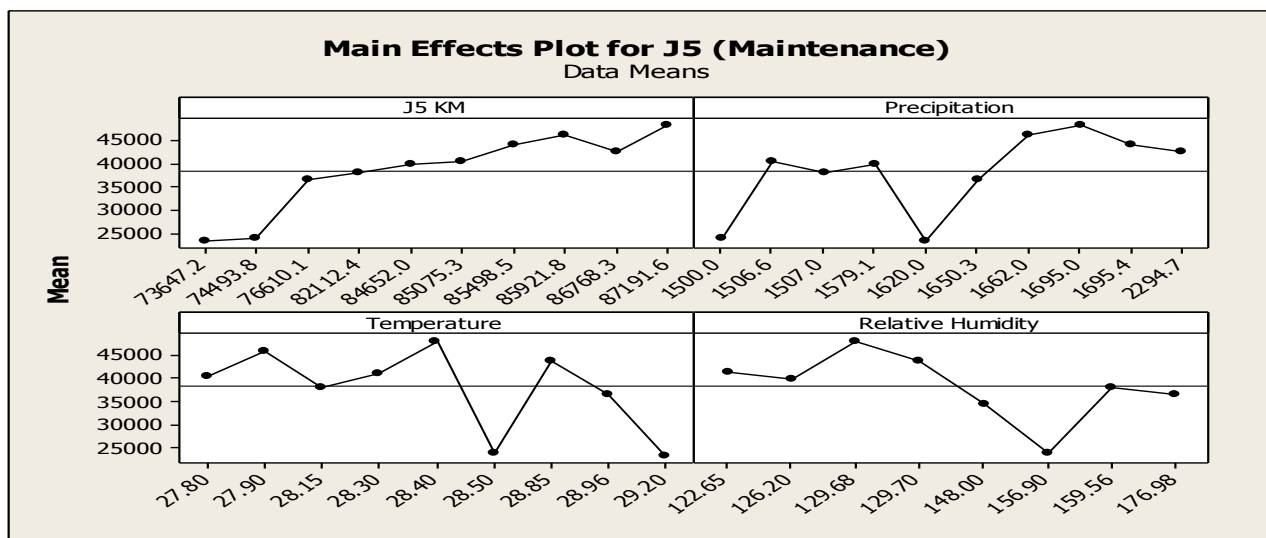


Figure 4.4.1a(iv): Main Effects Plot for J5 (Maintenance Cost) on the Environmental factors.

Figure 4.4.1a(iv) denoted the effect of the measurable environmental factors on the maintenance cost of J5 vehicle over the given periods. The output revealed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68 respectively while the lowest environmental influences were at points 1500.0 and 1620.0, points 28.50 and 29.20 and 156.90 respectively for the maintenance cost of J5 vehicle. Besides, it is observed that the maintenance cost increases as the length of the road increases as measured in kilometers.

4.4.1a(v): The Actual environmental factors and Maintenance Cost of Ford bus vehicle over the given period.

Time	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	Ford Bus(km)	FORD BUS(maint.cost, ₹) × 1000
1	2005	1620	29.2	148	32632.6	2165
2	2006	1500	28.5	156.9	34751.6	2298
3	2007	1650.3	28.96	176.98	35599.2	3116
4	2008	1507	28.15	159.56	37294.4	3489
5	2009	1579.1	28.3	126.2	39837.2	3690
6	2010	1506.6	27.8	122.65	40049.1	3695
7	2011	1695.4	28.85	129.7	38777.7	3780
8	2012	1662	27.9	148.0	43015.7	3905
9	2013	2294.7	28.3	122.65	41320.5	4160
10	2014	1695	28.4	129.68	40896.7	4245

Table 4.4.1a(v) depicted the effect of precipitation, temperature, relative humidity and the distance travelled by the said vehicle on the maintenance cost of Ford bus vehicle over the given period.

The figure 4.4.1a(v) show the effect of environmental factors on the maintenance cost of Ford Bus vehicle over the given period.

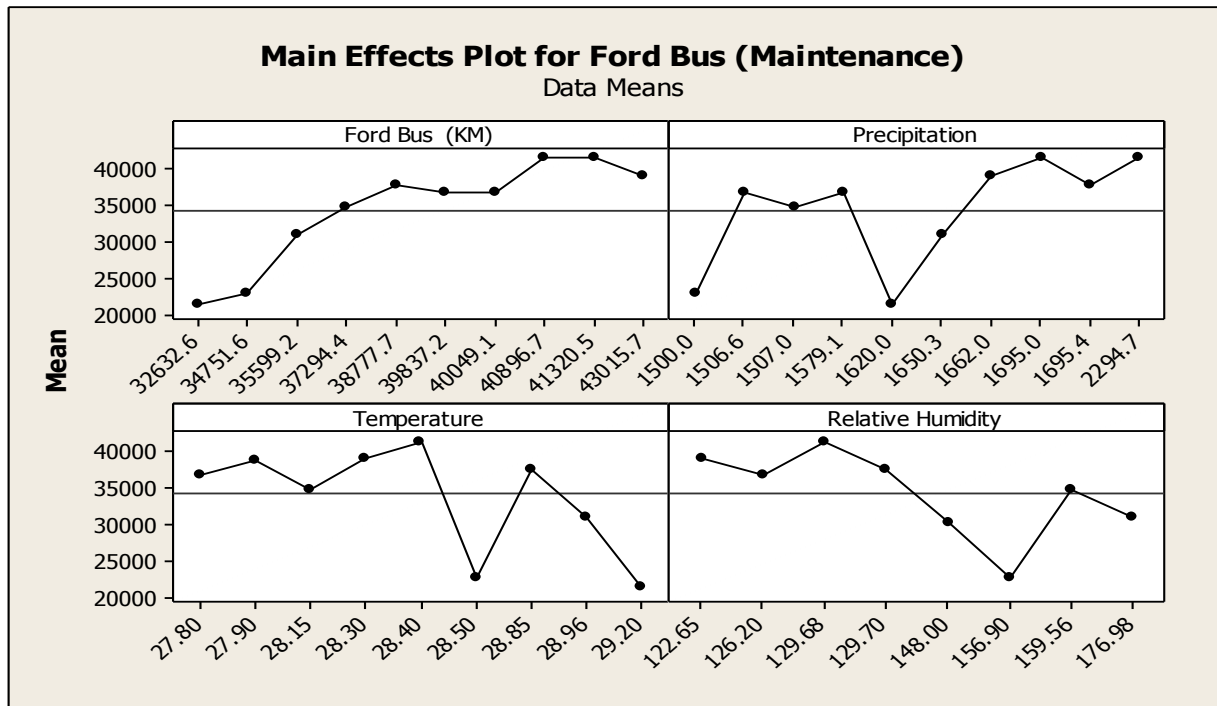


Figure 4.4.1a(v): Main Effects Plots for FORD BUS (Maintenance Cost) vs. environmental factors.

Figure 4.4.1a(v) implied the effect of environmental factors on the maintenance cost of Ford bus vehicle. The outcome showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68 respectively while the lowest environmental influences were at points 1500.0 and 1620.0, points 28.50 and 29.20 and 156.90, respectively, for the maintenance cost of Ford bus vehicle. It is observed that the maintenance cost increases as the distance increases for the Ford bus as measured in kilometers.

4.4.1a(vi):The Actual collected Data onthe environmental factors and Maintenance Cost of Toyota Hiace vehicle over the given periods.

Time	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	Toyota Hiace(km)	TOYOTA HIACE(maint.cost,₹)×1000
1	2005	1620	29.2	148	161059.2	2205
2	2006	1500	28.5	156.9	173774.4	2400
3	2007	1650.3	28.96	176.98	185430	2510
4	2008	1507	28.15	159.56	186489.6	2790
5	2009	1579.1	28.3	126.2	187549.2	3020
6	2010	1506.6	27.8	122.65	188608.8	3330
7	2011	1695.4	28.85	129.7	190728	3515
8	2012	1662	27.9	148.0	191787.6	3640
9	2013	2294.7	28.3	122.65	194966.4	3713
10	2014	1695	28.4	129.68	201324	3802

Table 4.4.1a (vi) represents

the effect of precipitation,temperature,relative humidity and the distance travelled by the said vehicle on the Maintenance Cost of Toyota vehicle over the given periods. The trend showed that the maintenance costs increase with increase in distance travelled.

Figure 4.4.1a(vi) is the effect of environmental factors on the maintenance cost of Toyota Hiace vehicle over the given periods.

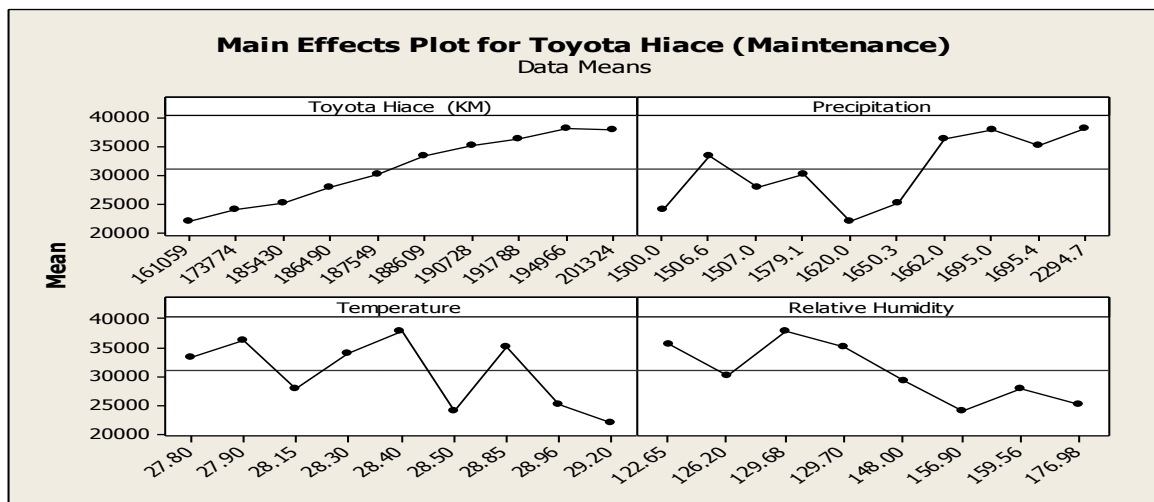


Figure 4.4.1a(vi): Main Effects Plot for TOYOTA HIACE (Maintenance Cost)vs. environmental factors.

Figure 4.4.1a(vi) characterized the effect of the measurable environmental factors on the maintenance cost of Toyota Hiace vehicle. The output shows that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68 respectively while the lowest environmental influences were at 1620.0, 29.20 and 156.90, respectively, for the maintenance cost of Toyota Hiace vehicle. Besides, It is observed that the maintenance cost increases as the length of the road increases as measured in kilometers.

4.4.1a(vii): The Actual environmental factors and Maintenance Cost of Taxi Cab vehicle over the given periods.

Time	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	Taxi Cab(km)	Taxi Cab(maint.cost,₦)×1000
1	2005	1620	29.2	148	45359.64	1890
2	2006	1500	28.5	156.9	48977.28	2080
3	2007	1650.3	28.96	176.98	50368.68	2160
4	2008	1507	28.15	159.56	52038.36	2310
5	2009	1579.1	28.3	126.2	52316.64	2500
6	2010	1506.6	27.8	122.65	52594.92	2910
7	2011	1695.4	28.85	129.7	53429.76	3012
8	2012	1662	27.9	148.0	56490.84	3220
9	2013	2294.7	28.3	122.65	54264.6	3370
10	2014	1695	28.4	129.68	53708.04	3405

Table 4.4.1a(vii) is the effect of precipitation, temperature, relative humidity and the distance travelled by the said vehicle on the maintenance cost of Taxi Cab vehicle over the given periods. The trend shows that the environmental factors affect the maintenance costs of vehicles under investigation.

Figure 4.4.1a(vii) represented the effect of environmental factors on the maintenance cost of Taxi Cab vehicle over the given period.

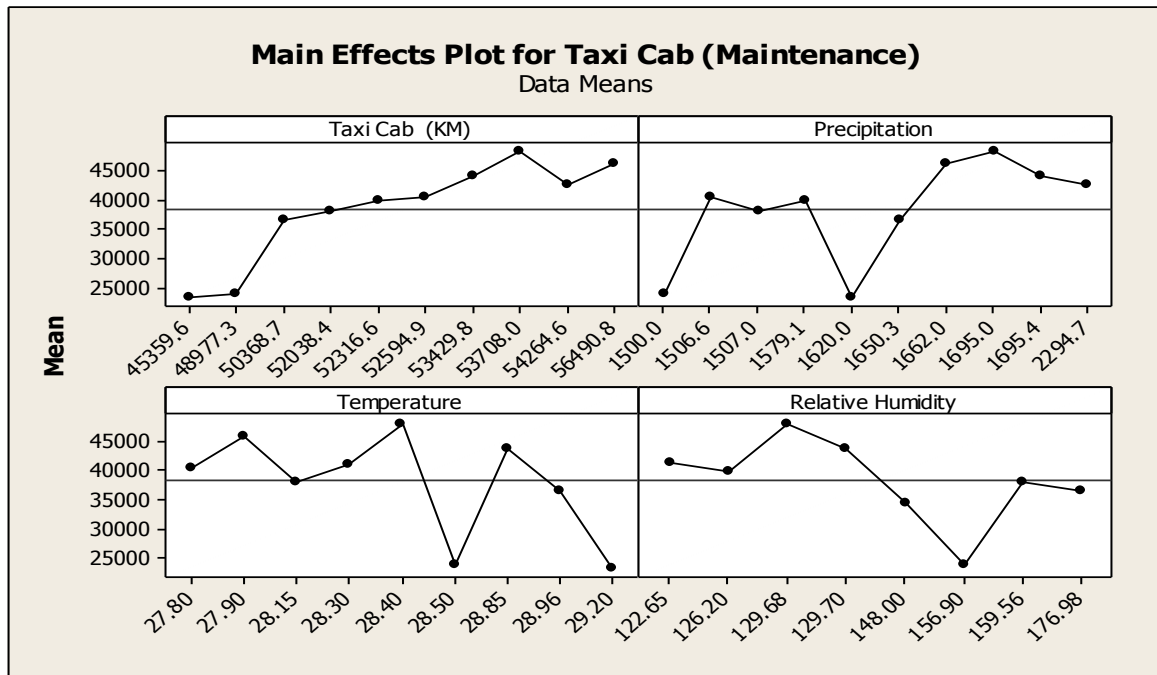


Figure 4.4.1a(vii): Main Effects Plots for TAXI CAB (Maintenance Cost) vs. environmental factors.

Figure 4.4.1a(vii) exhibited the effect of environmental factors on the maintenance cost of Taxi Cab vehicles. The results showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the maintenance cost of Taxi Cab vehicles. Besides, the plot revealed that the maintenance costs is directly proportional to the length of the road increases as measured in kilometer.

4.4.1b:Results of the Effect of Environmental Factors on Replacement Costs of Vehicle Types.

Tables {4.4.1b(i-vii)} showed the data on environmental factors and replacement costs of vehicle types andplotted in Figures [4.4.1b(i-vii)].

Table 4.4.1b(i):The Actual environmental factors and Replacement Cost of Nissan Urvan vehicles over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	Nissan Urvan(km)	Nissan Urvan(Repla .cost,₦)×1000
1	2005	1620	29.2	148	101616	1992
2	2006	1500	28.5	156.9	102784	2024
3	2007	1650.3	28.96	176.98	105120	2100
4	2008	1507	28.15	159.56	113296	2150
5	2009	1579.1	28.3	126.2	116800	2157
6	2010	1506.6	27.8	122.65	117384	2181
7	2011	1695.4	28.85	129.7	117968	2202
8	2012	1662	27.9	148.0	118552	2305
9	2013	2294.7	28.3	122.65	119720	2360
10	2014	1695	28.4	129.68	120304	2373

Table 4.4.1b(i) clarified the effect of precipitation,temperature,relative humidity and distance travelled by the said vehicleson the replacement cost of Nissan Urvan vehicle over the given period.

The figure 4.4.1b(i)displayedthe effect of environmental factors on the replacement cost of Nissan Urvan vehicles over the given period.

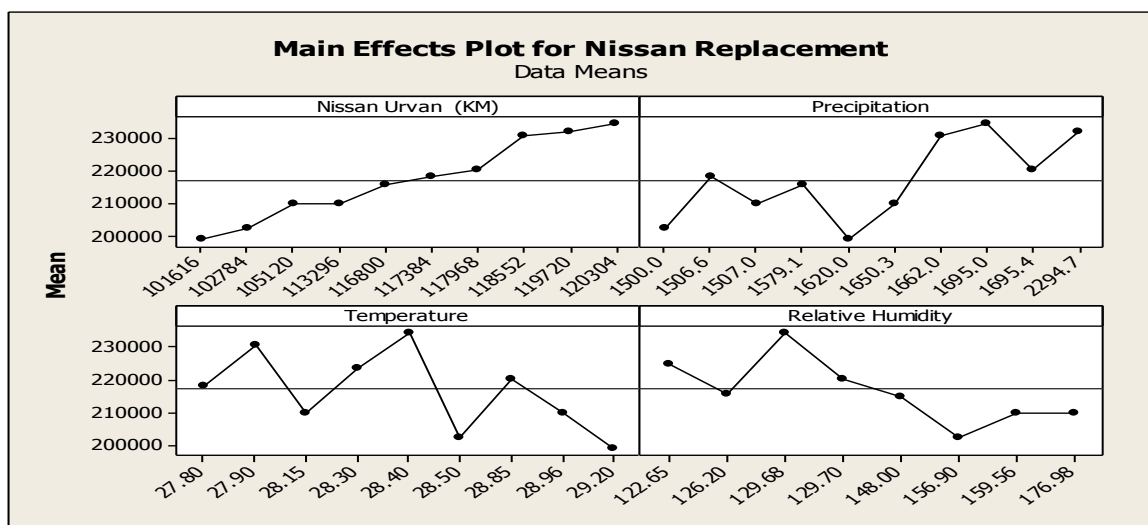


Figure 4.4.1b(i): Main Effects Plot for Nissan Urvan (Replacement Cost)vs. environmental factors.

Figure 4.4.1b(i) showed the effect of the measurable environmental factors on the replacement cost of Nissan Urvan vehicle. The outcome revealed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of Nissan Urvan vehicle. The plots showed also that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit.

Table 4.4.1b(ii): The Actual collected Data on the environmental factors and replacement Cost of Sienna vehicle over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	Sienna(km)	Sienna(Repla. Cost, ₦) × 1000
1	2005	1620	29.2	148	79042.98	1100
2	2006	1500	28.5	156.9	79951.52	1150
3	2007	1650.3	28.96	176.98	81768.6	1250
4	2008	1507	28.15	159.56	88128.38	1260
5	2009	1579.1	28.3	126.2	90854	1280
6	2010	1506.6	27.8	122.65	91308.27	1309
7	2011	1695.4	28.85	129.7	91762.54	1329
8	2012	1662	27.9	148.0	92216.81	1336
9	2013	2294.7	28.3	122.65	93125.35	1353
10	2014	1695	28.4	129.68	93579.62	1370

Table 4.4.1b(ii) represented the effect of precipitation, temperature, relative humidity and the distance travelled by the said vehicles on the Replacement Cost of Sienna vehicle over the given periods. The trend revealed that the replacement cost is directly proportional to the distance travelled.

Figure 4.4.1b(ii)denotedthe effect of environmental factors on the Replacement cost of Sienna vehicles over the given period.

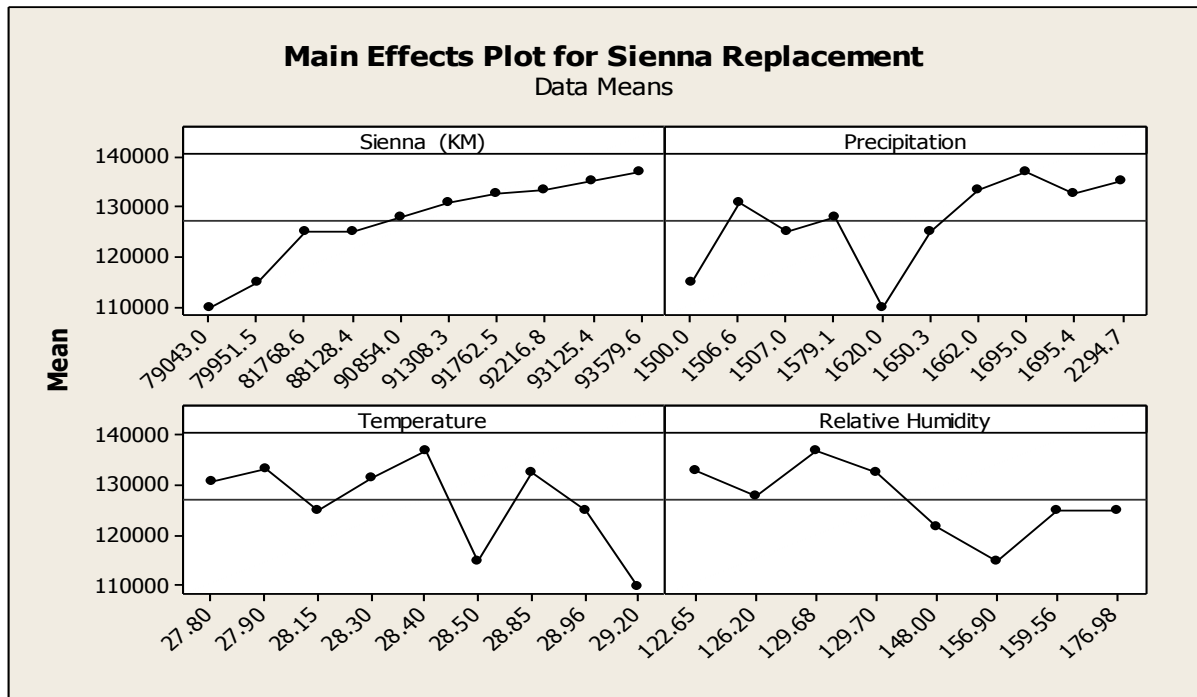


Figure 4.4.1b(ii): Main Effects Plot for Sienna (Replacement Cost)vs. environmental factors.

Figure 4.4.1b(ii) showed the effect of the measurable environmental factors on the replacement costs of Sienna vehicles. The output showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of Sienna vehicle. The plots showed also that at maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit.

Table 4.4.1b(iii):The Actual environmental factors and replacement Costs of Peugeot Expert vehicles over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	Peugeot Expert(km)	Peugeot Expert(Replac. Cost,₦)×1000
1	2005	1620	29.2	148	93849.14	1500
2	2006	1500	28.5	156.9	99943.24	1520
3	2007	1650.3	28.96	176.98	102380.9	1550
4	2008	1507	28.15	159.56	107256.2	1650
5	2009	1579.1	28.3	126.2	107256.2	1665
6	2010	1506.6	27.8	122.65	108475	1675
7	2011	1695.4	28.85	129.7	111522	1702
8	2012	1662	27.9	148.0	118225.5	1733
9	2013	2294.7	28.3	122.65	115178.5	1772
10	2014	1695	28.4	129.68	117616.1	1781

Table 4.4.1b(iii) connoted the effect of precipitation,temperature,relative humidity and the distance travelled by the said vehicle on the Replacement Cost of Peugeot Expert vehicle over the given period. The trend showed an increase in replacement cost as distance travelled increases.

The figure 4.4.1b(iii)depicted the effect of environmental factors on the replacement costs of Peugeot Expert vehicles.

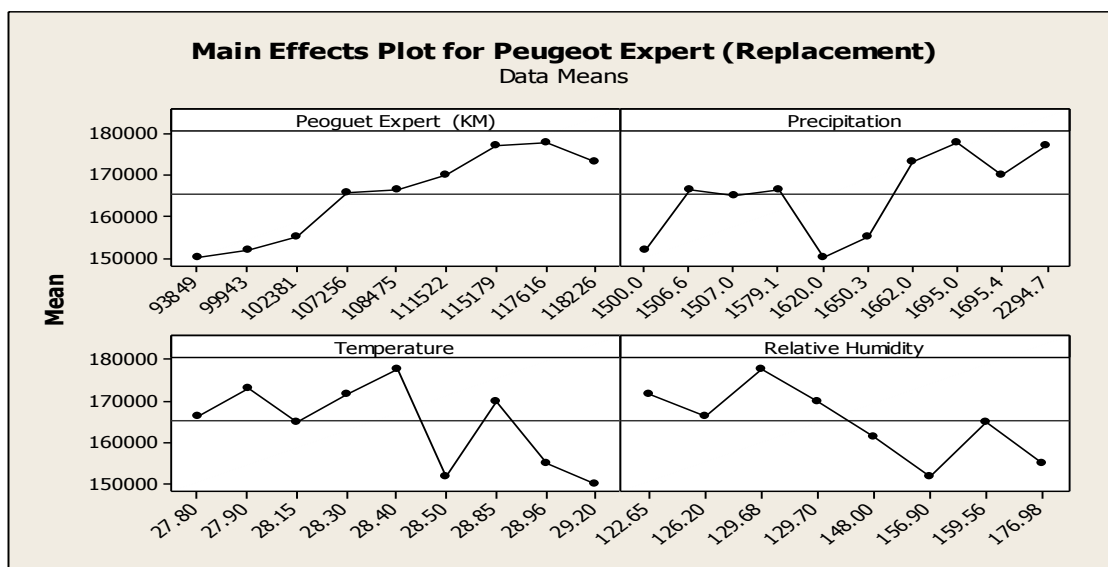


Figure 4.4.1b(iii): Main Effects Plot for Peugeot Expert (Replacement Cost)vs. environmental factors.

Figure 4.4.1b(iii) is a display of the effect of the measurable environmental factors on the replacement cost of Peugeot Expert vehicle. The output revealed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of Peugeot Expert vehicle. Besides, the plot showed that as the distance increases, there is a corresponding increment in replacement costs.

Table 4.4.1b(iv): The Actual environmental factors and replacement Cost of J5 vehicle over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	J5(km)	J5(Replac. Cost,₦) ×1000
1	2005	1620	29.2	148	73647.24	1803
2	2006	1500	28.5	156.9	74493.76	1809
3	2007	1650.3	28.96	176.98	76610.06	1817
4	2008	1507	28.15	159.56	82112.44	1830
5	2009	1579.1	28.3	126.2	84652	1852
6	2010	1506.6	27.8	122.65	85075.26	1866
7	2011	1695.4	28.85	129.7	85498.52	1884
8	2012	1662	27.9	148.0	85921.78	1901
9	2013	2294.7	28.3	122.65	86768.3	1920
10	2014	1695	28.4	129.68	87191.56	1935

Table 4.4.1b(iv) highlighted the collected data on the replacement costs of J5 vehicles, the distance travelled by the said vehicle and the environmental factors over the given period. The observation is that the replacement costs increase as distance travelled increases over the given period.

The figure 4.4.1b(iv) show the effect of environmental factors on the replacement costs of J5 vehicles.

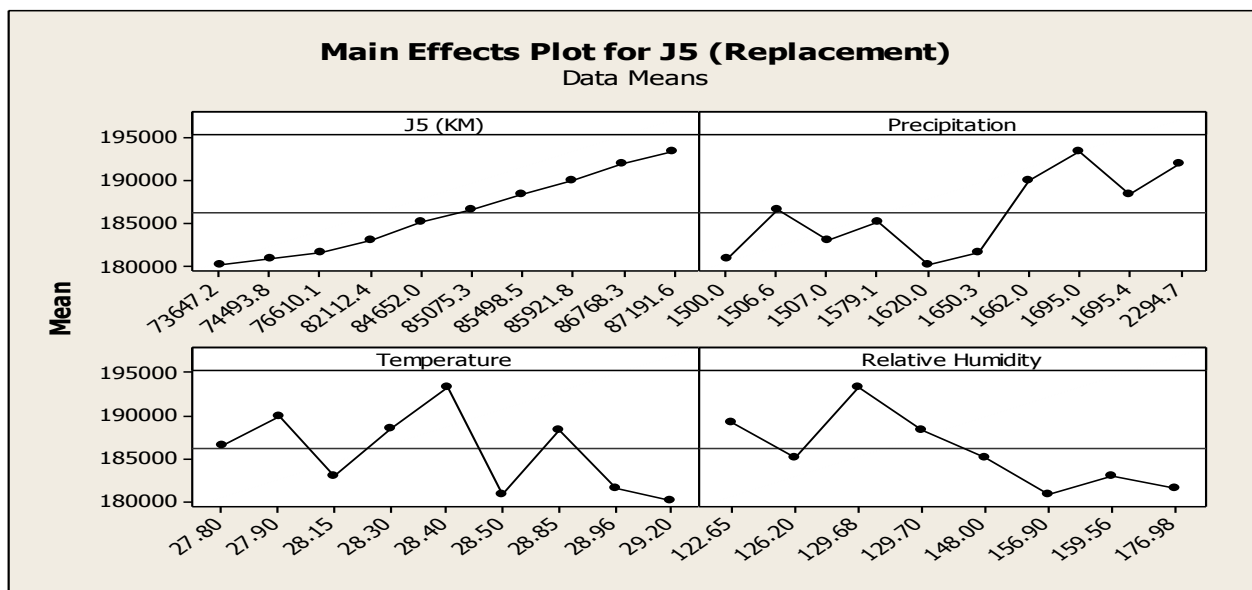


Figure 4.4.1b(iv): Main Effects Plot for J5 (Replacement Cost) Environ. factors

Figure 4.4.1b(iv) is the effect of environmental factors on the replacement cost of J5 vehicle. The plots further showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of J5 vehicle. The plots showed also that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit.

Table 4.4.1b(v):The Actual environmental factors and Replacement Cost of Ford bus vehicle over the given period.

Time	Year	Precipitation(cm³)	Temperat ure(°C)	Relative Humidi ty	Ford Bus(km)	Ford Bus(Replac. Cost,₦)×1000
1	2005	1620	29.2	148	32632.6	1804
2	2006	1500	28.5	156.9	34751.6	1812
3	2007	1650.3	28.96	176.98	35599.2	1813
4	2008	1507	28.15	159.56	37294.4	1825
5	2009	1579.1	28.3	126.2	39837.2	1825
6	2010	1506.6	27.8	122.65	40049.1	1836
7	2011	1695.4	28.85	129.7	38777.7	1840
8	2012	1662	27.9	148.0	43015.7	1862
9	2013	2294.7	28.3	122.65	41320.5	1876
10	2014	1695	28.4	129.68	40896.7	1879

Table 4.4.1b(v) is a display of the collected data on the replacement costs of Ford bus vehicle, the distance travelled by the said vehicle and the environmental factors over the given period. The trend shows that the replacement cost increases as the distance travelled increases while the environmental factors fluctuate.

Figure 4.4.1b(v) reflects the effect of environmental factors on the Replacement cost of Ford Bus vehicles.

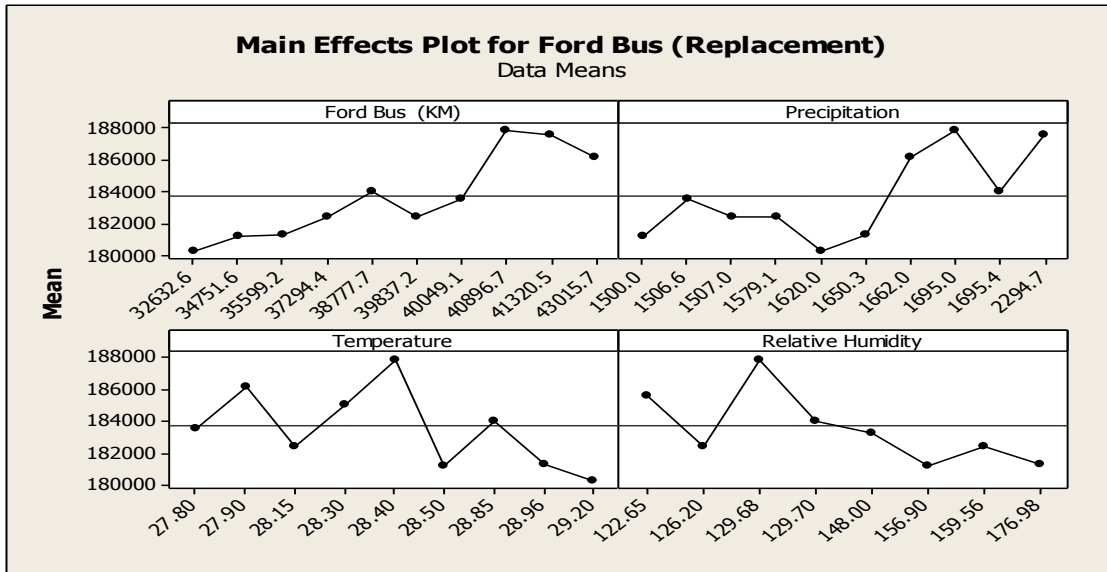


Figure 4.4.1b(v): Main Effects Plot for Ford Bus (Replacement Cost) vs. environmental factors. Figure 4.4.1b(v) highlighted the effect of environmental factors on the replacement cost of Ford bus vehicle over the given years. The plots showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of Ford Bus vehicle. The outcome also revealed that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated, on the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit.

Table 4.4.1b(vi): The Actual environmental factors and Replacement Cost of Toyota Hiace vehicle over the given period.

Time	Year	Precipitation (cm ³)	Temperature(°C)	Relative Humidity	Toyota Hiace(km)	Toyota Hiace(Replac. Cost,₦)×1000
1	2005	1620	29.2	148	161059.2	1893
2	2006	1500	28.5	156.9	173774.4	1898
3	2007	1650.3	28.96	176.98	185430	1900
4	2008	1507	28.15	159.56	186489.6	1912
5	2009	1579.1	28.3	126.2	187549.2	1933
6	2010	1506.6	27.8	122.65	188608.8	1944
7	2011	1695.4	28.85	129.7	190728	1950
8	2012	1662	27.9	148.0	191787.6	1966
9	2013	2294.7	28.3	122.65	194966.4	1967
10	2014	1695	28.4	129.68	201324	1970

Table 4.4.1b(vi) represented the collected data on the replacement costs of Toyota Hiace vehicle, the distance travelled by the said vehicles and the environmental factors over the given period.

The figure 4.4.1b(vi) is the effect of environmental factors on the Replacement cost of Toyota Hiace vehicles.

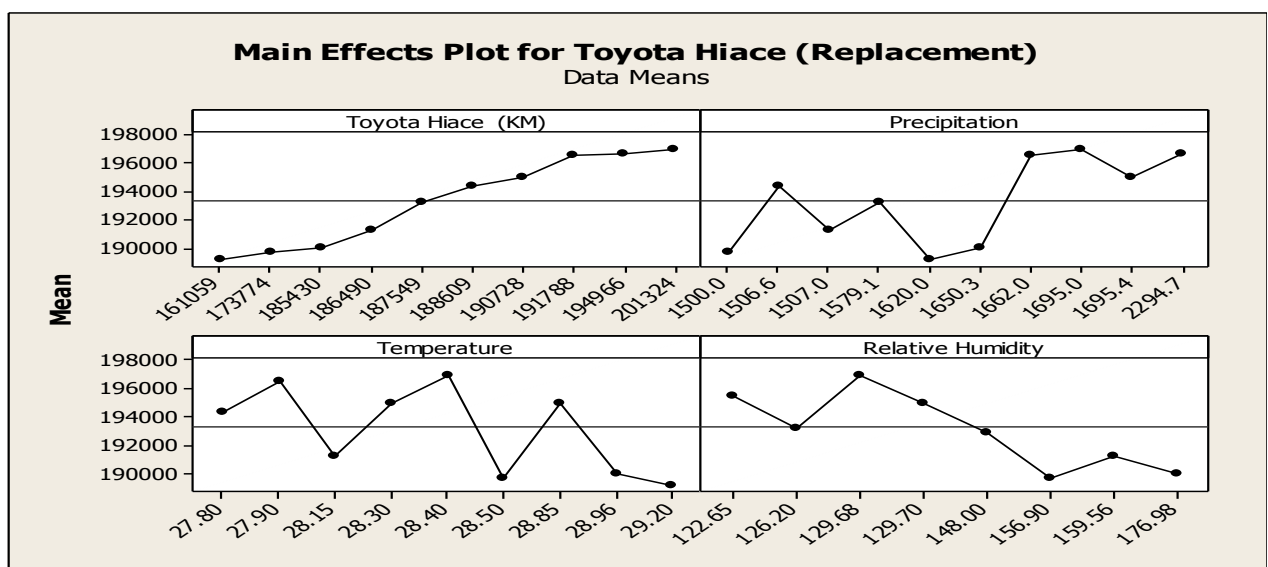


Figure 4.4.1b(vi): Main Effects Plot for Toyota Hiace (Replacement Cost) vs. environmental factors.

Figure 4.4.1b(vi) is a display of the effect of the environmental factors on the replacement cost of Toyota Hiace vehicle over the given years. The plots show that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement costs of Toyota Hiace vehicles. The plots showed also that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit. From the plots, it was observed that replacement costs increase as the length of the road increases .

Table 4.4.1b(vii):The Actual collected Data onthe environmental factors and Replacement Cost of Taxi Cab vehicle over the given period.

Time	Year	Precipitation(cm ³)	Temperature (°C)	Relative Humidity	Taxi Cab(km)	Taxi Cab(Replac. Cost,₦)×1000
1	2005	1620	29.2	148	45359.64	1000
2	2006	1500	28.5	156.9	48977.28	1011
3	2007	1650.3	28.96	176.98	50368.68	1102
4	2008	1507	28.15	159.56	52038.36	1152
5	2009	1579.1	28.3	126.2	52316.64	1164
6	2010	1506.6	27.8	122.65	52594.92	1170
7	2011	1695.4	28.85	129.7	53429.76	1195
8	2012	1662	27.9	148.0	56490.84	1202
9	2013	2294.7	28.3	122.65	54264.6	1206
10	2014	1695	28.4	129.68	53708.04	1210

Table 4.4.1b(vii) highlighted the data on the replacement costs of Taxi Cab vehicle, the distance travelled by the said vehicle and the environmental factors over the given period.

Figure 4.4.1b(vii) illustrated the effect of environmental factors on the Replacement cost of Taxi Cab vehicle.

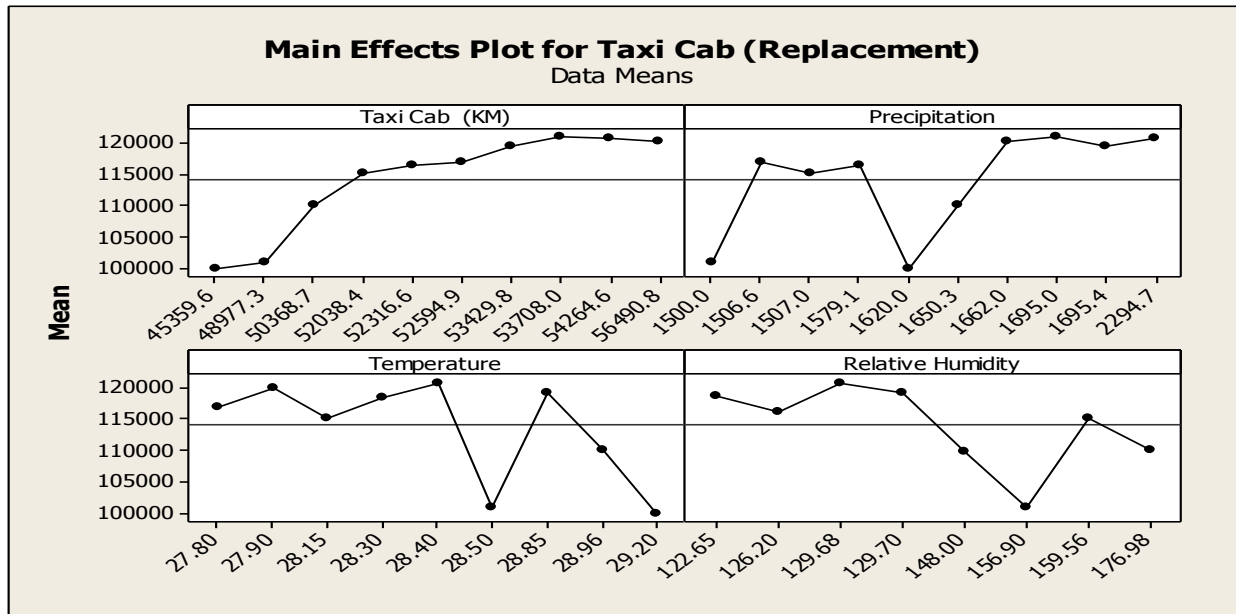


Figure 4.4.1b(vii): Main Effects Plot for Taxi Cab (Replacement Cost)

Figure 4.4.1b(vii) is the effect of environmental factors on the replacement cost of Taxi Cab vehicle. The output showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90, respectively, for the replacement cost of Taxi cab vehicle. The plots also showed that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less income would be generated. On the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit.

4.4.1c: Results of the Effect of Environmental Factors on the Income Generation of Vehicle Types.

The data on the environmental factors and income generation of vehicle types over the given period are exemplified in Tables {4.4.1c(i-vii)} and plotted in figures [4.4.1c(i-vii)].

Table 4.4.1c(i): The Actual environmental factors and Income generation of Nissan Urvan vehicle over the given period.

Time	Year	Precipitation (cm ³)	Temperature (°C)	Relative Humidity	Nissan Urvan(km)	Nissan Urvan (Inco. Cost,₹) ×1000
1	2005	1620	29.2	148	101616	98,073
2	2006	1500	28.5	156.9	102784	97,824
3	2007	1650.3	28.96	176.98	105120	96,000
4	2008	1507	28.15	159.56	113296	95,150
5	2009	1579.1	28.3	126.2	116800	90,200
6	2010	1506.6	27.8	122.65	117384	88,500
7	2011	1695.4	28.85	129.7	117968	86,100
8	2012	1662	27.9	148.0	118552	84,897
9	2013	2294.7	28.3	122.65	119720	83,400
10	2014	1695	28.4	129.68	120304	83,000

Table 4.4.1c(i) showed data on the replacement costs of Nissan Urvan vehicle, the distance travelled by the said vehicle and the environmental factors over the given period.

The figure 4.4.1c(i) emphasized the effect of environmental factors on the Income Generation of Nissan Urvan vehicles.

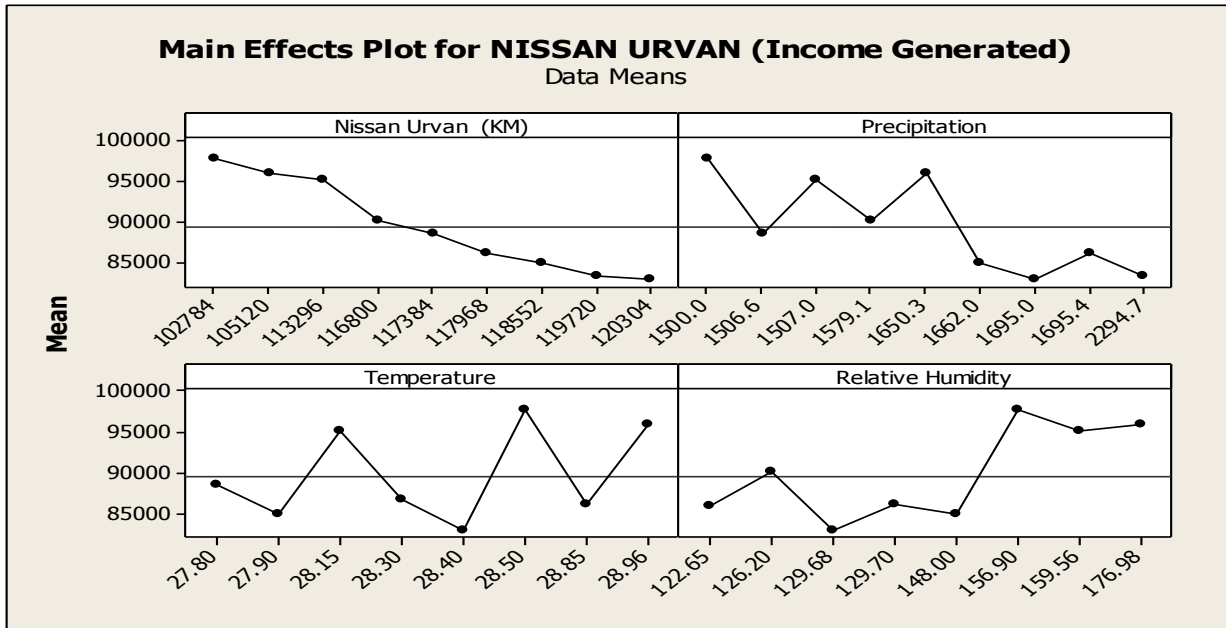


Figure 4.4.1c(i): Main Effects Plot for NISSAN URVAN (Income Generated)vs. environmental factors.

Figure 4.4.1c(i)highlightedthe effect of environmental factors on the Income generation of Nissan Urvan vehicles over the given period. The plots also showed that the precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68, respectively, for the Income generation of Nissan Urvan vehicles.

Table 4.4.1c(ii):The Actual environmental factors and Income generation of Sienna vehicle over the given period.

Time	Year	Precipitation(cm ³)	Temperature (°C)	Relative Humidity	Sienna(km)	Sienna(Inco. Cost,₦)×1000
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1	2005	1620	29.2	148	79042.98	9000
2	2006	1500	28.5	156.9	79951.52	8710
3	2007	1650.3	28.96	176.98	81768.6	8420
4	2008	1507	28.15	159.56	88128.38	8205
5	2009	1579.1	28.3	126.2	90854	8150
6	2010	1506.6	27.8	122.65	91308.27	8040
7	2011	1695.4	28.85	129.7	91762.54	7800
8	2012	1662	27.9	148.0	92216.81	7710
9	2013	2294.7	28.3	122.65	93125.35	7140
10	2014	1695	28.4	129.68	93579.62	7015

Table 4.4.1c(ii) underscored data on the Income generation of Sienna vehicle, the distance travelled by the said vehicles and the environmental factors over the given period.

Figure 4.4.1c(ii) highlighted the effect of environmental factors on the Income Generation of Sienna vehicle over the given period.

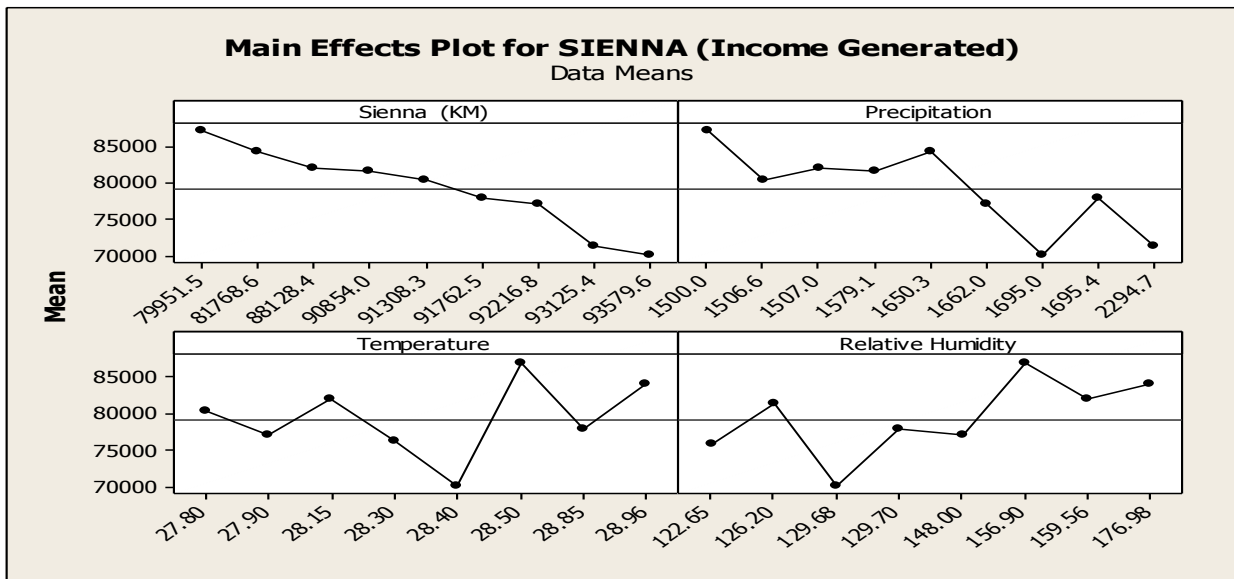


Figure 4.4.1c(ii): Main Effects Plot for SIENNA (Income Generated Cost) vs. environmental factors.

Figure 4.4.1c(ii) illustrated the effect of environmental factors on the income generation of Sienna vehicles. The results revealed that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and

129.68, respectively, for the Income generation of Sienna vehicles. It is also observed from the chart that as the length of the road increases, the income decreases and vice versa while the environmental factors fluctuate.

Table 4.4.1c(iii): The Actual environmental factors and Income generation of Peugeot Expert vehicles over the given period

TIME	Year	Precipitation (cm ³)	Temperature (°C)	Relative Humidity	Peugeot Expert (km)	PEUGEOT EXPERT (Inco. Gener, ₦) ×1000
1	2005	1620	29.2	148	93849.14	8830
2	2006	1500	28.5	156.9	99943.24	8600
3	2007	1650.3	28.96	176.98	102380.9	8420
4	2008	1507	28.15	159.56	107256.2	7990
5	2009	1579.1	28.3	126.2	107256.2	7755
6	2010	1506.6	27.8	122.65	108475	7605
7	2011	1695.4	28.85	129.7	111522	7415
8	2012	1662	27.9	148.0	118225.5	7050
9	2013	2294.7	28.3	122.65	115178.5	6805
10	2014	1695	28.4	129.68	117616.1	6760

Table 4.4.1c(iii) represented the data on the Income generation of Peugeot expert vehicle, the distance travelled by the said vehicle and the environmental factors over the given period. The trend showed that the income generation of Peugeot expert decreases with an increase in the distance travelled amidst the fluctuations of the environmental factors.

Figure 4.4.1c(iii) explained the effect of environmental factors on the Income Generation of Peugeot Expert vehicles.

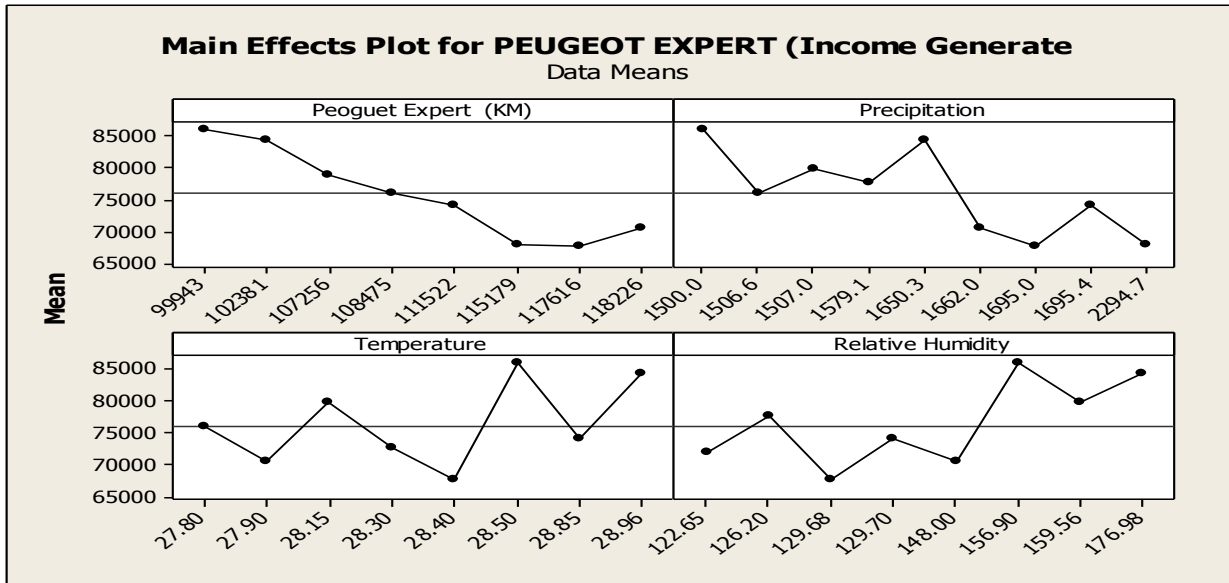


Figure 4.4.1c(iii): Main Effects Plot for PEUGEOT EXPERT (Income Generated)vs. environmental factors.

Figure 4.4.1c(iii) represented the effect of environmental factors on the Income generation of Peugeot Expert vehicle. The output shows that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68, respectively, for the Income generation of Peugeot Expert vehicle.

Table 4.4.1c(iv):The Actual environmental factors and Income generation of J5 vehicle over the given period.

TIME	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	J5(km)	J5(Inco. Generated,₦) ×1000
1	2005	1620	29.2	148	73647.24	8910
2	2006	1500	28.5	156.9	74493.76	8540
3	2007	1650.3	28.96	176.98	76610.06	8330
4	2008	1507	28.15	159.56	82112.44	8150
5	2009	1579.1	28.3	126.2	84652	7920
6	2010	1506.6	27.8	122.65	85075.26	7760
7	2011	1695.4	28.85	129.7	85498.52	7606
8	2012	1662	27.9	148.0	85921.78	7500
9	2013	2294.7	28.3	122.65	86768.3	7450
10	2014	1695	28.4	129.68	87191.56	6980

Table 4.4.1c(iv) underlined the collected data on the Income generation of J5 vehicle, the distance travelled by the said vehicle and the environmental factors over the given period.

The figure 4.4.1c(iv) showed the effect of environmental factors on the Income Generation of J5 vehicle.

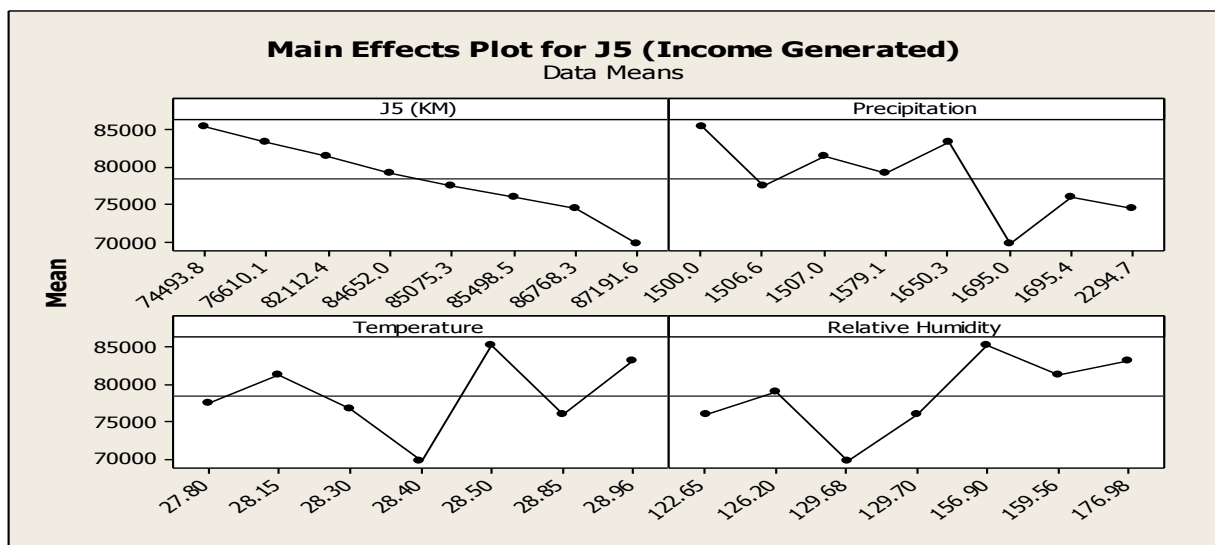


Figure 4.4.1c(iv): Main Effects Plot for J5 (Income Generated Cost) vs. environmental factors.

Figure 4.4.1c(iv) is the effect of environmental factors to the income generation of J5 vehicle. The plots showed that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90 respectively while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68, respectively, for the

Income generation of J5vehicle.Furthermore, the plot revealed that as the distance increases, the income decreases and vice versa.

Table 4.4.1c(v): The Actual environmental factors and Income generation of Ford bus vehicle over the given periods.

TIME	Year	Precipitation(cm ³)	Temperature(°C)	Relative Humidity	Ford Bus(km)	FORD BUS(Income. Generated₦) ×1000
1	2005	1620	29.2	148	32632.6	9200
2	2006	1500	28.5	156.9	34751.6	9020
3	2007	1650.3	28.96	176.98	35599.2	8713
4	2008	1507	28.15	159.56	37294.4	8614
5	2009	1579.1	28.3	126.2	39837.2	8290
6	2010	1506.6	27.8	122.65	40049.1	7880
7	2011	1695.4	28.85	129.7	38777.7	7740
8	2012	1662	27.9	148.0	43015.7	7550
9	2013	2294.7	28.3	122.65	41320.5	7195
10	2014	1695	28.4	129.68	40896.7	6875

Table 4.4.1c(v) demonstrated the data on the Income generation of Ford bus vehicle, the distance travelled by the said vehicle and the environmental factors over the given period. The trend revealed that the income decreases with increase in years and vice versa.

Figure 4. 4.1c(v)representedthe effect of environmental factors on the Income Generation of Ford Bus vehicle.

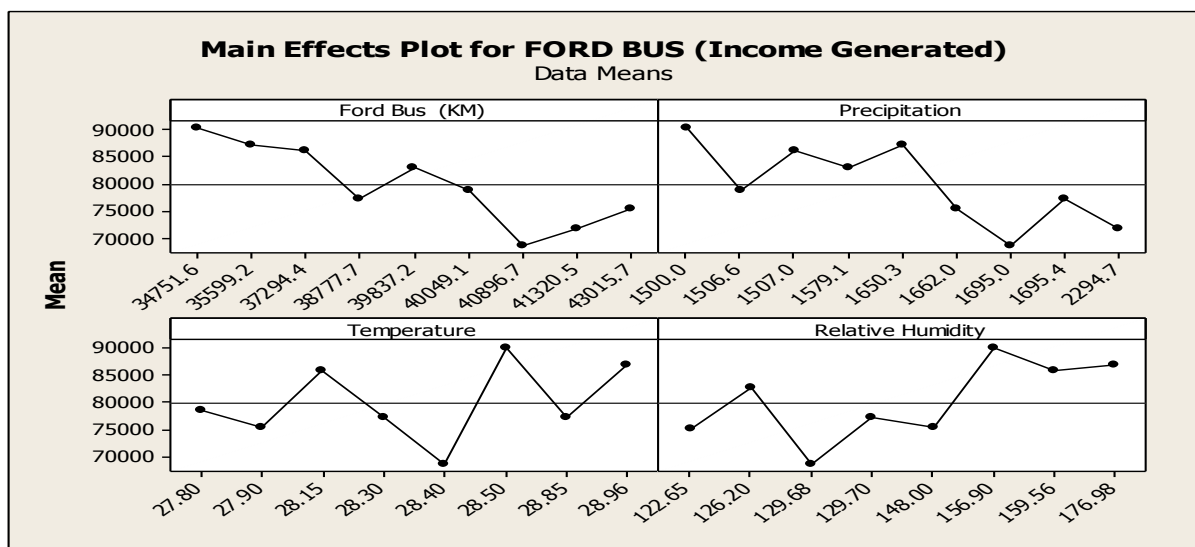


Figure 4.4.1c(v): Main Effects Plot for FORD BUS (Income Generated Cost)

Figure 4.4.1c(v)showedthe effect of environmental factors to the income generation of Ford Bus vehicle. The plots revealedthat precipitation,

temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68, respectively, for the income generation of Ford Bus vehicle. Besides, the plot revealed that as the length of the road increases, there is 70% probability decrease in income cost and vice versa.

Table 4.4.1c(vi): The Actual environmental factors and Income generation of Toyota Hiace vehicle over the given period.

TIME	Year	Precipitation	Temperature(°C)	Relative Humidity	Toyota Hiace(km)	TOYOTA HIACE(Incom.Generat, ₦)×1000)
1	2005	1620	29.2	148	161059.2	1001
2	2006	1500	28.5	156.9	173774.4	9706
3	2007	1650.3	28.96	176.98	185430	9550
4	2008	1507	28.15	159.56	186489.6	9220
5	2009	1579.1	28.3	126.2	187549.2	9019
6	2010	1506.6	27.8	122.65	188608.8	8812
7	2011	1695.4	28.85	129.7	190728	8600
8	2012	1662	27.9	148.0	191787.6	8330
9	2013	2294.7	28.3	122.65	194966.4	7911
10	2014	1695	28.4	129.68	201324	7880

Table 4.4.1c(vi) exemplified the data on the Income generation of Toyota Hiace vehicles, the distance travelled by the said vehicles and the environmental factors over the given period.

Figure 4.4.1c(vi) highlighted the effect of environmental factors on the income generation of Toyota Hiace vehicle.

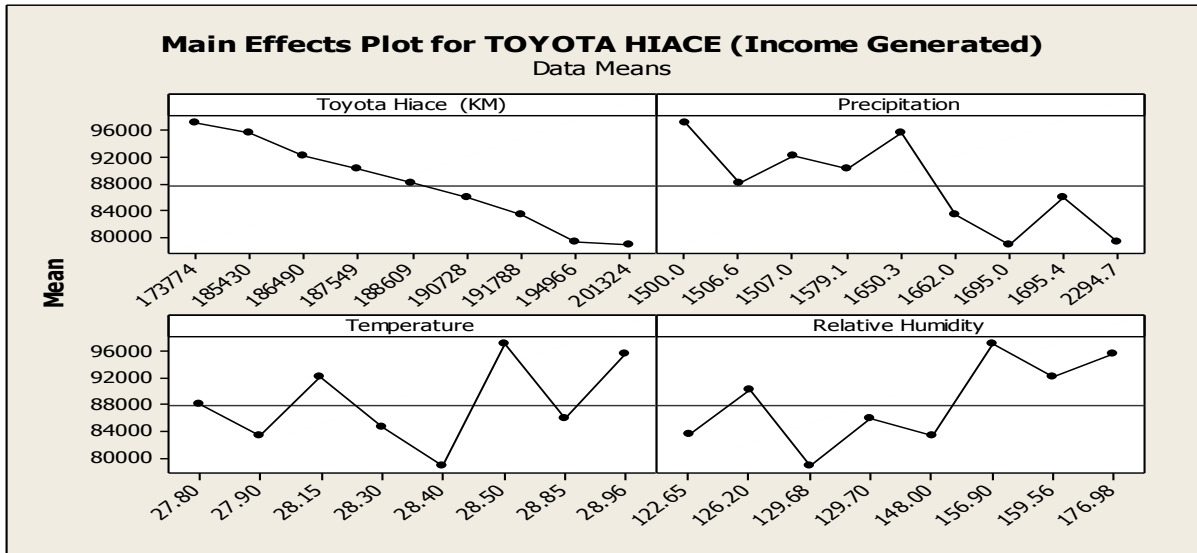


Figure 4.4.1c(vi): Main Effects Plot for TOYOTA HIACE (Income Generated)vs. environmental factors.

Figure 4.4.1c(vi) showed the effect of the measurable environmental factors to the income generation of Toyota Hiace vehicle. The outcome also reveals that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90, respectively, while the lowest environmental effects of precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68, respectively, for the Income generation of Toyota Hiace vehicle. Besides, the plots show that as the distance(km) increases, there is a corresponding decrease in income cost and vice versa.

Table 4.4.1c(vii): The Actual the environmental factors and Income generation of Taxi Cab vehicle over the given period.

TIME	Year	Precipitat	Temperatur	Relative	Taxi Cab(km)	TAXI
------	------	------------	------------	----------	--------------	------

		ion(cm ³)	e(°C)	Humidity		CAB(Incom.Generated,₦) ×1000
1	2005	1620	29.2	148	45359.64	7890
2	2006	1500	28.5	156.9	48977.28	7722
3	2007	1650.3	28.96	176.98	50368.68	7500
4	2008	1507	28.15	159.56	52038.36	7119
5	2009	1579.1	28.3	126.2	52316.64	6830
6	2010	1506.6	27.8	122.65	52594.92	6615
7	2011	1695.4	28.85	129.7	53429.76	6309
8	2012	1662	27.9	148.0	56490.84	5880
9	2013	2294.7	28.3	122.65	54264.6	5690
10	2014	1695	28.4	129.68	53708.04	5405

Table 4.4.1c(vii) depicted the collected data on the Income generation of Taxi Cab vehicle, the distance travelled by the said vehicle and the environmental factors over the given period.

Figure 4.4.1c(vii)described the effect of environmental factors on the Income Generation of Taxi Cab vehicles.

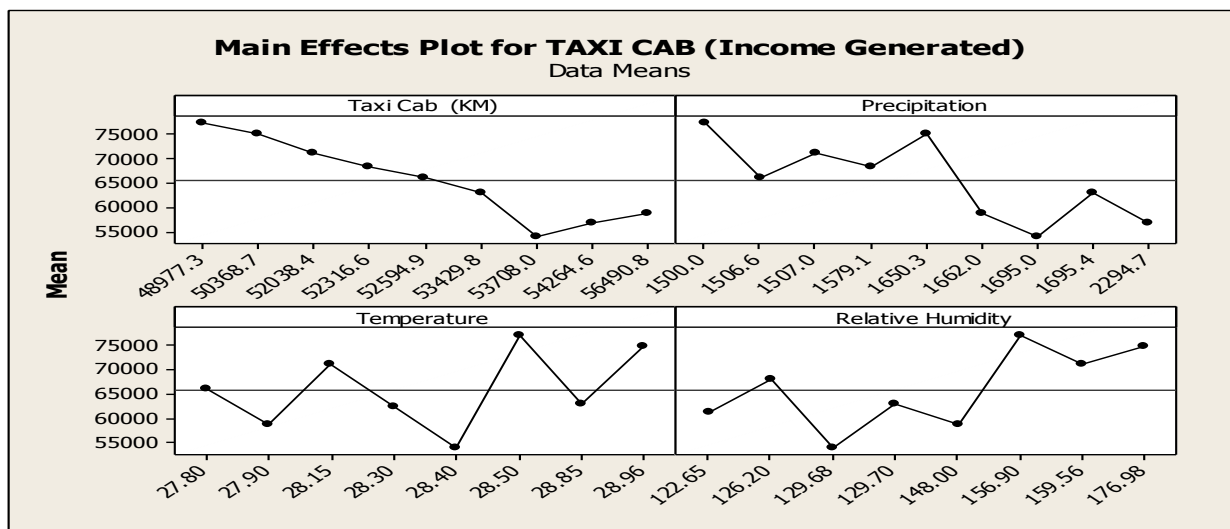


Figure 4.4.1c(vii): Main Effects Plot for TAXI CAB (Income Generated Cost)

Figure 4.4.1c(vii)is a display of the effect of the environmental factors on the Income generation of Taxi Cab vehicle. The output showed that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90 respectively while the lowest environmental effects of

precipitation, temperature and relative humidity were at 1695.0, 28.40 and 129.68 respectively for the Income generation of Taxi Cab vehicles.

4.5 Results of the Response Surface Method

The operational parameters for Nissan Urvan vehicles are shown in Tables 3.4(a,d,g), the results of the analysis of Box-Behnken design matrix for optimization of operational costs of the said vehicles are presented in Tables [4.1.3(a-c)] and test of analysis of variance (ANOVA) developed for the operational costs of the said vehicles are shown in Tables [4.5.1(a-c)]. While, Figures 4.5.1(a-c) illustrated the optimization plots of operational costs of Nissan Urvan vehicles. In same vein, results of the Contour plots and Surface plots of maintenance costs of Nissan Urvan vehicles are displayed in Figures {4.5.4(i-viii)}.

4.5.1 Results of Optimization Plots of the Operational Costs of Nissan Urvan Vehicles Using Response Surface Method.

The optimized plots obtained with the response surface optimizer of Minitab 16 software are presented in Figures 4.5.1(a-c). The optimal values of the factors

were indicated in the plots in parentheses. The optimization plots showed predicted values of ₦1,916,643.30 for maintenance costs, ₦1,971, 390.00 for replacement costs and ₦10,040,000.00 for income generated.

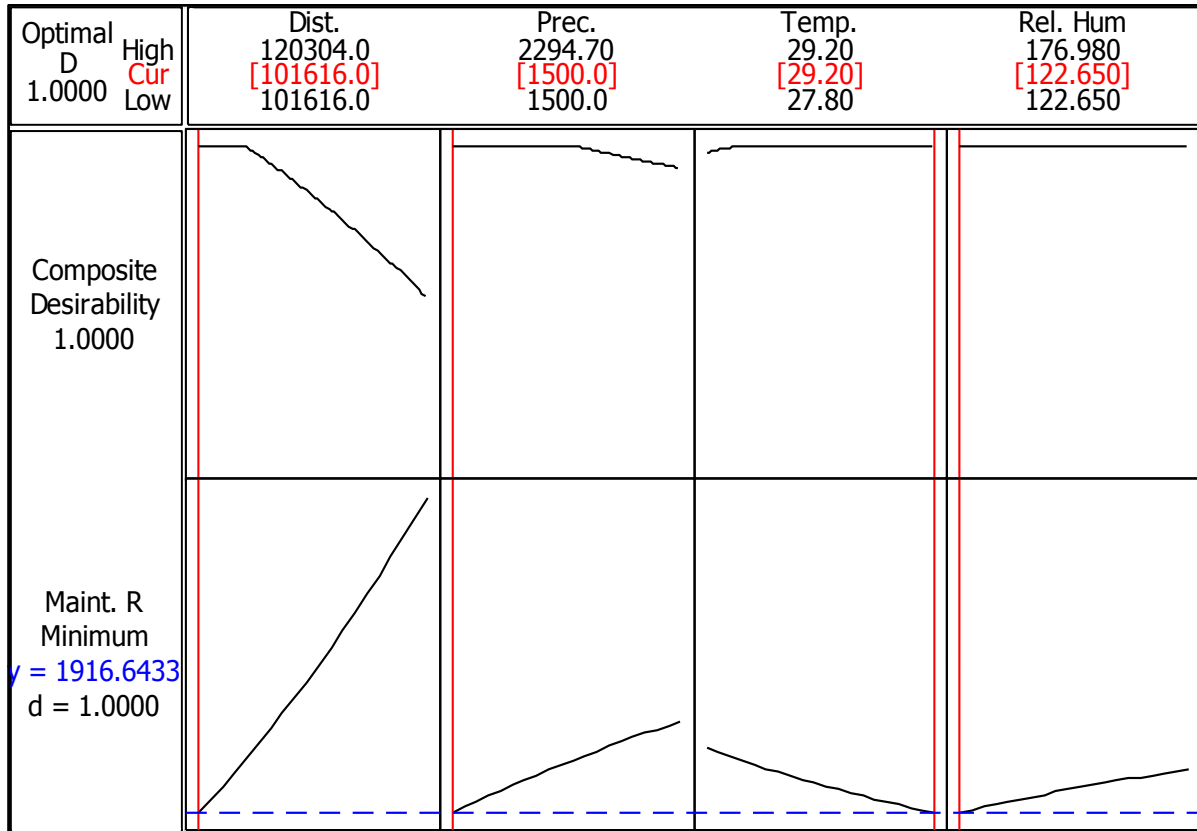


Figure 4.5.1(a): Optimization plot for maintenance cost.

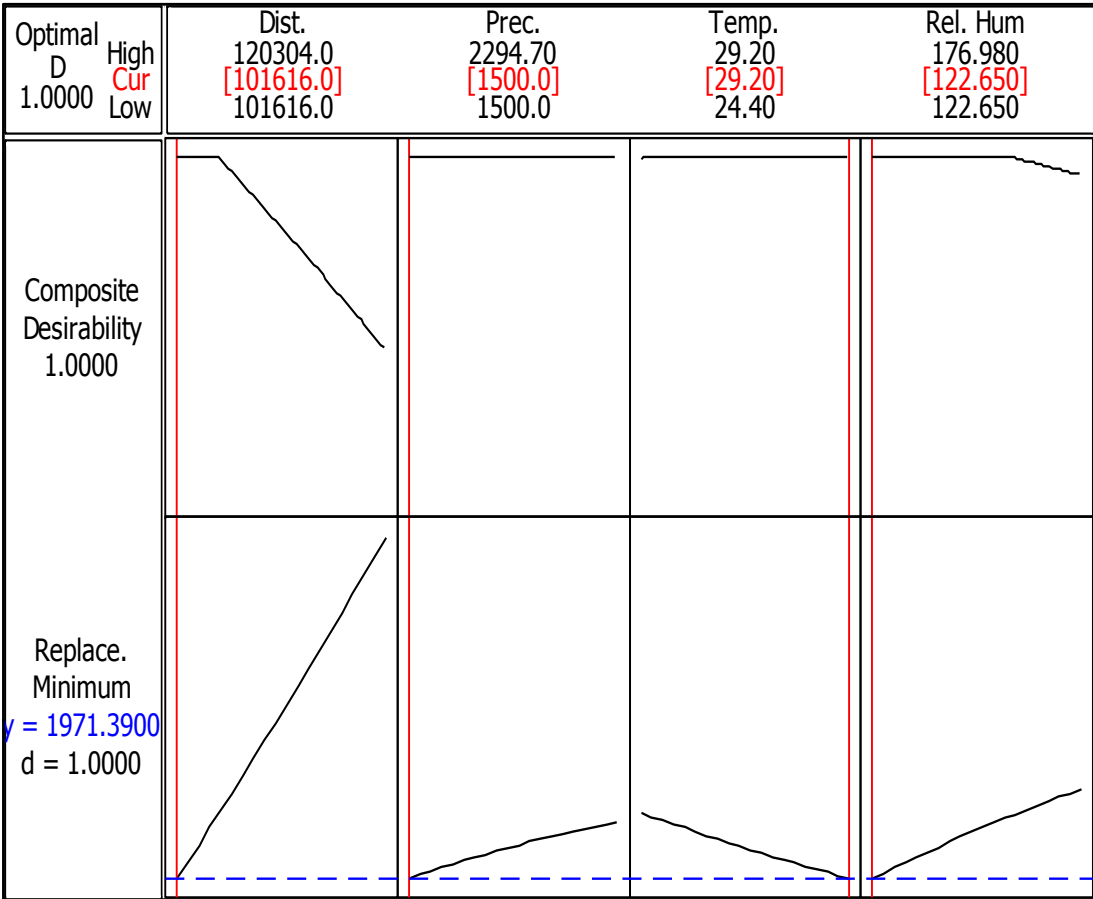


Figure 4.5.1(b): Optimization plot for replacement cost.

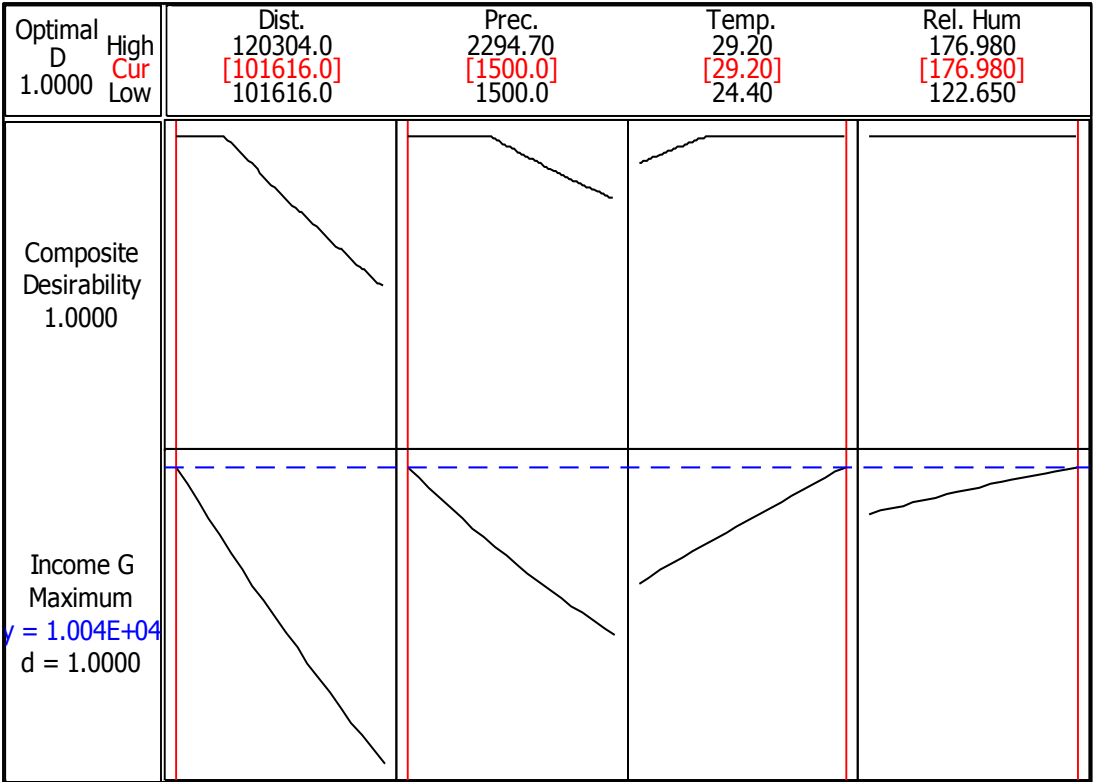


Figure 4.5.1(c): Optimization plot for income generated.

4.5.2 Validation of Response Surface Model Using Numerical Method

The fitted response surface models were checked to ensure that they provide adequate approximations to the real systems. Unless the models show adequate fits, proceeding with the optimization of the fitted response surfaces is likely to give misleading results. The response surface method was used as a primary tool for optimization and was validated using numerical method in which there are three optimization parameters namely; minimum, maximum and target that define each desirability index, d_i . The desirability function, d_i is defined differently based on the objective of the response according to Relia Wiki (2013) and is expressed as:

- (i) If the response is to be minimized, d_i is defined as:

$$d_i = \begin{cases} \left(\frac{U - Y_i}{U - T} \right)^1 & Y_i < T \\ \left(\frac{U - Y_i}{U - T} \right)_0 & T \leq Y_i \leq U \\ Y_i > U & \end{cases} \quad (50)$$

when U represents the acceptable upper limit of the response and T is the smallest value.

- (ii) If the response is to be maximized, d_i is defined as:

$$d_i = \begin{cases} \left(\frac{Y_i - L}{T - L} \right)^0 & Y_i < L \\ \left(\frac{Y_i - L}{T - L} \right)_1 & L \leq Y_i \leq T \\ Y_i > T & \end{cases} \quad (51)$$

where T represents the target value of the i^{th} response (the highest value) and L represents the acceptable lower limit value for the response and w represents 1, when weight is equal to 1, the function d_i is linear. If $w > 1$, then more importance is placed on achieving the target for response. When $w < 1$, less weight is assigned in achieving the target of the response.

The maintenance and replacement cost responses were evaluated by minimization method while the generated income response was evaluated by maximization method.

By the evaluation of equation (50) for minimization at a desirability index of 1, with the maximum and minimum values of maintenance cost response in Table 5 for $Y_i > U$.

$$1 = \left(\frac{4,473.01 - Y_i}{4,473.01 - 2,144.24} \right)$$

This gives, $Y_i < 2,144.24$

From the optimization plot of Figure 4.5.1(a), $Y_i = \text{₦}1,916.64$. The result of the validation of the model is an adequate approximation of the result obtained from the optimization plot.

Similarly, the replacement cost response was evaluated with equation (50) for minimization at a desirability index of 1, with the maximum and minimum values of replacement cost response in Table 6 for $Y_i > U$.

$$1 = \frac{3,127.48 - Y_i}{3,127.48 - 2,103.00}$$

This gives, $Y_i < 2,103.00$

From the optimization plot of Figure 4.5.1(b), $Y_i = \text{₦}1,971.39$. The result of the validation of the model is an adequate approximation of the result obtained from the optimization plot.

By the evaluation of equation (51) for maximization at a desirability index of 1, with the maximum and minimum values of income generated response in Table 7 for $Y_i > T$.

$$1 = \frac{Y_i - 8,189.29}{9,759.88 - 8,189.29}$$

This gives $Y_i > 9,759.88$

From the optimization plot of income generated of Figure 4.5.1(c), $Y_i = \text{₦}10,040.00$. The result of the validation of the model is an adequate approximation of the result obtained from the optimization plot.

4.5.3 Test for Statistical Significance

Analysis of variance (ANOVA) for RSM optimization for maintenance costs of Nissan Urvan vehicles is shown in Table 4.5.3(a).

Table 4.5.3(a): Analysis of Variance (ANOVA) for RSM Optimization for Maintenance Costs of Nissan Urvan Vehicles.

<i>Source</i>	<i>DF</i>	<i>Seq SS</i>	<i>Adj. SS</i>	<i>Adj. MS</i>	<i>F</i>	<i>P</i>
<i>Regression</i>	14	10902679	10902679	778763	17416.70	0.000
<i>Linear</i>	4	10800127	10800127	2700032	60385.08	0.000
<i>A</i>	1	8675135	8675135	8675135	194015.75	0.000
<i>B</i>	1	1176880	1176880	1176880	26320.44	0.000
<i>C</i>	1	641155	641155	641155	14339.15	0.000
<i>D</i>	1	306957	306957	306957	6864.96	0.000
<i>Square</i>	4	48595	48595	12149	271.70	0.000
<i>A * A</i>	1	42509	32412	32412	724.88	0.000
<i>B * B</i>	1	2499	1672	1672	37.38	0.000
<i>C * C</i>	1	2991	1885	1885	42.17	0.000
<i>D * D</i>	1	596	596	596	13.33	0.003
<i>Interaction</i>	6	53958	53958	8993	201.13	0.000
<i>A * B</i>	1	27857	27857	27857	623.02	0.000
<i>A * C</i>	1	15293	15293	15293	342.02	0.000
<i>A * D</i>	1	7276	7276	7276	162.73	0.000
<i>B * C</i>	1	2033	2033	2033	45.47	0.000
<i>B * D</i>	1	968	968	968	21.64	0.001
<i>C * D</i>	1	531	531	531	11.88	0.005
<i>Residual error</i>	12	537	537	45		
<i>Lack of fit</i>	10	537	537	54		
<i>Pure error</i>	2	0.0000	0.0000	0.0000		
<i>Total</i>	26	10903216				

The test for statistical significance of the response surface model is presented in the analysis of variance (ANOVA) as shown in Table 4.5.3(a) and the model developed there from stated in equation(52). From the analysis, it was shown that all the environmental factors considered are significant.

$$Y_{m_{cost}} = 12606.10 + 0.0945A + 0.8138B - 1223.83C + 6.0725D + 8.9287E - 07A^2 - 1.12127E - 04B^2 + 38.3707C^2 - 0.0143D^2 + 2.2477E - 05AB - 0.0095AC + 0.0002AD - 0.0811BC + 0.0014BD - 0.6060CD.$$

(52)

Analysis of variance (ANOVA) for RSM optimization for replacement costs of Nissan Urvan vehicles is presented in Table 4.5.3(b).

Table 4.5.3(b): Analysis of Variance (ANOVA) for RSM Optimization for Replacement Costs of Nissan Urvan Vehicles.

<i>Source</i>	<i>DF</i>	<i>Seq SS</i>	<i>Adj. SS</i>	<i>Adj. MS</i>	<i>F</i>	<i>P</i>
<i>Regression</i>	14	2209518	2209518	157823	131063.99	0.000
<i>Linear</i>	4	2204234	53	13	11.08	0.001
<i>A</i>	1	1875049	32	32	26.52	0.000
<i>B</i>	1	70943	2	2	1.87	0.197
<i>C</i>	1	93246	2	2	1.43	0.254
<i>D</i>	1	164996	5	5	4.09	0.066
<i>Square</i>	4	2592	2592	648	538.23	0.000
<i>A * A</i>	1	1594	979	979	812.90	0.000
<i>B * B</i>	1	256	260	260	215.51	0.000
<i>C * C</i>	1	397	159	159	131.78	0.000
<i>D * D</i>	1	345	345	345	286.79	0.003
<i>Interaction</i>	6	2692	2692	449	372.61	0.000
<i>A * B</i>	1	550	550	550	456.61	0.000
<i>A * C</i>	1	725	725	725	602.08	0.000
<i>A * D</i>	1	1278	1278	1278	1061.68	0.000
<i>B * C</i>	1	27	27	27	22.66	0.000
<i>B * D</i>	1	48	48	48	39.96	0.000
<i>C * D</i>	1	63	63	63	52.69	0.000
<i>Residual error</i>	12	14	14	1		
<i>Lack of fit</i>	10	14	14	1	*	*
<i>Pure error</i>	2	0.0000	0.0000	0.0000		
<i>Total</i>	26	2209533				

The test for statistical significance of the response model is presented in the analysis of variance (ANOVA) as displayed in Table 4.5.3(b) and the model developed for the replacement costs is stated in equation(53).From the analysis,

it was shown that all the control factors considered are significant, except those of factors (B,C&D).

$$Y_{rcost} = -187.9840 + 0.0074A + 0.0362B - 6.5263C + 0.7947D + 1.5515A^2 - 4.4196B^2 + 0.9467C^2 - 0.0109D^2 + 3.1573AB - 6.0032AC + 7.0441AD - 0.0027BC + 0.0003BD - 0.0610CD. \quad (53)$$

iii Income Generated

Analysis of variance (ANOVA) for RSM optimization for income generation of Nissan Urvan vehicles is displayed in Table 4.5.3(c).

Table 4.5.3(c): Analysis of Variance (ANOVA) for RSM Optimization for Income Generation of Nissan Urvan Vehicles.

<i>Source</i>	<i>DF</i>	<i>Seq SS</i>	<i>Adj. SS</i>	<i>Adj. MS</i>	<i>F</i>	<i>P</i>
<i>Regression</i>	14	4510855	4510855	322204	184137.62	0.000
<i>Linear</i>	4	4493294	26388	6597	3770.20	0.000
<i>A</i>	1	3046344	10862	10862	6207.74	0.000
<i>B</i>	1	934424	5518	5518	3153.46	0.000
<i>C</i>	1	442454	1673	1673	956.05	0.000
<i>D</i>	1	70072	383	383	218.63	0.000
<i>Square</i>	4	15833	15833	3958	2262.14	0.000
<i>A * A</i>	1	6598	6727	6727	3844.56	0.000
<i>B * B</i>	1	8867	6105	6105	3489.15	0.000
<i>C * C</i>	1	118	241	241	137.68	0.000
<i>D * D</i>	1	249	249	249	142.37	0.000
<i>Interaction</i>	6	1728	1728	288	164.55	0.000
<i>A * B</i>	1	997	997	997	569.95	0.000
<i>A * C</i>	1	470	470	470	268.61	0.000
<i>A * D</i>	1	75	75	75	42.79	0.000
<i>B * C</i>	1	144	144	144	82.33	0.000
<i>B * D</i>	1	23	23	23	13.11	0.004
<i>C * D</i>	1	18	18	18	10.52	0.007
<i>Residual error</i>	12	21	21	21		
<i>Lack of fit</i>	10	21	21	21	475431.43	0.000
<i>Pure error</i>	2	0.0000	0.0000	0.0000		
<i>Total</i>	26	4510876				

The test for statistical significance of the response model is underlined in the analysis of variance (ANOVA) shown in Table 4.5.3(c) and the model developed stated in equation(54).The outcome of the analysis indicated that all the control factors considered are significant.

$$Y_{income\ gen.} = 17296.9 - 0.1A - 1.8B + 203.2C + 7.0D + 0.0A^2 - 0.0B^2 - 1.2C^2 - 0.0D^2 + 0.0AB - 0.0AC - 0.0AD - 0.0BC - 0.0BD + 0.0CD. \quad (54)$$

4.5.4 Results of the Contour plots and Surface plots of maintenance costs of Nissan Urvan Vehicles.

Table 3.4(b) showed the operational parameters of maintenance costs of Nissan Urvan vehicles and plotted in figures [4.5.4(i-viii)].

Figure 4.5.4(i) illustrated the result of the Contour Plot of Nissan Urvan (Maintenance costs) vs. Precipitation, Nissan Urvan (km).

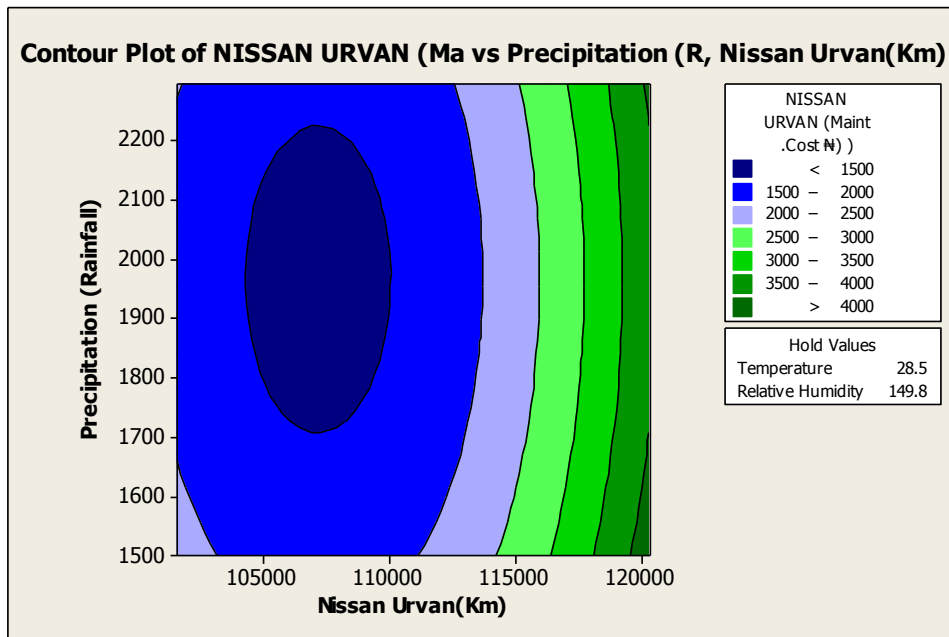


Figure 4.5.4 (i): Contour Plot of NISSAN URVAN (Maintenance costs) vs. Precipitation, (km).

The chart connoted the regional effects of the two control variables on the yield using contour plot. From the plot, it was noticed that as the maintenance costs increase, the distance travelled, as measured in kilometers, increase almost at a constant ratio. It was also observed that Nissan Urvan maintenance costs are influenced by the independent variables and the ranges at which this is done also highlighted.

Figure 4.5.4(ii) presented the Contour Plot of Nissan Urvan (Maintenance Costs) versus Temperature, Nissan Urvan (km).

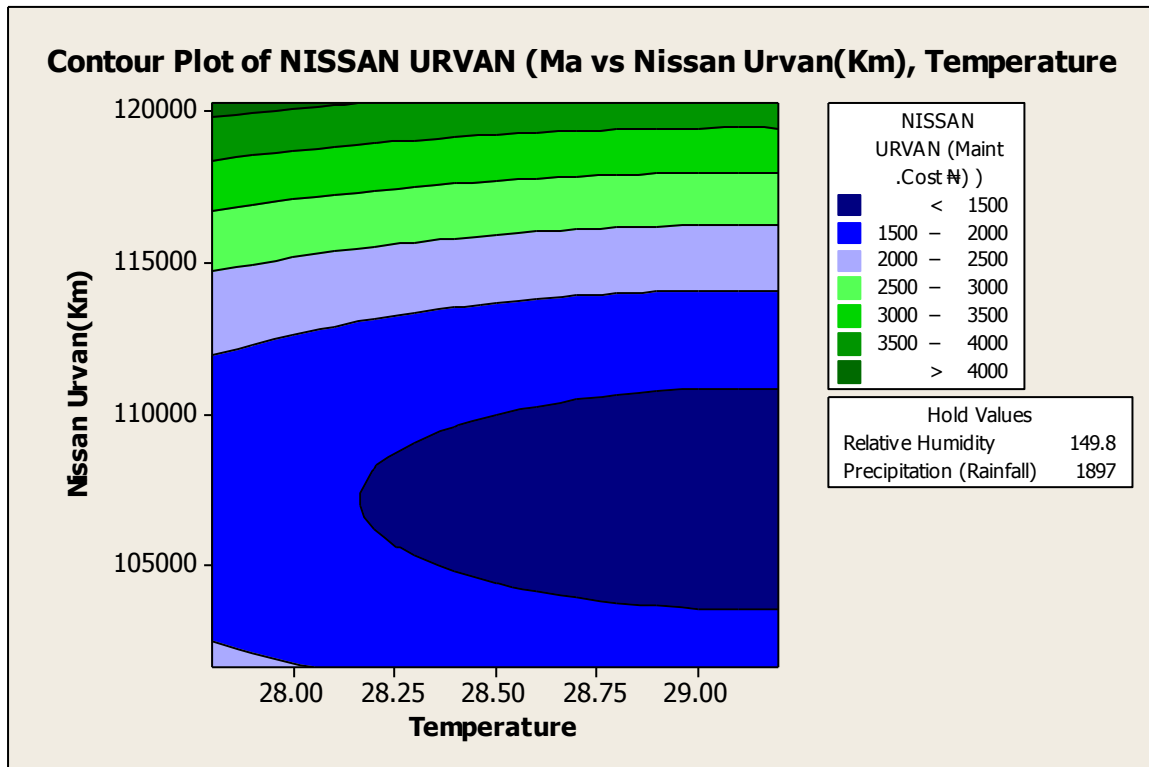


Figure 4.5.4(ii): Contour Plot of Nissan Urvan (Maintenance Cost) versus Temperature, Nissan Urvan (km).

The plot disclosed the regional effects of the two control factors (temperature and distance travelled (km)) on the response (maintenance costs of Nissan Urvan) using contour plot. From the chart, it was further observed that as the maintenance costs increase, the distance travelled, as measured in kilometers, increase, almost at a steady rate, while temperature decreases almost at a constant ratio.

Figure 4.5.4(iii) clarified the Contour Plot of Nissan Urvan (Ma) versus Relative Humidity, Nissan Urvan (km).

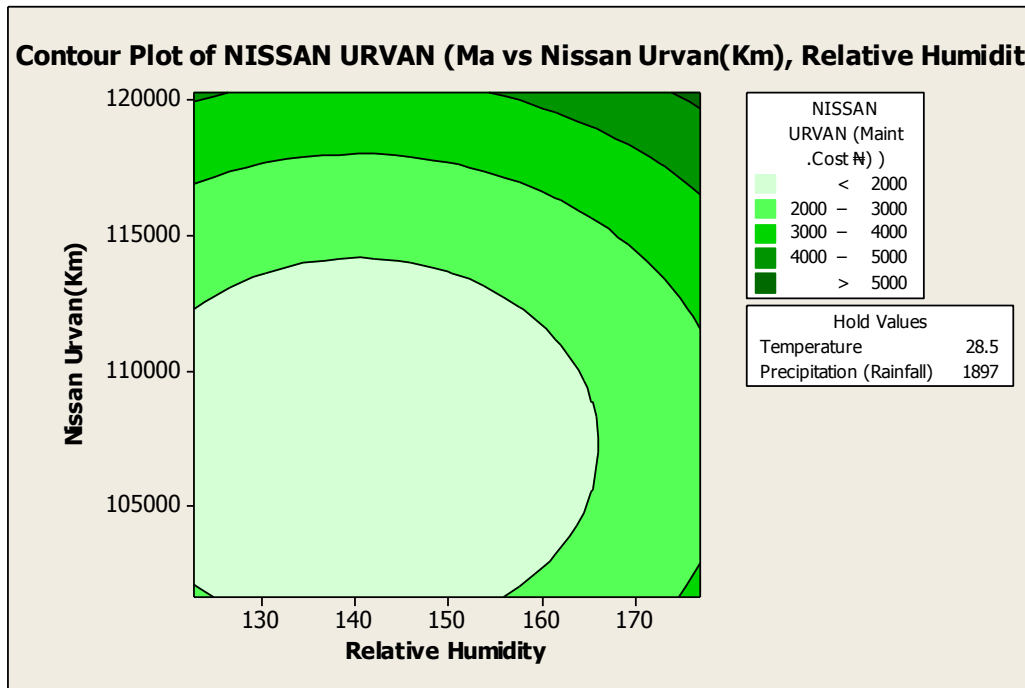


Figure 4.5.4(iii): Contour Plot of Nissan Urvan (Maintenance Cost) versus Relative Humidity, Nissan Urvan (km).

The plot showcased the regional effects of the two independent variables (Relative humidity and Nissan Urvan, km) on the response (maintenance cost) using contour plot. The plot further reflected the rate at which the independent variables influence the yield. It was also observed that, as the maintenance costs increase, the distance travelled, as measured in kilometers, increase while relative humidity increase at fairly equal rate.

Figure 4.5.4 (iv) provided the Contour Plot of Nissan Urvan (Maintenance Cost) versus Precipitation, Temperature.

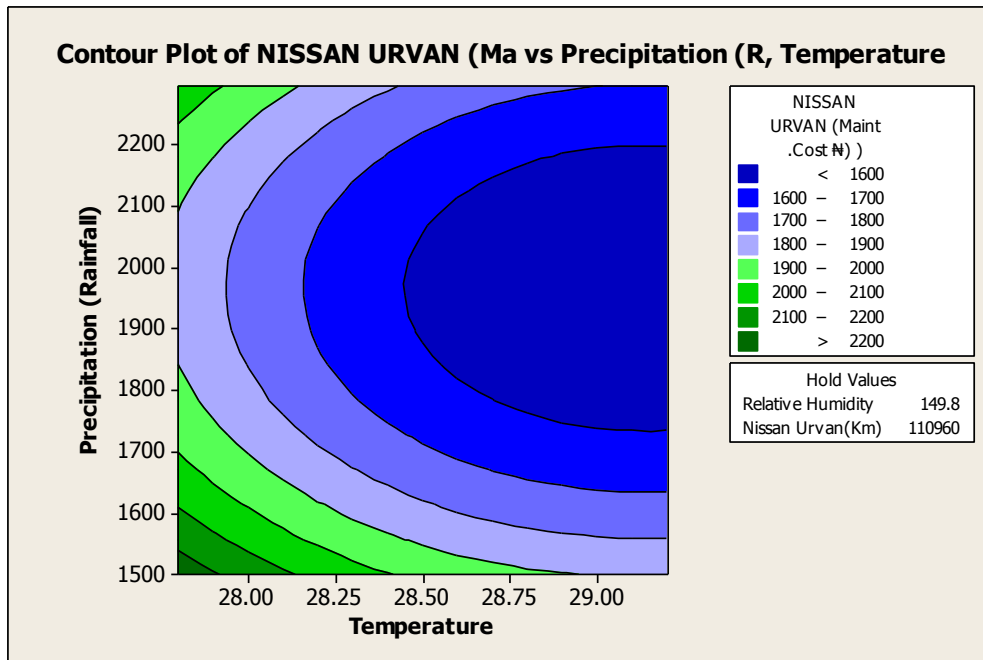


Figure 4.5.4 (iv): Contour Plot of Nissan Urvan (Maintenance Cost) versus Precipitation, Temperature.

The plot provided the effects of precipitation and temperature on the dependent variable (maintenance cost of Nissan Urvan) using contour plot. The plot revealed the range at which control factors influence the Nissan Urvan maintenance costs. From the chart, it was also noticed that as the maintenance costs increase, the precipitation also increases almost at a constant ratio, while temperature decreases at fairly steady rate.

Figure 4.5.4(v) revealed the Surface Plot of Nissan Urvan (Ma) versus Precipitation, Nissan Urvan (km).

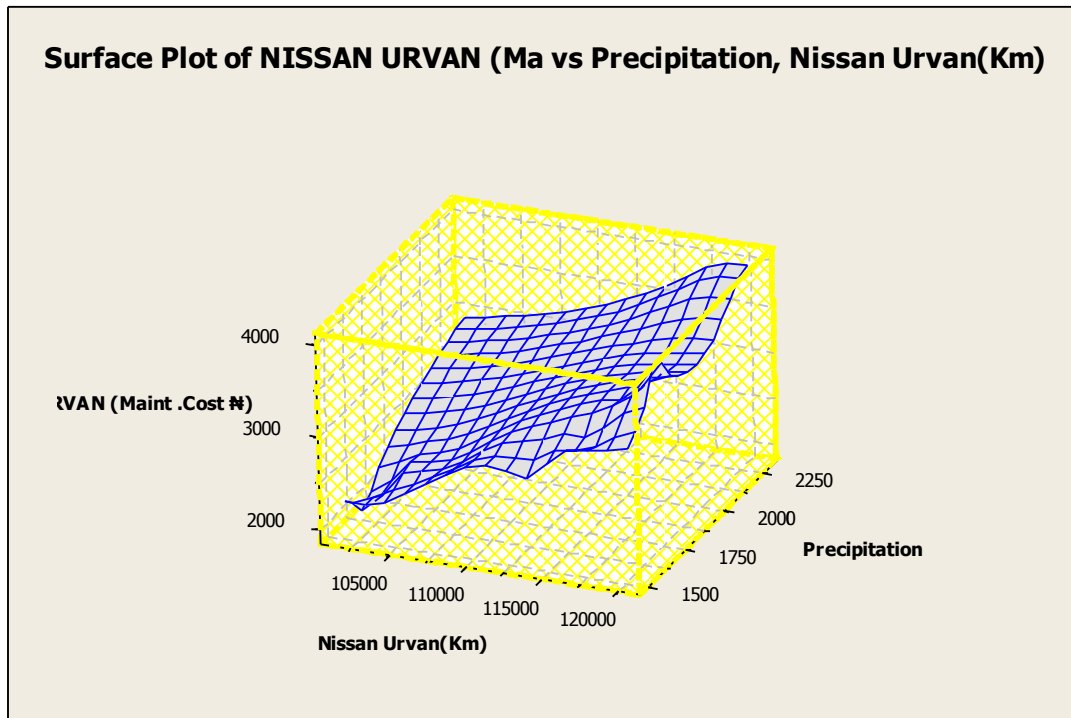


Figure 4.5.4(v): Surface Plot of NISSAN URVAN (Ma versus Precipitation, Nissan Urvan (km)).

Figure 4.5.4 (v) emphasized the Surface Plot of Nissan Urvan maintenance cost against Precipitation, Nissan Urvan (km) in three dimensional forms. The observation is that increase in precipitation decreases the distance travelled by Nissan Urvan thereby increasing the maintenance costs of the said vehicle which means that less profit would be generated. The chart also depicted the influence of distance travelled by Nissan Urvan and precipitation on the maintenance costs, while temperature and relative humidity are held constant.

Figure 4.5.4 (vi) demonstrated the Surface Plot of Nissan Urvan (Ma) versus Temperature, Nissan Urvan (km).

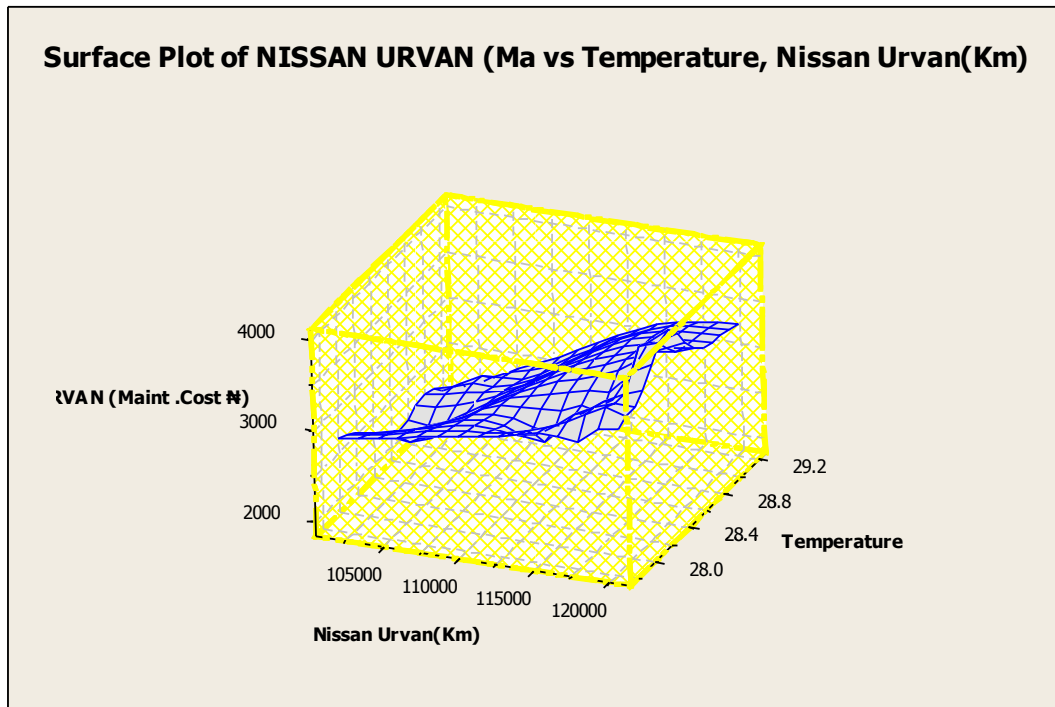


Figure 4.5.4(vi): Surface Plot of Nissan Urvan (Ma vs. Temperature, Nissan Urvan (km)).

Figure 4.5.4(vi) show cased the Surface Plot of Nissan Urvan maintenance cost against temperature, Nissan Urvan (km) in three dimensional forms reflecting the influence of the selected independent variables on the yield while holding precipitation and relative humidity constant.

Figure 4.5.4(vii) explained the Surface Plot of Nissan Urvan (Maintenance cost) versus Relative humidity, Nissan Urvan (km).

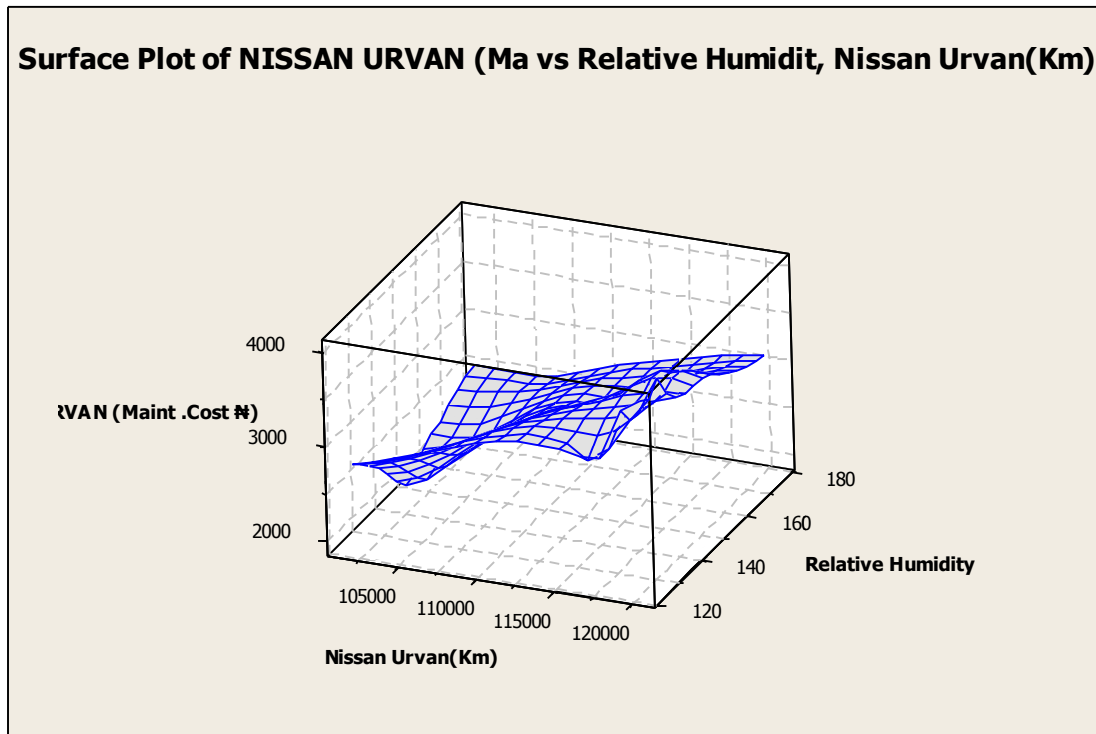


Figure 4.5.4(vii): Surface Plot of Nissan Urvan (Maintenance) vs. Relative humidity, Nissan Urvan (km).

Figure 4.5.4(vii) is the Surface Plot of Nissan Urvan maintenance costs against relative humidity, Nissan Urvan (km) in three dimensional forms showing the effect of relative humidity and distance covered on the yield, while holding precipitation and temperature constant.

Figure 4.5.4(viii) represented the Surface Plot of Nissan Urvan (Maintenance cost) versus Temperature, Relative humidity.

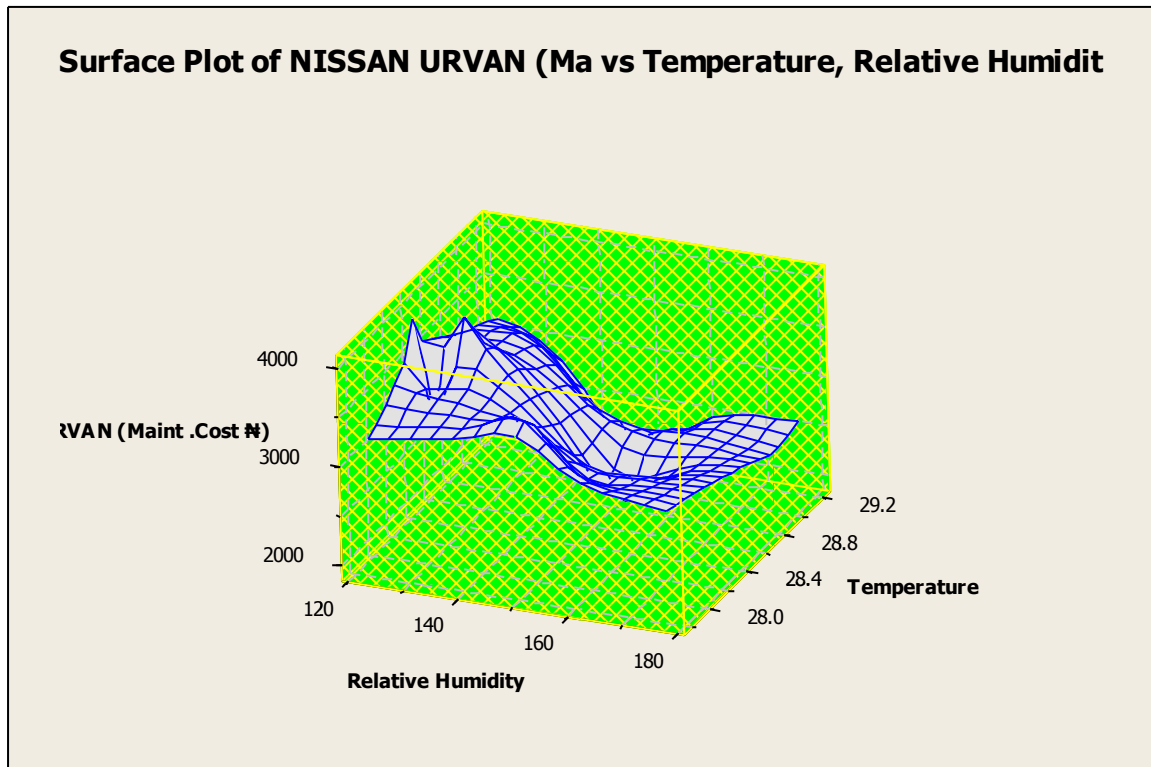


Figure 4.5.4(viii): Surface Plot of NISSAN URVAN (Maintenance) vs. Temperature, Relative humidity.

Figure 4.5.4 (viii) described the surface plot of Nissan Urvan maintenance costs against relative humidity, temperature in three dimensional forms and their impact on the dependent variable displayed. The trend revealed that increase in relative humidity and temperature would increase the maintenance costs of the vehicle and less income generated as other independent variables are kept constant.

The contour and surface plots of the operational costs of other vehicle types could be done the same way.

4.6 Discussion

Dynamic programming for recursive replacement analysis was applied to observe the optimal time necessary for the afore mentioned company of Anambra State to replace its vehicles when it has been utilized efficiently and the flow chart was shown in Figure 3.1. The results of the Dynamic Programming recursive model applied are presented in Tables [4.1.1(b,c,d,e,f,g,h)] and plotted in Figures 4.2(a,b,c,d,e,f,h). Table 4.2.2(a) is a summary of the optimal decision variable sequence for the studied vehicles as deduced from the computational analysis shown in Appendix A₁ and was validated with the Microsoft Excel Solver output shown in Figures 4.2.1(i,ii,iii,iv,v,vi,vii) and detailed in Appendix (B₁ to B₇). Clearly, non-adherence to the policy year replace action given the available data spells out the danger of ATS Ltd running at a loss. Keeping the said vehicles without replacing them at the start of the 12th, 7th, 8th, 9th, 8th, 9th, 9th year of the planned horizon results in the loss of {₦21,894,500, ₦8,750,845, ₦8,616,176, ₦20,730,300, ₦23,295,750, ₦36,565,900, ₦18,438,288} respectively. On the other hand, the net profit realized should ATS adhere to the policy year replace action is {₦18,613,400, ₦7,264,015, ₦5,862,286, ₦16,329,730, ₦18,190,395, ₦33,837,700, ₦15,482,395} for the said vehicles .

It is however interesting to note that, adherence to the policy year replace action yielded not only the desired profit but also made it possible to unearth the individual vehicle's contribution to the ATS's total net profit thereby buttressing any such decision to endorse the usage of one kind of vehicle over the other. This disagrees with literature review that sees dynamic programming as a method of solving problems in which the sub problems to be solved are overlapping in nature. Besides, from literature review, an intuitive method for identifying replacement candidates was used to define a replacement standard such as an equipment age standard. Vehicles that exceeded the age standard

were candidates for replacement without duly stating the criteria for making such replacement, which differs from the model applied in this research work which was able to detect the particular vehicle to be replaced and at what age.

To foresee the future operational costs of Anambra State transportation service, several forecasting techniques such as ARIMA (Auto Regression Integrated Moving Average), Moving Average Model, Weighted Moving Average, Winter Method Model, Double Exponential Smoothing Model, Time Series Decomposition Model, Trend Analysis Model etc. were applied and the selection was done using multi-regression analysis to show the significance of each factor utilized as shown in Appendices (D₁₁-D₁₇, D₂₁-D₂₇, D₃₁-D₃₇) with detail analysis displayed in Appendix A₂. The selected forecasting models were also based on the forecasting accuracy measures with least errors in the results which is the application of (trend analysis, double exponential smoothing, time series decomposition, winters method) models. However, the trend selected forecasting models showed that Sienna vehicles had the maintenance costs of ~~₦5559930-₦6921960~~ between 2015 and 2019. The Peugeot Expert vehicles had the maintenance costs of ~~₦4205750-₦4709230~~, respectively, for the trend forecasting model selected. The J5 vehicles had the maintenance costs of ~~₦5007420-₦5926970~~ from double exponential smoothing model results. Also, the output of Double Exponential Smoothing Model selected for Ford Bus and Toyota Hiace vehicles showed the maintenance costs of ~~₦4266030-₦4933040 and ₦3872780-₦3958510~~, respectively, for the reviewed period. More so, the Trend Forecasting Model selected for Taxi Cab vehicles revealed that between 2015 and 2019, the maintenance costs remained at ~~₦3875310-₦5136270~~ respectively. While the Trend Forecasting Model selected for Sienna, Peugeot Expert and Toyota Hiace vehicles had the replacement costs of ~~₦1370300-~~

~~₦1696750, ₦1808990-₦1880680, ₦1983070-₦2309770~~, respectively, between 2015 and 2019. The Double Exponential Smoothing Model selected for Nissan Urvan, J5, Taxi cab vehicles had the replacement cost of ~~₦2396040-2556220, ₦1951260-₦2014770, ₦1220060-₦1280320~~ respectively from 2015 to 2019. Meanwhile, the Winters' Forecasting Model selected for Ford Bus vehicles showed the replacement cost of ~~₦1878460-₦2110140~~ under the reviewed period. Besides, the Time Series Decomposition Forecasting Model selected for Nissan Urvan and Ford Bus vehicles from 2015 and 2019, had the income generation of ~~₦7926740-₦7144110, ₦6669670-₦5636300~~. While the Trend selected Forecasting Model for Sienna, Peugeot Expert, J5, Toyota Hiace vehicles had the income generation of ~~₦6792660-₦5895360, ₦6494420-₦5805070, ₦6914650-₦6282870, ₦7573330-₦6605580~~ respectively between 2015 and 2019.

More so, the Winters Forecasting Model selected for Taxi Cab vehicles revealed that between 2015 and 2019, income generation for the reviewed years remained at ~~₦5226230-₦4127570~~. This goes a long way to show that the income generated by the said vehicles decreases with increase in the age of the vehicles. Having observed so closely about the significance of the constraints, it was shown clearly that time was the only independent variable that is highly significant for the prediction of the yield. Although regression analysis is more complex when compared with times analysis because it can accommodate and predict with more than one independent variables that can reveal the future of dependent variable but it clearly showed that the data are dependent mostly on time to predict the future of the yield. However, condition of the road constitutes a remarkable influence on the operational costs. In the sense that most Nigerian roads are in a deplorable state especially during raining season, this invariably and terribly affect the operational costs by way of increasing the maintenance costs, replacement costs and decreasing the income generation.

To show the influence of environmental factors on the operational costs of ATS vehicles using main cause and effect tool. The data on maintenance costs, replacement costs, income generated and environmental factors are presented in Tables [4.4.1a(i-vii),4.4.1b(i-vii),4.4.1c(i-vii)] and plotted in Figures[4.4.1a(i-vii),4.4.1b(i-vii),4.4.1c(i-vii)].Figures[4.4.1a(i-vii)]displayed the effect of environmental factors on the maintenance costs of vehicle types over the given period. Figures{4.4.1b(i-vii)} illustrated the effect of environmental factors on the replacement costs of vehicle types reviewed. While Figures{4.4.1c(i-vii)} underlined the effect of environmental factors on the income generation of vehicle types over the stated period. From the plot, it is observed that the maintenance costs increase as the distance covered (km) increases. Precipitation, temperature and relative humidity had the highest effect at 1696.4, 28.40 and 129.68 respectively while the lowest influences were established at 1620.0, 29.20 and 156.90 respectively on maintenance costs of Nissan Urvan vehicles. The output also revealed that at the maximum environmental effect, the company would spend more on the maintenance of its vehicles and less income would be generated. Figures{4.4.1b(i-vii)} showed that precipitation, temperature and relative humidity had the highest environmental effect at 1695.0, 28.40 and 129.68 respectively while the lowest environmental effects of precipitation, temperature and relative humidity were at 1620.0, 29.20 and 156.90 respectively for the replacement costs of Sienna vehicles. The plots revealed also that at the maximum environmental effect, the company would spend more on the replacement of its vehicles and less profit would be generated, on the other hand, at the minimum environmental effect, the company would spend less on the replacement of its vehicles, thereby making more profit. Figure 4.4.1c(iii)] demonstrated the effect of environmental factors on the income generation of Peugeot Expert vehicles. The charts showed that precipitation, temperature and relative humidity had the highest environmental effect at 1620.0, 28.50 and 156.90 respectively while the lowest environmental

effects of precipitation, temperature and relative humidity were experienced at 1695.0, 28.40 and 129.68 respectively for the Income generation of Peugeot Expert vehicle.

In the same way, the analyses of the influence of environmental factors on the operational costs of other vehicles types were carried out.

Besides, the optimization of the operational costs of ATS vehicles was carried out. The analysis was done using Box – Behnken design which is a three level, four factors widely used in response surface method to fit second order model to the response surface. The outcome of the analysis of variance (ANOVA) for RSM optimization of operational costs of Nissan Urvan vehicles showed that all the environmental factors are significant for all the operational costs except control variables (B,C&D) of replacement costs. The analysis of variance developed with details in chapter three and Appendix A₃ was also used to measure the variations of errors for both the control factors and response to determine the degree of freedom and significance as reflected in F-critical and P-probability. The results of the analysis are presented in Tables [4.1.3(a-c)] for the design matrix and analysis of variance (ANOVA). The optimization plots are shown in Figures [4.5.1(a-c)] and was validated using numerical method. The result of the validation of the model is an adequate approximation of the result obtained from the optimization plot. The output of the contour plots, surface plots of Nissan Urvan maintenance costs against control factors are presented in Figures [4.5.4(i-viii)].

In a similar way, the RSM analyses of other vehicle types were carried out.

CHAPTER FIVE

Conclusion and Recommendation

5.1 Conclusion

At the end of this research work, the following conclusions were made:

(1) The analysis was done using recursive dynamic programming model to obtain the optimal replacement policy for Anambra State Transport Sector's Vehicles and was validated with Microsoft Excel Solver software. The results obtained revealed that: the vehicles optimal replacement policy of Nissan Urvan, Sienna, Peugeot Expert, J5, Ford Bus, Toyota Hiace and Taxi cab vehicles were at stage (year): 12, 7, 8, 9, 8, 9 and 9 with corresponding net profit of: ₦18,613,400, ₦7,264,015, ₦5,862,286, ₦16,329,730, ₦18,190,395, ₦33,837,700 and ₦15,482,395 and loss of ₦21,894,500, ₦8,750,845, ₦8,616,176, ₦20,730,300, ₦23,295,750, ₦36,565,900, ₦18,438,288, respectively.

(2) The results of the forecasting models applied revealed that: the maintenance costs and replacement costs of the said vehicles increase with increase in the age of the vehicles, while the income generated decreases with increase in the age of the vehicles. Also, the selected forecasting models utilized was able to achieve 95% confidence level.

(3) The results of the main cause and effect tool applied to analyze the influence

of environmental factors on the operational costs of ATSS showed that the maintenance and replacement costs of the said vehicles increase as the distance covered (km) increases and vice versa for the income generation of the said vehicles. Also, at maximum environmental influence for the maintenance and replacement costs of the said vehicles, it would cost the company more to maintain its vehicles at less income and vice versa for the minimum environmental influence.

(4) The RSM used revealed the optimized values of ₦1,916,640, ₦1,971,390, ₦10,040,000, respectively, for maintenance costs, replacement costs and income generated and the results of validation showed values of ₦2,144,240, ₦2,103,000, ₦9,759,880 respectively for maintenance costs, replacement costs and income generated which points to the fact that the result of the validation of the model is an adequate approximation of the result obtained from the optimization plots.

(5) Conclusively, The result of the optimization showed that all the environmental factors considered for the operational costs are significant, except control variables (B, C & D) of replacement costs.

5.2 Recommendation

- ❖ It is recommended that the company should employ dynamic recursive programming for the determination of its optimal replacement policy.
- ❖ Again, it is strongly recommended that ATS should dispose of all its Nissan Urvan vehicles stated herein after eleven (11) years of usage, Sienna vehicles after six (6) years of usage, Peugeot Expert vehicles after seven (7) years of usage, J5 vehicles after eight (8) years of usage, Ford vehicles after seven (7) years of usage, Toyota Hiace after eight years (8) and Taxi Cab after eight (8) years of usage.
- ❖ It is also recommended that theATS should keep their data bank well for easy access to information and data.
- ❖ More so, it is recommended that the company should always monitor the effect of environmental factors on their vehicles especially at its minimum and maximum points.
- ❖ Further research work, using other methods is highly recommended to overcome the weakness in information, data and the predicted values to achieve more accurate results and policies.

5.3 Contribution to Knowledge

- ✓ The models for determining optimum maintenance and replacement policies for ATS current fleet of vehicles have been successfully introduced.
- ✓ The models for evaluating the degree of significance of control variables for ATS present vehicles have been fruitfully established.
- ✓ With the results of main and cause effect obtained, ATS can now gainfully reposition its present fleet of vehicles especially at maximum and minimum environmental influence.
- ✓ Also mathematical models developed for optimizing the operational costs of ATS existing fleet of vehicles have been profitably implemented.
- ✓ These research contributions pursued can be customized to aid future researchers to solve a wide range of problems.

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APPENDIX

APPENDIX A₁(Computational Analysis for Dynamics programming)

Nissan Urvan Vehicle

At fifteen state, stage fourteen

$$i = 15$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = \#67958.28, C_k(i) = \#50076.39 \text{ and } R_k(i) = \#250732$$

$$V_k = 50076.39 - 67958.28 + 0 = -\#17881.89$$

Where $i = \text{state } 15, \text{ in stage } 14 \text{ for Nissan Urvan}$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the fifteen state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 250732 + 0 = 1918521.31$$

For state thirteen, stage fourteen

$$i = 13$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 73867.32, C_k(i) = 47691.8 \text{ and } R_k(i) = 238195.4$$

$$V_k = 47691.8 - 73867.32 + (-17881.89) = -\#24075.89$$

Where $i = \text{state } 13, \text{ in stage } 14 \text{ for Nissan Urvan}$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the thirteen state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 238195.4 + (-17881.89) = \#161433.82$$

For state twelve, stage fourteen

$$i = 12$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, I_k(0) = 95555.75$$

$$I_k(i) = 73867.7, C_k(i) = 47691.8, R_k(i) = 238195.4$$

$$V_k = 47691.80 - 73867.7 - 24075.89 = -\#30233.31$$

$$V_r = 36676.06 - 95555.75 + 236175.9 - \#24075.89 = \#133238.8$$

$$V_{k+1}(i + 1) = -\#30233.31$$

Where $i = \text{state } 11, \text{ in stage } 14 \text{ for Nissan Urvan}$

For state eleven, stage fourteen

$$i = 11$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 75345.05, C_k(i) = 46737.96 \text{ and } R_k(i) = 226285.6$$

Where $i = \text{state } 11, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 46737.96 - 75345.05 - 30233.31 = -\#31048.8$$

For replacement decision model,

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the eleven state of stage 14 in Nissan Urvan

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$V_r = 36676.06 - 95555.75 + 226285.6 + -30233.31 = \#38561.26$$

For state ten, stage fourteen

$$i = 10$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 76851.96, C_k(i) = 45803.2 \text{ and } R_k(i) = 214971.3$$

Where $i = \text{state } 10, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 45803.2 - 76851.96 + (-31048.80) = -\#33501.9$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the tenth state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 214971.3 + (-31048.80) = \#37812.69$$

For state nine, stage fourteen

$$i = 09$$

$$V_k = V_k(i), \text{ keep}$$

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 78388.99, C_k(i) = 44887.14 \text{ and } R_k(i) = 204222.8$$

$$V_{k+1}(i + 1) = -33501.9$$

Where $i = \text{state } 09$, in stage 14 for Nissan Urvan

$$V_k = 44887.14 - 78388.99 + (-33501.9) = -\#35967.4$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the nine state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 204222.8 + (-33501.9) = \#37601.55$$

For state eight, stage fourteen

$$i = 08$$

$V_k = V_k(i)$, keep

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 79956.77, C_k(i) = 43989.4 \text{ and } R_k(i) = 194011.6$$

$$V_{k+1}(i + 1) = -\#35967.4$$

Where $i = \text{state } 08$, in stage 14 for Nissan Urvan

$$V_k = 43989.4 - 79956.77 + (35967.4) = -\#38446.3$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the eight state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 194011.1 + (-35967.4) = \#39001.90$$

For state seven, stage fourteen

$$i = 07$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 81555.91, C_k(i) = 43109.61 \text{ and } R_k(i) = 184311.1$$

$$V_{k+1}(i + 1) = -\#38446.3$$

Where $i = \text{state } 07, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 43109.61 - 81555.91 + (-38446.3) = -\#40939.6$$

For replacement decision model

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the sevenstate of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 184311.1 + (-38446.3) = \#50314.58$$

For state six, stage fourteen

$$i = 06$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k 38445.60(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 83187.03, C_k(i) = 42247.42 \text{ and } R_k(i) = 175095.5$$

$$V_{k+1}(i + 1) = -\#40939.6$$

Where $i = \text{state } 06, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 422472.42 - 83187.03 + (-40939.6) = -\#43448.3$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the six state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 175095.5 + (-40939.6) = \#50069.35$$

For state five, stage fourteen

$$i = 05$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 84850.77, C_k(i) = 41402.47 \text{ and } R_k(i) = 166340.7$$

$$V_{k+1}(i + 1) = -\#43448.3$$

Where $i = \text{state } 05, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 41402.47 - 84850.77 + -(43448.3) = -\#45973.4$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the five state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 166340.7 + (-43448.3) = \#58386.39$$

For state four, stage fourteen

$$i = 04$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 86547.78, C_k(i) = 40574.42 \text{ and } R_k(i) = 158023.7$$

$$V_{k+1}(i + 1) = -\#45973.4$$

Where $i = \text{state } 04, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 40574.42 - 86547.78 + -45973.4 = -\#48515.8$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the four state of stage 14 in Nissan Urvan.

$$V_r = 36676.06 - 95555.75 + 158023.7 + (45973.4) = \#60287.58$$

For state three, stage fourteen

$$i = 03$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 88278.74, C_k(i) = 39762.93 \text{ and } R_k(i) = 150122.5$$

$$V_{k+1}(i + 1) = -\#48515.8$$

Where $i = \text{state } 03, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 39762.93 - 88278.74 + (-48515.8) = -\#51076.6$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the three state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 150122.5 + (-48515.8) = \#61793.21$$

For state two, stage fourteen

$$i = 02$$

$$V_k = V_k(i), \text{ keep}$$

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 90044.31, C_k(i) = 38967.67 \text{ and } R_k(i) = 142616.4$$

$$V_{k+1}(i + 1) = -\#51076.6$$

Where $i = \text{state } 02$, in stage 14 for Nissan Urvan

$$V_k = 38188.32 - 91845.2 + (-51076.6) = -\#53656.9$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the two state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 142616.4 + (-51076.6) = \#62924.52$$

For state one, stage fourteen

$$i = 01$$

$V_k = V_k(i)$, keep

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 91845.2, C_k(i) = 38188.32 \text{ and } R_k(i) = 135485.6$$

$$V_{k+1}(i + 1) = -\#53656.9$$

Where $i = \text{state } 01$, in stage 14 for Nissan Urvan

$$V_k = 37424.55 - 93682.1 + (-53656.9) = -\#56257.6$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the one state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 135485.6 + (-53656.9) = \#63698.8$$

For state 0, stage fourteen

$$i = 0$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 93682.1, C_k(i) = 37424.55 \text{ and } R_k(i) = 128711.3$$

$$V_{k+1}(i + 1) = -53657.57$$

Where $i = \text{state } 0, \text{ in stage } 14 \text{ for Nissan Urvan}$

$$V_k = 36676.06 - 95555.75 + (0) = -58879.69$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 36676.06, \quad I_k(0) = 95555.75$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Nissan Urvan

While $R_k(i)$ is the 0 state of stage 14 in Nissan Urvan

$$V_r = 36676.06 - 95555.75 + 0 + (0) = -58879.69$$

For stage 14, states(15,13,12,11,10,9,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 67958.28, C_k(i) = 50076.39, R_k(i) = 250732$$

$$V_k = 50076.28 - 67958.28 + 0 = -17881.89$$

$$C_k(0) = 36676.06, I_k(0) = 95555.75$$

$$V_r = 36676.06 - 95555.75 + 250732 + 0 = 191852.31$$

$$V_{k+1}(i + 1) = 0$$

The summary of results for all states/stages for Nissan Urvan vehicle is given below.

Table 1:Summary of results for all states of stage 14.

States(i)	V_k	V_r	$V_k(i)$	D_k
15	-17881.89	191852.31	17881.89	Keep
13	24057.41	161433.82	24057.41	Keep
12	-30233.31	-133238.8	30233.31	Keep
11	-31048.8	-28561.2585	31048.8	Keep
10	-33501.9	-32812.6911	33501.9	Keep
9	-35367.4	-34601.552	35367.4	Keep
8	-35446.3	-35001.969	35446.3	Keep
7	-40939.6	-40314.5831	40939.6	Keep
6	-43448.3	-40069.358	43448.3	Keep
5	-45973.4	-45386.395	45973.4	Keep
4	-48515.8	-46287.58	48515.8	Keep
3	51076.6	61793.705	51076.6	Keep
2	53656.9	62924.525	53656.9	Keep
1	56257.6	63698.803	56257.6	Keep
0	0	0	0	

For stage 13,states(14,12,11,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$C_k(0) = 25952.58, I_k(0) = 189754.7$$

$$I_k(i) = 69325.86, C_k(i) = 51870.58, R_k(i) = 247613$$

$$V_k = 51870.58 - 69325.86 + 0 = -\#17471.7$$

$$V_r = 25952.58 - 189754.7 + 247613 - \#26175.9 = \#81234.98$$

$$V_{k+1}(i + 1) = -\#17471.7.$$

Table 2:Summary of results for all states of stage 13.

States(i)	V_k	V_r	$V_k(i)$	D_k
14	-17471.7	81234.98	17471.7	Keep
12	53501.8	88810.77	53501.8	Keep
11	64362.7	100572.39	64362.7	Keep
10	75596.3	111745.92	75596.3	Keep
9	87248.2	122360.78	87248.2	Keep
8	99366.6	132444.9	99366.6	Keep
7	112003	142024.81	112003	Keep
6	-125212	-121125.73	125212	Keep
5	-139052	-129771.6	139052	Keep
4	-153586	-152985.17	153586	Keep
3	-168879	-165788.07	168879	Keep
2	-185004	-183200.82	185004	Keep
1	-202037	-190242.94	202037	Keep
0	0	0	0	

For stage 12,states(13,11,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 73915.51, C_k(i) = 146359.71, R_k(i) = 242751$$

$$C_k(0) = 24616.87, I_k(0) = 373058.07$$

$$V_k = 146359.71 - 73915.51 + 0 = -\#72444.2$$

$$V_r = 24616.87 - 373058.07 + 242751 + -\#53501.8 = -\#159192.43$$

$$V_{k+1}(i + 1) = -\#53501.8.$$

Table 3:Summary of results for all states of stage 12.

States(i)	V_k	V_r	$V_k(i)$	D_k
13	-72444.2	-159192.43	159192	Replace
11	-123338	-171330	171330	Replace
10	-143488	-182860.65	182861	Replace
9	-160919	-193814.79	193815	Replace
8	-177898	-204221.22	204221	Replace
7	-194470	-214107.33	214107	Replace
6	-180654	-223499.14	223499	Replace
5	-200645	-232421.35	232421.35	Replace
4	-221438	-240897.46	240897	Replace
3	-243113	-248949.76	248950	Replace
2	-255754	-266599.44	266599.44	Replace
1	-259450	-289450	289450	Replace
0	0	0	0	

For stage 11,states(12,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 77682.05, C_k(i) = 44235.77, R_k(i) = 239604$$

$$I_k(0) = 96626.52, C_k(0) = 35435.14$$

$$V_k = 44235.77 - 77682.05 + -\#159192 = -\#192639$$

$$V_r = 35435.14 - 96626.52 + 0 + \#159192 = \#854540.38$$

$$V_{k+1}(i + 1) = -\#159192$$

Table 4:Summary of results for all states of stage 11.

States(i)	V_k	V_r	$V_k(i)$	D_k
12	-192639	854540.38	192639	Keep
10	-207229	-202461.46	207229	Keep
9	221212	249422.68	221212	Keep
8	-234634	-22545.012	234634	Keep
7	247522	304055.28	247522	Keep
6	-259907	-248475.34	259907	Keep
5	271815	312807	271815	Keep
4	-251495	-237052.03	251495	Keep
3	-294302	-221212.16	294302	Keep
2	-304928	-225289.08	304928	Keep
1	-315173	-129284.47	315173	Keep
0	0	0	0	

For stage 10,states(11,9,8,7,6,5,4,3,2,1)

At eleventh state, stage 10

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#78850, C_k(i) = \#42052.5 \text{ and } R_k(i) = \#234,300,$$

$$C_k(0) = 33391.6, I_k(0) = 99192.68.$$

$$V_k = 42052.5 - 78850 + -192639 = -\#36797.5$$

$$V_r = 33391.6 - 99192.68 + 234,300 + -\#315173 = \#377001.08$$

$$V_{k+1}(i + 1) = -\#315173$$

Table 5:Summary of results for all states of stage 10.

States(i)	V_k	V_r	$V_k(i)$	D_k
11	-36799.50	377001.08	36799.5	Keep
9	78747.5	128015.42	78747.5	Keep
8	12515.6	79473.12	12515.6	Keep
7	-60404.68	-60244.72	60404.8	Keep
6	110794.20	299146.15	110794.20	Keep
5	165586	351762.7	165585	Keep
4	-209003.8	-207729.7	209003.8	Keep
3	115665.6	254089.2	115665.6	Keep
2	-176175.2	-175590.3	176175.2	Keep
1	-237039.1	-220800.5	237039.1	Keep
0	0	0	0	

For stage 9,states(10,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#62550, C_k(i) = \#47940 \text{ and } R_k(i) = \#231600,$$

$$C_k(0) =,33,988, I_k(0) = 97,716$$

$$V_k = 47940 - 62550 + -369436 = -\#234046$$

$$V_r = 33988.6 - 97716 + 231600 + -237045.5 = \#300237$$

$$V_{k+1}(i + 1) = -234046$$

Table 6: Summary of results for all states of stage 9.

States(i)	V_k	V_r	$V_k(i)$	D_k
10	-234046	300237	234046	Keep
8	-293518	-281539	293518	Keep
7	-311550	-304738	311550	Keep
6	-330815	-327003	330815	Keep
5	-348721	-339342	348721	Keep
4	-366224	-341497	366224	Keep
3	-373031	-363691	373031	Keep
2	-388001	-373746	388001	Keep
1	-415882	-408123	415882	Keep
0	0	0	0	

For stage 8, states(9,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#56199.06, C_k(i) = \#26418 \text{ and } R_k(i) = \#230500,$$

$$C_k(0) = 24140.49, I_k(0) = 91021.07$$

$$V_k = 26418 - 56199.06 + -234046 = -\#29781.06$$

$$V_r = 24140.49 - 91021.07 + 230,500 + -415882 = \#300237$$

$$V_{k+1}(i + 1) = -\#415882$$

Table7:Summary of results for all states of stage 8.

States(i)	V_k	V_r	$V_k(i)$	D_k
9	-29781.06	300237	-29781.06	Keep
7	-352626	394679	-352626	Keep
6	-372634	456803	-372634	Keep
5	392140	459961	392140	Keep
4	411041	461449	411041	Keep
3	-429680	-413661	429680	Keep
2	-447808	-565852	447808	Keep
1	-433752	-428023	433752	Keep
0	0	0	0	

For stage 7,states(8,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#56199.06, C_k(i) = \#26418 \text{ and } R_k(i) = \#230500,$$

$$C_k(0) = 24140.49, I_k(0) = 91021.07$$

$$V_k = 26418 - 56199.06 + -29781.06 = -\#29781.06$$

$$V_r = 24140.49 - 91021.07 + 230,500 + -\#433752 = -\#354280$$

$$V_{k+1}(i + 1) = -29781.06$$

Table 8:Summary of results for all states of stage 7.

States(i)	V_k	V_r	$V_k(i)$	D_k
8	-29781.06	354,280	-29781.06	Keep
6	-405126	515,298	-405126	Keep
5	-427203	525,755	-427203	Keep
4	-448790	-435,689	-448790	Keep
3	-469919	-445,127	-469919	Keep
2	-490621	-484,092	-490621	Keep
1	-510926	-562,610	-510926	Keep

For stage 6,states(7,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 9:Summary of results for all states of stage 6.

States(i)	V_k	V_r	$V_k(i)$	D_k
7	-401024	461250	-401024	Keep
5	-461226	-453431	-461226	Keep
4	-485721	-475590	-485721	Keep
3	-509749	-467728	-509749	Keep
2	-533341	-529844	-533341	Keep

1	-556531	-541939	-556531	Keep
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For stage 5,states(6,4,3,2,1)

$$C_k(0) = 25978.46, I_k(0) = 100507, R_k(i) = 215680, C_k(i) = 31815, I_k(i) = 85690$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 10:Summary of results for all states of stage 5.

States(i)	V_k	V_r	$V_k(i)$	D_k
6	-454899	-445380	454899	Keep
4	-521126	-515380	521126	Keep
3	-551646	-547536	551646	Keep
2	-577568	-560672	577568	Keep
1	-604532	-601785	604532	Keep
0	0	0	0	

For stage 4,states(5,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 11:Summary of results for all states of stage 4.

States(i)	V_k	V_r	$V_k(i)$	D_k
5	-515734	-500545	515734	Keep
3	-588126	-571045	588126	Keep
2	-624811	-601020	624811	Keep
1	-657065	-640496	657065	Keep
0	0	0	0	

For stage 3,states(4,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 12: Summary of results for all states of stage 3.

States(i)	V_k	V_r	$V_k(i)$	D_k
4	-580474	-574200	580474	Keep
2	-658926	-644700	658926	Keep
1	-658791	-654675	658791	Keep
0	0	0	0	

For stage 2, states(3,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 13: Summary of results for all states of stage 2.

States(i)	V_k	V_r	$V_k(i)$	D_k
3	-649782	-634723	649782	Keep
1	-734250	-728771	734250	Keep
0	0	0	0	

For stage 1, states(2,0)

$$C_k(i) = 21166.75, I_k(i) = 95621.18, R_k(i) = 199,200$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace.}$$

Table 14: Summary of results for all states of stage 1.

States(i)	V_k	V_r	$V_k(i)$	D_k
2	-724236	-713433	724236	Keep
0	0	0	0	

For Sienna Product

At fifteen state, stage fourteen for Sienna Vehicle Product

$$i = 15$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 56301.15, C_k(i) = 71079.66 \text{ and } R_k(i) = 138403$$

Where $i = \text{state } 15, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 71079.66 - 56301.15 + 0 = 14778.51$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the fifteen state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 138403 + 0 = 109851.1$$

For state thirteen, stage fourteen

$$i = 13$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 61196.9, C_k(i) = 65815.5 \text{ and } R_k(i) = 131482.9$$

Where $i = \text{state } 13, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 65815.5 - 61196.9 + (14778.51) = 54617.60$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the thirteen state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 131482.9 + (14778.51) = 102930.85$$

For state twelve, stage fourteen

$$i = 12$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 62420.84, C_k(i) = 64498.21 \text{ and } R_k(i) = 124908.7$$

Where $i = \text{state } 12, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 64498.21 - 62420.84 + (54617.60) = 22087.36$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the twelve state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 124908.7 + (54617.60) = 96456.81$$

For state eleven, stage fourteen

$$i = 11$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 63669.25, C_k(i) = 63208.25 \text{ and } R_k(i) = 118663.3$$

Where $i = \text{state } 11, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 63208.25 - 63669.25 + (22087.36) = 46100.90$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the eleven state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 118663.3 + (22087.36) = 90111.40$$

For state ten, stage fourteen

$$i = 10$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 64942.64, C_k(i) = 61944.08 \text{ and } R_k(i) = 112730.1$$

Where $i = \text{state } 10, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 61944.08 - 64942.64 + (46100.90) = 29980.56$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the ten state of stage 14 in $V_r = \text{Sienna}$

$$50612.82 - 79164.72 + 112730.1 + (46100.90) = 84178.23$$

For state nine, stage fourteen

$$i = 9$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 66241.49, C_k(i) = 60705.2 \text{ and } R_k(i) = 107093.6$$

$$V_{k+1}(i + 1) = 18015.76$$

Where $i = \text{state } 09, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 60705.2 - 66241.49 + (29980.56) = 5536.29$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the nine state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 107093.6 + (29980.56) = 78551.70$$

For state eight, stage fourteen

$$i = 08$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 67566.32, C_k(i) = 59491.1 \text{ and } R_k(i) = 101738.9$$

$$V_{k+1}(i + 1) = 5536.29$$

Where $i = \text{state } 08, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 59491.1 - 67566.32 + (5536.29) = 4404.25$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the eight state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 101738.9 + (12479.47) = 73187.02$$

For state seven, stage fourteen

$$i = 07$$

For stage 7, states(8,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 70200, C_k(i) = 46252.5, R_k(i) = \#132900$$

$$I_k(0) = 87840.67, C_k(0) = \#41472.2$$

Summary of results for all states of stage 7.

States(i)	V_k	V_r	$V_k(i)$	D_k
8	100352	104,197	104,197	Replace
6	109039	110,832	110,832	Replace
5	123062	171,145	171145	Replace
4	128424	160,142	160142	Replace
3	157423	178,840	178840	Replace
2	197317	234,252	234252	Replace
1	161460	239,394	239394	Replace

For state six, stage fourteen

$$i = 06$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 70296, C_k(i) = 57135.25 \text{ and } R_k(i) = 91819.38$$

$$V_{k+1}(i + 1) = -6212.13$$

Where $i = \text{state } 06, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 57135.25 - 70296 + (-6212.13) = -13160.80$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the six state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 91819.38 + (-6212.13) = 63367.50$$

For state five, stage fourteen

$$i = 05$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 71701.92, C_k(i) = 55992.54 \text{ and } R_k(i) = 87228.41$$

$$V_{k+1}(i + 1) = -19372.88$$

Where $i = \text{state } 05, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 55992.54 - 71701.92 + (-19372.88) = -35082.26$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the five state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 87228.41 + (-19372.88) = 58676.51$$

For state four, stage fourteen

$$i = 04$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 73135.96, C_k(i) = 54872.69 \text{ and } R_k(i) = 82866.99$$

$$V_{k+1}(i + 1) = -35082.26$$

Where $i = \text{state } 04, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 54872.69 - 73135.96 + (-35082.26) = -18263.30$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the four state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 82866.99 + (-35082.26) = 54315.09$$

For state three, stage fourteen

$$i = 03$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 74598.68, C_k(i) = 53775.25 \text{ and } R_k(i) = 78723.64$$

$$V_{k+1}(i + 1) = -53345.53$$

Where $i = \text{state } 03, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 53775.25 - 74598.68 + (-53345.53) = -74168.96$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the three state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 78723.64 + (-53345.53) = -80171.74$$

For state two, stage fourteen

$$i = 02$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 76090.65, C_k(i) = 52699.73 \text{ and } R_k(i) = 74787.46$$

$$V_{k+1}(i + 1) = -74168.96$$

Where $i = \text{state } 02, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 52699.73 - 76090.65 + (-74168.96) = -\#97559.88$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the two state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 74787.46 + (-74168.96) = -\#98235.56$$

For state one, stage fourteen

$$i = 01$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 77612.47, C_k(i) = 51645.74 \text{ and } R_k(i) = 71048.08$$

$$V_{k+1}(i + 1) = -97559.88$$

Where $i = \text{state } 01, \text{ in stage } 14 \text{ for Sienna}$

$$V_k = 51645.74 - 77612.47 + (-97559.88) = -25966.70$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the one state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 71048.08 + (-97559.88) = -42496.18$$

For state zero, stage fourteen

$$i = 0$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 95555.75, C_k(i) = 36676.06 \text{ and } R_k(i) = 0$$

$$V_{k+1}(i + 1) = -25966.70$$

Where $i = \text{state } 0, \text{ in stage } 14 \text{ for Sienna}$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$V_k = 50612.82 - 79164.72 + (-25966.70) = -58049.22$$

For replacement decision model,

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Sienna

While $R_k(i)$ is the 0 state of stage 14 in Sienna

$$V_r = 50612.82 - 79164.72 + 0 + (-25966.70) = -58049.22$$

Analytical analyses of other stages of Sienna Vehicle are computed in the same way.

For Peugeot Expert Product

At fifteen state, stage fourteen for Peugeot Expert Vehicle

$$i = 15$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 53671.32, C_k(i) = 49049.92 \text{ and } R_k(i) = 186510$$

Where $i = \text{state } 15, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 49049.92 - 53671.32 + 0 = -4621.4$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the fifteen state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 186510 + 0 = 144131$$

For state thirteen, stage fourteen

$$i = 13$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 59634.8, C_k(i) = 45207.3 \text{ and } R_k(i) = 177184.5$$

Where $i = \text{state } 13, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_k = 45207.3 - 59634.8 + (-4621.4) = -14427.51$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the thirteen state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 177184.5 + (-4621.4) = 34805.51$$

For state twelve, stage fourteen

$$i = 12$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 59754.07, C_k(i) = 44303.15 \text{ and } R_k(i) = 168325.3$$

Where $i = \text{state } 12, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 44303.15 - 59873.58 + (-19048.9) = -15450.90$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

While $R_k(i)$ is the twelve state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61294.05 + 168325.3 + (-19048.9) = 125946.30$$

For state eleven, stage fourteen

$$i = 11$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 59873.58, C_k(i) = 434117.09 \text{ and } R_k(i) = 159909$$

Where $i = \text{state } 11, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 434117.09 - 59873.58 + (-15450.90) = -16456.51$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.04$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the eleventh state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 - 159909 = -17530.01$$

For state ten, stage fourteen

$$i = 10$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 59993.32, C_k(i) = 42548.75 \text{ and } R_k(i) = 151913.6$$

Where $i = \text{state } 10, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 42548.75 - 59993.32 + (-16456.51) = -17444.6$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.0$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the tenth state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.04 + 151913.6 + (-16456.51) = -109534.6$$

For state nine, stage fourteen

$$i = 09$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60113.31, C_k(i) = 41697.77 \text{ and } R_k(i) = 144317.9$$

$$V_{k+1}(i + 1) = -17444.6$$

Where $i = \text{state } 09, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 41697.77 - 60113.31 + (-17444.6) = -18410.4$$

For replacement decision model,

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.04$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14

While $R_k(i)$ is the nine state of stage 14 in Peugeot Expert.

$$V_r = 34765.43 - 61204.04 + 41697.77 - 17444.6 = -101938.88$$

For state eight, stage fourteen

$$i = 08$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60233.54, C_k(i) = 40863.82 \text{ and } R_k(i) = 137102$$

$$V_{k+1}(i + 1) = -18410.4$$

Where $i = \text{state } 08, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 40863.82 - 60233.54 + (-18410.4) = -19369.7$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, I_k(0) = 61204.05, R_k(i) = 137102,$$

$$V_{k+1}(i + 1) = -18410.$$

$$V_r = 34765.43 - +61204.05 + (137102) - 208224.24 = -94722.99$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the eighth state of stage 14 in Peugeot Expert

For stage 8, states(9,7,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 63450, C_k(i) = 37975.8, R_k(i) = 173300$$

$$I_k(0) = 99200.58, C_k(0) = 26466.98$$

Summary of results for all states of stage 8.

States(i)	V_k	V_r	$V_k(i)$	D_k
9	122006	154,030	154,030	Replace
7	142633	157,496	157496	Replace
6	155030	160,893	160893	Replace
5	107739	164,221	164221	Replace
4	130797	167,484	167484	Replace
3	154244	170,681	170681	Replace
2	78121	113,814	113814	Replace
1	102468	176,884	176884	Replace
0	0	0	0	

For state seven, stage fourteen

$$i = 07$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60354.01, C_k(i) = 40046.54 \text{ and } R_k(i) = 130246.9$$

$$V_{k+1}(i + 1) = -19369.7$$

$$C_k(0) = 34765.43, I_k(0) = 61204.05,$$

Where $i = \text{state } 07, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 40046.54 - 60354.01 - 19369.7 = -20307.5$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.0$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the seventh state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 130246.9 + (-19369.7) = -87867.89$$

For state six, stage fourteen

$$i = 06$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60474.71, C_k(i) = 39245.61 \text{ and } R_k(i) = 123734.5$$

$$V_{k+1}(i + 1) = -20307.5$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

Where $i = \text{state } 06, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 39245.61 - 60474.71 + (-20307.5) = -21229.10$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_{k+1}(i + 1) = -247901.43$$

Where $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the six state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 123734.5 + (-20307.5) = -81355.55$$

For state five, stage fourteen

$$i = 05$$

$V_k = V_k(i)$, keep

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60595.66, C_k(i) = 38460.7 \text{ and } R_k(i) = 117547.8$$

$$V_{k+1}(i + 1) = -21229.10$$

Where $i = \text{state } 05$, in stage 14 for Peugeot Expert

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$V_k = 38460.7 - 60595.66 + (-21229.10) = -22135.0$$

For replacement decision model,

Where

$C_k(0)$ & $I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the fifth state of stage 14 in Peugeot Expert

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_{k+1}(i + 1) = -21229.10$$

$$V_r = 34765.43 - 61204.05 + 117547.8 + (-21229.10) = -75168.82$$

For state four, stage fourteen

$$i = 04$$

$V_k = V_k(i)$, keep

$V_r = V_k(i)$, replace

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60716.85, C_k(i) = 37691.49 \text{ and } R_k(i) = 111670.4$$

$$V_{k+1}(i + 1) = -22135.0$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

Where $i = \text{state } 04$, in stage 14 for Peugeot Expert

$$V_k = 37691.49 - 60716.85 + (-22135.0) = -23025.4$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage Peugeot Expert

While $R_k(i)$ is the fourth state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 111670.4 + (-22135.0) = -69291.43$$

For state three, stage fourteen

$$i = 03$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60838.29, C_k(i) = 36937.66 \text{ and } R_k(i) = 106086.9$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_{k+1}(i + 1) = -23025.4$$

Where $i = \text{state } 03, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 36937.66 - 60838.29 + (-23025.4) = -23900.6$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

Where $C_k(0)$ & $I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the third state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 106086.9 + (-23025.4) = -63707.91$$

For state two, stage fourteen

$$i = 02$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 60959.96, C_k(i) = 36198.9 \text{ and } R_k(i) = 100782.6$$

$$V_{k+1}(i + 1) = -23900.6$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

Where $i = \text{state } 02, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_k = 36198.9 - 60959.96 + (-23900.6) = -24761.1$$

For replacement decision model,

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 50612.82, \quad I_k(0) = 79164.72$$

Where, $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the second state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 100782.6 + (-338191.48) = -58403.56$$

For state one, stage fourteen

$$i = 01$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 61081.88, C_k(i) = 35474.92 \text{ and } R_k(i) = 95743.43$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_{k+1}(i + 1) = -24761.1$$

Where $i = \text{state } 01, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$V_k = 35474.92 - 61081.88 + (-24761.1) = -25607.00$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$R_k(i) = 95743.43$$

$$V_{k+1}(i + 1) = -362952.54$$

For replacement decision model,

Where , $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the one state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 95743.43 + -24761.1 = -53364.43$$

For state zero, stage fourteen

$$i = 0$$

$$V_k = V_k(i), \text{ keep}$$

$$V_r = V_k(i), \text{ replace}$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1)$$

$$I_k(i) = 61204.05, C_k(i) = 34765.43 \text{ and } R_k(i) = 0$$

$$V_{k+1}(i + 1) = -25607.00$$

Where $i = \text{state } 0, \text{ in stage } 14 \text{ for Peugeot Expert}$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1)$$

$$C_k(0) = 34765.43, \quad I_k(0) = 61204.05$$

$$V_k = 34765.43 - 61204.05 + (-25607.00) = -36498.12$$

For replacement decision model,

Where, $C_k(0) \& I_k(0)$ are the first state of stage 14 Peugeot Expert

While $R_k(i)$ is the 0 state of stage 14 in Peugeot Expert

$$V_r = 34765.43 - 61204.05 + 0 + (-25607.00) = -36498.12$$

J5 Product

For stage 14, states(15,13,12,11,10,9,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 61134.31, C_k(i) = 62383.03, R_k(i) = 199889$$

$$V_k = 62383.03 - 61134.31 + 0 = 1238.721$$

$$C_k(0) = 49993.07, I_k(0) = 66045.28$$

$$V_r = 49993.07 - 66045.28 + 199889 + 0 = 183827$$

$$V_{k+1}(i + 1) = 0$$

The summary of results for all states/stages for J5 vehicle is given below.

Table 1:Summary of results for all states of stage 14.

States(i)	V_k	V_r	$V_k(i)$	D_k
15	1238.721	183827	12388.721	Keep
13	24057.41	161433.82	24057.41	Keep
12	-30233.31	-133238.8	30233.31	Keep
11	-31048.8	-28561.2585	31048.8	Keep
10	-33501.9	-32812.6911	33501.9	Keep
9	-35367.4	-34601.552	35367.4	Keep
8	-35446.3	-35001.969	35446.3	Keep
7	-40939.6	-40314.5831	40939.6	Keep
6	-43448.3	-40069.358	43448.3	Keep
5	-45973.4	-45386.395	45973.4	Keep
4	-48515.8	-46287.58	48515.8	Keep
3	51076.6	61793.705	51076.6	Keep
2	53656.9	62924.525	53656.9	Keep
1	56257.6	63698.803	56257.6	Keep
0	0	0	0	

For stage 13,states(14,12,11,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$C_k(0) = 25952.58, I_k(0) = 189754.7$$

$$I_k(i) = 69325.86, C_k(i) = 51870.58, R_k(i) = 247613$$

$$V_k = 51870.58 - 69325.86 + 0 = -\#17471.7$$

$$V_r = 25952.58 - 189754.7 + 247613 - \#26175.9 = \#81234.98$$

$$V_{k+1}(i + 1) = -\#17471.7.$$

Table 2: Summary of results for all states of stage 13.

States(i)	V_k	V_r	$V_k(i)$	D_k
14	-17471.7	81234.98	17471.7	Keep
12	53501.8	88810.77	53501.8	Keep
11	64362.7	100572.39	64362.7	Keep
10	75596.3	111745.92	75596.3	Keep
9	87248.2	122360.78	87248.2	Keep
8	99366.6	132444.9	99366.6	Keep
7	112003	142024.81	112003	Keep
6	-125212	-121125.73	125212	Keep
5	-139052	-129771.6	139052	Keep
4	-153586	-152985.17	153586	Keep
3	-168879	-165788.07	168879	Keep
2	-185004	-183200.82	185004	Keep
1	-202037	-190242.94	202037	Keep
0	0	0	0	

For stage 12, states(13,11,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 73915.51, C_k(i) = 146359.71, R_k(i) = 242751$$

$$C_k(0) = 24616.87, I_k(0) = 373058.07$$

$$V_k = 146359.71 - 73915.51 + 0 = -\#72444.2$$

$$V_r = 24616.87 - 373058.07 + 242751 + -\#53501.8 = -\#159192.43$$

$$V_{k+1}(i + 1) = -\#53501.8.$$

Table 3: Summary of results for all states of stage 12.

States(i)	V_k	V_r	$V_k(i)$	D_k
13	-72444.2	-159192.43	159192	Replace
11	-123338	-171330	171330	Replace
10	-143488	-182860.65	182861	Replace
9	-160919	-193814.79	193815	Replace
8	-177898	-204221.22	204221	Replace
7	-194470	-214107.33	214107	Replace
6	-180654	-223499.14	223499	Replace
5	-200645	-232421.35	232421.35	Replace
4	-221438	-240897.46	240897	Replace
3	-243113	-248949.76	248950	Replace
2	-255754	-266599.44	266599.44	Replace
1	-259450	-289450	289450	Replace
0	0	0	0	

For stage 11, states(12,10,9,8,7,6,5,4,3,2,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 77682.05, C_k(i) = 44235.77, R_k(i) = 239604$$

$$I_k(0) = 96626.52, C_k(0) = 35435.14$$

$$V_k = 44235.77 - 77682.05 + -\#159192 = -\#192639$$

$$V_r = 35435.14 - 96626.52 + 0 + \#159192 = \#854540.38$$

$$V_{k+1}(i + 1) = -\#159192$$

Table 4: Summary of results for all states of stage 11.

States(i)	V_k	V_r	$V_k(i)$	D_k
12	-192639	854540.38	192639	Keep
10	-207229	-202461.46	207229	Keep
9	221212	249422.68	221212	Keep
8	-234634	-22545.012	234634	Keep
7	247522	304055.28	247522	Keep
6	-259907	-248475.34	259907	Keep
5	271815	312807	271815	Keep
4	-251495	-237052.03	251495	Keep
3	-294302	-221212.16	294302	Keep
2	-304928	-225289.08	304928	Keep
1	-315173	-129284.47	315173	Keep
0	0	0	0	

For stage 10, states(11,9,8,7,6,5,4,3,2,1)

At eleventh state, stage 10

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#78850, C_k(i) = \#42052.5 \text{ and } R_k(i) = \#234,300,$$

$$C_k(0) = 33391.6, I_k(0) = 99192.68.$$

$$V_k = 42052.5 - 78850 + -192639 = -\#36797.5$$

$$V_r = 33391.6 - 99192.68 + 234,300 + -\#315173 = \#377001.08$$

$$V_{k+1}(i + 1) = -\#315173$$

Table 5: Summary of results for all states of stage 10.

States(i)	V_k	V_r	$V_k(i)$	D_k
11	-36799.50	377001.08	36799.5	Keep
9	78747.5	128015.42	78747.5	Keep
8	12515.6	79473.12	12515.6	Keep
7	-60404.68	-60244.72	60404.8	Keep
6	110794.20	299146.15	110794.20	Keep
5	165586	351762.7	165585	Keep
4	-209003.8	-207729.7	209003.8	Keep
3	115665.6	254089.2	115665.6	Keep
2	-176175.2	-175590.3	176175.2	Keep
1	-237039.1	-220800.5	237039.1	Keep
0	0	0	0	

For stage 9, states(10,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#62550, C_k(i) = \#47940 \text{ and } R_k(i) = \#231600,$$

$$C_k(0) = ,33,988, I_k(0) = 97,716$$

$$V_k = 47940 - 62550 + -369436 = -\#234046$$

$$V_r = 33988.6 - 97716 + 231600 + -237045.5 = \#300237$$

$$V_{k+1}(i + 1) = -234046$$

Table 6: Summary of results for all states of stage 9.

States(i)	V_k	V_r	$V_k(i)$	D_k
10	-234046	300237	234046	Keep
8	-293518	-281539	293518	Keep
7	-311550	-304738	311550	Keep
6	-330815	-327003	330815	Keep
5	-348721	-339342	348721	Keep
4	-366224	-341497	366224	Keep
3	-373031	-363691	373031	Keep
2	-388001	-373746	388001	Keep
1	-415882	-408123	415882	Keep
0	0	0	0	

For stage 8, states(9,8,7,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#56199.06, C_k(i) = \#26418 \text{ and } R_k(i) = \#230500,$$

$$C_k(0) = 24140.49, I_k(0) = 91021.07$$

$$V_k = 26418 - 56199.06 + -234046 = -\#29781.06$$

$$V_r = 24140.49 - 91021.07 + 230,500 + -415882 = \#300237$$

$$V_{k+1}(i + 1) = -\#415882$$

Table7:Summary of results for all states of stage 8.

States(i)	V_k	V_r	$V_k(i)$	D_k
9	-29781.06	300237	-29781.06	Keep
7	-352626	394679	-352626	Keep
6	-372634	456803	-372634	Keep
5	392140	459961	392140	Keep
4	411041	461449	411041	Keep
3	-429680	-413661	429680	Keep
2	-447808	-565852	447808	Keep
1	-433752	-428023	433752	Keep
0	0	0	0	

For stage 7,states(8,6,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = \#56199.06, C_k(i) = \#26418 \text{ and } R_k(i) = \#230500,$$

$$C_k(0) = 24140.49, I_k(0) = 91021.07$$

$$V_k = 26418 - 56199.06 + -29781.06 = -\#29781.06$$

$$V_r = 24140.49 - 91021.07 + 230,500 + -\#433752 = -\#354280$$

$$V_{k+1}(i + 1) = -29781.06$$

Table 8:Summary of results for all states of stage 7.

States(i)	V_k	V_r	$V_k(i)$	D_k
8	-29781.06	354,280	-29781.06	Keep
6	-405126	515,298	-405126	Keep
5	-427203	525,755	-427203	Keep
4	-448790	-435,689	-448790	Keep
3	-469919	-445,127	-469919	Keep
2	-490621	-484,092	-490621	Keep
1	-510926	-562,610	-510926	Keep

For stage 6,states(7,5,4,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 9:Summary of results for all states of stage 6.

States(i)	V_k	V_r	$V_k(i)$	D_k
7	-401024	461250	-401024	Keep
5	-461226	-453431	-461226	Keep
4	-485721	-475590	-485721	Keep
3	-509749	-467728	-509749	Keep
2	-533341	-529844	-533341	Keep

1	-556531	-541939	-556531	Keep
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For stage 5,states(6,4,3,2,1)

$$C_k(0) = 25978.46, I_k(0) = 100507, R_k(i) = 215680, C_k(i) = 31815, I_k(i) = 85690$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 10:Summary of results for all states of stage 5.

States(i)	V_k	V_r	$V_k(i)$	D_k
6	-454899	-445380	454899	Keep
4	-521126	-515380	521126	Keep
3	-551646	-547536	551646	Keep
2	-577568	-560672	577568	Keep
1	-604532	-601785	604532	Keep
0	0	0	0	

For stage 4,states(5,3,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 11:Summary of results for all states of stage 4.

States(i)	V_k	V_r	$V_k(i)$	D_k
5	-515734	-500545	515734	Keep
3	-588126	-571045	588126	Keep
2	-624811	-601020	624811	Keep
1	-657065	-640496	657065	Keep
0	0	0	0	

For stage 3,states(4,2,1)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 12: Summary of results for all states of stage 3.

States(i)	V_k	V_r	$V_k(i)$	D_k
4	-580474	-574200	580474	Keep
2	-658926	-644700	658926	Keep
1	-658791	-654675	658791	Keep
0	0	0	0	

For stage 2, states(3,1,0)

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

Table 13: Summary of results for all states of stage 2.

States(i)	V_k	V_r	$V_k(i)$	D_k
3	-649782	-634723	649782	Keep
1	-734250	-728771	734250	Keep
0	0	0	0	

For stage 1, states(2,0)

$$C_k(i) = 21166.75, I_k(i) = 95621.18, R_k(i) = 199,200$$

$$V_k = C_k(i) - I_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = C_k(0) - I_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace.}$$

Table 14: Summary of results for all states of stage 1.

States(i)	V_k	V_r	$V_k(i)$	D_k
2	-724236	-713433	724236	Keep
0	0	0	0	

For stage 9, states(10,8,7,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 63325, C_k(i) = 51000, R_k(i) = 192000$$

$$I_k(0) = 110070, C_k(0) = 28195$$

Ford Bus Product

For stage 8, states(9,7,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 67950, C_k(i) = 39128.1, R_k(i) = 186200$$

$$I_k(0) = 106236.1, C_k(0) = 33900$$

Summary of results for all states of stage 8.

States(i)	V_k	V_r	$V_k(i)$	D_k
9	206535	219,892	219,892	Replace
7	223543	223,615	223,615	Replace
6	217010	227,265	227265	Replace
5	230205	250,203	250203	Replace
4	230267	234,346	234346	Replace
3	238831	247781	247781	Replace
2	247772	333768	333768	Replace
1	269497	344,439	344439	Replace
0	0	0	0	

Toyota Hiace

For stage 9, states(10,8,7,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 67243.5, C_k(i) = 45758.4, R_k(i) = 196700$$

$$I_k(0) = 116882, C_k(0) = 25298$$

Summary of results for all states of stage 9.

States(i)	V_k	V_r	$V_k(i)$	D_k
10	250917	289,218	289,218	Replace
8	257527	293,152	293,152	Replace
7	287077	302,790	302,790	Replace
6	305048	315,048	315,048	Replace
5	341646	350,645	350,645	Replace
4	367061	388,909	388,909	Replace
3	376325	396,759	396,759	Replace
2	411632	440,217	440,217	Replace
1	448125	513,302	513302	Replace
0	0	0	0	

Taxi Cab

For stage 9, states(10,8,7,6,5,4,3,2,1)

$$V_k = I_k(i) - C_k(i) + V_{k+1}(i + 1) \text{ keep}$$

$$V_r = I_k(0) - C_k(0) + R_k(i) + V_{k+1}(i + 1) \text{ replace}$$

$$I_k(i) = 42675, C_k(i) = 40440, R_k(i) = 120600$$

$$I_k(0) = 66667, C_k(0) = 28671$$

Summary of results for all states of stage 9.

States(i)	V_k	V_r	$V_k(i)$	D_k
10	118973	140,973	140,973	Replace
8	142358	144,179	144179	Replace
7	143655	148,373	148373	Replace
6	165090	174,555	174555	Replace
5	145725	181361.49	181361.49	Replace
4	197508	198,884	198884	Replace
3	213566	248,030	248030	Replace
2	229572	249,166	249166	Replace
1	181361	195,725	195725	Replace
0	0	0	0	

APPENDIX A₂

Trend Analysis for SIENNA (MAINTENANCE)

Data SIENNA (MAINTENANCE)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = 18144 + 3405 * t$$

Accuracy Measures

MAPE 4
MAD 1296
MSD 2753299

Time (MAINTENANCE)	SIENNA	Trend	Detrend
19000	21548.7	-2548.73	
2	24400	24953.8	-553.79
3	29050	28358.8	691.15
4	32300	31763.9	536.09
5	37000	35169.0	1831.03
6	39200	38574.0	625.97
7	44050	41979.1	2070.91
8	46100	45384.2	715.85
9	48800	48789.2	10.79
10	48815	52194.3	-3379.27

Forecasts

Period	Forecast
11	55599.3
12	59004.4
13	62409.5
14	65814.5
15	69219.6

Trend Analysis for PEUGEOT EXPERT (MAINTENANCE)

Data PEUGEOT EXPERT (MAINTENANCE)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = 16654 + 3299*t - 90.0*t**2$$

Accuracy Measures

MAPE 2
MAD 648
MSD 603977

Time	PEUGEOT EXPERT (MAINTENANCE)	Trend	Detrend
1	2090.0	19863.2	1036.82
2	2130.0	22892.3	-1592.27
3	2590.0	25741.4	158.56
4	2900.0	28410.7	589.32
5	3050.0	30900.0	-400.00
6	3310.0	33209.4	-109.39
7	3505.0	35338.9	-288.86
8	3790.0	37288.4	611.59
9	3990.0	39058.0	841.97
10	3980.0	40647.7	-847.73

Forecasts

Period	Forecast
11	4205.75
12	4328.73
13	4433.73
14	4520.73
15	4709.23

Trend Analysis for TAXI CAB (MAINTENANCE)

Data TAXI CAB (MAINTENANCE)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = 17859.5 * (1.07296**t)$$

Accuracy Measures

MAPE 3
MAD 759
MSD 997938

Time	TAXI CAB (MAINTENANCE)	Trend	Detrend
1	1890.0	19162.6	-262.62
2	2080.0	20560.8	239.20
3	2160.0	22061.0	-461.00
4	2310.0	23670.7	-570.66
5	2500.0	25397.8	-397.77
6	2910.0	27250.9	1849.11
7	3012.0	29239.2	880.77
8	3220.0	31372.6	827.35
9	3370.0	33661.7	38.28
10	3405.0	36117.8	-2067.82

Forecasts

Period	Forecast
11	3875.31
12	4158.07
13	4461.46
14	4786.99
15	5136.27

Double Exponential Smoothing for J5 (MAINTENANCE)

Data J5 (MAINTENANCE)
Length 10

Smoothing Constants

Alpha (level) 0.615117
Gamma (trend) 0.038769

Accuracy Measures

MAPE 10
MAD 3312
MSD 23382738

Time	J5 (MAINTENANCE)	Smooth	Predict	Error
1	2337.0	19724.5	13898.4	9471.57
2	2410.8	23713.2	23082.2	1025.75
3	3665.4	32921.5	26956.2	9697.77
4	3811.0	37026.7	35295.5	2814.53
5	3990.0	39733.7	39467.8	432.17
6	4050.0	41148.6	42185.1	-1685.07
7	4410.0	43892.1	43559.8	540.22
8	4600.0	46121.7	46316.2	-316.18
9	4250.0	44824.0	48538.3	-6038.26
10	4820.0	47775.3	47096.6	1103.41

Forecasts

Period	Forecast	Lower	Upper
11	5007.42	41958.7	58189.7
12	5237.31	42610.5	62135.7
13	5467.20	43104.2	66239.8
14	5697.08	43503.2	70438.4
15	5926.97	43842.6	74696

Double Exponential Smoothing for FORD BUS (MAINTENANCE)

Data FORD BUS (MAINTENANCE)
Length 10

Smoothing Constants

Alpha (level) 1.21676

Gamma (trend) 0.03664

Accuracy Measures

MAPE 8
MAD 2228
MSD 13082778

Time	FORD BUS (MAINTENANCE)	Smooth	Predict	Error
1	2165.4	23549.1	12911.5	8742.53
2	2297.7	23104.6	22388.5	588.51
3	3115.8	32607.8	24469.5	6688.46
4	3488.7	34987.1	34425.3	461.71
5	3690.0	36916.2	36825.1	74.87
6	3690.0	36497.3	38757.6	-1857.62
7	3780.0	37701.2	38255.9	-455.90
8	3905.0	38965.6	39439.4	-389.41
9	4160.0	41798.0	40686.5	913.54
10	4145.0	40992.7	43559.6	-2109.63

Forecasts

Period	Forecast	Lower	Upper
11	4266.03	37201.2	48119.3
12	4432.78	34673.2	53982.4
13	4599.53	32024.0	59966.7
14	4766.29	29339.1	65986.7
15	4933.04	26639.0	72021.9

Double Exponential Smoothing for TOYOTA HIACE (MAINTENANCE)

Data TOYOTA HIACE (MAINTENANCE)
Length 10

Smoothing Constants

Alpha (level) 0.26526
Gamma (trend) 4.77337

Accuracy Measures

MAPE 2
MAD 642
MSD 559393

Time	TOYOTA HIACE (MAINTENANCE)	Smooth	Predict	Error
1	2205.0	22343.4	22449.3	-399.27
2	2400.0	23119.1	22801.1	1198.95
3	2510.0	24989.0	24948.9	151.10
4	2790.0	27328.2	27121.7	778.30
5	3020.0	30381.0	30446.4	-246.35
6	3330.0	33217.2	33187.3	112.73
7	3515.0	35896.6	36166.2	-1016.18
8	3640.0	37251.5	37558.9	-1158.94
9	3813.2	37628.3	37446.4	685.62
10	3802.1	38513.5	38691.2	-670.25

Forecasts

Period	Forecast	Lower	Upper
11	3872.78	37155.5	40300.1
12	3894.21	*	*
13	3915.64	*	*
14	3937.08	*	*
15	3958.51	*	*

Double Exponential Smoothing for NISSAN URVAN (REPLACEMENT)

Data NISSAN URVAN (REPLACEMENT)
Length 10

Smoothing Constants

Alpha (level) 0.424802
Gamma (trend) 0.362627

Accuracy Measures

MAPE 1
MAD 1960
MSD 6245198

Time	NISSAN URVAN (REPLACEMENT)	Smooth	Predict	Error
1	1992.00	198604	198164	1035.73
2	2024.00	202847	203176	-776.31
3	2100.00	207739	206069	3930.83
4	2100.00	211237	212151	-2151.21
5	2156.80	215472	215318	361.80
6	2181.00	218968	219608	-1508.46
7	2201.50	221716	222872	-2721.86
8	2305.00	227452	225201	5299.49
9	2316.00	231688	231753	-153.01
10	2343.00	235258	235966	-1665.71

Forecasts

Period	Forecast	Lower	Upper
11	2396.04	234476	244082
12	2427.51	238035	248566
13	2476.13	241544	253098
14	2507.32	245017	257668
15	2556.22	248462	262265

Double Exponential Smoothing for J5 (REPLACEMENT)

Data J5 (REPLACEMENT)
Length 10

Smoothing Constants

Alpha (level) 0.889801
Gamma (trend) 0.902461

Accuracy Measures

MAPE 0
MAD 382
MSD 226834

Time	J5 (REPLACEMENT)	Smooth	Predict	Error
1	1803.00	180263	179968	331.60
2	1809.00	180845	180403	496.94
3	1817.00	181679	181509	191.03
4	1830.00	182938	182440	560.30

5	1852.00	185084	184149	1051.07
6	1866.00	186659	187139	-538.87
7	1884.00	188387	188281	118.64
8	1901.00	190100	190104	-4.17
9	1920.00	191980	191814	185.64
10	1935.00	193538	193843	-342.51

Forecasts

Period	Forecast	Lower	Upper
11	1951.26	194190	196062
12	1967.14	195373	198054
13	1983.02	196531	200072
14	1998.89	197678	202100
15	2014.77	198821	204134

Double Exponential Smoothing for TAXI CAB (REPLACEMENT)

Data TAXI CAB (REPLACEMENT)
Length 10

Smoothing Constants

Alpha (level) 1.48616
Gamma (trend) 0.05039

Accuracy Measures

MAPE 2
MAD 2584
MSD 19049881

TAXI CAB				
Time	(REPLACEMENT)	Smooth	Predict	Error
1	1000.00	105453	88783	11216.6
2	1011.00	100612	102103	-1003.3
3	1102.00	113857	102678	7522.3
4	1152.00	114995	115622	-422.2
5	1164.00	116240	116728	-328.3
6	1170.00	116538	117949	-949.4
7	1195.00	120144	118176	1323.7
8	1201.50	119309	121881	-1730.5
9	1206.00	120446	120916	-316.1
10	1210.00	120499	122030	-1030.0

Forecasts

Period	Forecast	Lower	Upper
11	1220.06	115675	128337
12	1235.12	110060	136965
13	1250.19	104367	145671
14	1265.26	98655	154396
15	1280.32	92937	163127

Trend Analysis for SIENNA (REPLACEMENT)

Data SIENNA (REPLACEMENT)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = (10^{**6}) / (7.16260 + 2.25479*(0.774197^{**t}))$$

Accuracy Measures

MAPE 1
MAD 1047
MSD 2245648

SIENNA			
Time	(REPLACEMENT)	Trend	Detrend
1	1100.00	112255	-2255.41
2	1150.00	117452	-2452.46
3	1250.00	121819	3181.22
4	1250.00	125429	-428.74
5	1280.00	128374	-373.95
6	1309.00	130751	149.13
7	1329.00	132652	247.59
8	1336.00	134163	-562.99
9	1352.40	135356	-116.31
10	1370.00	136295	705.14

Forecasts

Period	Forecast
11	1370.30
12	1376.05
13	1380.54
14	1384.03
15	1386.75

Trend Analysis for PEUGEOT EXPERT (REPLACEMENT)

Data PEUGEOT EXPERT (REPLACEMENT)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = (10^{**6}) / (4.93183 + 1.97816*(0.896692^{**t}))$$

Accuracy Measures

MAPE 1
MAD 1437
MSD 3113307

PEUGEOT EXPERT			
Time	(REPLACEMENT)	Trend	Detrend
1	1500.00	149128	871.52
2	1520.00	153318	-1318.27
3	1550.00	157281	-2280.59
4	1650.00	161012	3988.14
5	1665.00	164511	1988.51
6	1665.00	167782	-1281.52
7	1700.50	170826	-776.28
8	1733.00	173652	-352.02
9	1772.00	176267	933.47
10	1781.00	178679	-578.81

Forecast
 Period Forecast
 11 1808.99
 12 1829.37
 13 1848.04
 14 1865.10
 15 1880.68

Trend Analysis for TOYOTA HIACE (REPLACEMENT)

Data TOYOTA HIACE (REPLACEMENT)
 Length 10
 NMissing 0

Fitted Trend Equation
 $Y_t = 187383 + 1232*t - 21.7*t**2$

Accuracy Measures

MAPE 0
 MAD 429
 MSD 280149

Time	TOYOTA HIACE (REPLACEMENT)	Trend	Detrend
1	1892.40	188593	647.364
2	1897.50	189759	-9.364
3	1900.00	190883	-882.682
4	1912.50	191963	-712.591
5	1932.80	192999	280.909
6	1944.00	193992	407.818
7	1950.00	194942	58.136
8	1966.00	195848	751.864
9	1967.00	196711	-11.000
10	1970.00	197530	-530.455

Forecasts

Period Forecast
 11 1983.07
 12 1990.39
 13 1997.28
 14 2003.74
 15 2009.77

Winters' Method for FORD BUS(REPLACEMENT)

Multiplicative Method

Data FORD BUS (REPLACEMENT)
 Length 10

Smoothing Constants

Alpha (level) 0.2
 Gamma (trend) 0.2
 Delta (seasonal) 0.2

Accuracy Measures

MAPE 0
MAD 542
MSD 677457

FORD

Time	BUS (REPLACEMENT)	Smooth	Predict	Error
1	1803.50	179285	179938	411.85
2	1812.00	180855	181528	-327.67
3	1813.00	180691	181349	-48.52
4	1825.00	182060	182718	-217.55
5	1825.00	181943	182589	-89.42
6	1836.00	183270	183916	-315.68
7	1840.00	183137	183768	232.46
8	1862.00	184481	185123	1076.77
9	1876.00	184706	185388	2211.75
10	1879.00	186641	187415	484.72

Forecasts

Period	Forecast	Lower	Upper
11	1878.46	186519	189173
12	1891.78	187830	190526
13	1894.30	188059	190801
14	1907.67	189370	192163
15	1910.14	189590	192438

Trend Analysis Decomposition for NISSAN URVAN (INCOME GENERATED)

Multiplicative Model

Data NISSAN URVAN (INCOME GENERATED)
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = 101112 - 1962.83 * t$$

Seasonal Indices

Period	Index
1	0.99681
2	1.00319

Accuracy Measures

MAPE 1
MAD 894
MSD 951954

NISSAN URVAN
(INCOME GENERATED)

Time	GENERATED)	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	9807.3	99149.5	0.99681	0.98914	98387.0	98833.0	-760.03
2	9782.4	97186.6	1.00319	1.00656	97512.8	97496.8	327.19
3	9600.0	95223.8	0.99681	1.00815	96307.4	94919.9	1080.10
4	9515.0	93261.0	1.00319	1.02026	94847.3	93558.6	1591.38
5	9020.0	91298.1	0.99681	0.98797	90488.8	91006.8	-806.76
6	8850.0	89335.3	1.00319	0.99065	88218.4	89620.4	-1120.43
7	8610.0	87372.5	0.99681	0.98544	86375.7	87093.6	-993.62

8	8489.7	85409.6	1.00319	0.99400	84626.9	85682.2	-785.23
9	8340.0	83446.8	0.99681	0.99944	83667.0	83180.5	219.51
10	8300.0	81484.0	1.00319	1.01861	82735.9	81744.0	1255.96

Forecasts

Period	Forecast
11	7926.74
12	7780.58
13	7535.42
14	7386.77
15	7144.11

Trend Analysis Decomposition for FORD BUS (INCOME GENERATED)

Multiplicative Model

Data FORD BUS (INCOME GENERATED)
 Length 10
 NMissing
 Fitted Trend Equation

$$Y_t = 95319 - 2588.99 * t$$

Seasonal Indices

Period	Index
1	0.99785
2	1.00215

Accuracy Measures

MAPE 1
 MAD 577
 MSD 454223

Time	FORD BUS (INCOME GENERATED)	Trend	Seasonal	Detrend	Deseason	Predict	Error
1	9200.0	92730.4	0.99785	0.99212	92198.3	92531.0	-530.99
2	9020.0	90141.4	1.00215	1.00065	90006.4	90335.3	-135.29
3	8713.0	87552.4	0.99785	0.99518	87317.8	87364.1	-234.14
4	8614.0	84963.4	1.00215	1.01385	85955.1	85146.2	993.83
5	8290.0	82374.4	0.99785	1.00638	83078.7	82197.3	702.71
6	7880.0	79785.5	1.00215	0.98765	78630.9	79957.1	-1157.05
7	7740.0	77196.5	0.99785	1.00264	77566.8	77030.4	369.56
8	7550.0	74607.5	1.00215	1.01196	75338.0	74767.9	732.07
9	7195.0	72018.5	0.99785	0.99905	72105.1	71863.6	86.41
10	6875.0	69429.5	1.00215	0.99021	68602.5	69578.8	-828.81

Forecasts

Period	Forecast
11	6669.67
12	6438.97
13	6152.99
14	5920.06
15	5636.30

Trend Analysis model for Sienna (INCOME GENERATED)

Data Sienna (INCOME GENERATED)
Length 10

Smoothing Constants

Alpha (level) 0.723367
Gamma (trend) 0.204821

Accuracy Measures

MAPE 1
MAD 1036
MSD 2128741

Time	Sienna (INCOME GENERATED)	Smooth	Predict	Error
1	9000.0	90088.3	90319.3	-319.30
2	8710.0	87266.9	87703.4	-603.44
3	8420.0	84561.7	85507.4	-1307.38
4	8205.0	82171.9	82490.7	-440.66
5	8150.0	81094.9	80035.6	1464.39
6	8040.0	80061.3	79175.6	1224.42
7	7800.0	78089.5	78323.4	-323.37
8	7710.0	76879.7	76303.6	796.37
9	7140.0	72454.5	75211.9	-3811.86
10	7015.0	70169.9	70221.9	-71.88

Forecasts

Period	Forecast	Lower	Upper
11	6792.66	65387.7	70465.5
12	6568.34	62433.2	68933.6
13	6344.01	59418.9	67461.4
14	6119.69	56373.3	66020.4
15	5895.36	53309.9	64597.4

Trend Analysis for PEUGEOT EXPERT (INCOME GENERATE

Data PEUGEOT EXPERT (INCOME GENERATE
Length 10
NMissing 0

Fitted Trend Equation

$$Y_t = 91558 - 2930*t + 46.4*t**2$$

Accuracy Measures

MAPE 1
MAD 612
MSD 440313

Time	PEUGEOT EXPERT (INCOME GENERATE	Trend	Detrend
1	8830.0	88674.1	-374.09

2	8600.0	85883.5	116.52
3	8420.0	83185.7	1014.32
4	7990.0	80580.7	-680.68
5	7755.0	78068.5	-518.48
6	7605.0	75649.1	400.91
7	7415.0	73322.5	827.50
8	7050.0	71088.7	-588.71
9	6805.0	68947.7	-897.73
10	6760.0	66899.5	700.45

Forecasts

Period	Forecast
11	6494.42
12	6308.16
13	6131.18
14	5963.48
15	5805.07

Trend Analysis for J5 (INCOME GENERATED)

Data J5 (INCOME GENERATED)
 Length 10
 NMissing 1

Fitted Trend Equation

$$Y_t = 89992.0 * (0.97633^{**t})$$

Accuracy Measures

MAPE 1
 MAD 705
 MSD 818529

Time	J5 (INCOME GENERATED)	Trend	Detrend	
1	8910.0	87862.0	1238.00	
2	8540.0	85782.4	-382.36	
3	8330.0	83752.0	-451.95	
4	8150.0	81769.6	-269.60	
5	7920.0	79834.2	-634.17	
6	7760.0	77944.5	-344.55	
7	7606.0	76099.7	-39.65	
8	7501.0	* 74298.4		*
9	7450.0	72539.8	1960.17	
10	6980.0	70822.9	-1022.86	

Forecasts

Period	Forecast
11	6914.65
12	6750.99
13	6591.20
14	6435.19
15	6282.87

Trend Analysis for TOYOTA HIACE (INCOME GENERATED)

Data TOYOTA HIACE (INCOME GENERATED)
 Length 10
 NMissing 0

Fitted Trend Equation

$$Y_t = 102347 - 2419.39 * t$$

Accuracy Measures

MAPE 1
MAD 488
MSD 371357

TOYOTA HIACE
(INCOME

Time	GENERATED)	Trend	Detrend
1	10012.0	99927.3	192.73
2	9706.0	97507.9	-447.88
3	9550.0	95088.5	411.52
4	9220.0	92669.1	-469.09
5	9019.0	90249.7	-59.70
6	8812.0	87830.3	289.70
7	8600.0	85410.9	589.09
8	8330.0	82991.5	308.48
9	7911.0	80572.1	-1462.12
10	7880.0	78152.7	647.27

Forecasts

Period	Forecast
11	7573.33
12	7331.39
13	7089.45
14	6847.52
15	6605.58

Winters' Method for TAXI CAB (INCOME GENERATED)

Multiplicative Method

Data TAXI CAB (INCOME GENERATED)
Length 10

Smoothing Constants

Alpha (level) 0.2
Gamma (trend) 0.2
Delta (seasonal) 0.2

Accuracy Measures

MAPE 2
MAD 1130
MSD 1747824

TAXI CAB
(INCOME

Time	GENERATED)	Smooth	Predict	Error
1	7890.0	83268.2	80691.7	-1791.73
2	7721.5	77717.6	75155.7	2059.30
3	7500.0	77832.2	75278.4	-278.42
4	7119.0	73352.4	70851.2	338.77
5	6830.0	72684.2	70134.6	-1834.63
6	6615.0	68125.4	65564.2	585.83
7	6309.0	66981.7	64393.7	-1303.74
8	5880.0	62977.6	60385.0	-1585.04
9	5690.0	60971.0	58275.1	-1375.12
10	5405.0	56899.8	54201.1	-151.09

Forecasts

Period	Forecast	Lower	Upper
11	5226.23	49492.9	55031.6
12	4873.95	45926.8	51552.3
13	4676.90	43907.9	49630.1
14	4333.24	40418.1	46246.6
15	4127.57	38303.9	44247.6

(a) Models Developed for Maintenance Costs

The Fitted Linear Trend Maintenance Model developed for Sienna Vehicle is

$$Y_t = 18144 + 3405*t \quad (3.19)$$

Analytical analysis of forecasting results between (2015 – 2019) for the model developed for Sienna (i.e. $t = 0.002$)

$$Y_t = 18144 + 3405 \times 0.02 = 5559.9$$

The Fitted Quadratic Trend Maintenance Model developed for Peugeot Expert vehicle is $Y_t = 16654 + 3299*t - 90.0*t^2$ (3.20)

Analytical analysis of forecasting results between (2015 – 2019) for the model developed for Peugeot Expert (i.e. $t = 0.004$)

$$Y_t = 16654 + 3299 \times 0.004 - 90.0 \times 0.004^2 = 4206.28$$

The Fitted Growth Curve Trend Maintenance Model developed for taxi Cab vehicle is $Y_t = 17859.5 * (1.07296^{**t})$ (3.21)

Y_t = the dependent variable or the predicted maintenance cost

t = the predicted period

$$\text{for } t = 0.004, Y_t = 17859.5 \times 1.07296^{0.004} = 3879.06$$

(b) Models Developed for Replacement Costs

The Fitted S-Curve Trend Model developed for Replacement cost of Sienna Vehicle is

$$Y_t = (10^{**6}) / (7.16260 + 2.25479*(0.774197^{**t})) \quad (3.22)$$

Analytical analysis of forecasting results between (2015 – 2019) for the model developed for Sienna, (i.e. $t = 0.000474$)

$$Y_t = \frac{(10^6)}{(7.16260 + 2.25479(0.774197^{0.00474}))} = 1374.31$$

$$Y_t = \frac{(10^6)}{(7.16260 + 2.25479(0.774197)^{12})} = 1374.31$$

2. The Fitted S-Curve Trend Model developed for Replacement cost of Peugeot Expert Vehicle is $Y_t = (10^{**6}) / (4.93183 + 1.97816*(0.896692^{**t}))$

(3.23), for $t = 0.0014$

$$Y_t = \frac{[10^6]}{(4.93183 + 1.97816(0.896692^{0.0014}))} = 1809.87$$

The Fitted Quadratic Trend Model developed for Replacement cost of Toyota Hiace Vehicle is $Y_t = 187383 + 1232*t + 21.7*t^{**2}$ (3.24)

For $t = 0.00047$, $Y_t = 187383 + 1232 \times 0.00047 + 21.7 \times 0.00047^2 = 1985.06$

Y_t = the dependent variable or the predicted replacement cost

t = the predicted period

(c) Models Developed for Income Generated

The Fitted Quadratic Trend Model developed for Income Generated cost of Peugeot Expert Vehicle is $Y_t = 91558 - 2930*t + 46.4*t^{**2}$

(3.25)

for $t = 0.000010$, $Y_t = 91558 - 2930 \times 0.000010 + 46.4 \times 0.000010^2 = 6495.34$

The Fitted Growth Curve Trend Model developed for Income costs of J5 vehicle is $Y_t = 89992.0 * (0.97633^{**t})$ (3.26)

For $t = 0.002413$, $Y_t = 89992.0 \times (0.97633^{0.002413}) = 6913.70$

APPENDIX A₃

Table 1		Operational parameters for Nissan Urvan maintenance cost.									
Year	Factor A (Dist., Km)	Factor B (Precip, cubic)	Factor C (Temp. oC)	Factor D (Relat. hum.)	Response Y (Cost # x 1000)	Log A	Log B	Log C	Log D	Log Y	
2005	101616	1620	29.2	148	1969	5.007	3.2095	1.4654	2.1703	3.2942	
2006	102784	1500	28.5	156.9	2250	5.012	3.1761	1.4548	2.1956	3.3522	
2007	105120	1650.3	28.96	176.98	2520	5.0217	3.2176	1.4618	2.2479	3.4014	
2008	113296	1507	28.15	159.56	2815	5.0542	3.1781	1.4495	2.2029	3.4495	
2009	116800	1579.1	28.3	126.2	3030	5.0674	3.1984	1.4518	2.1011	3.4814	
2010	117384	1506.6	27.8	122.65	3240	5.0696	3.178	1.444	2.089	3.5105	
2011	117968	1695.4	28.85	129.7	3360	5.0718	3.2293	1.4601	2.1129	3.5263	
2012	118552	1662	27.9	148	3590	5.0739	3.2206	1.4456	2.1703	3.5551	
2013	119720	2294.7	28.3	122.65	3995	5.0782	3.3607	1.4518	2.0887	3.6015	
2014	120304	1695	24.4	129.68	4005	5.0803	3.2292	1.3874	2.1129	3.6026	
10	1133544	16710.1	280.36	1420.32	30774						
Mean =	113354.4	1671.01	28.036	142.032	3077.4						
Table 8		Determination of mean values of Transportation parameters for Replacement Cost.									
Year	Factor A (Dist., Km)	Factor B (Precip, cubic)	Factor C (Temp. oC)	Factor D (Relat. hum.)	Response Y (Cost # x 1000)	Log A	Log B	Log C	Log D	Log Y	
2005	101616	1620	29.2	148	1992	5.007	3.2095	1.4654	2.1703	3.2993	
2006	102784	1500	28.5	156.9	2240	5.012	3.1761	1.4548	2.1956	3.3502	
2007	105120	1650.3	28.96	176.98	2400	5.0217	3.2176	1.4618	2.2479	3.3802	
2008	113296	1507	28.15	159.56	2500	5.0542	3.1781	1.4495	2.2029	3.3979	
2009	116800	1579.1	28.3	126.2	2568	5.0674	3.1984	1.4518	2.1011	3.4096	
2010	117384	1506.6	27.8	122.65	2681	5.0696	3.178	1.444	2.089	3.4283	
2011	117968	1695.4	28.85	129.7	2705	5.0718	3.2293	1.4601	2.1129	3.4322	
2012	118552	1662	27.9	148	2805	5.0739	3.2206	1.4456	2.1703	3.4479	
2013	119720	2294.7	28.3	122.65	2856	5.0782	3.3607	1.4518	2.0887	3.4558	
2014	120304	1695	24.4	129.68	2943	5.0803	3.2292	1.3874	2.1129	3.4688	
10	1133544	16710.1	280.36	1420.32	25690						
Mean =	113354.4	1671.01	28.036	142.032	2569						
Table 13		Determination of mean values of Transportation parameters for Income Generated.									
Year	Factor A (Dist., Km)	Factor B (Precip, cubic)	Factor C (Temp. oC)	Factor D (Relat. hum.)	Response Y (Cost # x 1000)	Log A	Log B	Log C	Log D	Log Y	
2005	101616	1620	29.2	148	9807.3	5.007	3.2095	1.4654	2.1703	3.9915	
2006	102784	1500	28.5	156.9	9782.4	5.012	3.1761	1.4548	2.1956	3.9904	
2007	105120	1650.3	28.96	176.98	9660	5.0217	3.2176	1.4618	2.2479	3.985	
2008	113296	1507	28.15	159.56	9515	5.0542	3.1781	1.4495	2.2029	3.9784	
2009	116800	1579.1	28.3	126.2	9020	5.0674	3.1984	1.4518	2.1011	3.9552	
2010	117384	1506.6	27.8	122.65	8850	5.0696	3.178	1.444	2.089	3.9469	
2011	117968	1695.4	28.85	129.7	8610	5.0718	3.2293	1.4601	2.1129	3.935	
2012	118552	1662	27.9	148	8489.7	5.0739	3.2206	1.4456	2.1703	3.9289	
2013	119720	2294.7	28.3	122.65	8340	5.0782	3.3607	1.4518	2.0887	3.9212	
2014	120304	1695	24.4	129.68	8300	5.0803	3.2292	1.3874	2.1129	3.9191	
10	1133544	16710.1	280.36	1420.32	90374.4						
Mean =	113354.4	1671.01	28.036	142.032	9037.44						

APPENDIX B₁: MS Excel Output for Nissan Urvan

stage 14, 2019						
Nissan Urvan						
I	C	R	V _k	V _r	V _{k(i)}	D _k
67958.28	50076.39	250732	-17880.8	191851.03	-17881.9	keep
73867.7	47691.8	238195.4	-26174.8	61784.30	-26175.9	keep
75345.05	46737.96	226285.6	-28628.0	49893.44	-28628.1	keep
76851.96	45803.2	214971.3	-31058.8	38561.24	-31058.8	keep
78388.99	44887.14	204222.8	-33530.9	37812.70	-33530.9	keep
79956.77	43989.4	194011.6	-35977.4	37631.50	-35977.4	keep
81555.91	43109.61	184311.1	-38446.3	39020.70	-38446.3	keep
83187.03	42247.42	175095.5	-50948.3	-50313.60	-50948.3	keep
84850.77	41402.47	166340.7	-43448.25	50073.4	-43448.25	keep
86547.78	40574.42	158023.7	-45973.2	58485.4	-45973.2	keep
88278.74	39762.93	150122.5	-48554.5	60283.60	-48554.5	keep
90044.31	38967.67	142616.4	-51086.6	61783.61	-51086.6	keep
91845.2	38188.32	135485.6	-51664.0	62934.50	-51664.0	keep
93682.1	37424.55	128711.3	-56247.6	63680.80	56247.6	keep
95555.75	36676.06					
Stage 13, 2018						
69325.86	51870.56	247613	-17477.6	81233.12	-17477.6	Keep
75354.2	48028.3	235232.4	-53511.6	88810.77	-53511.6	Keep
81382.54	45626.89	223470.7	-64360.6	100572.39	-64360.6	Keep
87893.14	43345.54	212297.2	-75606.3	111745.92	-75606.3	Keep
94924.59	41178.26	201682.3	-87250.2	122360.78	-87250.2	Keep
102518.6	39119.35	191598.2	-99376.6	132444.9	-99376.6	Keep
110720	37163.38	182018.3	-142005	-132014.81	-142005	keep
119577.6	35305.21	172917.4	-151136	-141115.73	-151136	keep
129143.9	33539.95	164271.5	-157782	-149771.6	-157782	keep
139475.4	31862.96	156057.9	-159577	-151985.17	-153577	keep
150633.4	30269.81	148255	-168874	165778.07	-168874	keep
162684.1	28756.32	140842.3	-185014	-183205.82	-185014	keep
175698.8	27318.5	133800.2	-202047	190244.94	-202047	keep
189754.7	25952.58					
Stage 12, 2017						
146359.71	77901.48	242751	21875.30	18612.21	18612.21	Replace
77805.8	43278.6	230613.5	20134.8	171329.98	171348	Replace
84030.26	41114.67	219082.8	-143498	-182870.65	-182871	Replace
88231.78	39058.94	208128.6	-160929	-193826.79	-193827	Replace
92643.37	37105.99	197722.2	-177907	-204229.2	-204229	Replace
97275.53	35250.69	187836.1	-194470	-214119.3	-214119	Replace

102139.3	33488.16	178444.3	-180654	-223498.14	-223498	Replace
107246.3	31813.75	169522.1	-200645	-232421.5	-232421.5	Replace
112608.6	30223.06	161046	-221445	-240888	-240888	Replace
118239	28711.91	152993.7	-243133	-248954.8	-248954.8	Replace
124151	27276.31	145344	-255756	-266560.4	-266560.4	Replace
130358.5	25912.5	138076.8	-259460	-289455	-289455	Replace
373058.07	24616.87					

Stage 11, 2016

77682.05	44235.77	239604	-192649	854540.38	-192649	keep
79267.4	43368.4	234811.9	-207239	902464.5	-207239	keep
80852.75	42501.03	230115.7	-221222	949422.68	-221222	keep
82469.8	41651.01	225513.4	-234644	99545.012	-234644	keep
84119.2	40817.99	221003.1	-247532	304065.3	-247532	keep
85801.58	40001.63	216583	-259917	308375.34	-259917	keep
87517.61	39201.6	212251.4	-271825	312817	-271825	keep
89267.97	38417.57	208006.4	-251595	317152.03	-251595	keep
91053.33	37649.22	203846.2	-294312	421212.20	-294312	keep
92874.39	36896.23	199769.3	-304938	225289.08	-304938	keep
94731.88	36158.31	195773.9	-315176	329274.5	-315176	keep
96626.52	35435.14					

Stage 10, 2015

78850	42052.5	234,300	-369446	358001.08-	-369446	keep
83,000	40,050	229614	-78946.5	-42811.40	-78946.5	keep
84660	39249	225021.7	-42425.5	-39473.18	42425.5	keep
86353.2	38464.02	220521.3	-64044.7	-632260.43	-64044.7	keep
88080.26	37694.74	216110.9	-310595.2	-299147.2	-310595.2	keep
89841.87	36940.84	211788.6	-465681	-349775.3	-465681	keep
91638.71	36202.03	207552.9	-229030.8	-217744.7	-229030.8	keep
93471.48	35477.99	203401.8	-315675.5	-254166.1	-315675.7	keep
95340.91	34768.43	199333.8	-176185.5	-168603.0	-176185.5	keep
97247.73	34073.06	195347.1	-237046	-220799.69	-237046	keep
99192.68	33391.6					

Stage 9, 2014

62550	47940	231,600	-244056	-200238	-244056	keep
83,400	39,950	229,284	-293639	-202547	-293639	keep
85,068	39,151	226,991	-312544	-304845	-312544	keep
86,769	38,368	224,721	-330934	-317120	-330934	keep
88,505	37,601	222,474	-348832	-3409347	-348832	Keep
90,275	36,849	220,249	-366245	-361592	-366245	Keep
92,080	36,112	218,047	-383231	-313794	-383231	Keep
93,922	35,389	215,866	-368028	-355975	-368028	Keep
95,800	34,682	213,708	-415996	-408143	-415996	Keep

97,716	33,988	
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Stage 8, 2013

56199.06	26418	230,500	-29784	-280237	-29784	Keep
84,897	25,900	228195	-352629	-344685	-352629	Keep
85745.97	25641	225913.1	-372655	-356971	-372655	Keep
86603.43	25384.59	223653.9	-392147	-359224	-392147	Keep
87469.46	25130.74	221417.4	-411154	-401458	-411154	Keep
88344.16	24879.44	219203.2	-429700	-413674	-429700	Keep
89227.6	24630.64	217011.2	-447827	-435852	-447827	Keep
90119.88	24384.34	214841.1	-433759	-428035	-433759	Keep
91021.07	24140.49					

Stage 7, 2012

81795	35280	220,150	-29776.04	-254290	-29776.04	Keep
86,100	33,600	209142.5	-405128	-395288	-405128	Keep
87822	33264	198685.4	-427213	-415765	-427213	Keep
89578.44	32931.36	188751.1	-448794	-435687	-448794	Keep
91370.01	32602.05	179313.6	-469924	-445128	-469924	Keep
93197.41	32276.03	170347.9	-490628	-484096	-490628	Keep
95061.36	31953.27	161830.5	-510929	-502613	-510929	Keep
96962.58	31633.73					

Stage 6, 2011

86730	33048	218,100	-401026	-400251	-401026	Keep
88,500	32,400	215919	-461227	-453421	-461227	Keep
90270	31752	213759.8	-485725	-475594	-485725	Keep
92075.4	31116.96	211622.2	-509753	-467727	-509753	Keep
93916.91	30494.62	209506	-533345	-529844	-533345	Keep
95795.25	29884.73	207410.9	-556536	-541938	-556536	Keep
97711.15	29287.03	205336.8				

Stage 5, 2010

85690	31815	215,680	-454900	-445384	-454900	Keep
90,200	30,300	215680	-521128	-515383	-521128	Keep
94710	28785	213523.2	-551649	-547540	-551649	Keep
96604.2	28785	211388	-577570	-570675	-577570	Keep
98536.28	27345.75	209274.1	-604538	-601789	-604538	Keep
100507	25978.46	207181.3				

Stage 4, 2009

90392.5	29557.5	210,000	-515738	-510549	-515738	Keep
95,150	28,150	199500	-588127	-571048	-588127	Keep
99907.5	26742.5	189525	-624816	-601024	-624816	Keep
104902.9	25405.38	180048.8	-657071	-650498	-657071	Keep

110148 24135.11 171046.3

Stage 3, 2008

91200	26460	210,000	-580478	-574205	-580478	Keep
96,000	25,200	199500	-658930	-654700	-658930	Keep
97920	23940	189525	-658793	-654678	-658793	Keep
99878.4	22743	180048.8				

Stage 2, 2007

92932.8	23625	202,400	-649779	-634726	-649779	Keep
97,824	22,500	198352	-734254	-728776	-734254	Keep
100269.6	21937.5	193393.2				

Stage 1, 2006

95621.18	21166.75	199,200	-724239	-723438	-724239	Keep
98,073	19,690	189240				

APPENDIX B₂: MS Excel Output for Sienna

stage 14, 2019						
Sienna						
I	C	R	V _k	V _r	V _{k(i)}	D _k
56301.15	71079.66	138403	14779.6	149855.1	14779.6	keep
61196.9	65814.5	131482.9	54620.8	562934.0	54620.8	keep
62420.84	64498.21	124908.7	22088.4	96356.81	22088.4	keep
63669.25	63208.25	118663.3	-46102.1	90114.28	-46102.1	keep
64942.64	61944.08	112730.1	-2999.68	84178.21	-2999.21	keep
66241.49	60705.2	107093.6	-5537.30	78541.70	-5537.30	keep
67566.32	59491.1	101738.9	-8079.19	85187.29	-8079.19	keep
68917.65	58301.27	96651.98	-10618.6	68100.1	-10618.6	keep
70296	57135.25	91819.38	-13167.6	63267.5	-13167.6	keep
71701.92	55992.54	87228.41	-15714.5	58676.59	-15714.5	keep
73135.96	54872.69	82866.99	-18267.3	54318.1	-18267.3	keep
74598.68	53775.24	78723.64	-20827.4	50174.74	-20827.4	keep
76090.65	52699.73	74787.46	-23395.1	46238.56	-23395.1	keep
77612.47	51645.74	71048.08	-25967.8	42497.18	-25967.8	keep
79164.72	50612.82					

Stage 13, 2018

58364.89	67402.26	138054	23817.92	45498.19	23817.85	keep
63440.1	62409.5	124248.6	30359.4	31693.79	30359.4	Keep
64074.5	61161.31	118036.2	-8353.89	25481.36	-8353.89	keep
64715.25	59938.08	112134.4	-5239.18	19579.55	-5239.18	keep
65362.4	58739.32	106527.6	-9623.64	13973.12	-9623.64	keep
66016.02	57564.54	101201.3	-13988.7	86460.13	-13988.7	keep
66676.18	56413.24	96141.2	-18339.3	35860.819	-18339.3	keep
67342.94	55284.98	91334.14	-22678.3	-20223.17	-22678.3	keep
68016.37	54179.28	86767.43	-26998.7	-2587.38	-26998.7	keep
68696.54	53095.69	82429.06	-31318.2	-300128.8	-31318.2	keep
69383.5	52033.78	78307.61	-35616	-34247.20	-35616	keep
70077.34	50993.11	74392.23	-39964.7	-38163.58	-39964.7	keep
70778.11	49973.24	70672.62	-44196.5	-41882.20	-44196.5	keep
71485.89	48973.78					

Stage 12, 2017

62399.23	60184.49	137605	21607.11	45401.86	21607.11	keep
65683.4	59004.4	137605	25014.68	45303.82	25014.80	keep
66997.07	56054.18	134852.9	-11779.9	46549.76	-11779.9	keep
68337.01	53251.47	134852.9	-20326.7	47550.80	-20326.7	keep
69703.75	50588.9	134852.9	-28737.6	48549.76	-28737.6	keep
71097.82	48059.45	134852.9	-37027.3	48650.76	-37027.3	keep
72519.78	45656.48	134852.9	-45206.4	49549.76	-45206.4	keep
73970.18	43373.66	132155.8	-53274.8	59852.70	-53274.8	keep
75449.58	41204.97	130834.3	-61243.5	78531.14	-61243.5	keep
76958.57	39144.72	128217.6	-69128.4	70914.46	-69128.4	keep
78497.74	37187.49	128217.6	-76926.2	35914.46	-76926.2	keep
80067.7	35328.11	125653.2	-24650.4	33350.16	-24650.4	keep
81669.05	33561.71					

Stage 11, 2016

66568.07	56711.29	137030	21744.36	22519.02	21744.36	keep
67926.6	55599.3	137030	12687.49	20519.02	12687.49	keep
68266.23	54487.31	137030	-20557.6	25519.02	-20557.6	keep
68607.56	53397.57	137030	-25533.7	26519.02	-25533.7	keep
68950.6	52329.62	137030	-45357.5	50519.02	-45357.5	keep
70329.61	51283.02	137030	-56072.7	57519.02	-56072.7	keep
71736.21	50257.36	134289.4	-66680.3	67778.42	-66680.3	keep
75323.02	49252.22	132946.5	-79341.7	80435.526	-79341.7	keep
76829.48	48267.17	132946.5	-89804.8	94350.26	-89804.8	keep
77213.62	47301.83	130287.6	-92035.9	93776.59	-92035.9	keep

77599.69	46355.79	127681.8	-108167	11170.44	-108167	keep
77987.69	46124.01					

Stage 10, 2015

		137,000		-	-	
66642.5	51255.75		31642.39	-30493.38	31642.39	Keep
70,150	48,815	137100	-3647.51	-34630.38	-3647.51	keep
71553	47838.7	127000	-39271.9	-35930.38	-39271.9	keep
72984.06	46881.93	135000	-31635.8	-30920.38	-31635.8	keep
74443.74	45944.29	130150	-83856.9	-81343.38	-83856.9	keep
75932.62	45025.4	132150	-86980	-77343.38	-86980	keep
77451.27	44124.89	130450	-120007	-11343.38	-120007	keep
79000.29	43242.4	130170	-115100	-11343.38	-115100	keep
80580.3	42377.55	123642.5	-13808	-17850.88	-13808	keep
82191.91	41530	122406.1	-13969	-12987.31	-13969	keep
82602.87	41322.35					

Stage 9, 2014

		135,240		-	-	
53550	58560		41516.62	-37868	41516.62	Keep
71,400	48,800	133,888	-31247.5	-29220	-31247.5	Keep
72,828	47,824	132,549	-41275.9	-40559	-41275.9	keep
74,285	46,868	131,223	-39052.9	-28885	-39052.9	keep
75,770	45,930	129,911	-303697	-23197	-303697	keep
77,286	45,012	128,612	-39254	-34496	-39254	keep
78,831	44,111	127,326	-34727	-25782	-34727	keep
80,408	43,229	126,053	-52278	-51055	-52278	keep
82,016	42,365	124,792	-37659	-28316	-37659	keep
83,656	40,246	123,544				

Stage 8, 2013

		133,600		-66404	-63753	-66404	Keep
75558	47022		-62247.5	-55089	-62247.5	Keep	
77,100	46,100	132264	-66508	-6412	-66508	Keep	
77871	45639	130941.4	-52520	-47721	-52520	Keep	
78649.71	45182.61	129631.9	-68402	-759017	-68402	Keep	
79436.21	44730.78	128335.6	-155201	-80301	-155201	Keep	
80230.57	44283.48	127052.3	-71919	-71571	-71919	Keep	
81032.87	43840.64	125781.7	-70719	-62829	-70719	Keep	
81843.2	43402.23	124523.9					
82661.64	42968.21						

Stage 7, 2012

		132,900		8751.71	7263.00	7263.00	Replace
70200	46252.5		-109039	-110830	-110830	Replace	
78,000	44,050	126255					

79560	43609.5	119942.3	-142458	-171145	-171145	Replace
81151.2	43173.41	113945.1	-123498	-160142	-160142	Replace
82774.22	42741.67	108247.9	-128435	-178840	-178840	Replace
84429.71	42314.25	102835.5	-197317	-234252	-234252	Replace
86118.3	41891.11	97693.71	-161460	-239394	-239394	Replace
87840.67	41472.2					

Stage 6, 2011

78792	39984	130,900	-122995	-118580	-122995	Keep
80,400	39,200	130900	-132032	-131580	-132032	Keep
82008	38416	130900	-126050	-125580	-126050	Keep
83648.16	37647.68	130900	-136498	-135580	-136498	Keep
85321.12	36894.73	128282	-126861	-121198	-126861	Keep
87027.55	36156.83	126999.2	-138187	-132481	-138187	Keep
88768.1	35433.7					

Stage 5, 2010

77425	38850	128,000	-161570	-159277	-161570	Keep
81,500	37,000	128000	-166532	-159367	-166532	Keep
85575	35150	126720	-176475	-170557	-176475	Keep
87286.5	35150	125452.8	-158635	-151824	-158635	Keep
89032.23	33392.5	124198.3	-182501	-181079	-182501	Keep
90812.87	31722.88	122956.3				

Stage 4, 2009

80409	33915	125,000	-228064	-224791	-228064	Keep
82,050	32,300	118750	-246282	-231041	-246282	Keep
86152.5	30685	112812.5	-291943	-236979	-291943	Keep
90460.13	29150.75	107171.9	-319944	-302619	-319944	Keep
94983.13	27693.21	101813.3				

Stage 3, 2008

79990	30502.5	125,000	-237552	-226328	-237552	Keep
84,200	29,050	118750	-201432	-200578	-201432	Keep
85884	27597.5	112812.5	-250229	-248516	-250229	Keep
87601.68	26217.63	107171.9				

Stage 2, 2007

82745	25620	115,000	-334677	-320717	-334677	Keep
87,100	24,400	112700	-364132	-363017	-364132	Keep
89277.5	23790	109882.5				

Stage 1, 2006

87750	20425	110,000	-402002	-401132	-402002	Keep
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90,000	19,000	104500
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APPENDIX B₃: MS Excel Output for Peugeot Expert

stage 14, 2019

Peugeot Expert

I	C	R	V _k	V _r	V _{k(i)}	D _k
53671.32	49049.92	186510	-4021.4	44131	-4021.4	keep
	45207.3		-			
59634.8		177184.5	14427.5	348050.5	-14427.5	keep
			-			
59754.07	44303.15	168325.3	15450.9	16594.75	-15450.9	keep
			-			
59873.58	43417.09	159909	16456.5	16530.011	-16456.5	keep
			-			
59993.32	42548.75	151913.6	17444.6	109534.561	-17444.576	keep
			-			
60113.31	41697.77	144317.9	18415.5	101938.883	-18415.537	keep
			-			
60233.54	40863.82	137102	19369.7	94722.9885	-19369.72	keep
			-			
60354.01	40046.54	130246.9	20307.5	87867.8891	-20307.463	keep
			-			
60474.71	39245.61	123734.5	21229.1	81355.5446	-21229.102	keep
60595.66	38460.7	117547.8	-22135	75168.8174	-22134.963	keep
			-			
60716.85	37691.49	111670.4	23025.4	69291.4265	-23025.369	keep
			-			
60838.29	36937.66	106086.9	23900.6	63707.9052	-23900.632	keep
			-			
60959.96	36198.9	100782.6	24761.1	58403.5599	-24761.062	keep
61081.88	35474.92	95743.43	-25607	53364.432	-25606.96	keep
61204.05	34765.43					

Stage 13, 2018

56406.86	47884.28	184804	-13144	146231	-13144	keep
61311.8	44337.3	170019.7	-31402	101446	-31402	keep
			-			
62538.04	43450.55	156418.1	34538.4	87845.1056	-34538.4	keep
			-			
63788.8	42581.54	143904.7	37663.7	75331.6572	-37663.7	keep
			-			
65064.57	41729.91	132392.3	40779.2	63819.2846	-40779.2	keep
			-			
66365.86	40895.31	121800.9	43886.1	53227.9018	-43886.1	keep
			-			
67693.18	40077.41	112056.8	46985.5	48483.8297	-46985.5	keep
			-			
69047.05	39275.86	103092.3	50078.6	64519.2833	-50078.6	keep
70427.99	38490.34	94844.9	-	22710.9006	-13166.7	keep

			13166.7				
71836.55	37720.54	87257.31	-56251	86840.30	-56251	keep	
73273.28	36966.12	80276.72	-59332	11703.7239	-59332	keep	
74738.74	36226.8	73854.59	-24126	52810.585	-24126	keep	
			-				
76233.52	35502.27	67946.22	65492.3	-64600.78	-65492.3	keep	
77758.19	34792.22						

Stage 12, 2017

		182937					
59927.52	44153.05		28918.4	73673	-28918.446	keep	
	43287.3						
63081.6		164643.3	51196.3	55379.3	-51196.3	keep	
64343.23	42421.55	148179	56460.1	68914.97	-56460.1	keep	
65630.1	41573.12	133361.1	61720.7	74097.073	-61720.714	keep	
66942.7	40741.66	120025	66980.3	70760.9657	-66980.274	keep	
68281.55	39926.83	108022.5	72240.8	-70401.53	-72240.813	keep	
69647.18	39128.29	97220.22	77504.4	-82043.778	-77504.386	keep	
71040.13	38345.72	87498.2	-82773	-81765.8	-82773.051	keep	
72460.93	37578.81	78748.38	88048.9	-80515.62	-88048.865	keep	
73910.15	36827.23	70873.54	93333.9	-92390.458	-93333.888	keep	
75388.35	36090.69	63786.19	98630.2	-905477.8	-98630.183	keep	
76896.12	35368.88	57407.57	-103940	-101856.43	-103939.81	keep	
78434.04	34661.5						

Stage 11, 2016

61696.99	44160.38	180899	-46455	52156	-46455	keep	
64944.2	42057.5	162809.1	-74083	-73066.1	-74083	keep	
66243.08	41216.35	146528.2	81486.8	-80214.81	-81486.8	keep	
67567.95	40392.02	131875.4	88896.6	-86867.629	-88896.6	keep	
68919.3	39584.18	118687.8	96315.4	-95055.166	-96315.397	keep	
70297.69	38792.5	106819.1	-303746	-29023.949	-303746	keep	
71703.64	38016.65	96137.15	-41191	-40605.8	-41191	keep	
73137.72	37256.32	86523.43	-11865	-10219.59	-11865	keep	
74600.47	36511.19	77871.09	-126138	-11871.912	-126138.15	keep	
76092.48	35780.97	70083.98	-433645	42659.021	-433645.4	keep	
77614.33	35065.35	63075.58	-54179	-53667	-54179	keep	

79166.62 34364.04

Stage 10, 2015

		178,100		-			
64220	41790		68885.1	-58988.00	-68885.1	keep	
67,600	39,800	169195	-101883	-17893.00	-101883	keep	
70980	39004	160735.3	21346.3	-20352.75	-21346.3	keep	
74529	38223.92	152698.5	-125202	-124389.51	-125202	keep	
78255.45	37459.44	145063.6	-137111	-12724.44	-137111	keep	
82168.22	36710.25	137810.4	-149204	-148277	-149204	keep	
86276.63	35976.05	130919.9	-161492	-156168	-161492	keep	
90590.47	35256.53	124373.9	-173988	-162714	-173988	keep	
95119.99	34551.4	118155.2	-186707	-68933	-186707	keep	
99875.99	33860.37	112247.4	-199661	-74841	-199661	keep	
104869.8	33691.07						

Stage 9, 2014

		177,200		-			
57842.5	47880		78847.6	-76532	-78847.6	Keep	
68,050	39,900	168,340	-33033	-27474	-33033	keep	
71,453	37,905	159,923	-47010	-45891	-47010	keep	
75,025	36,010	151,927	-64217	-63887	-64217	keep	
78,776	34,209	144,331	-61679	-61483	-61679	keep	
82,715	32,499	137,114	-69420	-68700	-69420	keep	
86,851	30,874	130,258	-71469	-65556	-71469	keep	
91,194	29,330	123,745	-35852	-202069	-35852	keep	
95,753	27,864	117,558	-59596	-58256	-59596	keep	
100,541	26,470						

Stage 8, 2013

		173,300					
63450	37975.8		8614.15	5861.26.0	5861.26	Replace	
70,500	37,900	169834	-142633	-15749.6	-157496	Replace	
74025	36005	166437.3	-155030	-16089.3	-160893	Replace	
77726.25	34204.75	163108.6	-107739	-16422.1	-164221	Replace	
81612.56	32494.51	159846.4	13079.7	-16748.4	-167484	Replace	
85693.19	30869.79	156649.5	-154244	-170681	-170681	Replace	
89977.85	29326.3	153516.5	-78121	-113814	-113814	Replace	
94476.74	27859.98	150446.2	10246.8	-17688.4	-176884	Replace	
99200.58	26466.98						

Stage 7, 2012

		170,050		-			
70442.5	36802.5		17767.0	-17292.4	-177670	Keep	
74,150	35,050	161547.5	-181733	-19142.7	-181733	Keep	
75633	34699.5	153470.1	-259604	-249504	-259604	Keep	
77145.66	34352.51	145796.6	-150532	-20717.7	-150532	Keep	
78688.57	34008.98	138506.8	27547.6	-21446.7	-27547.6	Keep	
80262.34	33668.89	131581.4	-130837	-121393	-130837	Keep	
81867.59	33332.2	125002.4	-126656	-125972	-126656	Keep	
83504.94	32998.88						

Stage 6, 2011

		166,500		-123691	-114201	-123691	Keep
74529	33762		-144683	-134231	-144683	Keep	
76,050	33,100	166500	-171097	-164211	-171097	Keep	
77571	32438	166500	-197865	-112121	-197865	Keep	
79122.42	31789.24	166500	-125028	217531	-125028	Keep	
80704.87	31153.46	163170	-152626	219163	-152626	Keep	
82318.97	30530.39	161538.3					
83965.35	29919.78						

Stage 5, 2010

		166,500		-165339	246388	-165339	Keep
73672.5	32025		-191733	-126388	-191733	Keep	
77,550	30,500	166500	-123549	200053	-123549	Keep	
81427.5	28975	164835	-151946	-149701	-151946	Keep	
83056.05	28975	163186.7	-182219	-151333	-182219	Keep	
84717.17	27526.25	161554.8					
86411.51	26149.94						

Stage 4, 2009

		165,000		-113191	-104849	-113191	Keep
78302	30450		-342633	-203099	-342633	Keep	
79,900	29,000	156750					
83895	27550	148912.5	27989.4	-26093.7	-27989.4	Keep	
88089.75	26172.5	141466.9	21386.3	-20838.2	-21386.3	Keep	
92494.24	24863.88						

Stage 3, 2008

		155,000		-265986	-223090	-265986	Keep
79990	27195						
84,200	25,900	147250	-	-190840	-200933	Keep	

			20093.3				
85884	24605	139887.5	-241173	-238203	-241173	Keep	
87601.68	23374.75						
Stage 2, 2007							
81700	22365	152,000	-225320	-216555	-225320	Keep	
86,000	21,300	148960	-265633	-249595	-265633	Keep	
88150	20767.5						
Stage 1, 2006							
86092.5	22467.5	150,000	188946	253033	188946	Keep	
88,300	20,900						

APPENDIX B₄: MS EXCEL OUTPUT FOR J5

Stage 14 J5 2019

I	C	R	V _k	V _r	V _{k(i)}	D _k
61134.31	62383.03	199889	1248.721	183837	1248.721	keep
64351.9	56970.8	189894.6	-7381.1	173842.55	-7381.1	keep
64480.6	56401.09	180399.8	-8079.51	164347.823	8079.5118	keep
64609.57	55837.08	171379.8	-8772.48	155327.831	8772.4839	keep
64738.78	55278.71	162810.8	-9460.07	146758.84	9460.0739	keep
64868.26	54725.92	154670.3	-10142.3	138618.298	10142.339	keep
64998	54178.66	146936.8	-10819.3	130884.783	10819.334	keep
65127.99	53636.88	139589.9	-11491.1	123537.944	11491.117	keep
65258.25	53100.51	132610.4	-12157.7	116558.447	12157.742	keep
65388.77	52569.5	125979.9	-12819.3	109927.924	12819.263	keep
65519.54	52043.81	119680.9	-13475.7	103628.928	13475.736	keep
65650.58	51523.37	113696.9	-14127.2	97644.8816	14127.213	keep
65781.88	51008.14	108012	-14773.7	91960.0376	14773.748	keep
65913.45	50498.06	102611.4	-15415.4	86559.4357	15415.393	keep
66045.28	49993.07					

Stage 13, 2018						
60639.04	59045.76	198302	-34455.9	94061	-344.559	keep
65912	54672	182437.8	-18621.1	78196.84	-18621.1	keep
69207.6	51938.4	167842.8	-25348.7	63601.8128	25348.712	keep
72667.98	49341.48	154415.4	-32099	50174.3878	32098.984	keep
76301.38	46874.41	142062.2	-38887	37821.1568	38887.047	keep
80116.45	44530.69	130697.2	-45728.1	26456.1842	45728.101	keep
84122.27	42304.15	120241.4	-52637.5	16000.4095	-52637.45	keep
88328.38	40188.94	110622.1	-59630.6	63810.9672	59630.557	keep
92744.8	38179.5	101772.3	-66723	-24681.71	66723.048	keep
97382.04	36270.52	93630.54	-73930.8	-10610.457	73930.785	keep
102251.1	34457	86140.1	-81269.9	-18100.901	81269.885	keep
107363.7	32734.15	79248.89	-88756.8	-24992.109	-88756.77	keep
112731.9	31097.44	72908.98	-96408.2	-31332.02	96408.197	keep
118368.5	29542.57					

Stage 12, 2017

64134.41	53420.56	196714	-11058.4	14631	11058.402	keep
67509.9	52373.1	180976.9	-33757.9	-11061.2	-33757.9	keep
70885.4	49754.45	166498.7	-46479.7	-15584.27	-46479.7	keep
74429.66	47266.72	153178.8	-59261.9	-28904.169	-59261.93	keep
78151.15	44903.39	140924.5	-72134.8	-41158.475	72134.808	keep
82058.71	42658.22	129650.6	-85128.6	-52432.437	85128.589	keep
86161.64	40525.31	119278.5	-98273.8	-62804.482	-98273.8	keep
90469.72	38499.04	109736.2	-111601	-72346.76	-111601	keep
94993.21	36574.09	100957.3	-125142	-81125.7	-125142	keep
99742.87	34745.38	92880.75	-138928	-89202.25	-138928	keep
104730	33008.12	85450.29	-152992	-96632.7	-152991.8	keep
109966.5	31357.71	78614.27	-167366	-103468.7	-167366	keep
115464.8	29789.82					

Stage 11, 2016

65689.18	52577.91	195126	-26169.7	-24891	-26169.7	Keep
69146.5	50074.2	175613.4	-52830.2	-50403.6	-52830.2	Keep
72603.83	47570.49	158052.1	-71513	-70965	-71513	Keep
76234.02	45191.97	142246.9	-90304	-70770.2	-90304	Keep

80045.72	42932.37	128022.2	-109248	-121995	-109248	Keep
84048	40785.75	115220	-128391	-124797	-128391	Keep
88250.4	38746.46	103698	-147778	-146319	-147777	keep
92662.92	36809.14	93328.16	-167455	-156689	-167455	keep
97296.07	34968.68	83995.34	-187470	-166022	-187470	keep
102160.9	33220.25	75595.81	-207869	-174421	-207869	keep
107268.9	31559.23	68036.23	-228701	-181981	-228701	keep
112632.4	29981.27					

Stage 10, 2015

66310	50610	193,500	-70591	-61310.6	-70591	Keep
69,800	48,200	183825	-96004	-12278.1	-96004	Keep
73290	45790	174633.8	-119465	-111972	-119465	Keep
76954.5	43500.5	165902.1	-141224	-140372	-141224	keep
80802.23	41325.48	157607	-168999	-161472	-168999	keep
84842.34	39259.2	149726.6	-180379	-156879	-156879	keep
89084.45	37296.24	142240.3	-199566	-164366	199566	keep
93538.68	35431.43	135128.3	-225562	-171478	-225562	keep
98215.61	33659.86	128371.9	-252025	-178234	-252025	keep
103126.4	31976.86	121953.3	-279018	-184653	-279018	keep
108282.7	30378.02					

Stage 9, 2014

63325	51000	192,000	20720.10	16328.51	16328.51	Replace
74,500	42,500	188,160	154781	-172733	-172733	Replace
78,225	40,375	178,752	169822	-182141	-182141	Replace
82,136	38,356	169,814	-18500.4	-19107.9	-19107.9	Replace
86,243	36,438	161,324	-211276	-199567	-199567	Replace
90,555	34,617	153,257	-206319	-207636	-207636	Replace
95,083	32,886	145,595	-261763	-275300	-275300	Replace
99,837	31,241	138,315	-224158	-294578	-294578	Replace
104,829	29,679	131,399	-327175	-349494	-349494	Replace
110,070	28,195					

Stage 8, 2013

67500	46092	190,100	-18330.1	-17329.2	-18330.12	Keep
75,000	46,000	186298	-201733	-200194	-201733	Keep
76500	45080	182572	-213561	-210820	-213561	Keep
78030	44178.4	178920.6	-124930	-11447.1	-124930	Keep
79590.6	43294.83	175342.2	-247572	-22805.0	-247572	Keep

81182.41	42428.94	171835.3	-27507.2	-26155.7	-275072	Keep
82806.06	41580.36	168398.6	-302989	-301993	-302989	Keep
84462.18	40748.75	165030.7	-237871	-208361	-237871	Keep
86151.43	39933.77					

Stage 7, 2012

72257	46305	188,400	-193608	-18360.8	-193608	Keep
76,060	44,100	178980	-233693	-203028	-233693	Keep
77581.2	43659	170031	-247483	-211977	-247483	Keep
79132.82	43222.41	161529.5	-260841	-220479	-260841	Keep
80715.48	42790.19	153453	-285497	-228555	-285497	Keep
82329.79	42362.28	145780.3	-31504.0	-236228	-31504	Keep
83976.39	41938.66	138491.3	-345027	-243517	-345027	Keep
85655.91	41519.27					

Stage 6, 2011

76048	41310	186,600	-250991	-207495	-250991	Keep
77,600	40,500	186600	-270793	-208495	-270793	Keep
79152	39690	186600	-28694.5	-207995	-286945	Keep
80735.04	38896.2	186600	-302679	-208495	-302679	Keep
82349.74	38118.28	182868	-32972.9	-219227	-329729	Keep
83996.74	37355.91	181039.3	-361681	-21980.5	-361681	Keep
85676.67	36608.79					

Stage 5, 2010

75240	41895	185,200	-284336	-220522	-284336	Keep
79,200	39,900	185200	-310093	-230522	-310093	Keep
83160	37905	183348	-332200	-302374	-332200	Keep
84823.2	37905	181514.5	-34959.8	-264207	-349598	Keep
86519.66	36009.75	179699.4	-280239	-276023	-280239	Keep
88250.06	34209.26					

Stage 4, 2009

79870	40015.5	183,000	-264191	-258910	-264191	Keep
81,500	38,110	173850	-253483	-248060	-253483	Keep
85575	36204.5	165157.5	-251571	-240753	-251571	Keep
89853.75	34394.28	156899.6	-225057	-211010	-225057	Keep
94346.44	32674.56					

Stage 3, 2008

79135	38486.7	181,700	-264839	-256942	-264839	Keep
83,300	36,654	172615	-250129	-246027	-250129	Keep
84966	34821.3	163984.3	-279715	-274658	-279715	Keep
86665.32	33080.24					

Stage 2, 2007

81130	25313.4	180,900	-270655	-265845	-270655	Keep
85,400	24,108	177282	-269421	-268063	-269421	Keep
87535	23505.3					

Stage 1, 2006

86872.5	25122.75	180,300	-282405	286851	-282405	Keep
89,100	23,370					

**APPENDIX B₅:MS
EXCEL OUTPUT FOR
FORD**

stage 14, 2019

Ford Bus

I	C	R	V _k	V _r	V _{k(i)}	D _k
56240.57	52190.88	190767	-40491	71834	-40491	keep
59200.6	47662.9	186951.7	-11538	168019	-11537.7	keep
59319	47186.27	183212.6	-12133	164279.7	-12132.7	keep
59437.64	46714.41	179548.4	-12723	160615.4	-12723.2	keep
59556.51	46247.26	175957.4	-13309	157024.4	-13309.3	keep
59675.63	45784.79	172438.3	-13891	153505.3	-13890.8	keep
59794.98	45326.94	168989.5	-14468	150056.5	-14468	keep
59914.57	44873.67	165609.7	-15041	156676.7	-15041	keep
60034.4	44424.94	162297.5	-13610	143364.5	-13610	keep
60154.47	43980.69	159051.6	-13174	140118.6	-13174	keep
60274.78	43540.88	155870.5	-12734	136937.5	-12734	keep
60395.33	43105.47	152753.1	-12290	133820	-12289.9	keep
60516.12	42674.42	149698.1	-128412	130765.1	-12842	keep
60637.15	42247.67	146704.1	-18390	19771.1	-18390	keep
60758.42	41825.2					

Stage 13, 2018

56607.51	49674.92	189430	-82301	85395	-82301.3	keep
61529.9	45995.3	174275.6	-27072	30240.6	-27072.3	keep
64606.4	43695.54	160333.6	-33044	56298.6	-33043.6	keep
67836.71	41510.76	147506.9	-39049	43472	-39049.2	keep
71228.55	39435.22	135706.3	-26103	31671	-26103	keep
74789.98	37463.46	124849.8	-51217	60814.8	-51217	keep
78529.48	35590.29	114861.8	-57407	60826.8	-57407	keep
82455.95	33810.77	105672.9	-63686	64788.2	-63686	keep
86578.75	32120.23	97219.05	-74068	-73159.5	-74068	keep
90907.69	30514.22	89441.53	-76567	-7459.5	-76567	keep
95453.07	28988.51	82286.2	-23199	-22148.8	-23199	keep

100225.7	27539.09	75703.31	-28977	-27331.7	-28977	keep
105237	26162.13	69647.04	-26917	-24388	-26917	keep
110498.9	24854.02					

Stage 12, 2017

61170.22	45214.36	189178	-26938	273470	-26938	keep
64389.7	44327.8	179719.1	-27134	-21110.9	-27134.2	keep
67609.19	42111.41	170733.1	-28541	-21098	-28541	keep
70989.64	40005.84	162196.5	-70033	-66134.5	-70033	keep
74539.13	38005.55	154086.7	-18636.2	-17744.34	-18636.2	keep
78266.08	36105.27	146382.3	-33978.2	-32448.7	-33978.2	keep
82179.39	34300.01	139063.2	-30287	-32767.8	-30287	keep
86288.36	32585.01	132110.1	-317389	-29720.95	-317389	keep
90602.77	30955.76	125504.6	-29715	-26326.45	-29715	keep
95132.91	29407.97	119229.3	-42292	-32601.68	-42292	keep
99889.56	27937.57	113267.9	-55150	-48563.14	-55150	keep
104884	26540.69	107604.5	-168320	-17426.54	-168320	keep
110128.2	25213.66					

Stage 11, 2016

63361.86	44793.32	187846	-65507	-64574	-65507	Keep
66696.7	42660.3	172818.3	-71171	-70602	-71171	Keep
70031.54	40527.29	158992.9	-88046	-87427.2	-88046	Keep
73533.11	38500.92	146273.4	-105065	-104147	-105065	Keep
77209.77	36575.87	134571.6	-12270	-11848.45	-12270	keep
81070.26	34747.08	123805.8	-129701	-127614	-129701	keep
85123.77	33009.73	113901.4	-127401	-117518.6	-127401	keep
89379.96	31359.24	104789.3	-175410	-166630.8	-175410	keep
93848.95	29791.28	96406.11	-143773	-135014	-143773	keep
98541.4	28301.71	88693.62	-212532	-202726.4	-212532	keep
103468.5	26886.63	81598.13	-231732	-229821.9	-231732	keep
108641.9	25542.3					

Stage 10, 2015

65312.5	43522.5	187,900	-85364	124,362.00	-85364	Keep
68,750	41,450	172868	-105902	133,738.00	-105902	Keep
72187.5	39377.5	159038.6	-125237	147,567.44	-125237	Keep
75796.88	37408.63	146315.5	-143535	160,290.52	-143535	Keep
79586.72	35538.19	134610.2	-166319	171,995.76	-166319	Keep
83566.05	33761.28	123841.4	-189506	-	-	keep

				182,764.58	182764.58		
				-	-		
87744.36	32073.22	113934.1	-213072	192,671.90	192671.90	keep	
				-	-		
92131.58	30469.56	104819.4	-237072	201,786.62	201786.62	keep	
				-	-		
96738.15	28946.08	96433.83	-261565	210,172.17	210172.17	keep	
101575.1	27498.78	88719.12	-286608	217886-	217886-	keep	
106653.8	26123.84						

Stage 9, 2014

61157.5	49920	187,600	-135600	-177,713	-135600	Keep
71,950	41,600	178,220	-164088	-187,093	-164088	Keep
75,548	39,520	169,309	-183595	-196,004	-183595	Keep
79,325	37,544	160,844	-202071	-204,469	-202071	Keep
83,291	35,667	152,801	-219620	-212,512	-212512	keep
87,456	33,883	145,161	-243078	-220,152	-220152	keep
91,828	32,189	137,903	-272711	-227,410	-227410	keep
96,420	30,580	131,008	-302912	-234,305	-234305	keep
101,241	29,051	124,458	-333755	-240,855	-240855	keep
106,303	27,598					

Stage 8, 2013

67950	39128.1	186,200	23290.85	18187.20	18187.20	Replace
75,500	39,050	182476	223543	-243615	-243,615	Replace
79275	38269	178826.5	-217010	-227265	-227265	Replace
83238.75	37503.62	175250	-230205	-25020.4	-250204	Replace
87400.69	36753.55	171745	-230267	-234346	-234346	Replace
91770.72	36018.48	168310.1	-238831	-24778.1	-247781	Replace
96359.26	35298.11	164943.9	-247772	-333772	-333772	Replace
101177.2	34592.14	161645	-269497	-344,446	-344446	Replace
106236.1	33900.3					

Stage 7, 2012

73530	39690	184,000	-25373.1	-237,074	-237074	Keep
77,400	37,800	174800	-263215	-246,274	-246274	Keep
78948	37422	166060	-278536	-255,014	-255014	Keep
80526.96	37047.78	157757	-293684	-263,317	-263317	Keep
82137.5	36677.3	149869.2	-315727	-271,205	-271205	Keep
83780.25	36310.53	142375.7	-34630.0	-278,698	-278698	Keep
85455.85	35947.42	135256.9	-383281	-285,817	-235817	Keep
87164.97	35587.95					

Stage 6, 2011

77224	37638	183,600	-293317	-254328	-293317	Keep
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78,800	36,900	183600	-30511.5	-255328	-30511.5	Keep
80376	36162	183600	-322750	-256328	-322750	Keep
81983.52	35438.76	183600	-340229	-257328	-340229	Keep
83623.19	34729.98	179928	-36462.1	-258000	-36462.1	Keep
85295.65	34035.39	178128.7	-397561	-258799	-397561	Keep
87001.57	33354.68					

Stage 5, 2010

78755	38745	182,500	-333327	-275797	-333327	Keep
82,900	36,900	182500	-35111.5	-285797	-351115	Keep
87045	35055	180675	-374740	-277622	-374740	Keep
88785.9	35055	178868.3	-39395.9	-279429	-393959	Keep
90561.62	33302.25	177079.6	-421880	-281217	-421880	Keep
92372.85	31637.14					

Stage 4, 2009

84417.2	36631.35	182,500	-381113	-309,187	-381113	Keep
86,140	34,887	173375	-40236.8	-31831.2	-40236.6	Keep
90447	33142.65	164706.3	-432044	-326,981	-432044	Keep
94969.35	31485.52	156470.9	-457443	-335,216	-457443	Keep
99717.82	29911.24					

Stage 3, 2008

82773.5	32715.9	181,300	-43117.0	-338673	-43117.0	Keep
87,130	31,158	172235	-45834.0	-34773.8	-45834.0	Keep
88872.6	29600.1	163623.3	-491317	-356350	-491317	Keep
90650.05	28120.1					

Stage 2, 2007

85690	24125.85	181,200	-292735	-291295	-292735	Keep
90,200	22,977	177576	-325563	-322919	-325563	Keep
92455	22402.58					

Stage 1, 2006

89700	23278.05	180,350	313157	315559	313157	Keep
92,000	21,654					

APPENDIX B₆: MS EXCEL OUTPUT FOR TOYOTA HIACE

stage 14, 2019						
Toyota Hiace						
I	C	R	V _k	V _r	V _{k(i)}	D _k
65051.44	43111.03	200374	-21940	264646	-21940	keep
68475.2	39370.8	190355.3	-29104	354627.3	-29104.4	keep

					-	
68612.15	38977.09	180837.5	-29635	45109.5	29635.058	keep
68749.37	38587.32	171795.7	-30162	36067.65	-30162	keep
68886.87	38201.45	163205.9	-30685	127478	-30685	keep
					-	
69024.65	37819.43	155045.6	-31205.2	119317.6	31205.214	keep
69162.7	37441.24	147293.3	-31721.5	111565.3	-31721.5	keep
					-	
69301.02	37066.83	139928.6	-32234.2	104200.637	32234.195	keep
69439.62	36696.16	132932.2	-32743.5	97204.21	-32743.5	keep
					-	
69578.5	36329.2	126285.6	-33249.3	90557.6	33249.306	keep
					-	
69717.66	35965.9	119971.3	-33751.8	84243.32	33751.755	keep
69857.1	35606.25	113972.7	-34250.8	78244.75	-34250.85	keep
69996.81	35250.18	108274.1	-34746.6	72546.11	-34746.6	keep
70136.8	34897.68	102860.4	-35239	67132.41	-35239	keep
70277.08	34548.7					

Stage 13, 2018

65222.94	42288.91	199728	-44874.4	58332	-44874.4	keep
70894.5	39156.4	189741.6	-60842.5	84345.6	-60842.5	keep
74439.23	37198.58	180254.5	-66875.7	83858.52	-66875.7	keep
78161.19	35338.65	171241.8	-72984.6	92845.8	-72984.6	keep
82069.25	33571.72	162679.7	-79183	81283.70	-79183	keep
86172.71	31893.13	154545.7	-85484.8	130149.19	-85484.79	keep
90481.34	30298.48	146818.4	-91904.3	154224.31	-91904.33	keep
95005.41	28783.55	139477.5	-198456	-191848	-198456	keep
99755.68	27344.37	132503.6	-105155	-103236.41	-105155	keep
104743.5	25977.16	125878.5	-112016	-15517.55	-112016	keep
109980.6	24678.3	119584.5	-219054	-21811.5	-219054	keep
					-	
115479.7	23444.38	113605.3	-226286	-21790.695	226286.14	keep
121253.7	22272.16	107925	-133728	-33470.96	-133728	keep
127316.3	21158.56					

Stage 12, 2017

69648.21	39720.94	199039	-74801.7	-73974	-74801.4	Keep
73313.9	38942.1	183115.9	-95214.3	-94970.12	-95214.3	keep
78812.44	36995	168466.6	-108693	-107546.39	-108693	keep
84723.38	35145.25	154989.3	-122563	-121023.72	-122563	keep
91077.63	33387.98	142590.1	-136873	-135422.86	-136873	keep
					-	
97908.45	31718.58	131182.9	-151675	-142830.07	151674.66	keep
					-	
105251.6	30132.65	120688.3	-167023	-163324.71	167023.25	keep

113145.5	28626.02	111033.2	-182976	-172979.77	-182976	keep
					-	
121631.4	27194.72	102150.6	-199591	-181862.43	199591.41	keep
					-	
130753.7	25834.98	93978.53	-216934	-215034.47	216934.35	keep
140560.2	24543.24	86460.24	-235071	-227552.76	-235071	keep
					-	
151102.3	23316.07	79543.42	-254072	-244469.58	254072.32	keep
162434.9	22150.27					

Stage 11, 2016

71946.64	40664.19	198307	-156256	-155939	-156256	Keep
					-	
75733.3	38727.8	178476.3	-132220	-125769.7	-132220	Keep
79519.97	36791.41	160628.7	-151422	-193617.33	-151422	Keep
83495.96	34951.84	144565.8	-171107	-170680.2	-171107	Keep
87670.76	33204.25	130109.2	-191339	-184136.78	-191339	Keep
92054.3	31544.04	117098.3	-212185	-207147.7	-212185	Keep
					-	
96657.01	29966.83	105388.5	-233713	-228857.53	233713.44	Keep
					-	
101489.9	28468.49	94849.62	-255997	-249396.38	255996.86	Keep
					-	
106564.4	27045.07	85364.66	-279111	-268881.34	279110.71	keep
111892.6	25692.81	76828.19	-303134	-277417.81	-303134	keep
117487.2	24408.17	69145.38	-328150	-285100.62	-328150	keep
123361.6	23187.76					

Stage 10, 2015

74860	39922.05	197,000	-190877	-179432	-190877	Keep
					-	
78,800	38,021	187150	-216549	-209456.00	216548.70	keep
82740	36119.95	177792.5	-240237	-281813.50	-240237.4	keep
86877	34313.95	168902.9	-262243	-261703.13	-262243	keep
91220.85	32598.25	160457.7	-282759	-246148.27	-282759	keep
95781.89	30968.34	152434.8	-301961	-300171.16	-301961.3	keep
100571	29419.93	144813.1	-314864	-311792.90	-314864.5	keep
105599.5	27948.93	137572.4	-333647	-291033.55	-333647	keep
110879.5	26551.48	130693.8	-363439	-3475912	-363439	keep
116423.5	25223.91	124159.1	-394334	-382446.87	-394334	keep
122244.7	23962.71					

Stage 9, 2014

67243.5	45758.4	196,700	36560.75	33836.60	33836.60	Replace
					-	
79,110	38,132	192,766	25752.7	24315.2	24315.2	Replace
83,066	36,225	183,128	-28707.7	-30279.0	-30279.0	Replace
87,219	34,414	173,971	-305048	-315,947	-315,947	Replace

91,580	32,693	165,273	-341646	-350,645	-350645	Replace
96,159	31,059	157,009	-367061	-388,909	-388909	Replace
100,967	29,506	149,159	-376325	-396,759	-396759	Replace
106,015	28,031	141,701	-411632	-440,217	-440217	Replace
111,316	26,629	134,616	-448125	-513,302	-513302	Replace
116,882	25,298					

Stage 8, 2013

74970	36472.8	196,600	-327715	-315,611	-327715.2	Keep
83,300	36,400	192668	-340052	-339,543	-340052	Keep
84966	35672	188814.6	-336371	-333896	336371.48	Keep
86665.32	34958.56	185038.3	-366755	-358173	366754.65	Keep
88398.63	34259.39	181337.6	-395785	-333873	-395785	Keep
90166.6	33574.2	177710.8	-423654	-414500	-423654	Keep
91969.93	32902.72	174156.6	-435393	-428054	-435393	Keep
93809.33	32244.66	170673.5	-473197	-441538	-473196.6	Keep
95685.52	31599.77					

Stage 7, 2012

81700	36907.5	195,000	-372508	-371954	-372508	Keep
86,000	35,150	185250	-390902	-351704	-390902	Keep
87720	34798.5	175987.5	-389293	-380967	-389293	Keep
89474.4	34450.52	167188.1	-421779	-419766	421778.53	Keep
91263.89	34106.01	158828.7	-452943	-448125	-452942.8	Keep
93089.17	33764.95	150887.3	-482978	-476067	-482978	Keep
94950.95	33427.3	143342.9	-496916	-493611	-496916	Keep
96849.97	33093.03					

Stage 6, 2011

86357.6	33966	194,400	-424899	-419707	-424899.3	Keep
88,120	33,300	194400	-445722	-439707	-445722	Keep
89882.4	32634	194400	-446541	-439707	-446541.4	Keep
91680.05	31981.32	194400	-481477	-474707	-481477	Keep
93513.65	31341.69	190512	-515115	-503595	-515114.7	Keep
95383.92	30714.86	188606.9	-547647	-535500	-547646.9	Keep
97291.6	30100.56					

Stage 5, 2010

85680.5	31710	193,280	-478870	-460970	-478869.8	Keep
90,190	30,200	193280	-535712	-528970	-535712	Keep
94699.5	28690	191347.2	-542551	-530903	-542550.9	Keep
96593.49	28690	189433.7	-549381	-532816	-549381	Keep

98525.36	27255.5	187539.4	-566385	-534711	-566385	Keep
100495.9	25892.73					

Stage 4, 2009

90356	29295	191,250	-539931	-527947	-539931	Keep
92,200	27,900	181687.5	-570012	-567510	-570012	Keep
96810	26505	172603.1	-582856	-576594	582855.88	Keep
101650.5	25179.75	163973	-625852	-615224	-625852	Keep
106733	23920.76					

Stage 3, 2008

90725	26355	190,000	-614301	-602557	-604301	Keep
95,500	25,100	180500	-640412	-632057	-640412	Keep
97410	23845	171475	-656421	-641082	-656420.9	Keep
99358.2	22652.75					

Stage 2, 2007

92207	25200	189,750	-681308	-672758	-681308	Keep
97,060	24,000	185955	-713472	-706553	-713472	Keep
99486.5	23400					

Stage 1, 2006

97617	23703.75	189,240	-745221	-742302	-745221	Keep
100,120	22,050					

APPENDIX B7: MS EXCEL OUTPUT FOR TAXI CAB

stage 14, 2019						
Taxi Cab						
I	C	R	V _k	V _r	V _{k(i)}	D _k
39865.81	50263.4	126526	10397.59	69390	10397.59	keep
43332.4	47869.9	116403.9	45375	59267.92	45375	keep
45499.02	45476.41	107091.6	-22615	49955.6064	-22615	keep
47773.97	43202.58	98524.28	-45713.9	51388.2779	-45713.9	keep
50162.67	41042.46	90642.34	-91202.1	33506.34	-91202.1	keep
52670.8	38990.33	83390.95	-13680.5	26254.95	-13680.47	keep
55304.34	37040.82	76719.67	-18263.5	19583.6729	-18263.53	keep
58069.56	35188.78	70582.1	-22880.8	31446.0991	-22880.8	keep
60973.04	33429.34	64935.53	-27543.7	77991.3114	-27543.70	keep
64021.69	31757.87	59740.69	-32263.8	36046.865	-32263.8	keep
67222.77	30169.98	54961.43	-57052.8	-41074.664	-57052.8	keep
70583.91	28661.48	50564.52	-41922.4	-35714.811	-41922.44	keep
74113.11	27228.4	46519.36	-46884.7	-40616.643	-46884.7	keep
77818.76	25866.98	42797.81	-51951.8	-50338.91	-51951.8	keep

81709.7 24573.63

Stage 13, 2018

43027.48	48183.77	125019	15553.88	20597	-15553.88	Keep
46769	44614.6	118768.1	-23830.1	-22847.95	-23830.1	Keep
50510.52	42383.87	112829.6	-81496.7	-32786.353	-81496.7	Keep
54551.36	40264.68	107188.2	-38858.1	-38427.835	-38858.1	Keep
58915.47	38251.44	101828.8	-29784.2	-23787.243	-29784.2	Keep
63628.71	36338.87	96737.32	-49970.3	-48878.681	-49970.3	Keep
68719	34521.93	91900.45	-52460.6	-51715.547	-52460.6	Keep
74216.53	32795.83	87305.43	-64301.5	-63310.57	-64301.48	keep
80153.85	31156.04	82940.16	-76541.5	-75575.841	-76541.51	keep
86566.16	29598.24	78793.15	-89231.7	-76822.849	-89231.74	keep
93491.45	28118.33	74853.49	-802426	-70762.507	-802425.9	keep
100970.8	26712.41	71110.82	-71618.8	-64505.181	-71618.8	keep
109048.4	25376.79	67555.28	-30556.3	-28060.72	-30556.3	keep
117772.3	24107.95					

Stage 12, 2017

46302.53	74845.26	123512	-79450.35	-66913.6	-79450.35	Keep
48739.5	41580.7	117336.4	-34006.8	-33101.6	-34006.8	Keep
52638.66	39501.67	111469.6	-45923.3	-41178.42	-45923.3	Keep
55270.59	37526.58	105896.1	-56171.8	-55751.899	-56171.8	Keep
58034.12	35650.25	100601.3	-66171.1	-62046.704	-66171.1	Keep
60935.83	33867.74	95571.23	-75946.8	-67076.769	-75946.8	Keep
63982.62	32174.35	90792.67	-85523.8	-71855.33	-85523.8	Keep
67181.75	30565.64	86253.04	-100918	106394.96	-100918	Keep
			-		-	
70540.84	29037.35	81940.38	110707.62	-105707.62	110707.62	keep
74067.88	27585.49	77843.37	-135714	-114804.63	-135714	keep
77771.27	26206.21	73951.2	-153991	-118696.8	-153991	keep
81659.84	24895.9	70253.64	-172945	-162394.36	-172945	keep
85742.83	23651.11					

Stage 11, 2016

51217.05	39528.16	122006	-80824.9	-80315	-80824.9	keep
52262.3	38753.1	115905.7	-88820.8	-86415.3	-88820.8	keep
54875.42	36815.45	110110.4	-94238.4	-93210.585	-94238.39	keep
					-	
57619.19	34974.67	104604.9	-109396	-10716.106	109396.41	keep
60500.15	33225.94	99374.65	-119321	-114946.35	-119321	keep
					-	
63525.15	31564.64	94405.92	-129037	118915.083	-129037	keep
66701.41	29986.41	89685.62	-138570	-136353.79	-138570	keep
70036.48	28487.09	85201.34	-147944	-149119.66	-147944	keep

73538.3	27062.74	80941.27	-157183	-148379.73	-157183	keep
77215.22	25709.6	76894.21	-166310	-165426.79	-166310	keep
81075.98	24424.12	73049.5	-175349	-161271.5	-175349	keep
85129.78	23202.91					

Stage 10, 2015

51347.5	35752.5	121,000	-96419.9	-11673.8	-96419.9	Keep
54,050	34,050	118580	-108821	-107158.0	-108821	Keep
56752.5	32347.5	116208.4	-123643	-122529.6	-123643	keep
					-	
59590.13	30730.13	113884.2	-138256	-133853.8	138256.41	keep
62569.63	29193.62	111606.5	-152697	-151131.45	-152696.9	keep
65698.11	27733.94	109374.4	-167002	-166363.58	-167002	keep
68983.02	26347.24	107186.9	-181206	-180151.07	-181206	keep
72432.17	25029.88	105043.2	-195347	-194694.81	-195347	keep
76053.78	23778.38	102942.3	-209459	-204795.67	-209459	keep
79856.47	22589.47	100883.5	-223577	-221854.52	-223577	keep
83849.29	21459.99					

Stage 9, 2014

		120,600			--	
42675	40440		18437.18	15480.98	15480.98	Replace
56,900	33,700	119,394	172358	15341.79	15341.79	Replace
58,038	33,026	118,200	-14365.5	-14837.3	-148373	Replace
59,199	32,365	117,018	-165090	-174555	-174555	Replace
60,383	31,718	115,848	-181361	-195725	-195725	Replace
61,590	31,084	114,689	-197508	-198508	-198508	Replace
62,822	30,462	113,543	-213566	-248030	-248030	Replace
64,079	29,853	112,407	-229572	-249166	-249166	Replace
65,360	29,256	111,283	-245563	-250290	-250290	Replace
66,667	28,671					

Stage 8, 2013

57624	32844	120,150	-165753	-16444.2	-165753	Keep
58,800	32,200	118948.5	-168958	-167644	-168958	Keep
59388	31878	117759	-176165	-160833	-176165.4	Keep
59981.88	31559.22	116581.4	-193512.4	-195011	-193512.4	Keep
60581.7	31243.63	115415.6	-210699	-206176	-210699	Keep
61187.52	30931.19	114261.5	-227764	-226431	-227764	Keep
61799.39	30621.88	113118.8	-24474.4	-235473	-24474.4	Keep
62417.38	30315.66	111987.7	-261674	-256604	-261674	Keep
63041.56	30012.5					

Stage 7, 2012

59935.5	31626	119,500	-194063	-195867	-194062.5	Keep
63,090	30,120	113525	-20192.8	-209842	-201928	Keep
64351.8	29818.8	107848.8	-210698	-209518	-210698	Keep
65638.84	29520.61	102456.3	-22963.1	-22191.1	-229631	Keep
66951.61	29225.41	97333.5	-248426	-247034	-248426	Keep
68290.64	28933.15	92466.82	-267122	-271900	-267122	Keep
69656.46	28643.82	87843.48	-285756	-284524	-285756	Keep
71049.59	28357.38					

Stage 6, 2011

64827	29682	117,000	-229208	-225487	-229208	Keep
66,150	29,100	115830	-238978	-236657	-238978	Keep
67473	28518	114671.7	-25965.3	-257815	-259653.3	Keep
68822.46	27947.64	113525	-28050.5	-270962	-280505.4	Keep
70198.91	27388.69	112389.7	-291236	-290097	-291236	Keep
71602.89	26840.91	111265.8	-311884	-30122.1	-311884	Keep
73034.95	26304.1	110153.2				

Stage 5, 2010

64885	26250	116,400	-267843	-26015.5	-267843	Keep
68,300	25,000	116400	-282278	-280155	-282278	Keep
71715	23750	115236	-297618	-296319	-297618	Keep
73149.3	23750	114083.6	-319905	-302471	-319904.7	Keep
74612.29	22562.5	112942.8	-343286	-330612	-343286	Keep
76104.53	21434.38					

Stage 4, 2009

67630.5	24255	115,200	-311218	-301069	-311218	Keep
71,190	23,100	109440	-330368	-32645.2	-330368	Keep
74749.5	21945	103968	-350423	-341924	-350423	Keep
78486.98	20847.75	98769.6	-377544	-367122	-377544	Keep
82411.32	19805.36					

Stage 3, 2008

71250	22680	110,200	-359788	-35588.0	-359788	Keep
75,000	21,600	104690	-383768	-381390	-383768	Keep
76500	20520	99455.5	-406403	-400625	-406403	Keep
78030	19494					

Stage 2, 2007

73354.25	21840	101,100	-411302	-404168	-411302	Keep
77,215	20,800	99078	-440183	-436190	-440183	Keep
79145.38	20280					

Stage 1, 2006

76927.5	20317.5	100,000	-467912	-460183	-467912	Keep
78,900	18,900					

APPENDIX D₁₁: General Regression Analysis: NISSAN URVAN versus TIME, Precipitation, ...

Regression Equation

Regression Analysis: NISSAN URVAN versus Nissan Urvan KM, Precipitatio, ...

The regression equation is

$$\text{NISSAN URVAN (Maintenance)} = -133964 + 0.775 \text{ Nissan Urvan (KM)} + 8.78 \text{ Precipitation} + 1644 \text{ Temperature} - 28.4 \text{ Relative Humidity} + 3366 \text{ TIME}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	-133964	131913	-1.02	0.367	
Nissan Urvan (KM)	0.7749	0.5674	1.37	0.244	12.110
Precipitation	8.775	7.807	1.12	0.324	2.304
Temperature	1644	3374	0.49	0.652	1.638
Relative Humidity	-28.37	95.63	-0.30	0.781	2.230
TIME	3366	1462	2.30	0.083	13.755

S = 3581.48 R-Sq = 87.9% R-Sq(adj) = 72.8%

PRESS = 2802132501 R-Sq(pred) = 0.00%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	372814737	74562947	5.81	0.056
Residual Error	4	51308103	12827026		
Total	9	424122840			

DF=degree of Freedom

SS=sum of Square

MS=Mean Square

F Critical=Frequent Accumulation

P=Probability Value

SE Coef=Sum of error in coefficiencie

VIF=very important factor

T=T Critical

Seq SS=Sequence of Sum of Square

SE Fit=Sum of Error in fitness

St Resid= Standard residual

Cl= Confidence Level

Source	DF	Seq SS
Nissan Urvan (KM)	1	229783870
Precipitation	1	7400837
Temperature	1	11127209
Relative Humidity	1	56562371
TIME	1	67940451

Obs	Nissan Urvan (KM)	NISSAN URVAN (Maintenance)	Fit	SE Fit	Residual	St Resid
1	120304	19690	20653	3159	-963	-0.57
2	119720	22500	21110	2110	1390	0.48
3	118552	25200	25076	3060	124	0.07
4	117968	28150	25894	2185	2256	0.79
5	117384	30300	30633	2006	-333	-0.11

6	116800	32400	32188	2708	212	0.09	
7	113296	33600	36022	2866	-2422	-1.13	
8	105120	25900	30677	2660	-4777	-1.99	
9	102784	39950	39161	3553	789	1.74	
10	101616	40050	36324	3020	3726	1.94	
Predicted Values for New Observations							
		New Obs	Fit	SE Fit	95% CI		
95% PI							
1	20653	3159	(11883, 29423)	(7395, 33912)			
2	21110	2110	(15252, 26969)	(9569, 32651)			
3	25076	3060	(16579, 33573)	(11996, 38156)			
4	25894	2185	(19827, 31962)	(14245, 37543)			
5	30633	2006	(25064, 36202)	(19236, 42030)			
6	32188	2708	(24670, 39707)	(19722, 44655)			
7	36022	2866	(28064, 43979)	(23286, 48757)			
8	30677	2660	(23291, 38064)	(18290, 43064)			
9	39161	3553	(29297, 49025)	(25155, 53168)			
10	36324	3020	(27939, 44709)	(23317, 49332)			

Values of Predictors for New Observations

New Obs	Nissan			Relative		
	Urban (KM)	Precipitation	Temperature	Humidity	TIME	
1	120304	1620	29.2	148	1.0	
2	119720	1500	28.5	157	2.0	
3	118552	1650	29.0	177	3.0	
4	117968	1507	28.1	160	4.0	
5	117384	1579	28.3	126	5.0	
6	116800	1507	27.8	123	6.0	
7	113296	1695	28.9	130	7.0	
8	105120	1662	27.9	148	8.0	
9	102784	2295	28.3	123	9.0	
10	101616	1695	28.4	130	10.0	

APPENDIX D₁₂: General Regression Analysis: SIENNA (MAIN versus TIME, Precipitation, ...)
Regression Analysis: SIENNA (Main versus Sienna (KM), Precipitations, ...,

The regression equation is
SIENNA (Maintenance) = 18144 + 0.799 Sienna (KM) + 5.02 Precipitation
- 1106 Temperature + 49.3 Relative Humidity + 3405 TIME

Predictor	Coef	SE Coef	T	P	VIF
Constant	18144	57088	-0.76	0.491	
Sienna (KM)	0.7985	0.3157	2.53	0.065	12.110
Precipitation	5.019	3.378	1.49	0.212	2.304
Temperature	-1106	1460	-0.76	0.491	1.638
Relative Humidity	49.28	41.38	1.19	0.300	2.230
TIME	3405	43290	7.42	0.002	13.755

S = 1549.96 R-Sq = 99.0% R-Sq(adj) = 97.8%

PRESS = 338731731 R-Sq(pred) = 65.58%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	974464566	194892913	81.12	0.000
Residual Error	4	9609536	2402384		
Total	9	984074102			

Source	DF	Seq SS
Sienna (KM)	1	744749728
Precipitation	1	4389947
Temperature	1	53035689
Relative Humidity	1	40063325
TIME	1	132225877

Obs	Sienna (KM)	SIENNA (Maintenance)	Fit	SE Fit	Residual	St Resid
1	93580	19000	19252	1367	-252	-0.35
2	93125	24400	24196	913	204	0.16
3	92217	29050	29401	1324	-351	-0.44
4	91763	32300	33051	946	-751	-0.61
5	91308	37000	35936	868	1064	0.83
6	90854	39200	40283	1172	-1083	-1.07
7	88128	44050	42935	1240	1115	1.20
8	81769	46100	44337	1151	1763	1.70
9	79952	48800	49065	1538	-265	-1.35
10	79043	48815	50260	1307	-1445	-1.73

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	40592	7817	(18890, 62295)	(18468, 62717)XX
2	45432	8032	(23130, 67734)	(22719, 68145)XX
3	50430	8995	(25456, 75403)	(25088, 75771)XX
4	53977	8636	(30000, 77954)	(29617, 78337)XX
5	56758	8481	(33210, 80306)	(32820, 80696)XX
6	61001	8629	(37042, 84960)	(36658, 85344)XX
7	63032	8690	(38905, 87159)	(38524, 87539)XX
8	62983	6873	(43902, 82065)	(43423, 82544)XX
9	67297	7417	(46705, 87889)	(46260, 88334)XX
10	68285	6686	(49722, 86849)	(49230, 87341)XX

XX denotes a point that is an extreme outlier in the predictors.

Values of Predictors for New Observations

New Obs	Sienna (KM)	Precipitation	Temperature	Relative Humidity	TIME
1	120304	1620	29.2	148	1.0
2	119720	1500	28.5	157	2.0
3	118552	1650	29.0	177	3.0
4	117968	1507	28.1	160	4.0
5	117384	1579	28.3	126	5.0
6	116800	1507	27.8	123	6.0
7	113296	1695	28.9	130	7.0
8	105120	1662	27.9	148	8.0
9	102784	2295	28.3	123	9.0
10	101616	1695	28.4	130	10.0

APPENDIX D₁₃: General Regression Analysis: PEUGEOT EXPE versus TIME, Precipitatio, ...

Regression Analysis: PEUGEOT EXPE versus Peugeot (KM), Precipitatio, ...

The regression equation is
 PEUGEOT EXPERT (Maintenance) = 16654 + 0.342 Peugeot (KM) + 1.06 Precipitation
 - 1297 Temperature - 12.2 Relative Humidity
 + 3299 TIME-90TIME X TIME.

Predictor	Coef	SE Coef	T	P	VIF
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New Obs	(KM)	Precipitation	Temperature	Humidity	TIME
1	120304	1620	29.2	148	1.0
2	119720	1500	28.5	157	2.0
3	118552	1650	29.0	177	3.0
4	117968	1507	28.1	160	4.0
5	117384	1579	28.3	126	5.0
6	116800	1507	27.8	123	6.0
7	113296	1695	28.9	130	7.0
8	105120	1662	27.9	148	8.0
9	102784	2295	28.3	123	9.0
10	101616	1695	28.4	130	10.0

**APPENDIX D₁₄ :General Regression Analysis: J5 (MAINTENA versus TIME, Precipitatio, ...
Regression Analysis: J5 (Maintenance) versus J5 (KM), Precipitation, ...**

The regression equation is

$$J5 \text{ (Maintenance)} = -176630 + 1.60 J5 \text{ (KM)} - 0.11 \text{ Precipitation} + 978 \text{ Temperature} + 166 \text{ Relative Humidity} + 5828 \text{ TIME}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	-176630	101619	-1.74	0.157	
J5 (KM)	1.6019	0.6058	2.64	0.057	12.679
Precipitation	-0.108	5.907	-0.02	0.986	2.352
Temperature	978	2535	0.39	0.719	1.648
Relative Humidity	166.36	71.08	2.34	0.079	2.196
TIME	5828	1113	5.23	0.006	14.214

S = 2682.40 R-Sq = 95.5% R-Sq(adj) = 89.9%

PRESS = 977881255 R-Sq(pred) = 0.00%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	614242608	122848522	17.07	0.008
Residual Error	4	28781036	7195259		
Total	9	643023644			

**APPENDIX D₁₅:General Regression Analysis: FORD BUS (MA versus TIME, Precipitation,
Regression Analysis: FORD BUS (Ma versus Ford Bus (KM, Precipitatio, ...**

The regression equation is

$$FORD \text{ BUS (Maintenance)} = 22323 + 1.04 \text{ Ford Bus (KM)} + 0.20 \text{ Precipitation} - 1662 \text{ Temperature} + 14.4 \text{ Relative Humidity} + 3107 \text{ TIME}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	22323	96099	0.23	0.828	
Ford Bus (KM)	1.0392	0.7826	1.33	0.255	5.952
Precipitation	0.198	5.919	0.03	0.975	1.708
Temperature	-1662	3009	-0.55	0.610	1.681
Relative Humidity	14.39	73.37	0.20	0.854	1.693
TIME	3106.9	990.5	3.14	0.035	8.140

S = 3153.23 R-Sq = 91.2% R-Sq(adj) = 80.2%

PRESS = 127126268 R-Sq(pred) = 71.81%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	411132665	82226533	8.27	0.031
Residual Error	4	39771375	9942844		
Total	9	450904040			

There are no replicates.
Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
Ford Bus (KM)	1	251730947
Precipitation	1	2103756
Temperature	1	55839538
Relative Humidity	1	3622296
TIME	1	97836128

Obs	Ford Bus (KM)	FORD BUS (Maintenance)	Fit	SE Fit	Residual	St Resid
1	40897	21654	21839	2700	-185	-0.11
2	41321	22977	26654	1748	-3677	-1.40
3	43016	31158	31077	3054	81	0.10
4	38778	34887	30847	2117	4040	1.73
5	40049	36900	34560	1881	2340	0.92
6	39837	36900	38212	2530	-1312	-0.70
7	37294	37800	37070	2178	730	0.32
8	35599	39050	40251	2089	-1201	-0.51
9	34752	41600	41573	3127	27	0.07
10	32633	41450	42294	2584	-844	-0.47

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	21839	2700	(14342, 29335)	(10313, 33364)
2	26654	1748	(21800, 31508)	(16644, 36664)
3	31077	3054	(22596, 39557)	(18888, 43265)
4	30847	2117	(24969, 36725)	(20302, 41392)
5	34560	1881	(29337, 39783)	(24365, 44754)
6	38212	2530	(31188, 45237)	(26988, 49437)
7	37070	2178	(31024, 43116)	(26430, 47710)
8	40251	2089	(34452, 46050)	(29750, 50752)
9	41573	3127	(32891, 50254)	(29243, 53902)
10	42294	2584	(35119, 49468)	(30975, 53613)

Values of Predictors for New Observations

New Obs	Ford Bus (KM)	Precipitation	Temperature	Relative Humidity	TIME
1	40897	1620	29.2	148	1.0
2	41321	1500	28.5	157	2.0
3	43016	1650	29.0	177	3.0
4	38778	1507	28.1	160	4.0
5	40049	1579	28.3	126	5.0
6	39837	1507	27.8	123	6.0
7	37294	1695	28.9	130	7.0
8	35599	1662	27.9	148	8.0
9	34752	2295	28.3	123	9.0
10	32633	1695	28.4	130	10.0

APPENDIX D₁₆: General Regression Analysis: TOYOTA HIACE versus TIME, Precipitatio, ...

Regression Analysis: TOYOTA HIACE versus Toyota Hiace, Precipitatio, ...

The regression equation is

$$\text{TOYOTA HIACE (Maintenance)} = 2095 + 0.147 \text{ Toyota Hiace (KM)} + 0.302 \text{ Precipitation} - 296 \text{ Temperature} - 24.1 \text{ Relative Humidity} + 2332 \text{ TIME}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	2095	15178	0.14	0.897	
Toyota Hiace (KM)	0.14738	0.03159	4.66	0.010	6.049
Precipitation	0.3023	0.8198	0.37	0.731	1.714
Temperature	-296.3	426.5	-0.69	0.525	1.766
Relative Humidity	-24.06	10.26	-2.34	0.079	1.732
TIME	2332.4	146.8	15.89	0.000	9.354

S = 436.001 R-Sq = 99.8% R-Sq(adj) = 99.5%

PRESS = 70693038 R-Sq(pred) = 78.31%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	325228076	65045615	342.17	0.000
Residual Error	4	760388	190097		
Total	9	325988464			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
Toyota Hiace (KM)	1	226332007
Precipitation	1	5183562
Temperature	1	32324628
Relative Humidity	1	13406810
TIME	1	47981070

Obs	Toyota Hiace (KM)	TOYOTA HIACE (Maintenance)	Fit	SE Fit	Residual	St Resid
1	201324	22050	22377	330	-327	-1.15
2	194966	24000	23730	258	270	0.77
3	191788	25100	25020	332	80	0.28
4	190728	27900	27812	254	88	0.25
5	188609	30200	30612	238	-412	-1.13
6	187549	33300	32999	313	301	0.99
7	186490	35150	34752	368	398	1.70
8	185430	36400	36759	364	-359	-1.49
9	173774	38132	38057	434	75	1.76 X
10	161059	38021	38135	424	-114	-1.14

X denotes an observation whose X value gives it large leverage.

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	22377	330	(21461, 23294)	(20859, 23896)
2	23730	258	(23014, 24445)	(22324, 25136)
3	25020	332	(24099, 25941)	(23499, 26541)
4	27812	254	(27107, 28517)	(26411, 29212)

5	30612	238	(29951, 31272)	(29233, 31991)
6	32999	313	(32130, 33869)	(31509, 34490)
7	34752	368	(33730, 35774)	(33168, 36336)
8	36759	364	(35750, 37769)	(35183, 38336)
9	38057	434	(36852, 39261)	(36349, 39764)X
10	38135	424	(36957, 39313)	(36446, 39824)

X denotes a point that is an outlier in the predictors.

Values of Predictors for New Observations

New Obs	Toyota		Precipitation	Temperature	Relative Humidity	TIME
	Hiace (KM)					
1	201324		1620	29.2	148	1.0
2	194966		1500	28.5	157	2.0
3	191788		1650	29.0	177	3.0
4	190728		1507	28.1	160	4.0
5	188609		1579	28.3	126	5.0
6	187549		1507	27.8	123	6.0
7	186490		1695	28.9	130	7.0
8	185430		1662	27.9	148	8.0
9	173774		2295	28.3	123	9.0
10	161059		1695	28.4	130	10.0

APPENDIX D₁₇: General Regression Analysis: TAXI CAB (MA versus TIME, Precipitatio, ... Regression Analysis: TAXI CAB (Ma versus Taxi Cab (KM, Precipitation, ...

The regression equation is

$$\text{TAXI CAB (Maintenance)} = 17859.5 + 0.143 \text{ Taxi Cab (KM)} + 0.77 \text{ Precipitation} \\ - 483 \text{ Temperature} - 22.5 \text{ Relative Humidity} + \\ 1.07296 \text{ TIME} \times \text{TIME}$$

Predictor	Coef	SE Coef	T	P	VIF
Constant	17859	34686	0.72	0.510	
Taxi Cab (KM)	0.1431	0.2569	0.56	0.607	4.726
Precipitation	0.767	2.085	0.37	0.732	1.743
Temperature	-483	1059	-0.46	0.672	1.712
Relative Humidity	-22.47	26.85	-0.84	0.450	1.864
TIME	1.07296	302.8	6.01	0.004	6.255

S = 1099.64 R-Sq = 98.3% R-Sq(adj) = 96.2%

PRESS = 50354704 R-Sq(pred) = 82.52%

Analysis of Variance

Source	DF	SS	MS	F	P
Regression	5	283155618	56631124	46.83	0.001
Residual Error	4	4836792	1209198		
Total	9	287992410			

There are no replicates.

Minitab cannot do the lack of fit test based on pure error.

Source	DF	Seq SS
Taxi Cab (KM)	1	206518308
Precipitation	1	9409073
Temperature	1	22239313
Relative Humidity	1	1306643

TIME	1	43682282					
	Taxi Cab	TAXI CAB					
Obs	(KM)	(Maintenance)	Fit	SE Fit	Residual	St	Resid
1	53708	18900	18376	932	524		0.90
2	54265	20800	20322	636	478		0.53
3	56491	21600	21902	947	-302		-0.54
4	53430	23100	23957	644	-857		-0.96
5	52595	25000	26389	623	-1389		-1.53
6	52317	29100	28435	831	665		0.92
7	52038	30120	29695	921	425		0.71
8	50369	32200	31298	709	902		1.07
9	48977	33700	33780	1091	-80		-0.57
10	45360	34050	34416	1026	-366		-0.93

APPENDIX D₂₁: General Regression Analysis: NISSAN URVAN versus TIME, Precipitatio, ... Nissan Urvan for Replacement

Regression Equation

Nissan Urvan (Replacement) = 257544 + 3514.95 Time - 0.217837 Nissan (KM) + 1.81884

Precipitation - 1624.13 Temperature + 57.4099 Relative Humidity

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	257544	76769.0	3.35479	0.028	(44399.1, 470689)	
Time	3515	851.1	4.13008	0.014	(1152.0, 5878)	13.7547
Nissan (KM)	-0	0.3	-0.65973	0.545	(-1.1, 1)	12.1104
Precipitation	2	4.5	0.40034	0.709	(-10.8, 14)	2.3038
Temperature	-1624	1963.5	-0.82715	0.455	(-7075.8, 3827)	1.6379
Relative Humidity	57	55.7	1.03159	0.361	(-97.1, 212)	2.2297

Summary of Model

S = 2084.30 R-Sq = 98.70% R-Sq(adj) = 97.07%
PRESS = 848721039 R-Sq(pred) = 36.44%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	1317825103	1317825103	263565021	60.6688	0.000731
Time	1	1302736815	74103592	74103592	17.0576	0.014493
Nissan (KM)	1	7722581	1890848	1890848	0.4352	0.545477
Precipitation	1	134977	696280	696280	0.1603	0.709365
Temperature	1	2607636	2972273	2972273	0.6842	0.454642
Relative Humidity	1	4623094	4623094	4623094	1.0642	0.360554
Error	4	17377307	17377307	4344327		
Total	9	1335202410				

Fits and Diagnostics for All Observations

Obs	Nissan Urvan	Fit	SE Fit	Residual	St Resid
1	199200	198871	1838.26	329.13	0.33502
2	202400	203943	1228.01	-1542.61	-0.91596
3	210000	208391	1781.06	1608.95	1.48610
4	210000	212088	1271.80	-2088.04	-1.26447
5	215680	213703	1167.23	1977.47	1.14515
6	218100	217821	1575.91	278.92	0.20446
7	220150	221142	1667.92	-992.14	-0.79374

8	230500	228971	1548.28	1529.11	1.09582
9	231600	232040	2067.60	-440.49	-1.67252
10	234300	234960	1757.58	-660.29	-0.58935

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	422879071	102414173	(138531743, 707226399)	(138531743, 707226399)
2	420811970	101922568	(137829554, 703794386)	(137829554, 703794386)
3	416673925	100940843	(136417215, 696930635)	(136417215, 696930635)
4	414649576	100433203	(135802300, 693496852)	(135802300, 693496852)
5	412651070	99915946	(135239932, 690062208)	(135239932, 690062208)
6	410604179	99416781	(134578944, 686629414)	(134578943, 686629415)
7	398276374	96439048	(130518653, 666034095)	(130518653, 666034096)
8	369508512	89491956	(121039008, 617978016)	(121039008, 617978016)
9	361338688	87488678	(118431178, 604246199)	(118431177, 604246199)
10	357222001	86498774	(117062902, 597381100)	(117062902, 597381100)

Values of Predictors for New Observations

New Obs	Time	Nissan (KM)	Precipitation	Temperature	Relative Humidity
1	120304	1620.0	29.20	148.00	1 XX
2	119720	1500.0	28.50	156.90	2 XX
3	118552	1650.3	28.96	176.98	3 XX
4	117968	1507.0	28.15	159.56	4 XX
5	117384	1579.1	28.30	126.20	5 XX
6	116800	1506.6	27.80	122.65	6 XX
7	113296	1695.4	28.85	129.70	7 XX
8	105120	1662.0	27.90	148.00	8 XX
9	102784	2294.7	28.30	122.65	9 XX
10	101616	1695.0	28.40	129.68	10 XX

**APPENDIX D₂₂: General Regression Analysis: SIENNA (REPL versus TIME, Precipitatio, ...
Sienna versus Sienna (KM), Precipitatio, ...**

Regression Equation

$$\text{Sienna} = 101507.8 + 1.56016 \text{ Sienna (KM)} + 6.0339 \text{ Precipitation} - 769.549 \text{ Temperature} + 150.736 \text{ Relative Humidity} + 0.774197 \text{ Time}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI
Constant	101507.8	49594.9	-1.0386	0.358	(-189205, 86189.8)
Sienna (KM)	1.6	0.3	5.6892	0.005	(1, 2.3)
Precipitation	6.0	2.9	2.0558	0.109	(-2, 14.2)
Temperature	-769.5	1268.5	-0.6067	0.577	(-4291, 2752.4)
Relative Humidity	150.7	36.0	4.1926	0.014	(51, 250.6)
Time	0.774197	5.498	10.4492	0.000	(4219, 7271.6)

Term VIF

Constant	
Sienna (KM)	12.1104
Precipitation	2.3038
Temperature	1.6379
Relative Humidity	2.2297
Time	13.754

Summary of Model

S = 1346.52 R-Sq = 98.97% R-Sq(adj) = 97.68%
PRESS = 280478699 R-Sq(pred) = 60.09%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	695528180	695528180	139105636	76.722	0.000461
Sienna (KM)	1	430639184	58685633	58685633	32.367	0.004714
Precipitation	1	7844200	7662897	7662897	4.226	0.108969
Temperature	1	46769070	667301	667301	0.368	0.576821
Relative Humidity	1	12310870	31870745	31870745	17.578	0.013778
Time	1	197964857	197964857	197964857	109.185	0.000474
Error	4	7252460	7252460	1813115		
Total	9	702780640				

Fits and Diagnostics for All Observations

Obs	Sienna	Fit	SE Fit	Residual	St Resid
1	110000	109849	1187.57	150.90	0.23777
2	115000	116042	793.33	-1041.57	-0.95732
3	125000	123949	1150.61	1051.17	1.50290
4	125000	126118	821.62	-1117.99	-1.04799
5	128000	126445	754.06	1554.63	1.39357
6	130900	130894	1018.08	6.12	0.00695
7	132900	133780	1077.53	-880.39	-1.09027
8	133600	132891	1000.23	708.82	0.78629
9	135240	135490	1335.73	-249.97	-1.46915
10	137000	137182	1135.45	-181.73	-0.25109

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	109849	1187.57	(106552, 113146)	(104864, 114834)
2	116042	793.33	(113839, 118244)	(111702, 120381)
3	123949	1150.61	(120754, 127143)	(119031, 128866)
4	126118	821.62	(123837, 128399)	(121738, 130498)
5	126445	754.06	(124352, 128539)	(122161, 130730)
6	130894	1018.08	(128067, 133721)	(126207, 135581)
7	133780	1077.53	(130789, 136772)	(128992, 138569)
8	132891	1000.23	(130114, 135668)	(128234, 137548)
9	135490	1335.73	(131781, 139199)	(130224, 140756)
10	137182	1135.45	(134029, 140334)	(132291, 142072)

Values of Predictors for New Observations

New Obs	Sienna (KM)	Precipitation	Temperature	Relative Humidity	Time
1	93579.6	1620.0	29.20	148.00	1
2	93125.4	1500.0	28.50	156.90	2
3	92216.8	1650.3	28.96	176.98	3
4	91762.5	1507.0	28.15	159.56	4
5	91308.3	1579.1	28.30	126.20	5
6	90854.0	1506.6	27.80	122.65	6
7	88128.4	1695.4	28.85	129.70	7
8	81768.6	1662.0	27.90	148.00	8
9	79951.5	2294.7	28.30	122.65	9
10	79043.0	1695.0	28.40	129.68	10

APPENDIX D₂₃: General Regression Analysis: PEUGEOT EXPE versus TIME, Precipitatio, ...

Regression Equation

$$\text{PEUGEOT EXPERT (REPLACEMENT)} = 221558 + 0.896692\text{TIME} + 1.28788 \text{ Precipitation} - 2509.96 \text{ Temperature} - 21.5109 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	221558	66311.2	3.34118	0.021	(51099.2, 392016)	
TIME	0.89662	464.6	6.29489	0.001	(1730.1, 4118)	2.72008
Precipitation	1	4.8	0.26824	0.799	(-11.1, 14)	1.70772
Temperature	-2510	2399.8	-1.04592	0.344	(-8678.7, 3659)	1.62383
Relative Humidity	-22	59.5	-0.36138	0.733	(-174.5, 132)	1.69297

Summary of Model

S = 2558.41 R-Sq = 96.41% R-Sq(adj) = 93.54%
 PRESS = 91523157 R-Sq(pred) = 89.96%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	879282962	879282962	219820741	33.5837	0.000832
TIME	1	870431523	259367786	259367786	39.6256	0.001488
Precipitation	1	171811	470956	470956	0.0720	0.799231
Temperature	1	7824826	7160433	7160433	1.0940	0.343502
Relative Humidity	1	854802	854802	854802	0.1306	0.732585
Error	5	32727288	32727288	6545458		
Total	9	912010250				

Fits and Diagnostics for All Observations

Obs	PEUGEOT EXPERT (REPLACEMENT)	Fit	SE Fit	Residual	St Resid
1	150000	150094	1930.80	-93.96	-0.05598
2	152000	154429	1351.54	-2429.24	-1.11829
3	155000	155961	1945.54	-960.59	-0.57817
4	165000	161108	1470.30	3891.87	1.85883
5	166500	164466	1390.92	2033.61	0.94706
6	166500	168629	1836.97	-2128.67	-1.19539
7	170050	169009	1708.32	1040.99	0.54659
8	173300	173881	1649.62	-581.11	-0.29716
9	177200	177162	2536.65	38.43	0.11540
10	178100	178911	1960.22	-811.32	-0.49348

APPENDIX D₂₄: General Regression Analysis: J5 (REPLACEMENT versus TIME, Precipitation, ...

Regression Equation

$$J5 \text{ (REPLACEMENT)} = 162704 + 1510.57 \text{ TIME} + 0.608319 \text{ Precipitation} + 573.288 \text{ Temperature} - 15.2133 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	162704	14672.0	11.0894	0.000	(124988, 200420)	
TIME	1511	102.8	14.6962	0.000	(1246, 1775)	2.72008
Precipitation	1	1.1	0.5726	0.592	(-2, 3)	1.70772
Temperature	573	531.0	1.0797	0.330	(-792, 1938)	1.62383
Relative Humidity	-15	13.2	-1.1551	0.300	(-49, 19)	1.69297

Summary of Model

S = 566.075 R-Sq = 99.20% R-Sq(adj) = 98.57%

PRESS = 16229789 R-Sq(pred) = 91.95%
 Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	199918798	199918798	49979699	155.972	0.000020
TIME	1	198749121	69207777	69207777	215.977	0.000026
Precipitation	1	449169	105073	105073	0.328	0.591683
Temperature	1	292947	373553	373553	1.166	0.329583
Relative Humidity	1	427561	427561	427561	1.334	0.300243
Error	5	1602202	1602202	320440		
Total	9	201521000				

Fits and Diagnostics for All Observations

Obs	(REPLACEMENT)	Fit	SE Fit	Residual	St Resid
1	180300	179689	427.210	611.409	1.64626
2	180900	180589	299.043	310.535	0.64609
3	181700	182150	430.470	-449.697	-1.22330
4	183000	183374	325.319	-373.751	-0.80679
5	185200	185522	307.755	-321.693	-0.67710
6	186600	186756	406.448	-155.527	-0.39473
7	188400	188876	377.984	-475.648	-1.12876
8	190100	189543	364.996	557.125	1.28759
9	192000	192053	561.259	-53.305	-0.72346
10	193500	193149	433.718	350.552	0.96366

APPENDIX D₂₅: General Regression Analysis: FORD BUS (RE versus TIME, Precipitatio, ...

Regression Equation

$$\text{FORD BUS (REPLACEMENT)} = 186517 + 802.781 \text{ TIME} + 2.01014 \text{ Precipitation} - 439.23 \text{ Temperature} + 13.4728 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	186517	16776.8	11.1176	0.000	(143391, 229643)	
TIME	803	117.5	6.8303	0.001	(501, 1105)	2.72008
Precipitation	2	1.2	1.6548	0.159	(-1, 5)	1.70772
Temperature	-439	607.1	-0.7234	0.502	(-2000, 1121)	1.62383
Relative Humidity	13	15.1	0.8946	0.412	(-25, 52)	1.69297

Summary of Model

S = 647.279 R-Sq = 96.79% R-Sq(adj) = 94.23%
 PRESS = 10959240 R-Sq(pred) = 83.22%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	63215399	63215399	15803850	37.7207	0.000630
TIME	1	61836735	19546354	19546354	46.6533	0.001026
Precipitation	1	878613	1147318	1147318	2.7384	0.158866
Temperature	1	164725	219276	219276	0.5234	0.501825
Relative Humidity	1	335326	335326	335326	0.8004	0.411978
Error	5	2094851	2094851	418970		
Total	9	65310250				

Fits and Diagnostics for All Observations

Obs	(REPLACEMENT)	Fit	SE Fit	Residual	St Resid
1	180350	179745	488.494	605.218	1.42515
2	181200	180734	341.941	466.285	0.84843
3	181300	181907	492.222	-607.110	-1.44432
4	182500	182543	371.987	-42.917	-0.08102
5	182500	182975	351.903	-475.291	-0.87488
6	183600	183804	464.754	-204.123	-0.45308
7	184000	184620	432.206	-620.211	-1.28718
8	186200	186020	417.356	180.326	0.36447
9	187600	187577	641.773	22.956	0.27247
10	187900	187225	495.936	674.866	1.62245

APPENDIX D₂₆: General Regression Analysis: TOYOTA HIACE versus TIME, Precipitatio, ...

Regression Equation

$$\text{TOYOTA HIACE (REPLACEMENT) Precipitation} = 187383 + 1232\text{TIME} - 21.7\text{TIME} \times \text{TIME} - 0.0328352 \\ - 448.473 \text{Temperature} - 21.9811 \text{Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	187383	15451.0	13.2313	0.000	(164719, 244155)	
TIME	1232	10820	8.0873	0.000	(597, 1154)	2.72008
Precipitation	-0	1.1	-0.0294	0.978	(-3, 3)	1.70772
Temperature	-448	559.2	-0.8020	0.459	(-1886, 989)	1.62383
Relative Humidity	-22	13.9	-1.5848	0.174	(-58, 14)	1.69297

Summary of Model

S = 596.127 R-Sq = 97.90% R-Sq(adj) = 96.21%
 PRESS = 87122570 R-Sq(pred) = -3.21%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	82637323	82637323	20659331	58.1351	0.000222
TIME	1	81363938	23242380	23242380	65.4038	0.000468
Precipitation	1	35255	306	306	0.0009	0.977721
Temperature	1	345546	228602	228602	0.6433	0.458931
Relative Humidity	1	892584	892584	892584	2.5117	0.173857
Error	5	1776837	1776837	355367		
Total	9	84414160				

Fits and Diagnostics for All Observations

Obs	(REPLACEMENT)	Fit	SE Fit	Residual	St Resid
1	189240	188911	449.890	329.423	0.84228
2	189750	189908	314.919	-158.212	-0.31258
3	190000	190131	453.323	-130.994	-0.33838
4	191250	191757	342.590	-507.270	-1.03980
5	193280	193296	324.093	-16.317	-0.03261
6	194400	194476	428.026	-76.363	-0.18404
7	195000	194720	398.051	280.304	0.63166
8	196600	195620	384.374	980.016	2.15077
9	196700	196852	591.056	-152.437	-1.96461
10	197000	197548	456.744	-548.149	-1.43089

APPEDIX D₂₇: General Regression Analysis: TAXI CAB (RE versus TIME, Precipitatio, ...

Regression Equation

$$\text{TAXI CAB (REPLACEMENT)} = 166660 + 2364.59 \text{ TIME} - 2.55249 \text{ Precipitation} - 2246.16 \text{ Temperature} + 18.215 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	166660	105386	1.58143	0.175	(-104243, 437562)	
TIME	2365	738	3.20278	0.024	(467, 4262)	2.72008
Precipitation	-3	8	-0.33451	0.752	(-22, 17)	1.70772
Temperature	-2246	3814	-0.58895	0.581	(-12050, 7558)	1.62383
Relative Humidity	18	95	0.19255	0.855	(-225, 261)	1.69297

Summary of Model

S = 4065.98 R-Sq = 85.07% R-Sq(adj) = 73.12%
 PRESS = 343533340 R-Sq(pred) = 37.94%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	470889462	470889462	117722365	7.1208	0.026943
TIME	1	457959280	169583392	169583392	10.2578	0.023921
Precipitation	1	6927976	1849936	1849936	0.1119	0.751568
Temperature	1	5389281	5734404	5734404	0.3469	0.581495
Relative Humidity	1	612924	612924	612924	0.0371	0.854890
Error	5	82660788	82660788	16532158		
Total	9	553550250				

Fits and Diagnostics for All Observations

Obs	TAXI CAB (REPLACEMENT)	Fit	SE Fit	Residual	St Resid
1	100000	101997	3068.55	-1997.19	-0.74868
2	101100	106403	2147.95	-5302.50	-1.53593
3	110200	107716	3091.96	2484.02	0.94076
4	115200	111948	2336.69	3251.58	0.97719
5	116400	113184	2210.53	3215.60	0.94228
6	117000	116792	2919.42	207.54	0.07333
7	119500	116445	2714.97	3054.91	1.00931
8	120150	121362	2621.68	-1212.12	-0.39001
9	120600	120752	4031.39	-151.54	-0.28634
10	121000	124550	3115.29	-3550.29	-1.3587

APPENDIX D₃₁: General Regression Analysis: NISSAN URVAN versus TIME, Precipitation,....,

Regression Equation

$$\text{NISSAN URVAN (INCOME GENERATED)} = 105514 - 1770.89 \text{ TIME} - 0.061673 \text{ Precipitation} - 452.116 \text{ Temperature} + 52.8054 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	105514	29445.1	3.58340	0.016	(29822.6, 181205)	

TIME	-1771	206.3	-8.58481	0.000	(-2301.2,	-1241)	2.72008
Precipitation	-0	2.1	-0.02893	0.978	(-5.5,	5)	1.70772
Temperature	-452	1065.6	-0.42428	0.689	(-3191.3,	2287)	1.62383
Relative Humidity	53	26.4	1.99782	0.102	(-15.1,	121)	1.69297

Summary of Model

S = 1136.05 R-Sq = 98.01% R-Sq(adj) = 96.42%
PRESS = 304319525 R-Sq(pred) = 6.08%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	317569930	317569930	79392483	61.5159	0.000193
TIME	1	312226000	95115969	95115969	73.6989	0.000354
Precipitation	1	140397	1080	1080	0.0008	0.978041
Temperature	1	52356	232331	232331	0.1800	0.688994
Relative Humidity	1	5151177	5151177	5151177	3.9913	0.102223
Error	5	6453010	6453010	1290602		
Total	9	324022940				

Fits and Diagnostics for All Observations

NISSAN URVAN
(INCOME GENERATED)

Obs	GENERATED)	Fit	SE Fit	Residual	St Resid
1	98073	98256.3	857.36	-183.26	-0.24588
2	97824	97279.2	600.15	544.77	0.56477
3	96000	96351.4	863.90	-351.43	-0.47636
4	95150	94035.7	652.88	1114.28	1.19852
5	90200	90431.0	617.63	-230.98	-0.24225
6	88500	88703.2	815.70	-203.17	-0.25694
7	86100	86818.2	758.57	-718.19	-0.84925
8	84897	86445.2	732.51	-1548.21	-1.78293
9	83400	83115.8	1126.38	284.16	1.92171
10	83000	81708.0	870.42	1292.05	1.76982

APPENDIX D₃₂: General Regression Analysis: SIENNA (INCO versus TIME, Precipitatio, ...

Regression Equation

SIENNA (INCOME GENERATED) = 102072 - 2025.08 TIME - 3.03727 Precipitation -
70.4048 Temperature - 25.8191 Relative Humidity

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	102072	33914.5	3.00970	0.030	(14892.5, 189252)	
TIME	-2025	237.6	-8.52335	0.000	(-2635.8, -1414)	2.72008
Precipitation	-3	2.5	-1.23689	0.271	(-9.3, 3)	1.70772
Temperature	-70	1227.3	-0.05736	0.956	(-3225.4, 3085)	1.62383
Relative Humidity	-26	30.4	-0.84810	0.435	(-104.1, 52)	1.69297

Summary of Model

S = 1308.48 R-Sq = 97.61% R-Sq(adj) = 95.69%
PRESS = 381272825 R-Sq(pred) = -6.59%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
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Regression	4	349133362	349133362	87283340	50.9795	0.000305
TIME	1	344761485	124381856	124381856	72.6475	0.000366
Precipitation	1	3100049	2619363	2619363	1.5299	0.271053
Temperature	1	40334	5634	5634	0.0033	0.956477
Relative Humidity	1	1231495	1231495	1231495	0.7193	0.435091
Error	5	8560638	8560638	1712128		
Total	9	357694000				

Fits and Diagnostics for All Observations

Obs	SIENNA (INCOME GENERATED)	Fit	SE Fit	Residual	St Resid
1	90000	89249.9	987.50	750.08	0.87373
2	87100	87408.8	691.24	-308.81	-0.27795
3	84200	84376.4	995.03	-176.39	-0.20758
4	82050	83293.3	751.98	-1243.34	-1.16111
5	81500	81900.0	711.38	-400.04	-0.36426
6	80400	80222.0	939.51	177.98	0.19542
7	78000	77367.6	873.71	632.45	0.64930
8	77100	75038.3	843.69	2061.69	2.06137 R
9	71400	71717.9	1297.35	-317.90	-1.86659
10	70150	71325.7	1002.54	-1175.72	-1.39824

R denotes an observation with a large standardized residual.

APPENDIX D₃₃: General Regression Analysis: PEUGEOT EXPE versus TIME, Precipitatio, ...

Regression Equation

$$\text{PEUGEOT EXPERT (INCOME GENERATE)} = 91558 - 2930\text{TIME} + 46.4\text{TIME} \times \text{TIME} - 1.98175 \text{Precipitation} + 1586.08 \text{Temperature} + 6.81091 \text{Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI
Constant	91558	17493.5	2.6601	0.045	(1565.99, 91502.9)
TIME	-2930.1	122.6	-17.8951	0.000	(-2508.12, -1878.1)
Precipitation	-2.0	1.3	-1.5646	0.178	(-5.24, 1.3)
Temperature	1586.1	633.1	2.5054	0.054	(-41.30, 3213.5)
Relative Humidity	6.8	15.7	0.4337	0.683	(-33.56, 47.2)

Term	VIF
Constant	
TIME	2.72008
Precipitation	1.70772
Temperature	1.62383
Relative Humidity	1.69297

Summary of Model

S = 674.931 R-Sq = 99.53% R-Sq(adj) = 99.16%
 PRESS = 29475222 R-Sq(pred) = 93.97%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	486173342	486173342	121543335	266.816	0.000005
TIME	1	482911030	145876226	145876226	320.233	0.000010
Precipitation	1	167308	1115135	1115135	2.448	0.178446
Temperature	1	3009308	2859277	2859277	6.277	0.054135
Relative Humidity	1	85696	85696	85696	0.188	0.682560

Error	5	2277658	2277658	455532
Total	9	488451000		

Fits and Diagnostics for All Observations

Obs	PEUGEOT EXPERT (INCOME GENERATE)	Fit	SE Fit	Residual	St Resid
1	88300	88452.4	509.363	-152.405	-0.34418
2	86000	85447.5	356.549	552.513	0.96413
3	84200	83822.9	513.249	377.100	0.86037
4	79900	80510.4	387.878	-610.425	-1.10516
5	77550	78185.2	366.936	-635.151	-1.12124
6	76050	75318.5	484.608	731.480	1.55709
7	74150	74464.7	450.670	-314.675	-0.62631
8	70500	70955.6	435.185	-455.640	-0.88321
9	68050	67970.5	669.189	79.528	0.90528
10	67600	67172.3	517.122	427.674	0.98605

APPENDIX D₃₄: General Regression Analysis: J5 (INCOME G versus TIME, Precipitatio, ...

General Regression Analysis: J5 (Income G versus J5 (KM), Precipitatio, ...

Regression Equation

$$\begin{aligned}
 \text{J5 (Income Generated)} &= 89992 \times 0.97633 \text{Time} \times \text{Time} - 0.136165 \text{ J5 (KM)} + 3.6546 \\
 &\text{Precipitation} + \\
 &\quad 61.9918 \text{ Temperature} - 25.0126 \text{ Relative Humidity} - \\
 &\quad 2379.43 \text{ Time}
 \end{aligned}$$

9 cases used, 1 cases contain missing values

Coefficients

Term	Coef	SE Coef	T	P	95% CI
Constant	89992	25385.4	3.89863	0.030	(18180.7, 179756)
J5 (KM)	-0.1	0.1	-0.94091	0.416	(-0.6, 0)
Precipitation	3.7	1.3	2.74599	0.071	(-0.6, 8)
Temperature	62.0	603.4	0.10273	0.925	(-1858.3, 1982)
Relative Humidity	-25.0	15.9	-1.57518	0.213	(-75.5, 26)
Time	0.97633	248.4	-9.57967	0.002	(-3169.9, -1589)

Term	VIF
Constant	
J5 (KM)	13.3217
Precipitation	2.5536
Temperature	1.6528
Relative Humidity	2.3154
Time	13.8618

Summary of Model

S = 579.892 R-Sq = 99.64% R-Sq(adj) = 99.04%
 PRESS = 42836719 R-Sq(pred) = 84.70%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	5	278922376	278922376	55784475	165.890	0.000732

J5 (KM)	1	208710754	297705	297705	0.885	0.416167
Precipitation	1	21725292	2535673	2535673	7.540	0.070980
Temperature	1	13280953	3549	3549	0.011	0.924656
Relative Humidity	1	4345421	834364	834364	2.481	0.213293
Time	1	30859956	30859956	30859956	91.770	0.002413
Error	3	1008824	1008824	336275		
Total	8	279931200				

Fits and Diagnostics for All Observations

Obs	J5 (Income Generated)	Fit	SE Fit	Residual	St Resid	
1	89100	88745.4	517.814	354.647	1.35858	
2	85400	85719.0	367.088	-318.993	-0.71059	
3	83300	83530.4	495.598	-230.374	-0.76512	
4	81500	81070.4	392.138	429.624	1.00567	
5	79200	79855.8	330.694	-655.792	-1.37668	
6	77600	77326.8	440.083	273.169	0.72338	
7	76060	75871.9	498.709	188.064	0.63554	
8	*	73603.0	*	*	*	X
9	74500	74482.9	578.990	17.092	0.52865	X
10	69800	69857.4	573.063	-57.436	-0.64731	

X denotes an observation whose X value gives it large leverage.

Predicted Values for New Observations

New Obs	Fit	SE Fit	95% CI	95% PI
1	88745.4	517.814	(87097.4, 90393.3)	(86271.2, 91219.5)
2	85719.0	367.088	(84550.8, 86887.2)	(83534.8, 87903.2)
3	83530.4	495.598	(81953.2, 85107.6)	(81102.7, 85958.0)
4	81070.4	392.138	(79822.4, 82318.3)	(78842.6, 83298.2)
5	79855.8	330.694	(78803.4, 80908.2)	(77731.3, 81980.3)
6	77326.8	440.083	(75926.3, 78727.4)	(75010.1, 79643.6)
7	75871.9	498.709	(74284.8, 77459.1)	(73437.9, 78306.0)
8	73603.0	605.428	(71676.3, 75529.8)	(70935.1, 76271.0)
9	74482.9	578.990	(72640.3, 76325.5)	(71875.0, 77090.8)
10	69857.4	573.063	(68033.7, 71681.2)	(67262.9, 72452.0)

Values of Predictors for New Observations

New Obs	J5 (KM)	Precipitation	Temperature	Relative Humidity	Time	
1	87191.6	1620.0	29.20	148.00	1	
2	86768.3	1500.0	28.50	156.90	2	
3	85921.8	1650.3	28.96	176.98	3	
4	85498.5	1507.0	28.15	159.56	4	
5	85075.3	1579.1	28.30	126.20	5	
6	84652.0	1506.6	27.80	122.65	6	
7	82112.4	1695.4	28.85	129.70	7	
8	76610.1	1662.0	27.90	148.00	8	X
9	74493.8	2294.7	28.30	122.65	9	X
10	73647.2	1695.0	28.40	129.68	10	

APPENDIX D₃₅ : General Regression Analysis: FORD BUS (IN versus TIME, Precipitatio, ...

Regression Equation

$$\text{FORD BUS (INCOME GENERATED)} = 112797 - 2575.45 \text{ TIME} + 0.252617 \text{ Precipitation} - 718.235 \text{ Temperature} + 17.2251 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI	VIF
Constant	112797	21886.1	5.1538	0.004	(56537.1, 169057)	
TIME	-2575	153.3	-16.7972	0.000	(-2969.6, -2181)	2.72008
Precipitation	0	1.6	0.1594	0.880	(-3.8, 4)	1.70772
Temperature	-718	792.0	-0.9068	0.406	(-2754.2, 1318)	1.62383
Relative Humidity	17	19.6	0.8768	0.421	(-33.3, 68)	1.69297

Summary of Model

S = 844.406 R-Sq = 99.36% R-Sq(adj) = 98.84%
 PRESS = 17353494 R-Sq(pred) = 96.86%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	549637105	549637105	137409276	192.714	0.000012
TIME	1	548559760	201176990	201176990	282.147	0.000014
Precipitation	1	57268	18120	18120	0.025	0.879582
Temperature	1	471962	586327	586327	0.822	0.406084
Relative Humidity	1	548115	548115	548115	0.769	0.420734
Error	5	3565105	3565105	713021		
Total	9	553202210				

Fits and Diagnostics for All Observations

FORD BUS
(INCOME GENERATED)

Obs	GENERATED)	Fit	SE Fit	Residual	St Resid
1	92000	92207.7	637.263	-207.71	-0.37493
2	90200	90258.0	446.078	-58.01	-0.08092
3	87130	87736.0	642.126	-606.02	-1.10516
P 4	86140	85406.1	485.274	733.92	1.06206
5	82900	82166.5	459.073	733.52	1.03500
6	78800	79870.7	606.293	-1070.68	-1.82172
7	77400	76710.2	563.833	689.78	1.09737
8	75500	75123.9	544.460	376.13	0.58276
9	71950	71984.3	837.222	-34.30	-0.31207
10	68750	69306.6	646.971	-556.62	-1.02578

APPENDIX D₃₆: General Regression Analysis: TOYOTA HIACE versus TIME, Precipitation, ...

Regression Equation

TOYOTA HIACE (INCOME GENERATED) = 102347 - 2419.39TIME - 3.14643
 Precipitation + 1037.48 Temperature +
 1.31919 Relative Humidity

Coefficients

Term	Coef	SE Coef	T	P	95% CI
Constant	102347	9281.45	8.2691	0.000	(52890.7, 100608)
TIME	-2419.39	65.02	-33.9491	0.000	(-2374.6, -2040)
Precipitation	-3.1	0.67	-4.6820	0.005	(-4.9, -1)
Temperature	1037.5	335.89	3.0888	0.027	(174.1, 1901)
Relative Humidity	1.3	8.33	0.1583	0.880	(-20.1, 23)

Term	VIF
Constant	
TIME	2.72008
Precipitation	1.70772
Temperature	1.62383
Relative Humidity	1.69297

Summary of Model

S = 358.096 R-Sq = 99.87% R-Sq(adj) = 99.76%
 PRESS = 21724080 R-Sq(pred) = 95.54%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	485983438	485983438	121495859	947.47	0.000000
TIME	1	482911030	147793247	147793247	1152.54	0.000000
Precipitation	1	1815901	2811028	2811028	21.92	0.005424
Temperature	1	1253291	1223403	1223403	9.54	0.027197
Relative Humidity	1	3215	3215	3215	0.03	0.880388
Error	5	641162	641162	128232		
Total	9	486624600				

Fits and Diagnostics for All Observations

TOYOTA HIACE
(INCOME GENERATED)

Obs	GENERATED)	Fit	SE Fit	Residual	St Resid
1	100120	99934.5	270.251	185.451	0.78936
2	97060	97390.2	189.173	-330.169	-1.08591
3	95500	95213.5	272.313	286.460	1.23184
4	92200	92593.6	205.795	-393.627	-1.34319
5	90190	90270.9	194.684	-80.931	-0.26928
6	88120	87768.2	257.117	351.831	1.41158
7	86000	86065.3	239.110	-65.329	-0.24507
8	83300	83001.5	230.895	298.502	1.09056
9	79110	79184.9	355.049	-74.853	-1.60597
10	78800	78977.3	274.368	-177.334	-0.77062

APPENDIX D₃₇: General Regression Analysis: TAXI CAB (IN versus TIME, Precipitation, ...

Regression Equation

$$\text{TAXI CAB (INCOME GENERATED)} = 79507.8 - 2838.07 \text{ TIME} - 0.320374 \text{ Precipitation} + 115.358 \text{ Temperature} + 2.22523 \text{ Relative Humidity}$$

Coefficients

Term	Coef	SE Coef	T	P	95% CI
Constant	79507.8	20934.0	3.7980	0.013	(25695.4, 133320)
TIME	-2838.1	146.7	-19.3519	0.000	(-3215.1, -2461)
Precipitation	-0.3	1.5	-0.2114	0.841	(-4.2, 4)
Temperature	115.4	757.6	0.1523	0.885	(-1832.1, 2063)
Relative Humidity	2.2	18.8	0.1184	0.910	(-46.1, 51)

Term	VIF
Constant	
TIME	2.72008
Precipitation	1.70772
Temperature	1.62383
Relative Humidity	1.69297

Summary of Model

S = 807.671 R-Sq = 99.52% R-Sq(adj) = 99.14%
 PRESS = 75112628 R-Sq(pred) = 88.99%

Analysis of Variance

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	4	678887358	678887358	169721840	260.177	0.000006
TIME	1	678841282	244296241	244296241	374.496	0.000007
Precipitation	1	18821	29144	29144	0.045	0.840946

Temperature	1	18108	15125	15125	0.023	0.884927
Relative Humidity	1	9147	9147	9147	0.014	0.910347
Error	5	3261664	3261664	652333		
Total	9	682149022				

Fits and Diagnostics for All Observations

TAXI CAB (INCOME)						
Obs	GENERATED	Fit	SE Fit	Residual	St Resid	
1	78900	79848.6	609.540	-948.56	-1.79007	
2	77215	76988.0	426.673	227.01	0.33103	
3	75000	74199.5	614.191	800.48	1.52618	
4	71190	71275.2	464.163	-85.16	-0.12883	
5	68300	68357.1	439.102	-57.06	-0.08417	
6	66150	65476.6	579.918	673.36	1.19780	
7	63090	62714.9	539.305	375.10	0.62388	
8	58800	59818.7	520.774	-1018.67	-1.65005	
9	56900	56767.6	800.800	132.36	1.25911	
10	54050	54148.9	618.826	-98.88	-0.1905	

APPENDIX G: Programming Algorithm for Nissan Urvan and Sienna Vehicles.

stage 14, Nissan Urvan						
States	C=C, B=I, H= $V_{k(i)}$ & D=R		I	C	R	$V_{k(i)}$
State 15	V_k	=SUM(H5-G5)	67958.28	50076.39	250732	-17881.9
	V_r	=SUM(24482.21-200892.3+I5)				
State 13	V_k	=SUM(H6-G6)	73867.7	47691.8	238195.4	-26175.9
	V_r	=SUM(24482.21-200892.3+I6)				
State 12	V_k	=SUM(H7-G7)	75345.05	46737.96	226285.6	-28607.1
	V_r	=SUM(24482.21-200892.3+I7)				
State 11	V_k	=SUM(H8-G8)	76851.96	45803.2	214971.3	-31048.8
	V_r	=SUM(24482.21-200892.3+I8)				
State 10	V_k	=SUM(H9-G9)	78388.99	44887.14	204222.8	-33501.9
	V_r	=SUM(24482.21-200892.3+I9)				
State 9	V_k	=SUM(H10-G10)	79956.77	43989.4	194011.6	-35967.4
	V_r	=SUM(24482.21-200892.3+I10)				
State 8	V_k	=SUM(H11-G11)	81555.91	43109.61	184311.1	-38446.3
	V_r	=SUM(24482.21-200892.3+I11)				
State 7	V_k	=SUM(H12-G12)	83187.03	42247.42	175095.5	-40939.6
	V_r	=SUM(24482.21-200892.3+I12)				
State 6	V_k	=SUM(H13-G13)	84850.77	41402.47	166340.7	-43448.3
	V_r	=SUM(24482.21-200892.3+I13)				
State 5	V_k	=SUM(H14-G14)	86547.78	40574.42	158023.7	-45973.4
	V_r	=SUM(24482.21-200892.3+I14)				
State 4	V_k	=SUM(H15-G15)	88278.74	39762.93	150122.5	-48515.8
	V_r	=SUM(24482.21-200892.3+I15)				
State 3	V_k	=SUM(H16-G16)	90044.31	38967.67	142616.4	-51076.6
	V_r	=SUM(24482.21-200892.3+I16)				
State 2	V_k	=SUM(H17-G17)	91845.2	38188.32	135485.6	-53656.9
	V_r	=SUM(24482.21-200892.3+I17)				
State 1	V_k	=SUM(H18-G18)	93682.1	37424.55	128711.3	-56257.6
	V_r	=SUM(24482.21-200892.3+I18)				

stage 14, Sienna						
States	C=C, B=I, H= $V_k(i)$ & D=R		I	C	R	$V_k(i)$
State 15	V_k	=SUM(C6-B6)	56301.15	71079.66	138403	1477
	V_r	=SUM(50612.82-79164.72+D6)				8.51
State 13	V_k	=SUM(C7-B7+H6)	61196.9	65814.5	131482.9	1939
	V_r	=SUM(50612.82-79164.72+D7+H6)				6.11
State 12	V_k	=SUM(C8-B8+H7)	62420.84	64498.21	124908.7	2147
	V_r	=SUM(50612.82-79164.72+D8+H7)				3.48
State 11	V_k	=SUM(C9-B9+H8)	63669.25	63208.25	118663.3	2101
	V_r	=SUM(50612.82-79164.72+D9+H8)				2.48
State 10	V_k	=SUM(C10-B10+H9)	64942.64	61944.08	112730.1	1801
	V_r	=SUM(50612.82-79164.72+D10+H9)				3.92
State 9	V_k	=SUM(C11-B11+H10)	66241.49	60705.2	107093.6	1247
	V_r	=SUM(50612.82-79164.72+D11+H10)				7.62
State 8	V_k	=SUM(C12-B12+H11)	67566.32	59491.1	101738.9	4402.
	V_r	=SUM(50612.82-79164.72+D12+H11)				395
State 7	V_k	=SUM(C13-B13+H12)	68917.65	58301.27	96651.98	-
	V_r	=SUM(50612.82-79164.72+D13+H12)				6213.
State 6	V_k	=SUM(C14-B14+H13)	70296	57135.25	91819.38	98
	V_r	=SUM(50612.82-79164.72+D14+H13)				1937
State 5	V_k	=SUM(C15-B15+H14)	71701.92	55992.54	87228.41	4.7
	V_r	=SUM(50612.82-79164.72+D15+H14)				-
State 4	V_k	=SUM(C16-B16+H15)	73135.96	54872.69	82866.99	3508
	V_r	=SUM(50612.82-79164.72+D16+H15)				4.1
State 3	V_k	=SUM(C17-B17+H16)	74598.68	53775.24	78723.64	-
	V_r	=SUM(50612.82-79164.72+D17+H16)				7417
State 2	V_k	=SUM(C18-B18+H17)	76090.65	52699.73	74787.46	0.8
	V_r	=SUM(50612.82-79164.72+D18+H17)				9756
State 1	V_k	=SUM(C19-B19+H18)	77612.47	51645.74	71048.08	1.7
	V_r	=SUM(50612.82-79164.72+D19+H18)				-
						1235
						28