

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Road maintenance is primarily done using asphalt, where it is used as the glue or binder mixed with aggregates particles. Asphalt is a heavy, dark brown to black mineral substance, one of several mixtures of hydrocarbons called bitumen. Asphalt is a strong, versatile weather and chemical-resistant binding material which adapts itself to a variety of uses. Asphalt binds crushed stone and gravel (commonly known as aggregates) into firm, tough surface for roads, streets, and airport run-ways. Asphalt, also known as mineral pitch, is obtained from either natural deposits such as native asphalt or brea or as a by product of the petroleum asphalt. The implementation by early civilizations occurred naturally and were found in geologic strata as either soft, workable motars or as hard, brittle black veins of rock formations (also known as asphaltic coal). Natural asphalt were extensively used until the early 1900s when the discovery of refining asphalt from crude petroleum came in place. Modern petroleum asphalt has the same durable qualities as naturally occurring asphalt. However, the mix design ratio of asphalt produced by construction companies varies and this invariably determines the life span of any road built with it before it shows signs of cracking. In other words, the higher the durability of the asphalt, the

longer the life span of the road design asphalt, the smoother the road made with such quality of asphalt.

Consequently, many factors are responsible for maintenance cost of roads built by construction companies in Nigeria. These factors include material cost, labour cost, transportation cost, overhead cost, maintenance cost and taxes.

1.2 Statement of the Problem

With the increase in traffic volumes on the roads, characterized by varying composition and axle loads, there is corresponding deterioration and failure of roads. This ugly development has been affecting service delivery to rural and urban areas till date. The road transportation system began suffering losses due to high operating costs leading to some being grounded. These triggered the need to place emphasis on road maintenance. Unfortunately, the financial and technical requirements for effective maintenance, rehabilitation and reconstruction became so staggering that the rate of maintenance could not matched with the rate deterioration. The importance of road maintenance in achieving efficient road transport delivery cannot be overemphasized as the consequences of neglect are enormous and costly. Johanneck (2011) noted that rough pavements reduce fuel economy, accelerate vehicle deterioration, increase vehicle maintenance and tire wear, and cost more to maintain and rehabilitate. On the average, estimated rough roads cost a Minnesota driver about \$347 a year (Johanneck, 2011). The annual cost of rough roads for about

four million drivers in Minnesota amounted to an estimated \$1.3 billion in 2007. The consequences of road deterioration and the paucity of road infrastructure in Anambra State and Nigeria as a whole are arguably believed to exceed the Minnesota scenario considering the magnitude of the disrepair of the roads. The characteristic feature of most of the roads in Anambra State, even on the major Enugu – Onitsha expressway that is undergoing construction lately, is the deplorable condition of the roads in terms of dearth of road infrastructure and maintenance. Non-functioning road culverts and street light, absence of other road infrastructure, and presence of numerous potholes make most roads very uncomfortable for commuting.

Huge sums of money have been invested into road development in Nigeria so far. The road network is currently estimated at about 200,000 kilometres, with the Federal Government being responsible for about 17 percent, State Governments 16 percent and local Governments 67 percent (CBN, 2003). However, these roads have been plagued by a number of problems, faulty designs identified as one of the major problem, inadequate drainage system and poor maintenance culture, which have significantly reduced the utility of the roads. There are potholes, fallen bridges, etc, along most Nigerian roads. These problems have made it difficult, expensive and more arduous to move products and services from producers to consumers, farm produce from rural to urban centres, which often leads to loss of man-hours and high cost of goods and

services. As at 2003, the annual loss due to bad roads is valued at N80 billion, while additional vehicle operating cost resulting from bad roads is valued at N53.8 billion, bringing the total loss per annum to N133.8 billion (CBN, 2003). This figure does not take into account the man-hour losses in traffic due to bad roads and other emotional and physical trauma people go through while plying the roads and the consequent loss in productivity. Overall, the poor state of roads in Nigeria impacts negatively on cost of production, and represents a major trigger of cost-push inflation. Without doubt, it is believed that one of the greatest assets of any nation is its road network and can only be preserved through adequate maintenance. Hence, the evaluation of government involvement on road maintenance in Nigeria becomes a sine qua non. In addition, observing the massive construction of roads embarked on by the Anambra State government in recent times, thus the need for an efficient culture and approach for maintenance of the roads is necessary. This study seek to design a linear and nonlinear cost model for estimating the cost of road maintenance in Anambra State. Also, to determine between the linear and nonlinear model, the model that best estimate the cost of road maintenance in Anambra State and to determine the economic factors that impact on the cost of road maintenance in Anambra State.

1.3 Aim and Objectives of the Study

The aim of this study is to develop models for estimation of road maintenance cost in Anambra State. To achieve this aim, this study has the following objectives:

- a. To develop a linear cost model and non linear cost model for estimating the cost of road maintenance in Anambra State.
- b. To optimize the linear and non linear cost model there by determining the optimal cost of road maintenance.
- c. To determine between the linear and non linear cost model, the model that is more efficient for road maintenance in Anambra State.
- d. To ascertain the impact of economic factors on the cost of road maintenance in Anambra State.
- e. To develop a time series model for estimating maintenance cost of roads annually.
- f. To determine the impact of constituent materials for binder and wearing on maintenance cost of roads in Anambra State.
- g. To determine the impact of length of road on maintenance cost of roads in Anambra State.

1.4 Significance of the Study

Eze (2012) discussed the rate and factors of road accidents in Nigeria and noted that road traffic accidents occur worldwide but the incidence is more in developing countries. Annually, it causes about 1.2 million deaths globally. Road traffic accident is a leading cause of death in adolescents and young adults worldwide. Majority of mortalities and morbidities occur in developing countries. In Nigeria, trauma is the main reason for emergency room visits and road traffic accidents are responsible for the majority of death (Eze, 2012). The overall road traffic injury rate is about 41 per 1000 persons and mortality from road traffic injuries is about 1.6 per 1000 persons. This is significant when the fact that majority of these injuries and deaths could be prevented. It becomes worrisome with the fact that the incidence is increasing. He emphasized that road design and maintenance is one of the major factors that contribute to road traffic accidents in Nigeria. The causes of road traffic accidents are not just human error or driver negligence. Eze (2012), concluded that unfortunately, Nigerian highways are arguably one of the worst and most dangerous in the world. Delaney (2008) viewed transportation as the lifeline of economy and social interaction. Thus, an inefficient transport system connotes stagnation in all sectors of the economy. He believes that designing and implementation of an efficient policy on road maintenance will impact positively in putting the road in good condition and thereby boosting the economy. Hence, findings from this

study will be useful to the state government by enabling the government to have a true knowledge of maintenance cost of roads in Anambra state thereby checkmating overestimation of cost of maintenance by contractors. This study will not only be useful in the engineering field rather the procedure and model proposed in this study can be employed in other discipline such as Management sciences, Physical sciences, who work in the area of modelling.

1.5 Scope of the Study

This study covered road maintenance, factors that influence road maintenance in Anambra State and constituent parameters involved in production of asphalt used for maintenance of roads in Anambra state from 2004-2013.

CHAPTER TWO

LITERATURE REVIEW

2.1 Review of Road Maintenance

Road maintenance means the activities and inputs of preserving and keeping of road structures as near as possible in their original state. It consists of correcting deficiencies that have developed as a result of age, use and the effects of the elements, and taking steps to prevent or delay the development of other deficiencies. Road maintenance is vital in order to prolong its life. Also well-maintained roads reduce the cost of operating vehicles by providing good running surface. Proper maintenance also keeps the roads open and ensures greater regularity, punctuality and safety of transport services. In their contribution, Abdulkareem and Adeoti (2007) noted that road maintenance involves activities programmed to preserve the road infrastructure. This means that within the design life of the road, conscious efforts must be made to arrest the various deteriorations that could take place on it. Road infrastructure is comprises of the carriage way, the pedestrian facilities where applicable, drainage system, culverts (Box or Ring types), bridges and flyovers, street light installations, traffic signs and traffic islands. The purpose of road maintenance is to ensure that the roads provide an acceptable level of service to the users for

substantial period of its service life. According to Abdulkareem and Adeoti (2007), the Nigerian road system is classified into four broad categories:

1. *The Federal Trunk 'A' Roads:* These are roads owned and maintained by the Federal Government of Nigeria.
2. *The Federal Trunk 'F' Roads:* These were roads formerly under state ownership, but were taken over by the Federal Government, with a view to upgrading them to Federal highway standards.
3. *The State Trunk 'B' Roads:* These are under owned and managed by states.
4. *The Local Government Trunk 'C' Roads:* These are owned and managed by Local Government. Each tier of government has the responsibility for planning, construction and maintenance of the network of roads under its jurisdiction.

2.1.1 Causes of Road Deterioration and Failure

According to Abdulkareem and Adeoti (2007), failure/collapse of roads is not peculiar to Nigeria, it happens in the advanced countries of the world. The sand stone dust-chippings-Bitumen ratios, is the key factor in the production of asphalt. This is because asphalt do not withstand the weight of loads for a long period when wrong mixture is used its production. Road infrastructure has been

identified as an important factor for country's development in sectors such as education, power and infrastructure in general (Tarawneh and Sarireh, 2013).

According to Tarawneh and Sarireh (2013), the main causes of deterioration resulting into failures of a road pavement in Jordan are as follows.

- i. Lack of appropriate engineering design
- ii. Topography of the road in question
- iii. Inadequate implementation of government policies on road design and maintenance
- iv. Lack of maintenance culture
- v. The action of traffic, with heavy goods vehicles having the greatest detrimental effect: The predominant cause of deterioration is due to vertical deformation in the wheel tracks.
- vi. The action of weather, rain and heat.
- vii. Unstable ground conditions and poor drainage.
- viii. Construction materials and methods.
- ix. Post construction activities like, digging of trenches along the road. Dumping of building materials and other obstructions on the road such as uncontrolled street trading.
- x. Poor workmanship
- xi. Inadequate maintenance.

2.1.2 Classification of Road Maintenance Activities according to Abdulkareem and Adeoti (2007).

Abdulkareem and Adeoti (2007) suggested that in order to ensure proper planning preparatory to actual budgeting for maintenance, there is need to categorize the options available for maintenance activities.

- a. *Routine maintenance:* Routine maintenance is required continually on every road, irrespective of its engineering features or volume of vehicular traffic. Routine maintenance expenses are treated as fixed-cost items in the maintenance budget. This consists of operations that normally need to be repeated one or more times every year, e.g. control of vegetation, maintenance of bridges, crack sealing, seal coats, maintenance of road signalization and repairs to shoulders, lane marking, drainage clearing, bridges and culvert maintenance, grass cutting and so on.
- b. *Recurrent maintenance:* These activities may be required at intervals throughout the year; the frequency varies with traffic, Topography and climate. They include repairing pot-holes, surface patching, edge repairs, and road surface markings.
- c. *Periodic maintenance:* This involves major repairs or rehabilitation of those parts of the road that have deteriorated over the years. The frequency involves intervals of some years. As a pavement is subjected to significant traffic and the ageing process progress, sufficient distress

occurs. These activities are required to maintain acceptable safety, adequate drainage and adequate riding surface, and retard the failure of the various pavement layers. Such activities include, re-graveling of gravel roads, re-surfacing of bituminous surface dressing and paved roads.

- d. *Urgent or special maintenance works:* These include removal of debris, fallen trees, broken down vehicles, erection of warning signs and construction of diversions. They must be carried out with minimum delay to avoid danger to traffic.

Abdulkareem and Adeoti (2007) noted that execution of road maintenance can be based on these two methods:

1. *Direct Labour Maintenance:* The agency undertakes the repair through their work force, equipment and procurement of maintenance materials.
2. *Maintenance by Contract:* The services of reputable contractors having asphalt plants, necessary equipment and man power are engaged. The supervision is done by the client or through consultants engaged by the-clients. This sector is presently dominated by foreign multinational executing about 85% of road construction, rehabilitation and maintenance.

2.2 Review of Hot Mix Asphalt (HMA) Production in Nigeria

Hot Mix Asphalt (HMA) production is generally subcontracted to the HMA producers by state ministries of works, Federal Road Maintenance Agency, etc. As a control procedure, these government institutions evaluate the performance of the final asphalt product and determine the pay factor (Russell *et. al.* 2001), which ultimately determines the amount of payment to the subcontractor. Not surprisingly, one of the main elements of the pay factor determination is the quality of the asphalt.

Schmitt *et. al.* (1997) reported that quality control costs of a typical asphalt manufacturer are approximately 2% of total HMA construction costs. They added that an inferior quality of asphalt products may lead to repaving of a road, the actual quality costs would be higher where mixing, trucking, and paving costs correspond to 38% of total HMA construction costs.

Aggregates are temporarily stored at the cold feed bins (to be used in the production), and are released onto the main conveyor in specific amounts as required by the job mix formula (JMF). In general, the JMF is dictated based on the type of project. The aggregate mix is then conveyed to the drum where the mix is heated and bitumen and the other required components are added. Lastly, the finished hot mix asphalt is stored in silos before it is transferred to paving

site. An asphalt producer basically works on a project basis and each project can have different specifications.

Schmitt *et. al.* (1997) added that the quality of the asphalt product is affected by the quality of inputs (aggregates) and the production process. Among those, the consistency of the aggregate gradations and the fluctuations in the moisture levels of aggregates are the most critical. They identified the aggregates to include sand, stone and other elements that are fed to the system from the cold feed bins. Again, the primary issue for the aggregates is the high variation in their gradation values. Obviously, low variation on the gradation is a desired property for the aggregates. The levels of variation in the gradation of an aggregate vary from supplier to supplier, and even from one lot of aggregates to another of the same supplier. More interestingly, different batches of the same aggregate from the same lot can be different from each other due to storage and pick up conditions. As aggregates are stored (generally) in an open area, weather conditions of the storage area, such as humidity, temperature and rain, affect the moisture content and gradation of aggregates (Schmitt *et. al.* ,1997).

The important point is that there is no easy way to change input aggregate quality. A typical quarry (aggregate provider) does not crush their aggregates, rather aggregates are sold as they are. One solution is to crush all aggregates into specific percentages of gradation piles using crusher machines. However, this would be a very costly and time consuming process for both the quarry and

the asphalt company. Al-Rousan *et al.* (2005) proposed an image analysis method that can be used in monitoring HMA; however, the aggregates are processed separately in his work. West (2005) proposed state-of-the-art equipment that can be used in monitoring HMA production such as, microwave probes (for moisture). In his study, video imaging techniques are mentioned as near future technology.

2.3 Review on Performance Record of Hot Mix Asphalt (HMA)

The need for close temperature control at the asphalt plant to control the drying process, particularly with high moisture content ash, was also noted (Ormsby, 1988).

There is no large-scale commercial use of municipal waste combustor ash in asphalt paving mixes in Nigeria at the present time. Difficulties were noted with residues that contained high organic content (measured as loss on ignition - LOI), compared with residues with low organic content. Residues having LCI's greater than 10 percent exhibited high and uneven absorption of asphalt during the asphalt production process. High asphalt demand and dusting during drying was attributed to the high fines content in the ash. Base course applications were generally considered to be better suited for use as ash pavements than wearing coarse applications. The results of more recent demonstrations, conducted during the past 10 years, found ash sections in general to be comparable in

performance to conventional mixes; however, some difficulty in the asphalt production process because of baghouse clogging (Chesner Engineering, 1995) and high ash moisture content were reported. A breakdown in ash particles to a finer graded product during the production process was also reported, (American Association of State Highway and Transportation Officials. Standard Method of Test, 2007).

During the asphalt production process, the introduction of aggregates blended with a large fraction of ash (that contains a high moisture and fines content) could result in potential operational problems. This includes lower plant throughput rates to provide greater time for drying and potential clogging of the asphalt plant baghouse with excessive fines from the ash. Asphalt pavements incorporating municipal waste combustor ash can be expected to benefit from the low unit weight of the ash compared with conventional aggregate and the resultant higher yield expressed in terms of volume per ton. Pavements that contain higher percentages of ash require higher percentages of asphalt binder (cement) compared with conventional aggregate mixes. This results from the highly absorptive characteristics of ash particles. Due to the relatively low durability of ash particles compared with that of natural aggregates, and the high percentage (approximately 20 to 30 percent) of glass that is present in ash, the introduction of high percentages of ash into wearing course mixes could result in ravelling or stripping problems.

2.4 Design Considerations of Asphalt

2.4.1 Mix Design

Asphalt mixes can be designed using standard laboratory procedures. Care must be taken, however, to ensure that the asphalt cement content is adequate to account for the high absorption of ash particles during the mix design process. Recent work has suggested that Marshall mix design methods could lead to overestimating the required asphalt content of the mix and could result in subsequent pavement failure due to rutting. The use of a Gyrotory Test Machine as specified in ASTM D3387 has been proposed as an alternative for preparation of the mix, using gyrotory compatibility and stability indices to determine the optimum asphalt content (Chesner Engineering, 1995). Lower ash contents may be more suitable in paving mixes to reduce the asphalt cement requirements resulting from the introduction of a large fraction of highly absorptive ash particles into the mix. As long as percentages of ash introduced into a mix remain low (less than 20 percent), additional asphalt cement requirements should be reasonably low. Lower ash contents in surface mixes can also eliminate the need for anti-tripping agents such as hydrated lime.

Thompson (1996) noted that in wearing course material section guidelines developed from functional performance considerations of unpaved public roads, the selection criteria from mine haul road were discussed by Paige-Green

(1989) in his development of the guidelines. A shrinkage product of 100-365 (preferably less than 240) together with a grading coefficient of 16-34 are recommended in the light of slipperiness and traction considerations.

Wearing course material specifications associated with the structural design of mine haul roads have been proposed (Monismith, 1976) in terms of TRH 14 (NITRR, 1985).

Study by Bester (1981) and Shear *et al.* (1986), identified variables that affect the measurement of rolling resistance for asphalt production to include road geometry and roughness, tyre temperature, cold pressure and warm-up time, ambient temperature, wind speed and direction.

Ullidtz *et al.* (1979) proposed a model for the static coefficient or rolling resistance (CR.) for asphalt production which used roughness of the asphalt and tyre pressure as independent variables. Substituting values for the variables in the model, it was found that tyre pressure of 640pa gives a positive relationship.

Monismith and Vallerga (1956) conducted a study which showed that densification of some asphalt mixtures by traffic over a period of time actually resulted in a decrease of stability (resistance to deformations). This is contrary to the concept in wide use today that on increase in density of an asphalt paving mixture results in an increase in stability.

Lingle (1956) Analyzed their data in light of the voids in the mineral aggregate (VMA) and asphalt contents. When the density of the pavement approaches the theoretical maximum density and when the mix could no longer consolidate, it rapidly loses stability and begins to rut and shove.

Based on the laboratory studies, many theoretical models have been developed to predict the permanent deformation (resulting in rutting and shoving) in aspect of pavements. These were exclusively discussed on the state-of-the-art report on "Rutting prediction asphalt concrete pavements" by Monismith (1979).

Federal ministry of Works (2013) noted that funding of road infrastructure projects remains a major constraint in the delivery of efficient and improved road networks across the country. They noted that the funding of road projects has been through the budgetary provisions and executed by traditional method of direct contract award. This method has proved to be inadequate and most often unimplemented thereby creating a funding gap for execution of road projects. On the average, the annual funding requirement is estimated at NGN500b against an average budgetary allocation of NGN120bn with a deficit of NGN380bn in Nigeria. In 2012, out of the NGN143bn budgetary allocation for road infrastructure development only NGN110bn was released with deficit of NGN33bn unimplemented. The deficit had negative consequences on the

maintenance of road infrastructure thereby undermining national economic growth and responsible for loss of lives and properties across the country. In addition, Federal ministry of Works (2013) noted that reports have further shown that Nigeria has the second highest road traffic accident fatalities among 193 countries in the world. It was observed that Nigeria records 152 deaths for every 100,000 people, making road accidents the third highest killer in the country. It was further revealed that eighty per cent of injuries in Nigeria are traffic accident related.

Abdukareem and Adeoti (2007) explained that over the years, the federal, state and local governments have shared the responsibility for the development and maintenance of roads in Nigeria. The roads therefore fall into three main categories. First the federal trunk roads, which link the major parts of the country, the main urban centres and state capitals, the major centres of economic activity and the major border crossings, to neighbouring countries. Also there exist state roads which feed into federal trunk roads and the farm-to-market roads. Third category consists of rural roads and city streets, which are the responsibilities of local governments.

Abdulkareem (2003) noted that the World Bank and the Ten Year Road Recovery Programme (TYRRP) estimated the following funding requirements for bringing all roads to good and fair conditions within Ten Years, Annual

Road maintenance N34bn (\$300m) and Annual Rehabilitation N45Bn (\$400m) making the Total N79bn (\$700m). Funding for Road maintenance comes from annual budget. The inadequate and irregular funding from this source contributes to the poor condition of the road network in Nigeria.

2.5 Review of Economic Benefits of Road Maintenance

Transport has extensive coverage on the road, in the air and on the sea and through the rail system. Transportation is an economic function that serves along with other productive functions in the production of goods and services in the economy. A well developed transportation sector requires substantial expenditure. A good road network is very essential in its ability to support the growth and development of other sectors in the economy such as agriculture, commerce and industry. In sub Saharan Africa, (Heggie, 1994) stated that road transport dominates other modes of transport as it carries over ninety percent of passengers and provides the only form of access to most rural communities. In Nigeria, roads play significant role in her social and economic life development and are seen as the centre of connectivity of all other mode of transport with an approximate total network of about 193,200kms. Nigerian road sector carries more passengers domestically, and the transport sector contributes about 2.4% to real Gross Domestic Product (GDP) with road transport accounting for about 86% of the transport sector output. Road network represents the arteries of the

Nigerian economy through which the country's economic activities flow to local, state and national levels.

The World Bank report on infrastructural development carried out by the African Infrastructure Country Diagnostic (Cecilia *et al.*, 2008), provided an overview of the status of public expenditure, investment needs and sector performance as some infrastructure sectors that included, energy, information and communication techniques, irrigation, transport, water and sanitation covering twenty four nations including Nigeria. The report states that "any plan for scaling up infrastructure in Africa must rest on a thorough evaluation of how fiscal resources are allocated and financed because the public sector retains the lion's share of infrastructure financing with private participation remaining limited". Provision of physical infrastructure particularly road is vital to economic growth of nations itching to take advantages of global connections. However, the issue of government expenditure is an important arm of public financing. Expenditures will be illusion without the source of revenue to the government. Revenue generation through taxing system constitutes the most important source of earnings by government. Adequate cooperation from all the sectors in the economy in terms of taxes will enhance government's desire to expand on every facet of the economy. Roads and other infrastructure therefore are very essential to rural and urban welfare of residents of any nation and a pivotal key critical for the acceleration of the economy.

In the opinion of Okonjo-Iwuela (2007), Nigeria would require a minimum of US\$5billion yearly and for the next 10 years to maintain and expand all types of infrastructure. This huge requirement to finance infrastructure would need private partnership to handle in order to, at least reduce the alarming rate of road accidents in Nigeria, and stimulate the economy through increased productivity arising from increased funding and improving the maintenance culture of roads. The essence of good roads in Nigeria is to facilitate improvement in the economic and business activities and translate these to making living more meaningful to the citizens, because excellent roads will cause considerable reduction in the cost of production and save time of movement of goods and persons from place to place.

In a study conducted by Kweka and Morrissey (1999), in Tanzania on government spending and economic growth, it was established that public investment on physical infrastructure and human capital contributed positively to economic growth.

However, Al-Faris (2002) in his work on Public Expenditure and Economic Growth concluded that an insignificant relationship exists between government consumption expenditure and the rate of economic growth. Barro (1991) considered expenditure as either productive or unproductive; where productive expenditure has direct impact on the rate of economic growth, while

unproductive expenditure has indirect or no effect on the growth rate of the economy. Anyanwu, Adebunsi, and Kukah (2003) in their article on maintenance of Highway in Nigeria observed that the growth of economic activities in Nigeria depended on the level of improvement on the roads. Nworji and Oluwalaiye (2012), in their study on infrastructure opined that, infrastructure variables have positive correlation with private investment and economic growth, and the infrastructure to create new capacities and equally maintaining the existing ones. Expenditure on roads enhances distribution of goods and services through national and international markets and good transport linkages reduce transport costs, while promoting industrial development.

Bush (1991), asserted that inter- state highway system propelled development in the USA for a generation which unites the states economically, politically, and socially. Thus economic infrastructure such as road provides the foundation where upon a solid structure of growth and development can be erected, but a weak and fragile foundation might not provide for a super structure to build on.

On the situation of road network in Nigeria, Delaney (2008), says “Identifying the extent of decay in Nigeria’s infrastructure is not a difficult task; from transport to health, from energy to utilities, decades of malaise and underinvestment have taken over their toll on the nation’s infrastructure” This state of decay was captured in 1999 at the inception of the democratic

dispensation after long era of military aberration in governance in Nigeria, when the then President Obasanjo said, “Transport is the lifeline of the economy and social interaction. An inefficient transport system implies stagnation in all sectors. Our priorities in this sector will be the design and implementing a new policy on road maintenance” The setting up of the Federal Roads Maintenance Agency (FERMA) was perhaps the fall-out from the President’s observation and as the new policy direction of restoring dignity on Nigerian roads, despite the earlier intervention of the Petroleum Trust Fund (PTF) on some road rehabilitation. These government agencies have not been able to impact positively in putting the roads in good condition, rather rapid deterioration is being witnessed all over the country. Most of these roads constructed more than three decades have become very deplorable due to neglect and lack of proper maintenance.

Speaking on the responsibility of the Federal Ministry of Works on infrastructural development in Nigeria, Federal Ministry of Works (2013) explained that the Ministry is charged with the responsibility of developing the Nation's Federal Highway infrastructure. Also, the Ministry has a critical role to play in the Transformation Agenda of the present administration. The Ministry has identified road infrastructure not only as critical in the socio-economic development of the country but also a crucial and pivotal resource required to fast track the development of other modes of transportation. To this end, the

federal ministry of works has a four-fold mandate which includes the following; (a) planning, construction, rehabilitation and maintenance of Federal Roads; (b) planning, construction, rehabilitation and maintenance of bridges along Federal Highways; (c) provision of facilities such as street lights, road signs and markings on Federal Roads; and (d) providing professional services to other ministries department and agencies.

Now, Road Infrastructure is a generic term for basic structures and facilities that are essential to the generation of economic growth and development in modern economies. It covers many facilities generally referred to as economic and social overhead capital which include education, water supply, sewage systems, energy, postal and telecommunication services, transport systems, hospitals and roads (CBN, 1999). Efficient provision of infrastructure is usually characterized by heavy capital outlay, indivisibility of benefits and high externalities. In view of these properties, government is usually called upon to provide such facilities, especially in the developing economies. In countries where the development of these infrastructures has followed a rational, coordinated and harmonized path, growth has received a big boost (CBN 2003). This is because infrastructure provision and development serve as input into private sector production, thereby facilitating output growth and productivity. Examples are Japan and Korea. On the other hand, where the growth of infrastructure has not followed such a harmonized path, development is usually stunted as exemplified by most

African countries. Infrastructure provision can be through public ownership with private sector management and operations, public ownership and operation through public enterprises or government departments, private ownership/operation and community provisioning. The provision of infrastructure in Nigeria is characterized by the predominance of public enterprises. The extent to which a nation's land mass is covered by road network is an index of the degree of mobility of people, goods and services within the country, and the quality of the network measures the ease and cost of that mobility. In addition, it is evident that transportation plays a crucial role in shaping the destiny of many nations because modern industry and commercial activities rest on proper, well-developed and efficient transport system. Today, 95% of both passenger and freight movements are by road in Nigeria largely due to inadequacy of other forms of transportation in the country. The federal roads account for only about 17% of the total national road network but accommodate more than 80% of national vehicular and freight traffic bearing in mind a 2.533% population growth rate per annum. In addition, new vehicle importation in the country increased by 45% in 2011, and the first half of 2012 recorded an increase by 15% compared with the same period in 2011. Apparently, Nigeria is getting more cars on the road making reformation and maintenance of the roads very essential (Federal Ministry of Works, 2013).

Road transportation is considered the most patronized among other modes of transportation especially in developing nations like Nigeria because of its large coverage and ability to provide door to door services. It was estimated that road transportation carries about 95% of the national passenger and freight services and provides the only access to rural communities where majority of the economically active population lives. CBN (2003) explained that the integrated road development in Nigeria dates back to 1925, when the Road Board was established by the then colonial administration. The Board had the responsibility to evolve blueprints for trunk road network, connecting major administrative centres in the colonial time. As at 1951, 1,782km out of the total of 44,414km of road built in Nigeria was surfaced. The roads were however lacking in standard designs and were in single lane, with sharp bends and poor drainage system. The growth of economic activities prompted the need, for improvement in roads. Consequent upon this, the quality of road construction was improved as the length and network continued to increase such that by 1952, 15,785km of bituminous surface and 75,200km of earth/gravel surface roads were already in place in Nigeria. Road construction in Nigeria received a major boost in the 1970's during the "oil boom" era and has since then become a major component of annual capital budgets at both the states and national levels. The national road network grew from its total length of 6,500Km in 1960 to 10,000Km in 1970 to 29, 000Km in 1980 and in the year 2003 estimated at

200,000Km (Abdulkareem, 2003). The age of the roads, the continuous use of the roads coupled with untimely maintenance or sometimes near neglect manifest as rough surfaces and pot holes with resultant human discomfort, man hour lost, increased vehicular maintenance cost, vehicular accidents, loss of lives and property.

A part from savings in the cost of preservation of national, investment on roads, substantial reduction in vehicle operating cost and other road user's benefits, other economic benefits of road maintenance that enhances national development are as follows:

A. Employment Creation: All road maintenance agencies create employment opportunities for various categories of citizens and help in poverty eradication. The establishment of Kwara Waste Management Company (KWMC) in 2003 and the recently established Anambra State Road maintenance Agency by the State government, to undertake routine maintenance on Intra city roads among other activities has provided employment opportunity to hundreds of Youths in the State. Also, FERMA has provided employment opportunities to thousands of Nigerian in its operations since being established.

B. Agricultural Production: Past and present efforts in rural road maintenance are focused on improved Agricultural production and creation of links between rural and urban areas for free movement of agricultural products.

C. *Industrial Development*: The level of Industrialization in any economy depends largely on the condition of its road network. This is why governments continued to pay great attention to road development and maintenance, as a catalyst for industrial growth.

D. *Man power Development*: The acquisition of technical skill in road maintenance by Nigerian engineers and technologists through the various road maintenance agencies will assist Nigeria in its drive towards technological independence.

E. *Research and Development*: Challenges created by the road maintenance needs have opened up tremendous opportunities for our Research Institutions, Universities and Polytechnics in the area of cheaper road maintenance materials and methods. These challenges still exist.

2.6 Review of Standard of Road Maintenance

Wasike (2001), observed that a major problem culminating in the poor state of the Nigerian roads is that construction standard has always been very low and ineffective coordination. Eboh *et. al.* (2005) expresses similar opinion, they noted that most roads in Nigeria were not constructed with the standard specification, and without providing the necessary facilities like drainages, pavements, road signs, etc. which lead to the degradations of the road networks

caused by the blockages of turnouts, thereby leading to ingredients of water to the sub-grade of the soil.

Speaking on poor standard of road construction and maintenance by all tiers of government, the views of Adesanya (1999) captures the consequence that when maintenance is deferred, two things happen thus: the costs of operating vehicles in the short run will likely increase; while in the long-run the rehabilitation of paved roads every 10-20 years will be more than three times as expensive for the government, in terms of cash as carrying out road maintenance on regular basis. This position is backed by most researchers, that in the event that a road is not maintained, every dollar saved on road maintenance increases vehicle operating cost by US\$2 to US\$3 (Abdukareem and Adeoti 2007). The implication is that, by cutting back on maintenance, the cost of road transport and the net cost to the economy is being inadvertently increased. The long neglect and maintenance of roads in Nigeria has caused the collapse of integrated transport system and contributed to the continued deterioration of the road network. The devastating effect of deferred maintenance on commodity flow, cost of goods and services, and the associated socio-economic costs might be very abnormal. If the issue of playing politics with the lives of the people could be set aside, and corrupt practices minimized, allowing for transparency in government then the poor maintenance culture might be put in the past and expenditure by governments on the roads would become visible.

Nworji and Oluwalaiye (2012) in their study focused on the impact of government expenditure on road infrastructure would have on economic growth of Nigeria. The output they derived was used to test the hypothesis which confirmed that government expenditure on road infrastructure would expedite the growth of the economy. They noted that the huge fund sunk into the construction, rehabilitation, and maintenance of roads in Nigeria in the last three decades was badly reciprocated by the poor and deplorable current state of these roads. Road remains the major tool of facilitating the mode of moving goods and people across the country to accelerate economic and business activities. The poor conditions of the Nigerian roads have created grave danger to lives and properties resulting from several accidents. Maintenance and supervision of these roads coupled with sharp practices of corruption by government agents and lack of transparency are part of what created the present state of these roads. They concluded that several Nigerian roads were constructed without proper design and where, they existed, construction works were not followed to specification. Hence, sub-standard materials such as quality of asphalt used in delivery of poor work could not withstand the stress of use and soon became worn out. To avoid this, it is suggested that all road designs, construction and rehabilitation work should be handled by competent engineers who must give guarantee on the roads for a specified period.

Speaking on the categories of roads in Nigeria, Federal Ministry of Works (2013) explained that trunk A roads are roads that form the skeleton of the national road grid. They cut across regional boundaries in the country and even extend to the international borders of neighbouring West African countries. These categories of roads are under Federal Government's ownership. They are designed, constructed, maintained and financed by the Federal government through the Federal Ministry of Works. The Federal Road Maintenance Agency (FERMA) is in charge of carrying out maintenance of this class of roads. Trunk B roads are the second category of main roads in Nigeria. They link the major cities within States with the State capitals. These roads are designed, developed, financed and maintained by the State governments through their Ministries of Works, Transport or Infrastructure. The primary objectives of Trunk B roads are to enhance the socio-economic development of the various States in the country. In addition, truck C roads are local feeder roads constructed and maintained by the Works Department of Local Government Authorities in Nigeria. This class of roads are primarily not concrete asphalted and are affected by seasonal weather changes. The roads link villages and communities in the remote parts of each local government region. Rilwani and Agbanure (2010) explained that there are two major types of road pavement in Nigeria. Those finished with asphalt wearing course, are referred to as flexible pavement roads, while those finished with a reinforced concrete, which are referred to as rigid pavement

roads. More than 90 percent of all the roads constructed in Nigeria are of the flexible pavement type. A release by the Federal Ministry of Works and Housing, Highways Management Services Division in 1994 showed that of all the 32,097km of Federal Highways, 18,250km are of asphalt concrete wearing course carriage and another 7,877km are made up of asphalt surface dressing, both types being flexible pavement (FMWH 1994). The remaining 5970km are the then yet to be constructed earth roads.

2.7 Review of Institutional arrangements on Road Maintenance in other Countries

A review of other countries experiences regarding institutional arrangements for road maintenance will provide valuable insights from which useful lessons can be learnt in the effort to provide an efficient and sustainable road maintenance system in Nigeria. In this regard, CBN (2003) noted that the Africa Road Network Initiative (RNI) launched by the United Nations Economic Commission for Africa and the World Bank (Under the auspices of the Sub-Saharan Africa Transport Program) in 1997 provided a veritable springboard. The initiative was to identify the underlying causes of poor road maintenance policies in some African countries, including Nigeria, and to develop an agenda for reform. The programme revealed three valuable insights.

1. Public financing does not hold the key for the reform of the road sector; the need to involve the road users and business community is vital;
2. The real causes of problems associated with poor road maintenance policies were weak or unsuitable institutional arrangements for managing and financing roads; and
3. Poor road maintenance policies are a subset of the underlying issues of managing and financing the road network as a whole. The above-mentioned insights point to the fact that a distinct body, which is relatively independent of Government and affiliated to the private sector, is indeed a vital tool in the efficient and sustainable management of road networks. Consequently, many countries are finding it useful to establish such a separate body, which will be responsible for the management of road maintenance. This usually takes the form of a broad based Authority, which helps in insulating the relevant road management authority from political interference, while enabling it to draw upon the skills and expertise of its board members. The various arrangements in this respect for some selected countries are discussed below. The selection and choice of countries has been based on the availability of information. Countries covered are Ghana, Honduras, Guatemala, Costa Rica, Nicaragua, Armenia, Lesotho, Tanzania and Namibia.

GHANA

The Ghana Highway Authority (GHA) was established under the National Redemption Council (NRC) decree 298 of December 1974 and charged with the responsibility for planning, development, maintenance and administration of all trunk roads and related facilities in Ghana (Bahl, 1991). Ghana's total network is 38,757km as at 2003. GHA controls 14,982 (or 38.6%) of which paved roads are 5,913km while 9,069km are graded. The GHA hopes to achieve a trunk road condition mix of 67% good, 20% fair and not more than 13% poor and to close up missing links in the existing network under a Trunk Road Network Stabilization Program (TRNSP). Under the TRNSP, it will use both National and International competitive bidding to execute 90% of periodic maintenance works by private road contractors, with the Mobile Maintenance Unit (MMU) and Bridge Maintenance Unit (BMU) of the GHA executing the remaining 10%. The MMU carries out periodic and emergency maintenance of trunk roads while the BMU maintains bridges across the country. GHA's funding comes chiefly from the consolidated fund and foreign donor agencies. For instance, its total approval funding for 1996 was 238.42 billion cedis (Afemia Road Network Initiative). In addition, the Ghana Road Fund was established in 1996 to finance routine periodic maintenance and rehabilitation of public roads; to provide for the management of the Fund and provide for related matters (Bahl, 1991,

Adebusuyi, 1994). The fund is used to assist the Metropolitan, Municipal and District Assemblies in the exercise of their functions relevant to public roads.

Monies for the Fund are derived from:

- a) Proportion of government levy on petrol, diesel, kerosene and refined fuel oil as may be determined by the cabinet with the approval of parliament.
- b) Bridge, ferry and road tolls collected by the authority
- c) Vehicle license and inspection fees
- d) International transit fees, collected from foreign vehicles entering the country
- e) Such funds as the Minister of Finance in consultation with the Minister of Works may determine with the approval of Parliament.

The GHA functioned fairly effectively in its role of managing the country's trunk road network. Available data showed that by the end of 1995, the

Authority was able to achieve a network condition mix of 40% good, 27% fair and not more than 33% poor with a total funding support of 71.81 billion cedis. Its 1996 target was 51% good, 22% fair and 27% poor but was only able to achieve 38 % good, 28% fair and not more than 34% poor.

HONDURAS

In Honduras, the Road Maintenance Fund was created in 1993. The fund is supervised by a Board, which consists of 4 representatives from the central government, one representative from the municipalities and 3 representatives from the direct road users. The principal financial source of the fund is a levy on fuel in the form of a dedicated tax. The Board is responsible for the routine and periodic maintenance of the official road network, excluding urban and municipal roads. Up to 10% of the funds can be disbursed for road rehabilitation works. All works as well as services have to be contracted out to the private sector. In addition, to avoid creating another bureaucracy, the administrative cost of the fund has been restricted to 2.5% of its annual budget. Recently, a law was passed, stipulating that a specific portion of the fuel tax be dedicated to the fund (Ziettow and Bull, 2002).

GUATEMALA

In 1996, Guatemala increased the taxes on motor fuel and dedicated the increase and part of the existing fuel taxes to a special fund disbursed exclusively for road maintenance and improvement. A board made up of three government officials and three members from the private sector were saddled with the responsibility of managing the funds. The administrative cost of the Fund was limited to 2% of its annual turnover. All works and services are contracted out

to the private sector. This fund is believed to have worked very effectively, creating a very favourable Perception in the general public (Zietlow and Bull, 2002).

COSTA RICA

Costa Rica created its Road Fund, which is funded mainly by a levy on fuel in 1998. The fund takes care of the maintenance, rehabilitation and improvement of the national road network but with priority given to routine and periodic maintenance. The Board has three members from the central government (all from the Ministry of Public Works and Transport), one representative each nominated by their respective organizations. The board is obliged to contract out all works and services to the private sector and has to abide by the government rules concerning wages and contracts (Zietlow and Bull, 2002, CBN, 2003).

LESOTHO

In Lesotho, the Road Fund was set up in 1995 under the name Roads Relief Fund with the basic objective of routine and periodic maintenance of all roads in Lesotho, including those under jurisdiction of the Ministries of Works and Local Government. The sources of finance for the fund are: (a) Road toll-gate fees, border fees/short-term Southern African Customs Union; (b) Permits, license fees on motor vehicles, road maintenance levy on petrol and diesel; fines

on over loaded vehicles, any other road user charges or donor funding from donors that may from time to time be allocated to the fund, and any sums appropriated to the fund. The fund is supervised by a Board composed of a chairman, six ex-officio members each representing the Finance, Works, transport and Communication, Local Government, Natural Resources and planning, five non-governmental members, each representing such organizations as the

Chamber of Commerce and Industry, Bus and mini-bus transport operators Association, Association of Architects, Engineers, Surveyors and Lawyers.

The Minister appoints the Chairman and the Board serves for two years from the date of appointment.

TANZANIA

In Tanzania, a Road Fund was set up with the objectives of financing of rehabilitation and maintenance of major and core roads. The revenues of the fund would come from road tolls charged from diesel and petrol, as well as various levies and duties from motor vehicles such as licenses, registration and transferring of vehicles. The Ministry of Works is responsible for monitoring the Fund. The Fund, furthermore, requires authority from the Planning Commission and Ministry of Finance before embarking on any project (Bahl, 1991).

NAMIBIA

The Namibia road sector underwent fundamental change on April 2000 as three new road sector organizations, the Road Fund Administration (RFA), the Roads Authority (RA) and the Roads Contractor Company (RCC) were created and about 2,500 persons who were previously employed in the

Namibian civil service were transferred to the road sector. Some of the notable aspects of the reform are that:

- (1) The road sector is fully self-financed by way of road user charges. The self-financing system, which comprises the Road User Charging System and the Road Fund, is administered by the RFA, an autonomous state agency under the Ministry of Finance.
- (2) The national road network is managed by the RA, a state agency with considerable autonomy under the Ministry of Works, Transport and Communication.

All road works are to be executed subject to competitive bidding procedures, but during a three-year period the state-owned RCC will have almost exclusive rights to do maintenance work on the national road network (CBN, 2003).

However, it can be deduced that the general experience in the developing world tends to show that adequate resources for road maintenance cannot be sourced

from the treasury alone. In addition, the rules and regulations of the public administrative system do not allow for an effective and efficient management of road maintenance. Most countries have, therefore, resorted to the creation of autonomous authorities, which are given the responsibility for road maintenance. Generally, both the public and private sectors are represented on the boards, with the private sector dominating in many countries. In almost all the countries, the sources for revenue for the road maintenance authority are levy on gasoline, toll gates fees, license fees on motor vehicles, international transit fees, fees on over loaded vehicles and allocations by parliament. The proportion of the authorized budget that goes to general administration is specified, while works and services are contracted out to the private sector. Thus, road maintenance agencies are said to have improved the conditions of roads in these countries.

2.8 Review of Methods used in the Analysis of the Study

2.8.1 Curve Fitting and Regression Analysis

Curve fitting is the process of constructing a curve or mathematical function that has the best fit to a series of data points, possibly subject to constraints (Arlinghaus, 1994). Curve fitting captures the trend in a data set by assigning a single function across the entire range of observed data. Curve fitting has been observed in recent times as one of the most powerful and most widely used analytical tools in analyzing the relationship between one or more predictors

(independent variables) and the response variable (dependent variable) by fitting a custom fitting function. Curve fitting can involve either interpolation, where an exact fit to a data set is required, or smoothing, in which a smooth function can be constructed to approximately fit the data set. One of the usefulness of fitted curves is that it can aid data visualization, thereby aid in inferring values of a function where no data are available.

Regression is a statistical inference that focuses on how much uncertainty is present in a curve that is fitted to data observed with random errors. To perform regression analysis on a dataset, a regression model is first developed and the best fit parameters are estimated using test functions like the least-square method. Finally, the quality of the model is assessed using one or more hypothesis tests. However, from a mathematical point of view, there are two basic types of regression: linear and nonlinear regression models. A model where the fit parameters appear linearly in the Least Squares normal equations is known as a "linear model"; otherwise it is "nonlinear". In many scientific experiments, the regression model has only one or two predictors, and the aim of regression is to fit a curve or a surface to the experimental data. So it will not be out of context to refer to the regression analysis as curve fitting analysis or "surface fitting analysis.

2.8.2 Optimization Analysis

Optimization methods have evolved greatly over the past few decades. The traditional methods of maintenance optimization were largely based on subjective ranking and prioritisation rules (Morcoux and Lounis, 2005).

2.8.3 General-Purpose Unconstrained Optimization Method

Unconstrained minimization is among the most applied case of optimization method, and it was observed that many general-purpose unconstrained optimization methods have been applied to image reconstruction problems.

The calculus of variations is concerned with the determination of extrema (maxima and minima) or stationary values of functions. A functional can be defined as a function of several other functions. The calculus of variations is a powerful method for the solution of problems in optimal economic operation of power systems. In the unconstrained optimization problem, there is need to find the value of the vector $X = [x_1, \Lambda, x_n]^T$ that minimizes the function $f(x_1, \Lambda, x_n)$ provided that the function f is continuous and has a first-order derivative. To obtain the minimum and/or maximum of the function (f) we set its first derivative with respect to x to zero

$$\begin{aligned}\frac{\partial f(x_1, \Lambda, x_n)}{\partial x_1} &= 0 \\ \frac{\partial f(x_1, \Lambda, x_n)}{\partial x_2} &= 0 \\ &\cdot \\ &\cdot\end{aligned}$$

$$\frac{\partial f(x_1, \Lambda, x_n)}{\partial x_1} = 0$$

The equations represent n equations in n unknowns and the solution of these equations produces candidate solution points. If the function f has second partial derivatives, then we calculate the Hessian matrix,

$$H = \frac{\partial^2 f(x_1, \Lambda, x_n)}{\partial x_1^2}$$

If the matrix H is positive definite, then the function f is a minimum at the candidate points, but if the matrix H is negative definite then f is a maximum at the candidate points. Nielsen (2000) solved the equation given below using then general-purpose unconstrained optimization method

$y = (1 - x_1)^2 + 100(x_2 - x_1^2)^2$. Hence, any equation of this form can be solved using the general-purpose unconstrained optimization method.

Unconstrained minimization is the problem of finding a vector x that is a local minimum to a scalar function $f(x)$:

$$\min_x f(x) \tag{2.1}$$

the quadratic approximation of the objective function f at the point x

$$f(x) + \nabla f(x) \cdot (y - x) + 1/2 (y - x) \cdot \nabla^2 f(x) (y - x) \tag{2.2}$$

$$y = x - (\nabla^2 f(x))^{-1} \nabla f(x) \tag{2.3}$$

2.8.4 General-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms

The general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms is an optimization method that includes an option for box-constrained optimization and simulated annealing. The approach denoted as "optim ()" requires the following; an initial values for the parameters to be optimized over usually referred to as "par" in R-package, a function of interest to be minimized (or maximized) with first argument being the vector of parameter over which minimization is to take place, a function to return the gradient for BFGS and L-BFGS-B method. Method "L-BFGS-B" is that of Byrd *et. al.* (1995) which allows *box constraints*, that is each variable can be given a lower and upper bound. The initial value must satisfy the constraints. This uses a limited-memory modification of the BFGS quasi-Newton method. If non-trivial bounds are supplied, this method will be selected, with a warning.

Quasi-Newton Methods

Considering the quasi-Newton approximations, it can be noted that most of the numerical studies of interior-point methods have focused on the use of exact Hessian information. It is well known, however, that in many practical applications, second derivatives are not available, and it is therefore of interest to compare the performance of active-set and interior-point methods in this context.

The Quasi-Newton methods are methods used to either find zeroes or local maxima and minima of functions, as an alternative to Newton's method. They can be used if the Jacobian or Hessian is unavailable or is too expensive to compute at every iteration. The "full" Newton's method requires the Jacobian in order to search for zeros, or the Hessian for finding extrema.

More recently quasi-Newton methods have been applied to find the solution of multiple coupled systems of equations (e.g. fluid-structure interaction problems). They allow the solution to be found by solving each constituent system separately (which is simpler than the global system) in a cyclic, iterative fashion until the solution of the global system is found (Haelterman, 2009)

Observing that the search for a minimum or maximum of a single-valued function is nothing other than the search for the zeroes of the gradient of that function, quasi-Newton methods can be readily applied to find extrema of a function. In other words, if g is the gradient of f then searching for the zeroes of the multi-valued function g corresponds to the search for the extrema of the single-valued function f ; the Jacobian of g now becomes the Hessian of f . The main difference is that the Hessian matrix now is a symmetrical matrix, unlike the Jacobian when searching for zeros. In optimizing a function, the quasi-Newton methods (a special case of variable metric method) are algorithms for finding local maxima and minima of functions. Quasi-Newton methods are

based on Newton's method to find the stationary point of a function, where the gradient is zero. Newton's method assumes that the function can be locally approximated as a quadratic in the region around the optimum, and uses the first and second derivatives to find the stationary point. In higher dimensions, Newton's method uses the gradient and the Hessian matrix of second derivatives of the function to be minimized.

In quasi-Newton methods the Hessian matrix does not need to be computed rather the Hessian is updated by analyzing successive gradient vectors. Quasi-Newton methods are a generalization of the secant method to find the root of the first derivative for multidimensional problems. In multiple dimensions the secant equation is under-determined, and quasi-Newton methods differ in how they constrain the solution, typically by adding a simple low-rank update to the current estimate of the Hessian.

The first quasi-Newton algorithm was proposed by William Davidon C., a physicist who developed algorithm in 1959; the DFP updating formula, was later popularized by Fletcher and Powell in 1963. The most common quasi-Newton algorithms are currently the SR1 formula (for symmetric rank one), the BHHH method, the widespread BFGS method (suggested independently by Broyden, Fletcher, Goldfarb, and Shanno, in 1970), and its low-memory

extension, L-BFGS (Nocedal and Wright, 1999). The Broyden's class is a linear combination of the DFP and BFGS methods.

The SR1 formula does not guarantee the update matrix to maintain positive-definiteness and can be used for indefinite problems. The Broyden's method does not require the update matrix to be symmetric and it is used to find the root of a general system of equations (rather than the gradient) by updating the Jacobian (rather than the Hessian). One of the chief advantages of quasi-Newton methods over Newton's method is that the Hessian matrix (or, in the case of quasi-Newton methods, its approximation) B does not need to be inverted. Newton's method, and its derivatives such as interior point methods, requires the Hessian to be inverted, which is typically implemented by solving a system of linear equations and is often quite costly. In contrast, quasi-Newton methods usually generate an estimate of B^{-1} directly. This can be expressed as

$$B_k P_k = -\nabla f(x) \tag{2.4}$$

$$S_k = \alpha_k P_k \tag{2.5}$$

$$y_k = \nabla f(x_{k+1}) - \nabla f(x_k) \tag{2.6}$$

$$B_{k+1} = B_k + \frac{y_k y_k^\tau}{y_k^\tau s_k} - \frac{B_k s_k s_k^\tau B_k}{s_k^\tau B_k s_k} \tag{2.7}$$

where, B is an approximation to the Hessian Matrix (H), s is the trial step, and P_k is the search direction

The L-BFGS Algorithm

The Limited-memory Broyden-Fletcher-Goldfarb-Shanno (L-BFGS) algorithm is employed for solving high-dimensional minimization problems in scenarios where both the objective function and its gradient can be computed analytically (Liu and Nocedal, 1989). The L-BFGS algorithm belongs to the class of quasi-Newton optimization routines, which solve the given minimization problem by computing approximations to the Hessian matrix of the objective function. At each iteration, quasi-Newton algorithms locally model f at the point x^k using a quadratic approximation:

$$Q(x) = f(X^k) + (X - X^k)^T g^k + 1/2 (X - X^k)^T B^k (X - X^k) \quad (2.8)$$

The procedure is iterated until the gradient is zero, with some degree of convergence tolerance. In order to optimize memory usage, the L-BFGS algorithm avoids storing the sequential approximations of the Hessian matrix. Instead, L-BFGS stores curvature information from the last m iterations of the algorithm, and uses them to find the new search direction. More specifically, the algorithm stores information about the spatial displacement and the change in gradient, and uses them to estimate a search direction without storing or computing the Hessian explicitly. Explaining the application of the method,

Nash and Varadhan (2011) solved using the general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms the equation with the form $y=100(x_2 - x_1 \times x_1)^2 + (1 - x_1)^2$.

2.8.5 General-purpose optimization Method

General-purpose optimization method provides modification/extension to the `optim()` function to unify and stream-line optimization capabilities for smooth, possibly box constrained functions of several or many parameters (Nash & Varadhan, 2011). The `optimx` function was introduced by the Nash and Varadhan (2011) and this function wrapper's function by calling other R-package tools for optimization, including the existing general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms called with the `optim()` function. The general-purpose optimization method usually called with the `optimx` function in R-package also tries to unify the calling sequence to allow a number of tools to use the same front-end. Note that general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms itself allows Nelder–Mead, quasi-Newton and conjugate-gradient algorithms as well as box-constrained optimization via L-BFGS-B. Nash (2014) discussed best-practice methods for optimization to replace the default algorithms available in `optim` which were developed more than 40 years ago such best practice method like the package `optimx` (Nash &

Varadhan, 2011) contains several of such best-practice algorithms. According to Nash (2014) the `optimx` function has been found especially useful as a way to compare the performance of more than a dozen optimizers on particular problems. It also standardizes the call to these optimizers, so allows simpler changing from one method to another. However, it could and should be modified to allow much more guidance about methods to users unfamiliar with nonlinear parameter estimation (NLPE) methods.

The `optimx()` does not call the SANN method because it was found that SANN does not return a meaningful convergence code (`conv`). By default the `optimx()` function performs minimization, but it will maximize a function if control `maximize` (`control$maximize`) is `TRUE` while the original `optim()` function allows the control function scale (`control$fnscale`) to be set negative. This method appears to work best with analytic gradients. ("Rvmmmin" provides a box-constrained version of this algorithm, but there are some differences in detail so that the trajectories of the minimization of an unconstrained problem will not match exactly. Method "CG" is a conjugate gradients method based on that by Fletcher and Reeves (1964) (but with the option of Polak–Ribiere or Beale–Sorenson updates). The particular implementation is now dated, and improved yet simpler codes exist, and one of them is provided via `Rcgmin`. Furthermore this permits box constraints on parameters. Conjugate gradient methods will generally be more fragile than the BFGS method, but as they do

not store a matrix they may be successful in much larger optimization problems. The user objective function (fn) can commonly return NA (not available) if the function cannot be evaluated at the supplied parameters. optimx requires that the initial parameters must give a computable finite value of fn. However, some methods, of which "L-BFGS-B" is known to be a case, require that the values returned should always be finite. To control for excursions outside the domain where function fn and, if provided, gr and hess, can be computed, optimx wraps these function using ufn, ugr and uhess. While optim can be used recursively, and for a single parameter as well as many, this may not be true for optimx. optim also accepts a zero-length par, and just evaluates the function with that argument; such usage is strongly discouraged for optimx. Method "Rcgmin" is from the package of that name. It implements a conjugate gradient algorithm with the Yuan/Dai update (Birgin *et al.*, 2001) and also allows bounds constraints on the parameters. (Rcgmin also allows mask constraints – fixing individual parameters – but there is no interface from "optimx").

2.8.6 The Barzilai-Borwein (BB) steplengths algorithm Optimization Method

The Barzilai-Borwein steplength methods for the solution and optimization of large-scale nonlinear systems was proposed by Barzilai and Borwein (1988).

This is gradient method for the unconstrained minimization of a differentiable function

$f : \mathbb{R}^n \rightarrow \mathbb{R}$ that uses a novel and nonstandard strategy for choosing the step length.

Starting from a given $x^0 \in \mathbb{R}^n$, the Barzilai-Borwein (BB) iteration is given by

$$x^{k+1} = x^k - \lambda_k \nabla f(x^k),$$

where the initial step length $\lambda_0 > 0$ is arbitrary and, for all $k = 1, 2, \dots$,

$$\lambda_k = \frac{S_{k-1}^T \times S_{k-1}}{S_{k-1}^T \times y_{k-1}}$$

where, $S_{k-1}^T = x^k - x^{k-1}$ and $y_{k-1} = \nabla f(x^k) - \nabla f(x^{k-1})$

when $f(x) = 1/2 x^T A x + b^T x + c$ is a quadratic function and A is a symmetric positive definite (SPD) matrix, then the step length becomes

$$\lambda_k = \frac{\nabla f(x^{k-1})^T \times \nabla f(x^{k-1})}{\nabla f(x^{k-1})^T A \nabla f(x^{k-1})} \quad (2.9)$$

The Barzilai-Borwein steplength methods for the solution and optimization of large-scale nonlinear system in R-package has the ability of providing a robust strategy for real valued function optimization and solving systems of nonlinear equations by calling a function code the same with different algorithm control settings, until a successfully converged solution is obtained.

2.8.7 Spectral Projected Gradient (SPG) method

The SPG method (Birgin *et al.*, 2000, 2001, 2003) is the spectral option for solving convex constrained optimization problems. As its unconstrained counterpart, the SPG method has the form

$$x^{k-1} = x^k + \alpha_k d_k, \quad (2.10)$$

where the search direction d_k has been defined in (Birgin *et al.*, 2000) as

$$d_k = P_{\Omega}(x^k - \lambda_k \nabla f(x^k)) - x^k,$$

P_{Ω} denotes the Euclidean projection onto the closed and convex set Ω , and λ_k is the spectral choice of step length. The feasible direction d_k is a descent direction, i.e.,

$$d_k^T \nabla f(x^k) < 0, \text{ Which implies that } f(x^k + \alpha d_k) < f(x^k) \text{ for } \alpha \text{ small enough. This}$$

means that, in principle, one could define convergent methods imposing sufficient decrease at every iteration. However, as in the unconstrained case, this leads to very inefficient practical results. A key feature is to accept the initial BB-type step length as frequently as possible while simultaneously guarantee global convergence. For this reason, the SPG method employs a nonmonotone line search that does not impose functional decrease at every iteration (Birgin *et al.*, 2003).

2.8.9 Multi-Start Method of Optimization

The optimization method with Multi-start values strategically samples the solution space of an optimization problem. The most successful of the method of multi start values have two phases that are alternated for a certain number of global iterations. The first phase generates a solution and the second seeks to improve the outcome. Each global iteration produces a solution that is typically

a local optimum, and the best overall solution is the output of the algorithm. The interaction between the two phases creates a balance between search diversification (structural variation) and search intensification (improvement), to yield an effective means for generating high-quality solutions. This survey briefly sketches historical developments that have motivated the field, and then focuses on modern contributions that define the current state-of-the-art. Ribeiro and Resende (2012) in their study considered two categories of multi-start methods: memory-based and memoryless procedures. The former are based on identifying and recording specific types of information (attributes) to exploit in future constructions. The latter are based on order statistics of sampling and generate unconnected solutions. According to Ribeiro and Resende (2012), the early multi-start methods from the optimization setting can be interpreted as using a binary representation of decision variables, starting from a null solution and selecting variables to set to 1, thus identifying assignments of jobs to machines, or edges to tours, or items to compose a knapsack, and so forth. This construction process continued until obtaining a complete or maximally feasible construction, at which point all remaining variables were implicitly assigned values of 0.

Multi-start procedures were originally conceived as a way to exploit a local or neighbourhood search procedure, by simply applying it from multiple random initial solutions. Modern multi-start methods usually incorporate a powerful

form of diversification in the generation of solutions to help overcome local optimality. Without this diversification, such methods can become confined to a small region of the solution space, making it difficult, if not impossible, to find a global optimum. The explicit use of memory structures constitutes the core of a large number of intelligent solvers, including tabu search (Glover, 1989), scatter search (Laguna and Mart'ı, 2003), and path-relinking (Ribeiro and Resende, 2012). These methods, generically referred to as adaptive memory programming, exploit a set of strategic memory designs. The re-start mechanism of multi-start methods can be superimposed on many different search methods. Once a new solution has been generated, a variety of options can be used to improve it, ranging from a simple greedy routine to a complex procedure. An open question in order to design a good search procedure is whether it is better to implement a simple improving method that allows a great number of global iterations or, alternatively, to apply a complex routine that significantly improves a few generated solutions. A simple procedure depends heavily on the initial solution but a more elaborate method takes much more running time and therefore can only be applied a few times, thus reducing the sampling of the solution space (Ribeiro and Resende, 2012). The multi-start value optimization method in R-package has the ability of starting the optimization process from multiple starting points to obtain multiple solutions and to test sensitivity to starting values.

The equation of the multi-start value optimization method is expressed as:

$$x_{k+1} = x_k - B_k^{-1} F(x_k) \quad (2.11)$$

$$B_{k+1} = B_k + \frac{F(x_{k+1})(x_{k+1} - x_k)^\tau}{(x_{k+1} - x_k)^\tau (x_{k+1} - x_k)} \quad (2.12)$$

where, B is an approximation to the Hessian Matrix (H), F is the function and x is the independent variable

2.8.10 Time Series Analysis

Time series is an ordered sequence of values of a variable at equally spaced time intervals. Time series analysis accounts for the fact that data points taken over a period of time may have an internal structure (such as trend or seasonal variation) that should be accounted for. Time series model can be employed in obtaining an understanding of the underlying forces and structure the produce the observed data of interest. It can also be used to fit a model and proceed to forecasting, monitoring or even feedback and feed forward control. Time Series can be defined as a collection of observations X_t , each one being recorded at time t (where time could be discrete, $t = 1, 2, 3, \dots$, or continuous $t > 0$). In their contribution, Ihueze and Onyechi (2011) defined a time series as a collection of observations of well-defined data items obtained through repeated measurement over time.

2.8.11 Trend, seasonality, cycles and residuals

One simple method of describing a series is that of classical decomposition. The notion is that the series can be decomposed into four elements:

1. Trend (T_t): This implies the long term movements in the mean;
2. Seasonal effects (I_t): This deals with the cyclical fluctuations related to the calendar. In other words it can be referred to as a systematic and calendar related effect, for example the sharp escalation in most retail series which occurs around the month December in response to the Christmas period or an increase in water consumption in summer due to warmer weather (Ihueze and Onyechi, 2011);
3. Cycles (C_t): other cyclical fluctuations (such as a business cycles);
4. Residuals (E_t) : other random or systematic fluctuations.

The idea of decomposing the series is to create separate models for these four elements and then expresses them, either

$$\text{additively } X_t = T_t + I_t + C_t + E_t \quad (2.13)$$

or

$$\text{multiplicatively } X_t = T_t \cdot I_t \cdot C_t \cdot E_t . \quad (2.14)$$

(see Ihueze and Onyechi, 2011).

2.8.12 The Least Square Method of fitting Time Series Trend

The least square method of fitting trend line to a time series is the most widely used method for finding trend. The linear trend equation is given as:

$$Y_t = \alpha_0 + \alpha_1 t \quad (2.15)$$

where, Y_t = the estimated trend value for a given time period (t)

α_0 = the trend line value when $t=0$,

α_1 = the gradient or slope of the trend line (the change in Y_t per unit of time)

t = the time unit

The formulas for the parameter estimates are:

$$\hat{\alpha}_0 = \bar{Y} - \hat{\alpha}_1 \bar{t} \quad (2.16)$$

$$\hat{\alpha}_1 = \frac{\sum(t - \bar{t})(Y - \bar{Y})}{\sum(t - \bar{t})^2} \quad (2.17)$$

2.8.13 Stationarity of a Time Series

A stationary time series is one whose statistical properties such as mean, variance or autocorrelation are all constant over time. Most time statistical forecasting methods are based on the assumption that the time series can be rendered approximately stationary through the use of mathematical transformations. Stationarity of a process implies that predictions of the statistical properties will be the same in the future as they have been in the past.

In addition, the stationary assumption allows the straight forward calculation of the long run equilibrium distribution of the process (Tran and Carmichael, 2012). In this study the augmented Dickey-Fuller test (ADF) will be employed in testing for unit root and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test for testing Stationarity of the process.

The augmented Dickey-Fuller test is a test for a unit root in a time series sample data. The augmented Dickey-Fuller statistic, used in the test is a negative number. The more negative it is, the stronger the rejection of the hypothesis that there is a unit root at some level of confidence. The one classical procedure for testing for unit root is to test using augmented Dickey Fuller and with intercept. If the test statistic $<$ critical value (i.e. less than the negative value) reject H_0 . No unit root. Otherwise choose first difference and continue with until you reject H_0 . The amount of differencing required to reject H_0 =order of integration=number of unit roots.

The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is used for testing the null hypothesis that the observed time series is stationary around a deterministic trend. Kwiatkowski *et al.* (1992) proposed a test of the null hypothesis that an observed series is trend stationary (stationary around a deterministic trend). The series is expected as the sum of deterministic trend, random walk, and stationary error, and the test is the Lagrange multiplier test of the hypothesis that the random walk has zero variance. The KPSS type test are intended to compliment

unit root test, such as the Dickey-Fuller tests. By testing both the unit root hypothesis and the stationarity hypothesis, the researcher can distinguish series that appear to be stationary, series that appear to have unit root, series for which the data are not sufficiently informative to be sure whether they are stationary or integrated and series that are fit to be used in predicting future behaviour of the data of interest.

2.8.14 Bivariate Regression Analysis

Bivariate regression analysis is an extension of simple regression analysis to applications involving the use of two independent variables (predictors) to estimate the value of the dependent variable (response variable).

A bivariate linear regression model is the process of associating a random response Y to a set of predictor variables x_1, x_2 is an equation of the form

$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon \quad (2.18)$$

Where Y is a random variable called response/ dependent variable; β_0, \dots, β_2 are constants/parameters whose exact values are not known and hence must be estimated from experimental data; x_1, x_2 are mathematical variables called regressors/covariates/predictors/independent non random variables, whose values are controlled or at least accurately observed by the experimenter and ε is a random variable representing an error term which accounts for unexplained random variation in response.

The system of linear equation for the regression model can be expressed using matrix notation as

$$y = X\beta + \varepsilon \quad (2.19)$$

where β_k for $k=0, 1, 2$ are the coefficient of the regression model parameters

2.8.15 Response Surface Analysis

Response surface analysis explores the relationship between several explanatory variables and one or more response variables. The main ideal behind the response surface method was to use a sequence of designed experiments to obtain an optimal response. The response surface methodology (RSM) can be viewed as a collection of mathematical and statistical techniques for empirical model building. The fundamental methods for quantitative variables involve fitting first-order (linear) or second-order (quadratic) functions of the predictors to one or more response variables, and then examining the characteristics of the fitted surface to decide what action is appropriate. Given that, it may seem like response-surface analysis is simply a regression problem. However, there are several intricacies in this analysis and in how it is commonly used that are enough different from routine regression problems that some special help is warranted. These intricacies include the common use (and importance) of coded predictor variables; the assessment of the fit; the different follow-up analyses that are used depending on what type of model is fitted, as well as the outcome

of the analysis; and the importance of visualizing the response surface. Response-surface methods also involve some unique experimental-design issues, due to the emphasis on iterative experimentation and the need for relatively sparse designs that can be built-up piece-by-piece according to the evolving needs of the experimenter (Kuhn, 2009). The mathematical form of the response surface model can be written as

$$y = f(x_1, x_2) + \varepsilon \quad (2.20)$$

where ε represents the noise or error observed in the response y and the surface represented by $f(x_1, x_2)$ is known as the response surface.

2.8.16 Generalized nonlinear Model

The nonlinear regression model is a form of regression analysis in which observational data are modelled by a function which is a nonlinear combination of the model parameters and depends on one or more independent variables. The data are usually fitted by a method of successive approximations. The generalized non linear models allow dependence on the parameters to take place in a certain “linear” fashion.

The deviance in the generalized non linear model is a measure of goodness of fit, similar to techniques used in “classical” linear regression. Just as in the case of “classical” linear regression, considering the model with no structure imposed on the mean response; that is, with no assumption of a smooth function

of covariates. McCullagh and Nelder (1989) provided an expression for the deviance under other distributions in the scaled exponential family class. They stated that the deviance has the nice property that it is additive for nested sets of models, so it is in fact used as the basis for a sort of extension of the usual analysis of variance for examining the importance of factors in regression models.

In R package the "gnm" is the package for executing the generalized non linear model analysis and its main purpose is to provide a flexible framework for the specification and estimation of generalized models with nonlinear terms. The facility provided with gnm for the specification of nonlinear terms is designed to be compatible with the symbolic language used in formula objects. Primarily, nonlinear terms are specified in the model formula as calls to functions of the class "nonlin". According to Turner and Firth (2012), a model where the predictor variable(s) has a nonlinear behaviour can be classified as a generalized nonlinear model. The generalized nonlinear model from the binomial family is given as

$$Y \sim \text{binomial}(n, p)$$

$$p = \frac{\lambda \beta_1^{\times \gamma}}{1 - \lambda \beta_1^{\times \gamma}} \quad (2.21)$$

where, the parameters are β_1 and γ

2.8.17 Pareto Chart Analysis

Pareto Chart is a sorted bar chart that displays the frequency (or count) of occurrences that fall in different categories, from greatest frequency on the left to least frequency on the right, with an overlaid line chart that plots the cumulative percentage of occurrences. The vertical axis on the left of the chart shows frequency (or count), and the vertical axis on the right of the chart shows the cumulative percentage.

The Pareto Chart is typically used to separate the “vital few” from the “trivial many” using the Pareto principle, also called the 80/20 Rule, which asserts that approximately 80% of effects come from 20% of causes for many systems.

The Pareto chart analysis will be employed in this study to determining the major factors that contribute about 80% of road maintenance problems in Anambra State.

2.8.18 Correlation Analysis

Correlation analysis measures the extent of linear relationship between two variables with the same number of observation. Note that in correlation analysis though interest is still on the relationship between two variables, but no assumptions about the nature of this relationship is made. That is, in correlation analysis, it is no longer assumed that one of the variables is depended variable and the other is an independent variable rather the two variables are random.

The correlation is often concerned with describing the strength of the relationship between two variables by measuring the degree of “scatter” of data values. Correlation can exist in such a way that increases in the value of one variable tend to be associated with increases in the value of the other; this is known as positive (or direct) correlation.

The formula to compute the value of correlation coefficient (r) in quantitative terms is given as

$$r = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}} \quad (2.22)$$

where x and y are the two variables of interest (Okoli *et al*, 2015).

In the present study, the correlation analysis will be employed to determine the extent of relationship between road condition and factors that contribute to road condition in Anambra State.

2.9 Summary of Literature Review

Road maintenance in any nation involves activities designed to preserve road infrastructures with the main aim of ensuring that the road provides an acceptable level of service to the users for substantial period of its service life. In this chapter, the researcher reviewed lots of relevant literature with the purpose of identifying gap in the existing literature.

Review on road maintenance has identified factors such as lack of maintenance culture and inadequate implementation of government policies on roads design and maintenance as the major causes of road deterioration and failure in Nigeria.

It was learnt from the review of hot mix asphalt (HMA) production in Nigeria that one of the main elements of the pay factor determination on the production of asphalt in Nigeria is the quality of the asphalt. The quality of the asphalt product is affected by the quality of inputs (aggregates) and the production process. The aggregates which include sand, stone and other elements that are fed to the system from the cold feed bins.

Review on funding of road maintenance revealed that funding of road maintenance activities remains a major constraint in the delivery of efficient and improved road networks across the country. Even the advent of funding from the budgetary provision and executed by traditional method of direct contract award still has proven to be inadequate and most often unimplemented thereby creating a funding gap for execution of road maintenance projects.

Review on economic benefits of road maintenance revealed that lack of road maintenance cripples transportation. Transportation which is an economic function that serves along with other productive functions in the production of goods and services in the economy. A good road network is very essential in its

ability to support the growth and development of other sectors in the economy such as agriculture, commerce and industry especially in country like Nigeria where roads play significant role in her social and economic life development and are seen as the centre of connectivity of all other mode of transport.

Also, it was found that a part from savings in the cost of preservation of national, investment on roads, substantial reduction in vehicle operating cost and other road user's benefits, other economic benefits of road maintenance that enhances national development includes: employment creation, agricultural production, Industrial development, man power development and research development.

Observation on review of institutional arrangements on road maintenance in other countries revealed the need for a distinct body, which is relatively independent of Government and affiliated to the private sector as a vital tool in the efficient and sustainable management of road networks since;

(a) public financing does not hold the key for the reform of the road sector; the need to involve the road users and business community is vital;

(b) The real causes of problems associated with poor road maintenance policies were weak or unsuitable institutional arrangements for managing and financing roads; and

(c) Poor road maintenance policies are a subset of the underlying issues of managing and financing the road network as a whole.

It is clear from the review that previous researches have not been able to provide any maintenance cost model for estimating the cost of road maintenance in Nigeria. Though some literature noted some factors that influence road maintenance, there have not been enough empirical evidence on determining the economic factors that impact on the cost of road maintenance using mathematical modelling. This study therefore seeks to employ adequate mathematical modelling techniques in evaluating government involvement in road maintenance in Anambra State. In achieving this, various modelling techniques which will be elaborated in the next chapter will be employed.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Method of Data Collection

3.1.1 Sources of Data

The first source of data for this study was secondary source of data collection obtained from the records department of Consolidated Construction Company, Uli Asphalt Plant, Anambra State, Nigeria. The data comprises material cost, labour cost, overhead cost, and transport cost for the production of binder and wearing respectively for the period 2004-2013. Also, economic data were extracted from the Central Bank of Nigeria Statistical Bulletin 2013.

3.2 Theoretical Formulation

3.2.1 Modelling Cost Variables using the linear function

Considering the cost components for the production of binder and wearing in Consolidated Construction Company, Anambra state, the optimization approach for a manufacturing problem as stated in Edgar *et. al.* (2001) was employed.

The business cost can be split into two categories, namely:

1. The carrying cost or the cost of inventory which comprises taxes, clerical and inventory controls, warehouse expenses, insurance and cost of money.
2. The production cost- for the production of binder it comprises material cost of binder, labour cost of binder, overhead cost of binder and

transportation cost of binder while similarly, for the production of wearing it comprises of material cost of wearing, labour cost of wearing, overhead cost of wearing and transportation cost of wearing

Let x_1 and x_2 be the number of units produced in one run for binder and wearing respectively. Also, Q_1 and Q_2 represent the average annual production level for binder and wearing per ton respectively.

Letting k_1x_1 and k_2x_2 be the cost of carrying the inventory for binder and wearing respectively. Where, k_1 and k_2 fundamentally comprises of cost of working capital for the inventory, the warehouse expenses and tax for the two products. However, the production cost in the objective function is proportional to the number of production runs required for both binder and wearing. Assuming the cost per run to be a linear function given by the form

$$\text{cost per run for binder} = k_3 + k_4x_1 + k_5x_1 + k_6x_1 + k_7x_1 \quad (3.1)$$

The cost parameter k_3 is setup cost and denotes a fixed cost of production for binder which includes equipments being cleaned and maintained. The parameter $k_4 =$ material cost of binder, $k_5 =$ labour cost of binder, $k_6 =$ overhead cost of binder and $k_7 =$ transportation cost of binder are operating cost parameters.

Similarly,

$$\text{cost per run for wearing} = k_8 + k_9x_2 + k_{10}x_2 + k_{11}x_2 + k_{12}x_2 \quad (3.2)$$

Where, the cost parameter k_8 is setup cost and denotes a fixed cost of production for wearing which includes equipment being clean up and maintenance. The

parameter k_9 = material cost of wearing, k_{10} = labour cost of wearing, k_{11} = overhead cost of wearing and k_{12} = transportation cost of wearing representing operating cost parameters. The operating cost is assumed to be proportional to the number of units produced for both binder and wearing.

The total production cost (C_T) is the sum of the carrying costs and the production cost of binder and wearing. This connotes summing Equations (3.1) and (3.2) which has the form

$$C_T = k_1x_1 + k_2x_2 + n_1(k_3 + k_4x_1 + k_5x_1 + k_6x_1 + k_7x_1) + n_2(k_8 + k_9x_2 + k_{10}x_2 + k_{11}x_2 + k_{12}x_2) \quad (3.3)$$

The objective function labelled Equation (3.3) is a function of four variables comprising of x_1 , x_2 , n_1 and n_2 . Here, n_1 and n_2 represent the number of production run per year for binder and wearing respectively. In addition, x_1 and n_1 are directly related; similarly, x_2 and n_2 are also directly related. Hence,

$$n_1 = \frac{Q_1}{x_1} \quad \text{and} \quad n_2 = \frac{Q_2}{x_2} .$$

Therefore, only two independent variables exist for this case these are x_1 and x_2 while the dependent variables are n_1 and n_2 . Eliminating n_1 and n_2 from the objective function Equation (3.3), we shall obtain the form

$$C_T = k_1x_1 + k_2x_2 + \frac{Q_1}{x_1}(k_3 + k_4x_1 + k_5x_1 + k_6x_1 + k_7x_1) + \frac{Q_2}{x_2}(k_8 + k_9x_2 + k_{10}x_2 + k_{11}x_2 + k_{12}x_2)$$

$$C_T = k_1x_1 + k_2x_2 + k_3n_1 + k_4Q_1 + k_5Q_1 + k_6Q_1 + k_7Q_1 + k_8n_2 + k_9Q_2 + k_{10}Q_2 + k_{11}Q_2 + k_{12}Q_2 \quad (3.4)$$

To obtain the optimal solution for the cost function labelled Equation (3.4) we shall introduce the General Purpose Unconstrained Optimization Method,

General Purpose Optimization based on Nelder-Mead, Quasi-Newton and Conjugate-Gradient Algorithms and General-Purpose Optimization Method.

3.2.2 Modelling Cost Variables using the Non-Linear function

Similarly, assessing the cost components for the production of binder and wearing in Consolidated Construction Company, Anambra state, the optimization approach for a manufacturing problem as stated in Edgar *et. al.* (2001) was employed. The business cost can be split into two categories, namely:

1. The carrying cost or the cost of inventory which comprises taxes, clerical and inventory controls, warehouse expenses, insurance and cost of money.
2. The production cost- for the production of binder it comprises material cost of binder, labour cost of binder, overhead cost of binder and transportation cost of binder while similarly, for the production of wearing it comprises of material cost of wearing, labour cost of wearing, overhead cost of wearing and transportation cost of wearing.

Let x_1 and x_2 be the number of units produced in one run for binder and wearing respectively. Also, Q_1 and Q_2 represent the average annual production level for binder and wearing respectively.

Letting k_1x_1 and k_2x_2 be the cost of carrying the inventory for binder and wearing respectively. Where, k_1 and k_2 fundamentally comprises of cost of

working capital for the inventory, the warehouse expenses and tax for the two products. However, the production cost in the objective function is proportional to the number of production runs required for both binder and wearing. Assuming the cost per run to be a non-linear function given by the form

$$\text{cost per run for binder} = k_3 + k_4 x_1^{\frac{1}{2}} + k_5 x_1^{\frac{1}{2}} + k_6 x_1^{\frac{1}{2}} + k_7 x_1^{\frac{1}{2}} \quad (3.5)$$

The cost parameter k_3 is setup cost and denotes a fixed cost of production for binder which includes equipments being cleaned and maintained. The parameter $k_4 =$ material cost of binder, $k_5 =$ labour cost of binder, $k_6 =$ overhead cost of binder and $k_7 =$ transportation cost of binder are operating cost parameters.

Similarly,

$$\text{cost per run for wearing} = k_8 + k_9 x_2^{\frac{1}{2}} + k_{10} x_2^{\frac{1}{2}} + k_{11} x_2^{\frac{1}{2}} + k_{12} x_2^{\frac{1}{2}} \quad (3.6)$$

The total production cost (C_T) is the sum of the carrying costs and the production cost of binder and wearing. This connotes summing Equations (3.5) and (3.6) which has the form

$$C_T = k_1 x_1 + k_2 x_2 + n_1 (k_3 + k_4 x_1^{\frac{1}{2}} + k_5 x_1^{\frac{1}{2}} + k_6 x_1^{\frac{1}{2}} + k_7 x_1^{\frac{1}{2}}) + n_2 (k_8 + k_9 x_2^{\frac{1}{2}} + k_{10} x_2^{\frac{1}{2}} + k_{11} x_2^{\frac{1}{2}} + k_{12} x_2^{\frac{1}{2}}) \quad (3.7)$$

The objective function labelled Equation (3.7) is a function of four variables comprising of x_1 , x_2 , n_1 and n_2 . Here, n_1 and n_2 represents the number of production runs per year for binder and wearing respectively. In addition, x_1 and n_1 are directly related; similarly, x_2 and n_2 are also directly related. Hence,

$$n_1 = \frac{Q_1}{x_1} \quad \text{and} \quad n_2 = \frac{Q_2}{x_2} .$$

Therefore, only two independent variables exists for this case which are x_1 and x_2 while the dependent variables are n_1 and n_2 .

Eliminating n_1 and n_2 from the objective function Equation (3.7), we shall obtain the form

$$C_T = k_1x_1 + k_2x_2 + \frac{Q_1}{x_1}(k_3 + k_4x_1^{\frac{1}{2}} + k_5x_1^{\frac{1}{2}} + k_6x_1^{\frac{1}{2}} + k_7x_1^{\frac{1}{2}}) + \frac{Q_2}{x_2}(k_8 + k_9x_2^{\frac{1}{2}} + k_{10}x_2^{\frac{1}{2}} + k_{11}x_2^{\frac{1}{2}} + k_{12}x_2^{\frac{1}{2}})$$

$$C_T = k_1x_1 + k_2x_2 + k_3Q_1/x_1 + k_4Q_1/x_1^{1/2} + k_5Q_1/x_1^{1/2} + k_6Q_1/x_1^{1/2} + k_7Q_1/x_1^{1/2} + k_8Q_2/x_2 + k_9Q_2/x_2^{1/2} + k_{10}Q_2/x_2^{1/2} + k_{11}Q_2/x_2^{1/2} + k_{12}Q_2/x_2^{1/2} \quad (3.8)$$

To obtain the optimal solution of the non linear cost function, Equation (3.8) we shall introduce the Barzilai-Borwein (BB) Step-lengths Algorithm Optimization Method, Spectral Projected Gradient (SPG) Method and Multi-Start Method of Optimization.

For the present study, R-programming shall be employed to call the general-purpose unconstrained optimization method, general purpose optimization method, and the quasi-Newton and conjugate-gradient algorithms, the Barzilai-Borwein (BB) Steplengths method, the nonlinear optimization with multi start values method and the spectral projected gradient method for large-scale optimization for solving the optimal solution of the designed objective function labelled Equation (3.4) where $k_1, k_2, K_3, k_4, k_5, k_6, k_7, k_8, k_9, k_{10}, k_{11}, K_{12}, Q_1$ and Q_2 shall be assigned a start up cost value as by the methods. The choice of R-programming is because of its robustness in solving algorithms such as that of Newton's method with an advantage of accommodating massive data sets.

To obtain the initial guess cost as required by the methods we shall differentiate Equation (3.4) and Equation (3.8) with respect to $x=x_1$ (representing initial guess for binder) and $y=x_2$ (representing initial guess for wearing) and then solve the corresponding equations accordingly.

For the linear maintenance cost model (Equation (3.4)) it was obtained as given differentiate the linear function with respect to x and solve the corresponding equation to obtain the unknown parameter

$$\frac{\partial C_T}{\partial x} = k_1 - k_3 Q_1 * u \quad (3.8)$$

$$(u = x^{-2})$$

$$k_1 - k_3 Q_1 * u = 0$$

$$k_3 Q_1 * u = k_1$$

$$u = \frac{k_1}{k_3 Q_1}$$

$$x^2 = \frac{k_3 Q_1}{k_1}$$

$$x = \sqrt{\frac{k_3 Q_1}{k_1}} \quad (3.9)$$

Substituting the start up cost given as $Q_1=2514.70$, $K_3= 1000$ and $K_1=710.65$ as obtained from the company. We shall obtain as

$$x = \sqrt{\frac{2514700}{710.65}} = 59.5$$

differentiate the linear function with respect to y and solve the corresponding equation to obtain the unknown parameter

$$\frac{\partial C_T}{\partial y} = k_2 - k_8 Q_2 * y^{-2} \quad (3.10)$$

$$(z=y^{-2})$$

$$k_2 - k_8 Q_2 * z = 0$$

$$k_8 Q_2 * z = k_2$$

$$z = \frac{k_2}{k_8 Q_2}$$

$$y^2 = \frac{k_8 Q_2}{k_2}$$

$$y = \sqrt{\frac{k_8 Q_2}{k_2}}$$

Substituting the start up cost given as $Q_2=272$, $K_8= 1000$ and $K_2=600.30$ as obtained from the company. We shall obtain as

$$y = \sqrt{\frac{272000}{600.3}} = 21.3$$

Hence, the guess value for binder and wearing shall be in percentage and hence we shall divide by 100 to obtain 0.595 ($59.5/100=0.595$) and 0.213 ($21.3/100=0.213$) respectively.

For the non linear maintenance cost model (Equation (3.8)) it was obtained as given

differentiate the non linear function with respect to x and solve the corresponding equation to obtain the unknown parameter

$$\frac{\partial C_T}{\partial x} = k_1 + k_3 Q_1 / x^2 + k_4 Q_1 / 2x_1^{3/2} + k_5 Q_1 / 2x_1^{3/2} + k_6 Q_1 / 2x_1^{3/2} + k_7 Q_1 / 2x_1^{3/2} \quad (3.11)$$

$$k_1 - \frac{k_3 Q_1}{x^2} - \frac{1}{2x_1^{3/2}} [k_4 Q_1 + k_5 Q_1 + k_6 Q_1 + k_7 Q_1] = 0$$

Substituting the start up cost given as $Q_1=2514.70$, $Q_2=272$, $k_1=710.65$, $k_2=600.30$, $k_3= 1000$, $k_4=14213.00$, $k_5=2000$, $k_6=2000$, $k_7=600$, $k_8= 1000$, $k_9=13760.00$, $k_{10}=2000$, $k_{11}=2000$, and $k_{12}=600$ as obtained from the company and solving the equation accordingly

$$710.65 - \frac{2514700}{x^2} - \frac{1}{2x_1^{3/2}} [35741431 + 5029400 + 5029400 + 1508820] = 0$$

$$1.58 \times 10^{-13} x^4 + 1.79 \times 10^{-15} x^3 - 1.98 \times 10^{-6} = 0$$

$$x = 1.98 \times 10^{-6}, x = 0 \text{ and } x = -0.02$$

Similarly, differentiate the non linear function with respect to y and solve the corresponding equation to obtain the unknown parameter

$$\frac{\partial C_T}{\partial y} = k_2 - \frac{k_8 Q_2}{y^2} - \frac{k_9 Q_2}{2y \frac{3}{2}} - \frac{k_{10} Q_2}{2y \frac{3}{2}} - \frac{k_{11} Q_2}{2y \frac{3}{2}} - \frac{k_{12} Q_2}{2y \frac{3}{2}} \quad (3.12)$$

$$k_2 - \frac{k_8 Q_2}{y^2} - \frac{1}{2y \frac{3}{2}} [k_9 Q_2 + k_{10} Q_2 + k_{11} Q_2 + k_{12} Q_2] = 0$$

$$600.3 - \frac{272000}{y^2} - \frac{1}{2y \frac{3}{2}} [37427200 + 544000 + 544000 + 163200] = 0$$

Substituting the start up cost given as $Q_1=2514.70$, $Q_2=272$, $K_1=710.65$, $K_2=600.30$, $K_3= 1000$, $K_4=14213.00$, $K_5=2000$, $K_6=2000$, $K_7=600$, $K_8= 1000$,

$K_9=13760.00$, $K_{10}=2000$, $K_{11}=2000$, and $K_{12}=600$ as obtained from the company and solving the equation accordingly

$$1.35 \times 10^{-11} y^4 + 1.60 \times 10^{-13} y^3 - 2.78 \times 10^{-6} = 0$$

$$y = 2.78 \times 10^{-6}, y = 0 \text{ and } y = -2.15$$

Hence, the guess value for binder and wearing shall be 0.0002 ($0.02/100=0.0002$) and 0.0215 ($2.15/100=0.0215$).

3.3 Presentation of Data

Table 1: Summary of data on Maintenance cost of roads in Anambra State and Economic Variables

Year	Qbp (tons)	Mcb (Naira)	Lcb (Naira)	OAcB (Naira)	Tcb (Naira)	MTcb (Naira)	Pcb (Naira)	Tb (Naira)
2004	2,514.70	35,741,431.10	5,029,400.00	5,029,400	1,508,820	2,514,700	49,823,751	2,491,188.00
2005	1,227.90	17,452,142.00	2,455,800.00	2,455,800	736,740	1,227,900	24,328,382	1,216,419.00
2006	1,479.60	21,029,554.00	2,959,200.00	2,959,200	887,760	1,479,600	29,315,314	1465766.00
2007	2,328.50	33,379,230.00	4,697,000.00	4,697,000	1,409,100	2,348,500	38,070,830	1903542.00
2008	3,325.70	47,268,174.00	6,651,400.00	6,651,400	1,995,420	3,325,700	65,892,094	3294605.00
2009	2,344.00	33,315,272.00	4,688,000.00	4,688,000	1,406,400	2,344,000	46,441,672	2322084.00
2010	4,901.30	69,662,176.00	9,802,600.00	9,802,600	2,940,780	4,901,300	97,109,456	4855473.00
2011	2,992.60	42,533,823.00	5,985,200.00	5,985,200	1,795,560	2,992,600	59,292,383	2,964,619.00
2012	3,394.60	48,247,449.00	6,789,200.00	6,789,200	2,036,760	3,394,600	67,257,209	3,362,860.00
2013	2,777.70	39,479,450.00	5,555,400.00	5,555,400	1,666,620	2,777,700	55,034,570	2,751,729.00

Year	Qwp (tons)	Mcw (Naira)	Lcw (Naira)	OAcw (Naira)	Tcw (Naira)	MTcw (Naira)	Pcw (Naira)	Tw (Naira)
2004	272.00	3,744,352.00	544,000.00	544,000.00	163,200.00	272,000	5,267,552	263,378.00
2005	1,754.00	24,145,564.00	3,508,000.00	3,508,000.00	1,052,400.00	1,754,000	33,967,964	1,698,398.00
2006	2,571.00	35,392,386.00	5,142,000.00	5,142,000.00	1,542,600.00	2,571,000	49,789,986	2489499
2007	5,521.00	76,002,086.00	11,042,000.00	11,042,000.00	3,312,600.00	5,521,000	106,919,686	5345984
2008	6,529.00	89,878,214.00	13,058,000.00	13,058,000.00	3,917,400.00	6,529,000	126,440,614	6322031
2009	4,028.00	55,449,448.00	8,056,000.00	8,056,000.00	2,416,800.00	4,028,000	78,006,248	3900312
2010	3,973.00	54,692,318	7,946,000.00	7,946,000.00	2,383,800.00	3,973,000	76,941,118	3847056
2011	1,715.00	23,608,690.00	3,430,000.00	3,430,000.00	1,029,000.00	1,715,000	33,212,690	1,660,635.00
2012	3,670.00	50,521,220.00	7,340,000.00	7,340,000	2,202,000	367,000	67,770,220	3,388,511.00
2013	6,597.00	90,814,302.00	13,194,000.00	13,194,000	3,958,260	6,597,000	127,757,502	6,387,874.00

Year	Mcr (Naira)	Hi (%)	Ci (%)	IASPCA (Naira)	SCRGDP (%)	MCQCC (Naira)	MCQCM (Naira)	MCQCBM (Naira)
2004	57,845,868.00	10.00	5.90	20,899.90	1.45	9,051,680.45	40,024.01	120,079,841.10
2005	61,211,163.00	11.60	6.80	30,500.08	1.59	10,161,295.40	39,900.50	114,692,868.20
2006	83,060,565.00	8.57	17.27	35,448.00	1.62	16,602,698.50	38,496.50	358,477,246.70
2007	152,240,042.00	5.20	8.22	52,911.00	1.72	38,232,556,440.00	1,250,520.00	498,299,115,836.20
2008	201,949,343.00	15.10	18.00	65,919.00	1.84	106,870,970,581.90	1,290,520.00	177,229,727,731.20
2009	130,670,316.00	13.90	15.5	123,730.70	1.92	50,299,219,376.50	1,290,520.00	300,124,243,598.25
2010	182,753,103.00	11.80	12.7	219,637.70	2.00	82,163,680,211.41	1,290,520.00	314,432,324,985.52
2011	97,130,327.00	10.30	11.00	304,898.40	2.08	90,238,504,432.20	1,300,024.00	391,311,432,659.70
2012	141,778,801.00	12.00	11.30	462,811.00	2.19	98,860,910,113.30	1,300,024.00	400,133,248,622.17
2013	191,931,676.00	8.00	15.50	468,728.00	2.15	102,667,732,611.87	1,300,024.00	456,420,222,113.42

Year	CGFCFPME (Naira)	CGFCFPME (Naira)	GDPBPBC (Naira)	GDPBPBC (Naira)	GDPBPBCN (Naira)	LR (%)	MMT (°C)	MRH (%)
2004	10,889.52	215,004.01	7,664.02	200,786.09	4,999,349.74	534.1	32.00	72
2005	16,942.98	314,990.30	8,544.48	215,786.12	5,664,883.21	554.4	32.8	74.9
2006	34,576.54	829,374.27	9,654.79	250,332.27	6,982,935.44	554.4	35.3	73.05
2007	37,145.72	911,144.40	10,912.56	266,463.99	7,533,042.60	745.5	36.7	75.5
2008	35,422.21	1,029,870.10	12,338.83	306,581.64	9,097,750.70	745.5	32.5	72.7
2009	33,470.70	1,448,992.70	13,816.34	347,690.73	7,418,148.91	745.5	32.7	74.00
2010	32,567.54	1,468,100.70	146,284.91	456,284.91	15,285,004.21	754.5	33.1	79.7
2011	35,942.28	1,800,012.10	14,890.40	539,676.12	15,004,619.95	754.5	32.8	78.2
2012	37,119.26	2,001,120.90	15,014.26	606,581.64	18,110,721.12	754.5	32.5	80.9
2013	43,289.10	2,216,732.10	16,146.83	689,232.24	20,533,042.20	754.5	34.4	79.8

Year	MRR (%)	MF (%)	MR (%)	ME (%)	VMIME (Naira)	OERN (Naira)	(AFEM/DAS)ERN (Naira)	ICPI (Naira)
2004	121.3	94.5	17.8	3.5	458,917.10	133.5	133.00	145.00
2005	13.3	94.5	18.00	4.3	613,387.50	132.15	131.10	111.80
2006	159.2	91.8	18.00	4.3	680,765.76	128.65	128.14	144.00
2007	168.9	89.9	18.1	4.2	856,717.67	125.83	125.07	112.50
2008	171.4	88.9	18.3	4.2	1,141,756.57	118.57	117.78	136.70
2009	189.45	89.9	18.6	4.2	1,137,818.77	148.90	147.27	106.60
2010	162.9	89.9	18.6	4.3	1,777,174.90	150.30	148.31	176.70
2011	151.71	88.9	18.7	4.3	3,219,250.34	153.86	151.83	171.33
2012	163.5	89.7	18.9	4.2	2,217,192.24	157.50	155.45	148.72
2013	166.8	90.4	19.00	4.4	3,214,182.10	159.50	156.21	147.42

Year	CTT (Naira)	ISMB (Naira)	ISV (Naira)	QA (%)	MCQCA T (Naira)	SGRBC (Naira)
2004	86.43	788,244.98	280,615.41	98.40	3,500,489.42	11.89
2005	103.31	829,374.30	300,200.15	97.20	5,294,090.00	12.82
2006	107.97	829,374.30	380,615.60	97.10	10,956,622.40	12.99
2007	69.12	911,144.40	519,071.20	96.70	31,525,103,728.00	13.03
2008	61.96	1,029,870.09	496,022.01	99.30	17,466,607,846.70	13.07
2009	115.75	1,448,992.70	1,003,780.70	98.00	8,073,488,207.50	11.97
2010	111.43	1,931,013.70	1,404,496.30	97.20	22,031,488,444.10	12.08
2011	144.59	1,931,013.70	1,404,496.30	97.90	30,455,661,222.20	12.11
2012	99.62	2,031,000.70	1,500,063.01	96.10	30,899,289,821.70	12.58
2013	100.61	2,203,007.10	1,807,300.80	95.20	45,451,001,923.40	12.89

Key: (Qbp = Quantity of binder produced, Mcb = Material cost of binder, 3. Lcb - Labour cost of binder, Oacb = Overhead and asphalt plant cost of binder, Tcb = Transportation cost of binder, MTcb = Maintenance cost of binder, Pcb = Production cost of binder, Tb = Tax of binder, Qwp = Quantity of wearing produced, Mcw = Material cost of wearing, Lcw = Labour cost of wearing, Oacw = Overhead and asphalt plant cost of wearing, Tcw = Transportation cost of wearing, MTcw = Maintenance cost of wearing, MTcw = Maintenance cost of wearing, Tb = Tax of wearing, Tb = Tax of wearing, Hi = Headline inflation, Ci = Core inflation, IAPCA = Imports of Articles of Stone, Plaster, Cement, SCRGDP = Sectoral Contribution to Real GDP, MCQCC = Market Capitalization of Quoted Company for Cosntruction, MCQCM = Market Capitalization of Quoted Companies for Machinery (marketing), MCQCBM = Market Capitalization of Quoted Companies Building Material, CGECFPME = Composition of Gross Fixed Capital Formation at 1990 Purchasers Value Machinery & Equipment, CGFCFCPME = Composition of Gross fixed Capital Formation at Current Purchase Value Machinery and Equipment, GDPCBPBC = GDP at Constant Basic Price for Building and Construction, GDPBPBC = GDP at Current Basic Price for Building at Construction, GDPCBPBCN = GDP at Current Basic Price for Crude Petroleum and Natural gass, LR = Total Length of Federal Government Roads in the, MRR = Mean Relative Rain fall, MF = Mean Efficiency, MR = Mean Radiation, ME = Mean Evaporation, VMIME = Value of Major Imports for Machinery & Transport Equipment, (AFEM/DAS) ERN = (AFEM/DAS) Exchange Rate of the Naira, ICPI = Import Commodity Price Index, CTT = Commodity Terms of Trade, ISBM = Imports by Section on Boilers, Machinery Price Index, ISV = Imports by Section vehicles Price index, QA = Quantity of asphalt, MCQCAT = Market capitalization of Quoted Company Automobile & Tyres, SGRBC = Sectoral Growth Rate Building & Construction)

Table 2: Asphalt Cost Parameter (Naira) Per Ton for year 2004-2013

Mix Design	k4	K5	K6	K7	K3	K1
Binder	14,213.00	2,000	2,000	600	1,000	710.65
	K9	K10	K11	K12	K8	K2
Wearing	13,760.00	2,000	2,000	600	1,000	600.3

CHAPTER FOUR

RESULTS AND DISCUSSION

The data obtained for this research study were analyzed using the linear and non linear model and methods discussed in the previous chapters.

4.1 Optimizing the Linear cost function using the General-Purpose Unconstrained Optimization method with R-programming Language

The linear cost function using the general-purpose unconstrained optimization method on R-command window was carried out; computer program based on section is presented as shown in Appendix II

The value of the estimated minimum was N52,416,540 while the estimated points at which the minimum value of the function were 60.33 and 19.22 for cost of binder (x[1]) and cost of wearing (x[2]), respectively. This result implies that the minimum maintenance cost of roads using the linear cost function was N52,416,540. Hence, after substituting the estimated points for binder and wearing the linear cost function can be rewritten as:

$$CT.linear.uncmin = k_1*60.33 + k_2*19.22 + (k_3*Q_1/ 60.33) + k_4*Q_1 + k_5*Q_1 + k_6*Q_1 + k_7*Q_1 + (k_8*Q_2/ 19.22) + k_9*Q_2 + k_{10}*Q_2 + k_{11}*Q_2 + k_{12}*Q_2 \quad (4.1)$$

4.2 Optimizing the Linear cost function using the General-Purpose Optimization method with R-programming Language

The linear cost function using the general-purpose unconstrained optimization method on the R-command window was carried out; computer program based on section is presented as shown in Appendix III

The value of the estimated minimum was N52,416,579.36 while the estimated points at which the minimum value of the function were obtained at 59.34 and 21.27 for cost of binder (x[1]) and cost of wearing (x[2]), respectively. This result implies that the minimum maintenance cost of roads using the linear cost function is N52,416,579.36. Hence, after substituting the estimated points for binder and wearing the linear cost function can be rewritten as

$$CT.linear.optimx= k_1*59.34 + k_2*21.27 + (k_3*Q_1/59.34) + k_4*Q_1+ k_5*Q_1 + k_6*Q_1 + k_7*Q_1 + (k_8*Q_2/21.27) + k_9*Q_2 + k_{10}*Q_2 + k_{11}*Q_2 + k_{12}*Q_2 \quad (4.2)$$

4.3 Optimizing the Linear cost function using the General-Purpose Optimization method based on Quasi-Newton and Conjugate-gradient algorithms with R-programming Language

The linear cost function using the general-purpose unconstrained optimization method on the R-command window was carried out computer program based on section is presented as shown in Appendix IV

The value of the estimated minimum is N52,416,579.36 while the estimated points at which the minimum value of the function were 59.34 and 21.27 for cost of binder (x[1]) and cost of wearing (x[2]) respectively. This result implies that the minimum maintenance cost of roads using the linear cost function was N52,416,579.36. Hence, after substituting the estimated points for binder and wearing the linear cost function can be rewritten as

$$CT.linear.optim = k_1*59.34 + k_2*21.27 + (k_3*Q_1/59.34) + k_4*Q_1 + k_5*Q_1 + k_6*Q_1 + k_7*Q_1 + (k_8*Q_2/21.27) + k_9*Q_2 + k_{10}*Q_2 + k_{11}*Q_2 + k_{12}*Q_2 \quad (4.3)$$

From the result of the optimization obtained in section (4.1) - (4.3), the 3D plot for cost of binder, cost of wearing and the fitted values of CT.linear.uncmin, CT.linear.optimx and CT.linear.optim was plotted and the result presented as figure 1:

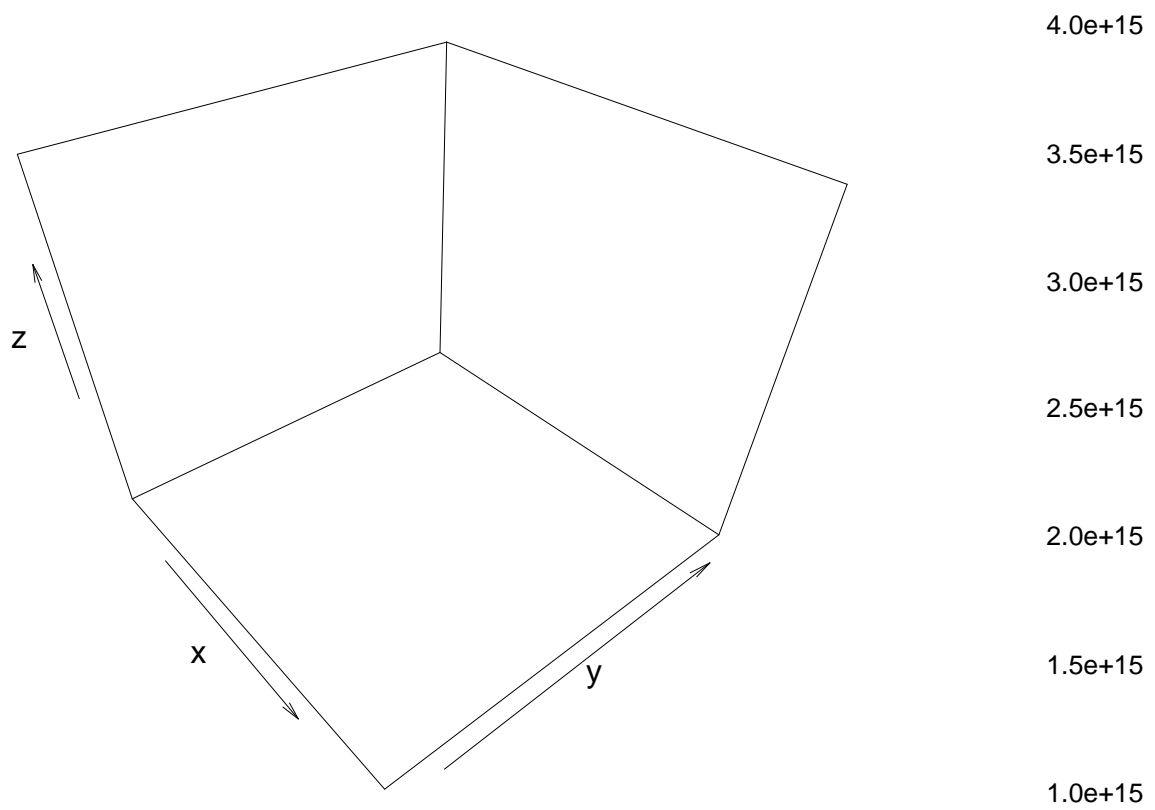


Figure 1: 3D plot of CT.linear.uncmin, cost.binder and cost.wearing over the observed period

Figure 1, shows that there exist dispersion among the cost generated by CT.linear.uncmin, cost for binder and cost for wearing over the observed period.

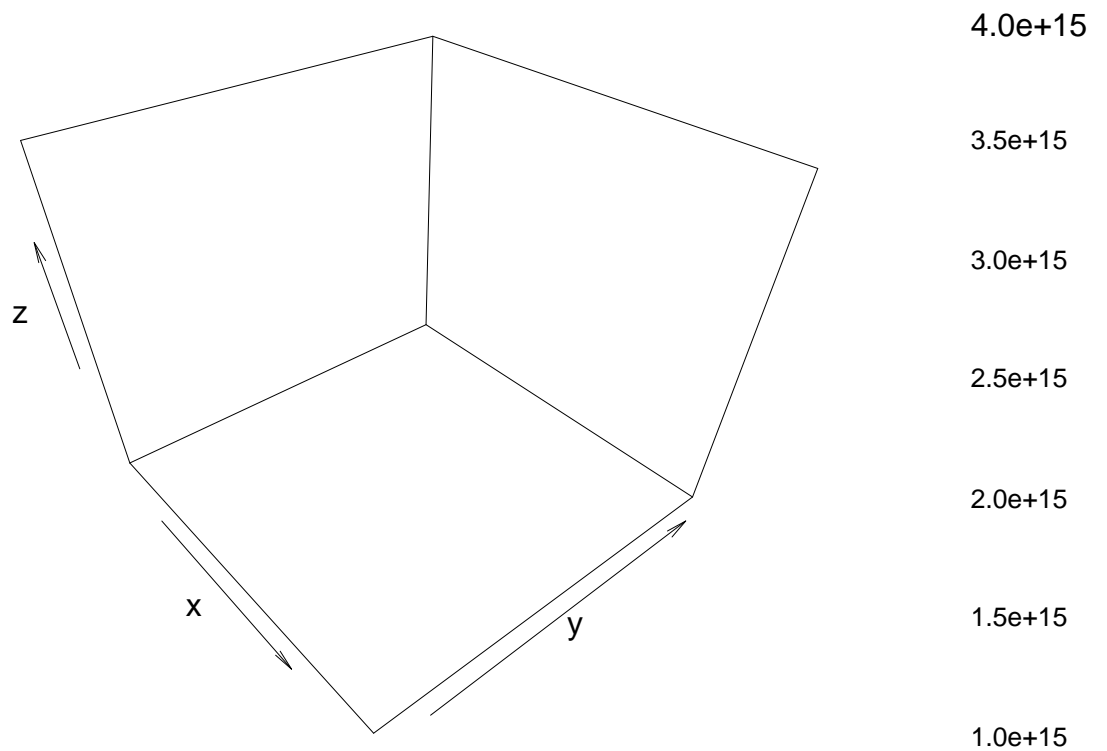


Figure 2: 3D plot of CT.linear.optimx, cost.binder and cost.wearing over the observed period

Figure 2, showed that there exist dispersion among the cost generated by CT.linear.optimx, cost for binder and cost for wearing over the observed period.

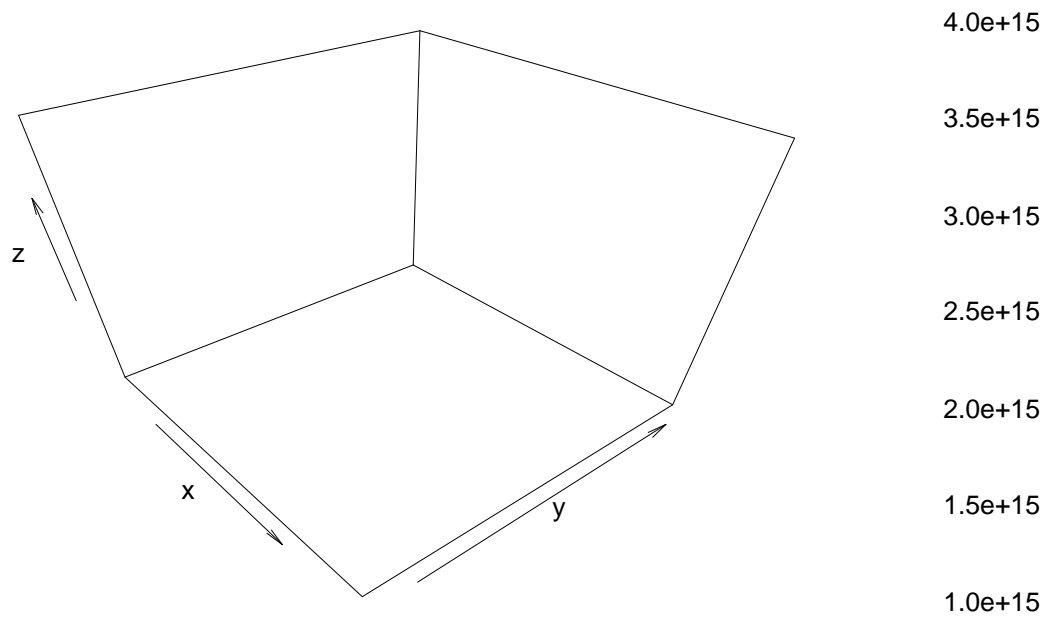


Figure 3: 3D plot of CT.linear.optim, cost.binder and cost.wearing over the observed period

Figure 3, showed that there exist dispersion among the cost generated by CT.linear.optim, cost for binder and cost for wearing over the observed period.

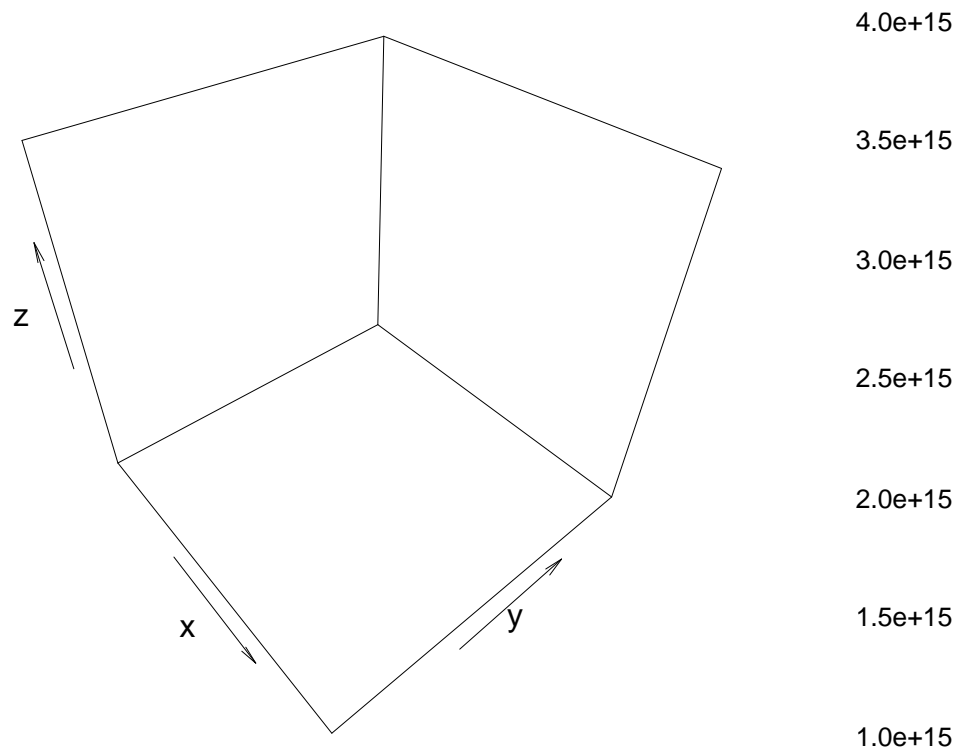


Figure 4: 3D plot of CT.linear.uncmin, CT.linear.optimx & CT.linear.optim over the observed period

It is revealed in Figure 4 that there exist no dispersion among the costs generated by CT.linear.uncmin, CT.linear.optimx and CT.linear.optim. This result implies that cost generated for any of the optimization model can represent others in further analysis such as the bivariate regression analysis.

4.4 Validation of the Optimization result for the Linear maintenance cost model using the Bivariate Regression Analysis

The bivariate regression analysis was used to corroborate the optimization result obtained for the linear maintenance cost model. The bivariate model employed in this section was the CT.linear.uncmin (predicted maintenance cost of the linear cost model using the general-purpose unconstrained optimization approach), CT.linear.optimx (predicted maintenance cost of the linear cost model using the general purpose optimization method) and CT.linear.optim (predicted maintenance cost of the linear cost model using quasi-Newton and conjugate-gradient method) which represents the response (dependent variable) against the explanatory variables cost of binder and cost of wearing over the observed years (2004-2013).

The proposed model can be expressed as

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \varepsilon$$

where,

y= CT.linear.uncmin or CT.linear.optimx or CT.linear.optim,

x₁=cost of binder,

x₂= cost of wearing and

ε= residual

4.5 Bivariate Regression analysis on estimating the CT.linear.uncmin

The result of the bivariate regression analysis using the R-console programming window obtained the following result

Call:

```
lm (formula = CT.linear.uncmin ~ cost.binder + cost.wearing)
```

Residuals:

Min	1Q	Median	3Q	Max
-2354472	-1466497	-633304	210468	5635654

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	1.214e+06	2.677e+06	0.454	0.664
cost.binder	9.197e-01	4.500e-02	20.439	1.68e-07 ***
cost.wearing	9.736e-01	2.310e-02	42.157	1.10e-09 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 2757000 on 7 degrees of freedom

Multiple R-squared: 0.9975, Adjusted R-squared: 0.9968

F-statistic: 1410 on 2 and 7 DF, p-value: 7.56e-10

The result of the analysis found a multiple R-square value of 0.998 (99.8%) which implies that the explanatory variables were able to estimate about 99.8% behaviour of the response variable. This result implies a very strong fit of cost of binder and cost of wearing on the maintenance cost of roads using the linear cost model. Also, it was found that the independent variables contributed significantly to the model with even p-value = 0 which falls on the rejection region of the hypothesis.

Table 3: Distribution of observed and estimated maintenance cost of roads in Anambra state using the linear cost function

year	mcr	CT.linear.uncmin	CT.linear.optimx	CT.linear.optim	Estimation.linear
2004	57845868	52416540	52416579	52416579	52164151
2005	61211163	55482162	55474413	55474413	56660544
2006	83060565	75269095	75257320	75257320	76651808
2007	152240042	145963300	145936971	145936971	140327646
2008	201949343	182928934	182897821	182897821	184920427
2009	130670316	118380449	118361606	118361606	119874874
2010	182753103	165520331	165502471	165502471	165435627
2011	97130327	87992410	87985345	87985345	88080636
2012	141778800	131569147	131552389	131552389	129052184
2013	191931676	173862753	173831147	173831147	176217224

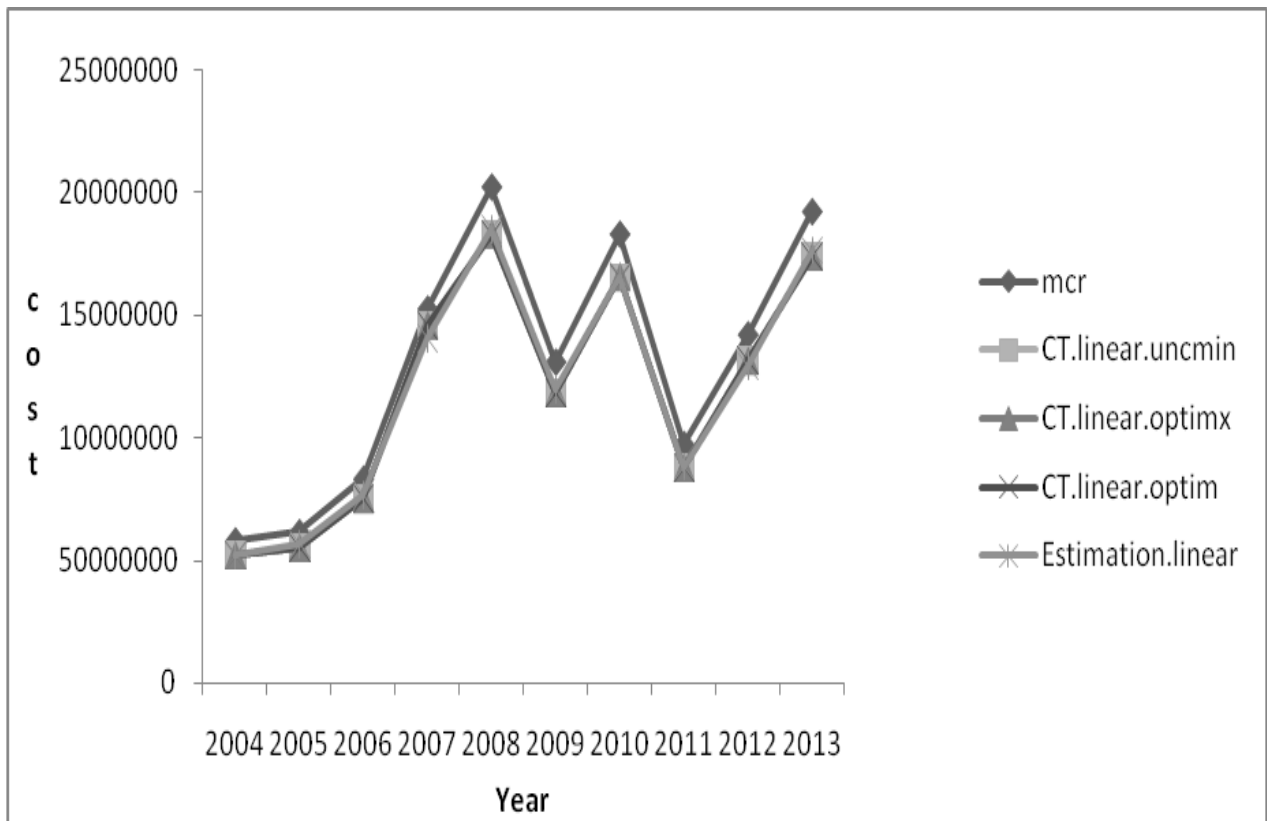


Figure 5: Distribution of mcr, CT.linear.uncmin, CT.linear.optmx, CT.linear.optim & Estimation.linear

The result of figure 5 showed that the cost values generated by the bivariate regression analysis has a perfect fit on the cost values of the linear maintenance cost model. This result connotes that the bivariate regression fitted values (Estimated. linear) were able to fit perfectly to the resemblance of the cost values obtained by the linear maintenance cost model.

4.6 Optimizing the non-Linear cost function using the Barzilai-Borwein (BB) Steplengths algorithm with R-programming Language

The non linear cost function using the general-purpose unconstrained optimization method on R-command window was carried out; computer program based on section is presented as shown in Appendix V

The value of the estimated minimum was N2697251.47 while the estimated points at which the minimum value of the function were obtained at 1037.03 and 237.26 for cost of binder (x[1]) and cost of wearing (x[2]), respectively. This result implies that the minimum maintenance cost of roads using the non-linear cost function is N2697251.47. Hence, after substituting the estimated points for cost binder and wearing the non-linear maintenance cost function can be rewritten as

$$\begin{aligned}
 CT.nonlinear.BB = & k_1 * 1037.03 + k_2 * 237.26 + (k_3 * Q_1 * 1037.03^{-1}) + (k_4 * Q_1 * 1037.03^{-(1/2)}) + \\
 & (k_5 * Q_1 * 1037.03^{-(1/2)}) + (k_6 * Q_1 * 1037.03^{-(1/2)}) + (k_7 * Q_1 * 1037.03^{-(1/2)}) + (k_8 * Q_2 * 237.26^{-1}) + \\
 & (k_9 * Q_2 * 237.26^{-(1/2)}) + (k_{10} * Q_2 * 237.26^{-(1/2)}) + (k_{11} * Q_2 * 237.26^{-(1/2)}) + (k_{12} * Q_2 * 237.26^{-(1/2)})
 \end{aligned}
 \tag{4.4}$$

4.7 Optimizing the non-Linear cost function using the Nonlinear Optimization Method with Multi Start values with R-programming Language

The non linear cost function using the general-purpose unconstrained optimization method on R-command window was carried out; computer program based on section is presented as shown in Appendix VI

The value of the estimated minimum was N2697251.47 while the estimated points at which the minimum value of the function were obtained at 1037.03 and 237.26 for cost of binder (x[1]) and cost of wearing (x[2]), respectively. This result implies that the minimum maintenance cost of roads using the non-linear cost function is N2697251.47. Hence, after substituting the estimated points for cost binder and wearing the non-linear maintenance cost function can be rewritten as

$$\begin{aligned}
 CT.nonlinear.multi.start = & k_1 * 1037.03 + k_2 * 237.26 + (k_3 * Q_1 * 1037.03^{-1}) + (k_4 * Q_1 * 1037.03^{-(1/2)}) \\
 & + (k_5 * Q_1 * 1037.03^{-(1/2)}) + (k_6 * Q_1 * 1037.03^{-(1/2)}) + (k_7 * Q_1 * 1037.03^{-(1/2)}) + (k_8 * Q_2 * 237.26^{-1}) \\
 & + (k_9 * Q_2 * 237.26^{-(1/2)}) + (k_{10} * Q_2 * 237.26^{-(1/2)}) + (k_{11} * Q_2 * 237.26^{-(1/2)}) + (k_{12} * Q_2 * 237.26^{-(1/2)})
 \end{aligned}
 \tag{4.5}$$

4.8 Optimizing the non-Linear cost function using the Spectral projected gradient (spg) method for large-scale optimization with R-programming Language

The non linear cost function using the general-purpose unconstrained optimization method on R-command window was carried out; computer program based on section is presented as shown in Appendix VII

The value of the estimated minimum was N2697251.47 while the estimated points at which the minimum value of the function were obtained at 1037.03 and 237.26 for cost of binder (x[1]) and cost of wearing (x[2]), respectively. This result implies that the minimum maintenance cost of roads using the non-linear cost function is N2697251.47. Hence, after substituting the estimated points for cost binder and wearing the non-linear maintenance cost function can be rewritten as

$$\begin{aligned}
 CT.nonlinear.spg = & k_1*1037.03 + k_2*237.26 + (k_3*Q_1*1037.03^{-1}) + (k_4*Q_1*1037.03^{-(1/2)}) + \\
 & (k_5*Q_1*1037.03^{-(1/2)}) + (k_6*Q_1*1037.03^{-(1/2)}) + (k_7*Q_1*1037.03^{-(1/2)}) + (k_8*Q_2*237.26^{-1}) + \\
 & (k_9*Q_2*237.26^{-(1/2)}) + (k_{10}*Q_2*237.26^{-(1/2)}) + (k_{11}*Q_2*237.26^{-(1/2)}) + (k_{12}*Q_2*237.26^{-(1/2)})
 \end{aligned}
 \tag{4.6}$$

From the result of the optimization obtained in section (4.6) - (4.8), the 3Dplot for cost of binder, cost of wearing and the fitted values of CT.nonlinear.BBoptim, CT.nonlinear.multi.start and CT.nonlinear.spg was plotted and the result presented as figure 6;

The 3Dplot for cost of binder, cost of wearing and the fitted values of CT.nonlinear.BBoptim, CT.nonlinear.multi.start and CT.nonlinear.spg is presented as

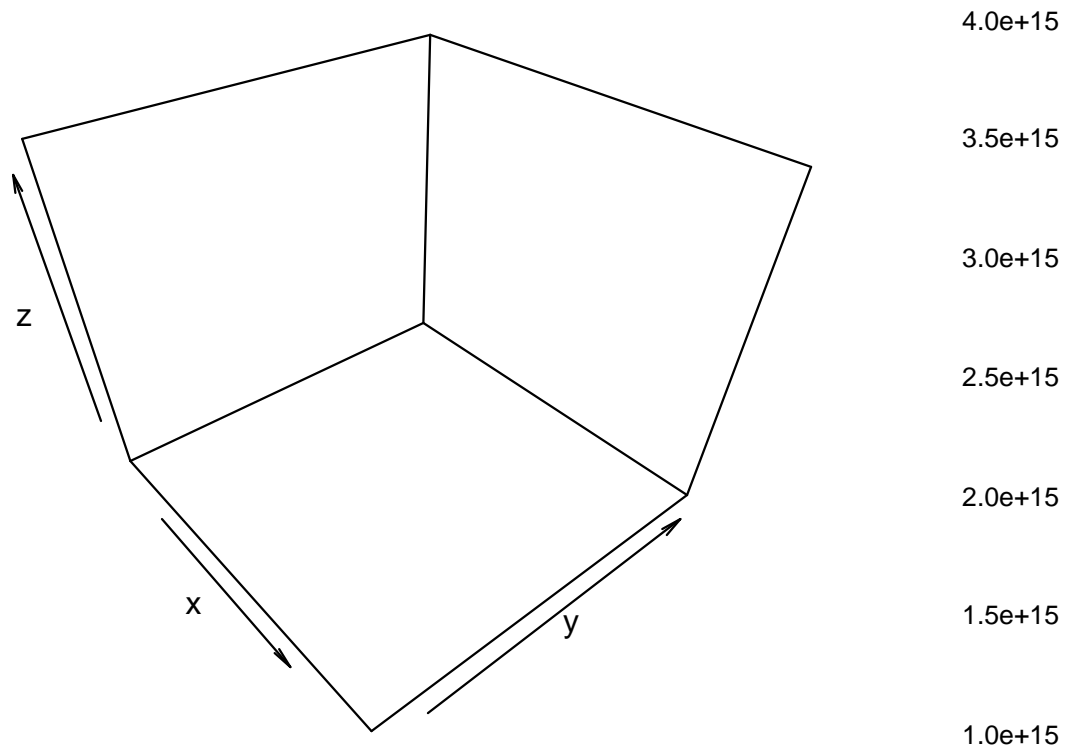


Figure 6: 3D plot of CT.nonlinear.BB, cost.binder and cost.wearing over the observed period

Figure 6, shows that there exist dispersion among the cost generated by CT.nonlinear.BB, cost for binder and cost for wearing over the observed period.

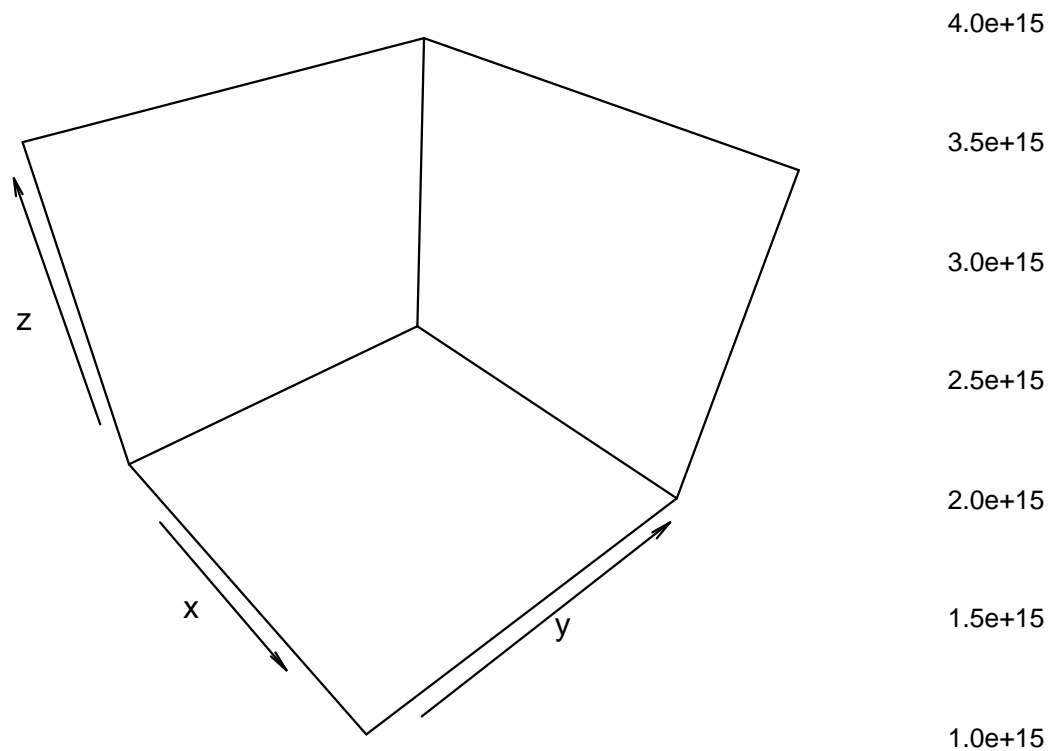


Figure 7: 3D plot of CT.nonlinear.multi.start, cost.binder and cost.wearing over the observed period

Figure 7, showed that there exist dispersion among the cost generated by CT.nonlinear.multi.start, cost for binder and cost for wearing over the observed period.

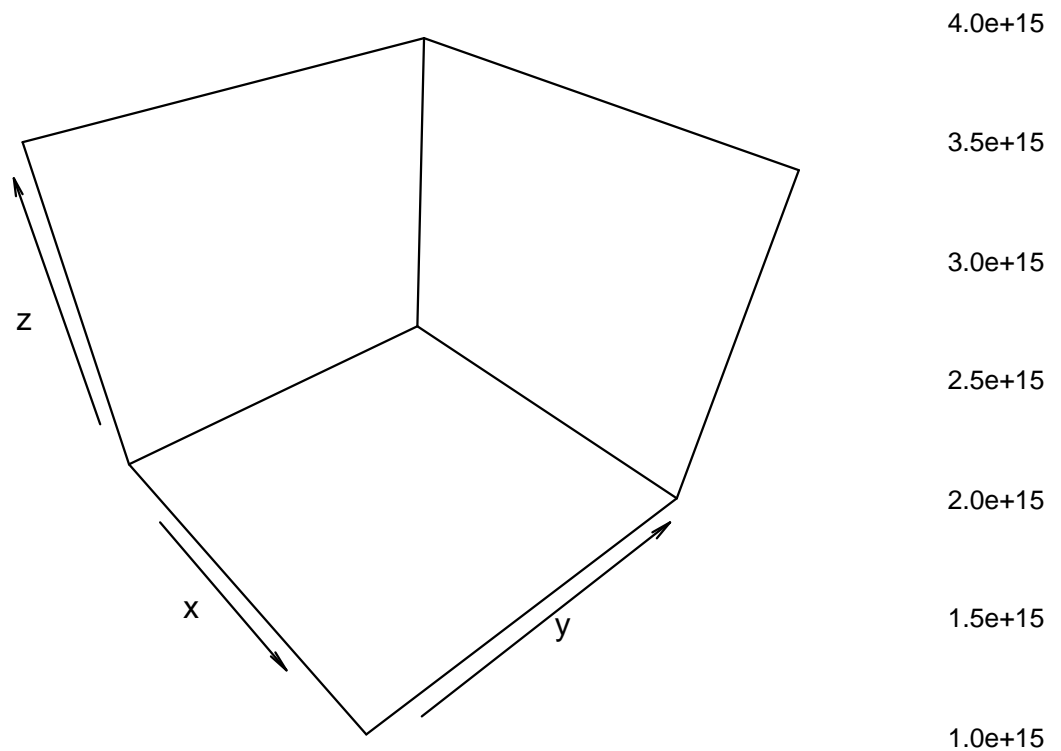


Figure 8: 3D plot of CT.nonlinear.spg, cost.binder and cost.wearing over the observed period

Figure 8, showed that there exist dispersion among the cost generated by CT.nonlinear.spg, cost for binder and cost for wearing over the observed period.

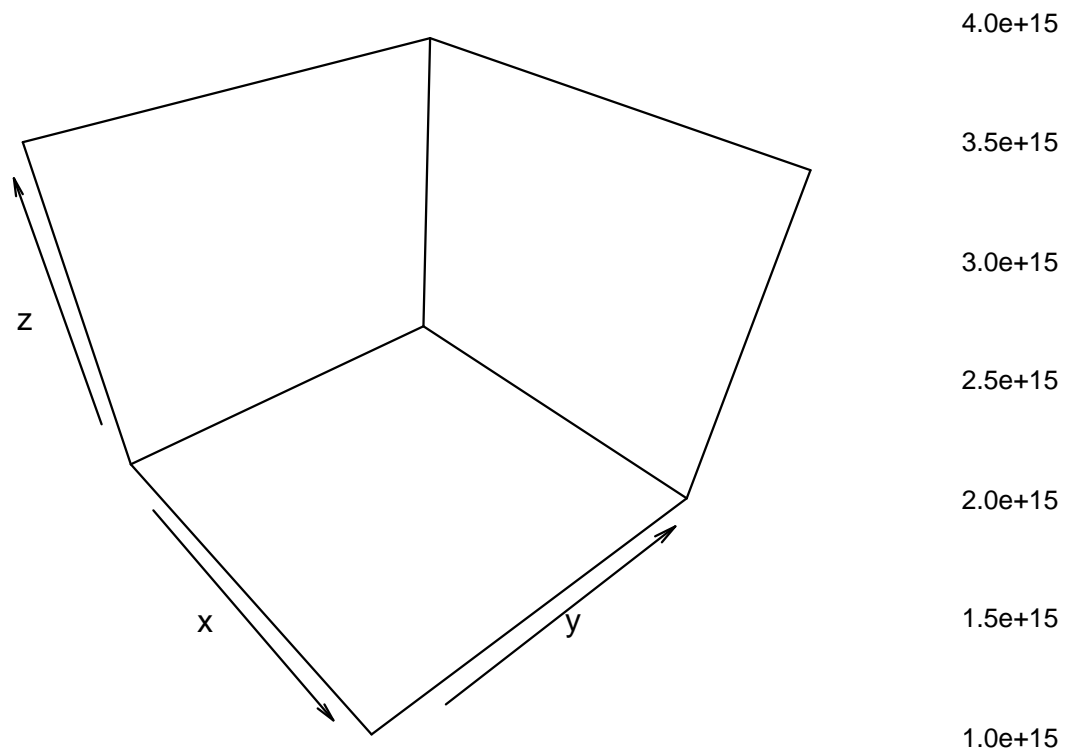


Figure 9: 3D plot of CT.nonlinear.BB, CT.nonlinear.multi.start & CT.nonlinear.spg over the observed period

It was revealed in figure 9 that there exist no dispersion among the cost generated by CT.nonlinear.BB, CT.nonlinear.multi.start and CT.nonlinear.spg. This result implies that cost generated for any of the optimization model can represent others in further analysis such as the response surface analysis.

4.9 Response Surface analysis on estimating CT.nonlinear

The response surface method was employed to corroborate the Optimization result obtained for the non-linear maintenance cost model. The response surface model designed in this section was the CT.nonlinear.BB or CT.nonlinear.multi.start or CT.nonlinear.spg (predicted maintenance cost using the non-linear cost model) which represents the response (dependent variable) against the explanatory variables cost of binder and cost of wearing over the observed years (2004-2013).

The result of the response surface analysis was obtained as

Call:

```
rsm(formula = CT.nonlinear.BB ~ SO(cost.binder, cost.wearing))
```

Coefficients:

(Intercept)

5.354e+05

FO(cost.binder, cost.wearing)cost.binder

3.541e-02

FO(cost.binder, cost.wearing)cost.wearing

7.035e-02

TWI(cost.binder, cost.wearing)

-1.236e-10

$$PQ(\text{cost.binder}, \text{cost.wearing})\text{cost.binder}^2$$

$$1.532\text{e-}11$$

$$PQ(\text{cost.binder}, \text{cost.wearing})\text{cost.wearing}^2$$

$$-1.044\text{e-}11$$

The result of the response surface analysis generated a full second order model which will be used to estimate CT.nonlinear (predicted maintenance cost using the non-linear cost model).

Table 4: Distribution of observed and estimated maintenance cost of roads in Anambra state using the nonlinear cost function

year	mcr	CT.nonlinear.BB	CT.nonlinear.multi.start	CT.nonlinear.spg	Estimation.nonlinear
2004	57845868	2697251	2697251	2697251	2675734
2005	61211163	3717564	3717564	3717564	3681622
2006	83060565	4842440	4842440	4842440	4883391
2007	152240042	8880745	8880745	8880745	8805723
2008	201949343	10658702	10658702	10658702	10634552
2009	130670316	7091646	7091646	7091646	7189958
2010	182753103	8522279	8522279	8522279	8546843
2011	97130327	4703539	4703539	4703539	4770788
2012	141778800	7278052	7278052	7278052	7143214
2013	191931676	10419397	10419397	10419397	10479790

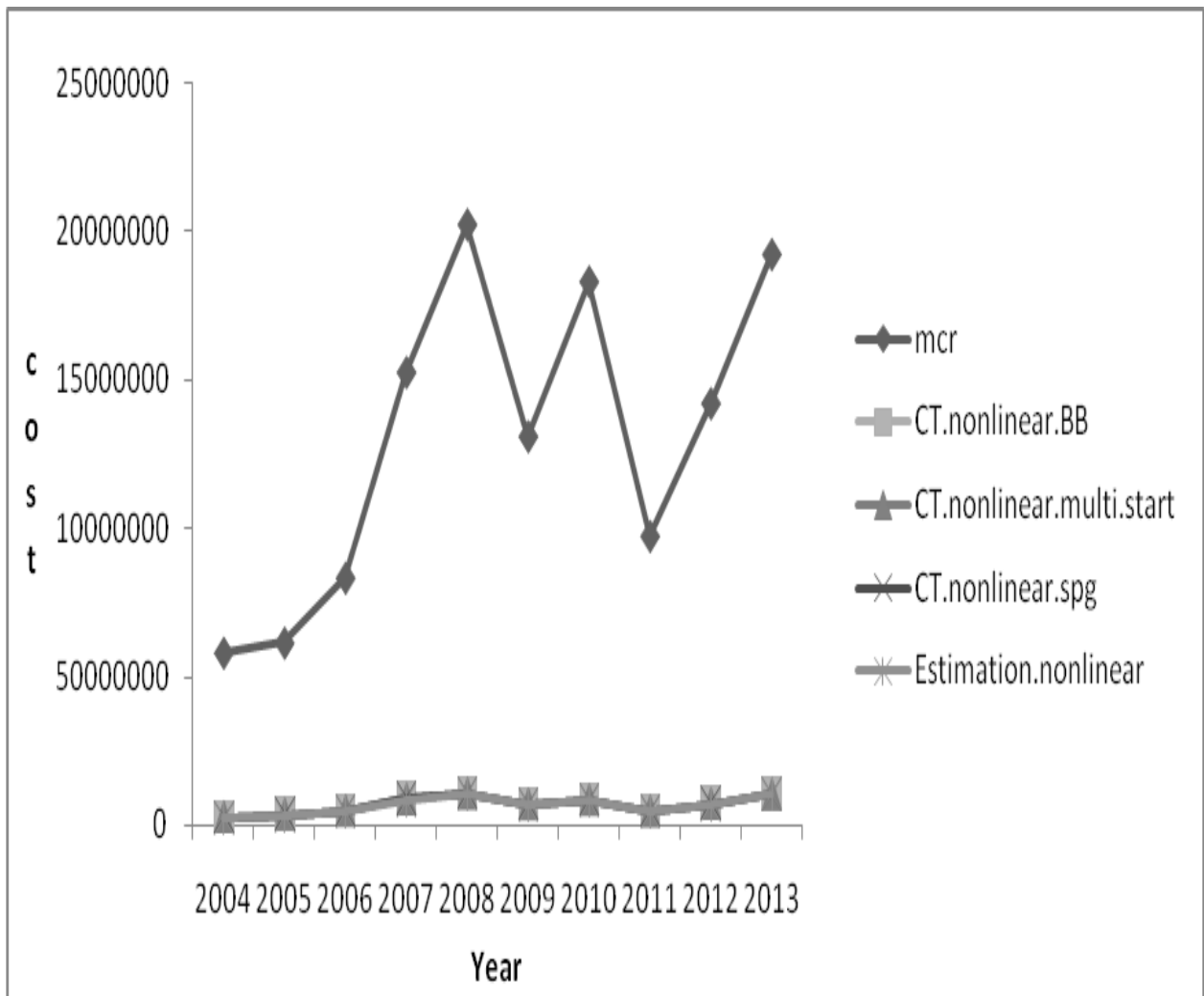


Figure 10: Distribution of mcr, CT.nonlinear.BB, CT.nonlinear.multi.start, CT.nonlinear.spg & Estimation.nonlinear

Figure 10 shows that the cost values generated by the response surface method has a perfect fit on the cost values of nonlinear maintenance cost model. This result connotes that the fitted values obtained using the response surface analysis were able to fit perfectly to the resemblance of the cost values obtained by the nonlinear maintenance cost model.

4.10 Appraisal of Strategic Roads in Anambra State, Nigeria

Table 5: Sampled roads and factors facing road maintenance in Anambra State

S/No	NAME OF ROADS MAINTAINED BY GOVERNMENT OF ANAMBRA STATE 2003 - 2014	ROAD DIVIDER	ROAD DIRECTION	ROAD CONDITION	TRAFFIC CIRCLE	DRAINAGE	WALKWAYS	STREETLIGHT	TRAFFIC CONGESTION	BUSTOP_ PEDESTRAIN_ BRIDGE
1	Ziks Residence -Nkpor Junction	1	0	1	1	1	1	0	1	0
2	Nkpor Junction - Nnobi Road	1	1	1	1	1	1	0	0	0
3	Ogidi – Abatete	1	1	1	1	1	1	0	0	0
4	Nnobi – Nnewi	1	1	0	0	1	1	0	0	0
5	Nibo	1	1	0	0	1	1	0	0	0
6	Mbaukwu – Agulu	1	1	1	0	1	1	0	0	0
7	Ifite Dunu - Ukpo - Abba	1	1	0	1	1	0	0	0	0
8	Abagana - Enugwu Agidi	0	1	1	1	0	0	0	0	0
9	Afor Igwe - Eziowelle with sports cardinal Arnze's - Abatete- Abacha Raod	1	1	0	0	1	1	1	0	1
10	Owerre Ezukala - Umunze	1	1	0	1	1	1	0	1	0
11	Nnewi - Township Roads	1	1	0	1	1	0	0	1	1
12	Awkuzu – Igbariam	1	1	1	1	1	1	0	1	1
13	Umunzu – Umuchu	1	1	0	1	1	1	0	1	0
14	Uga – Igboekwu	0	1	0	1	1	1	0	1	0
15	Service Lane/Awka - Onitsha express	1	1	0	0	1	1	0	1	1
16	Oraukwu/Alor Nnokwa with Sport	1	1	0	1	1	1	1	1	0
17	New Trazan - Nkpor	0	1	0	0	1	0	0	1	1

18	Ogbunike - Nkwelle Ezuka	1	0	0	1	1	0	0	0	0
19	Obodoukwu Road Onitsha	0	0	1	0	1	0	0	1	0
20	Oguta Road, Onitsha	1	0	0	0	1	1	0	0	0
21	Francis Street Onitsha	0	0	1	0	1	0	0	0	0
22	Ven Road (North & South)	1	0	1	0	1	0	0	1	0
23	Ozomagala Street, Onitsha	0	0	1	0	1	0	0	0	0
24	Ziks Avenue	0	0	1	0	1	0	0	1	0
25	Nibo – Umuawala	0	0	0	0	1	1	0	0	0
26	Amaokpala – Oko	1	1	0	0	1	1	0	0	0
27	Sokoto Road	0	0	1	0	1	0	0	1	0
28	Uga Road	1	1	0	0	1	1	0	1	0
29	Oraifite Street	0	0	0	0	0	0	0	1	0
30	Awka Road	1	1	0	1	1	0	1	1	0
31	Oldmarket Road	1	1	0	0	1	1	0	1	1
32	New Road	1	1	0	0	1	1	0	1	0
33	Ugwunabankpa Road	1	1	0	0	1	0	0	0	0
34	Bright Street	1	1	0	0	1	0	0	1	0
35	Egeston	1	1	0	0	1	0	0	0	0
36	Creek road	0	0	1	0	1	0	0	0	0
37	Nigger	0	0	1	1	1	0	0	0	0
38	Harouna Street	0	0	1	0	1	0	0	0	0

39	Roads and drainage in Iyiagu Housing Estate	0	0	1	0	1	0	0	0	0
40	Arthur Eze Avenue	0	0	1	0	1	0	0	0	0
41	Nimo – Neni	1	0	0	1	1	0	0	0	0
42	Nnaka – Oko	1	1	1	1	1	1	0	0	0
43	Awka Inner Ring Road	1	0	0	1	1	1	0	0	0
44	Court road with Spur to Eke-Awka	1	1	1	0	1	0	0	1	0
45	Akamdi - Illo Ngworo	0	0	1	0	1	0	0	1	0
46	Udoka Estate Access roads	0	1	1	0	1	0	0	0	0
47	Ifite Road - Pass t University Gate Ezioye	0	0	1	0	1	0	0	0	0
48	Ebenebe - Holy Family Road	0	1	1	0	1	0	0	0	0
49	Amodu Bridge Okpuno Awka	0	0	1	0	1	0	0	0	0
50	Acess road to Ngozika Housing Road	1	1	1	1	1	1	0	0	0
51	Commissioner Quarters - Esther Obiakor raod	1	1	1	0	1	1	0	0	0
52	Premer road Fegge Onitsha	1	0	1	1	1	0	0	0	0
53	Esther Obiakor or Awka Anevue	1	1	1	0	1	1	0	0	0
54	33 Junction to Nwafor Orizu (NOCEN)	1	0	1	1	1	1	0	0	0
55	Agulu Street	1	0	0	0	1	1	0	0	0
56	Enugwu Agidi -Nawgu	1	0	1	0	1	1	0	0	0
57	Ukwulu - Achalla raod	1	1	0	0	1	1	0	0	0
58	Ugwuoba Obosi	1	0	1	0	1	1	0	0	0
59	Afor Nnobi - Nkwo Nnewi Road about	1	1	1	1	1	1	0	0	0

60	Ufuma junction - Mamu bridge	1	1	0	0	1	1	0	0	0
61	Amawbia town Hall - Agbata Street road	0	0	0	0	1	1	0	0	0
62	Enugwu Ukwu - Nimo	0	0	0	0	1	0	0	0	0
63	Nise – Nneogidi	1	0	0	0	1	1	0	0	0
64	Oyeagu – Abagana	1	0	0	0	1	1	0	0	0
65	Ukpo - Abba Junction by express	1	0	0	1	1	1	0	0	0
66	Abazuonu Street in Iyiowa Layout	0	0	1	0	1	0	0	0	0
67	Acha - Madona Cath. Chur. Street in Iyiowa Odekpe	1	0	1	0	1	0	0	0	0
68	Amawbia by pass	1	0	1	0	1	0	0	0	0
69	Motor Parts road at Nnewi	1	0	1	1	1	0	0	0	0
70	FGC, Nise Road/Akabo Mbaukwu Haba River	1	1	1	0	1	1	0	0	0
71	Intend road in Anambra State Teaching Hospital Amaku Awka	0	0	1	0	1	0	0	0	0
72	Awkuzu - Igbariam with spur to Achalla	1	1	0	0	1	1	0	0	0
73	ASWAMA Dump Site Agu Awka	1	0	1	0	1	0	0	0	0
74	Goodwill road Okpuno Awka	0	0	1	0	0	1	0	0	0
75	Nteje - Umunya road	1	1	1	0	1	1	0	0	0
76	Enugu/Anambra State Boundary - Agu Awka road	1	0	1	0	1	1	0	0	0
77	Ekwulobia - Nkpologwu	1	0	1	1	1	1	0	1	0

Source: Field Survey, 2015

Key: Road Divider, Road Direction, Traffic Circle, Drainage, Walkways, Street Light, Traffic Congestion, Bustop/PD: Available=1 and Not Available =0, while Road Condition: Good=1 and Bad=0.

Table 6: Frequency and Percentage Distribution of Factors of Road Maintenance in Anambra State

S/N	FACTOR	NUMBER AVAILABLE (%)	NUMBER NOT AVAILABLE (%)	TOTAL
1.	Road Divider	52(67.5)	25(32.5)	77(100)
2.	Road direction	37(48.1)	40(51.9)	77(100)
3.	Traffic Circle	24(31.2)	53(68.8)	77(100)
4.	Drainage	74(96.1)	3(3.9)	77(100)
5.	Walk Ways	41(53.2)	36(46.8)	77(100)
6.	Street Light	3(3.9)	74(96.1)	77(100)
7.	Traffic Congestion	22(28.6)	55(71.4)	77(100)
8.	Bustop/PD	6(7.8)	71(92.2)	77(100)

Details presented in Table 6 were employed to run the pareto chart analysis using R-console with the aim of determining the major factors that contribute to about 80% of road maintenance problems in Anambra State.

Table 7: Result of Pareto chart analysis for Road Maintenance in Anambra State

Factors	Frequency	Cum. Freq.	Percentage	Cum. Percent.
STREET LIGHTS	74	74	20.7283	20.728
BUSTOP/PD.	71	145	19.888	40.616
TRAFFIC CONGEST.	55	200	15.4062	56.022
TRAFFIC CIRCLE	53	253	14.8459	70.868
ROAD DIRECTION	40	293	11.2045	82.073
WALKWAYS	36	329	10.084	92.157
ROAD DIVIDER	25	354	7.0028	99.16
DRAINAGE	3	357	0.8403	100

Source: R-console

The result of the pareto analysis obtained in table 7 was expressed graphically as displayed in Figure 11.

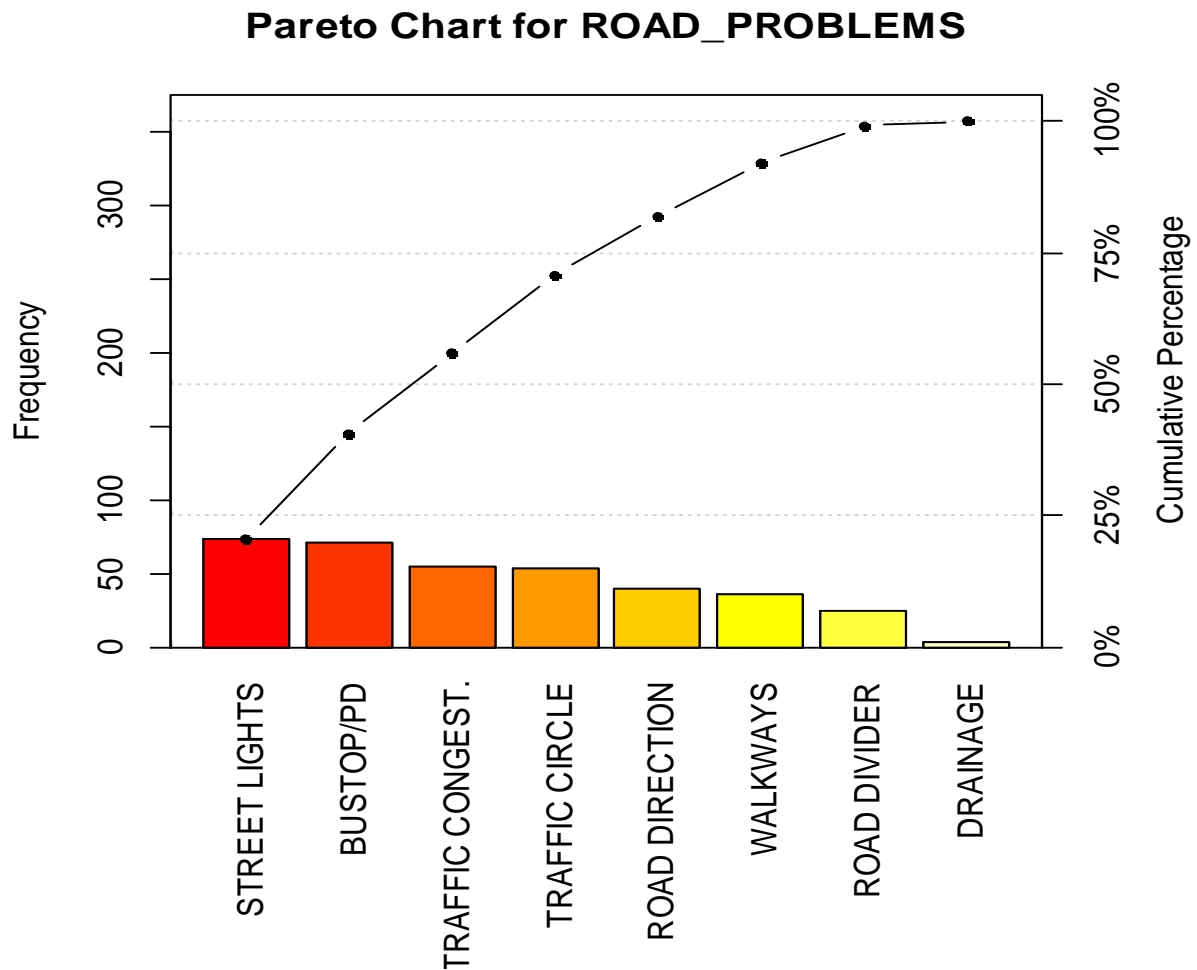


Figure 11: Pareto Chart for Road Maintenance in Anambra State

The result of the pareto analysis revealed that unavailability of Street lights, Bustop/PD, Traffic Congestion, traffic circle and road direction constitute 80% of factors affecting road maintenance in Anambra State. This was graphically expressed in the pareto graph (Figure 11).

Correlation analysis was performed using Table 5 in order to determine the extent of relationship between road condition and the factors since it was found from the Pareto analysis that unavailability of Street lights,

Bustop/PD, Traffic Congestion, traffic circle and road direction constitute 80% of factors affecting road maintenance in Anambra State.

Table 8: Summary Result of Correlation matrix for Road Condition on Road divider, Road direction, Traffic Circle, Drainage, Walkways, street light, traffic congestion and Bustop/ Pedestrian Bridge in Anambra State

Correlations

			ROAD_	ROAD_	ROAD_	TRAFFIC_	DRAINAGE	WALKWAYS	STREETLIGH	TRAFFIC_	BUSTOP_
			CONDITION	DIVIDER	DIRECTION	CIRCLE			T	CONGESTION	PEDESTRAIN_
											BRIDGE
Spearman's rho	ROAD_CONDITION	Correlation Coefficient	1.000	-.281 [*]	-.296 ^{**}	-.023	-.044	-.257 [*]	-.226 [*]	-.190	-.229 [*]
		Sig. (2-tailed)	.	.013	.009	.844	.705	.024	.048	.098	.045
		N	77	77	77	77	77	77	77	77	77
	ROAD_DIVIDER	Correlation Coefficient	-.281 [*]	1.000	.389 ^{**}	.287 [*]	.290 [*]	.518 ^{**}	.140	.009	.098
		Sig. (2-tailed)	.013	.	.000	.011	.010	.000	.226	.940	.396
		N	77	77	77	77	77	77	77	77	77
	ROAD_DIRECTION	Correlation Coefficient	-.296 ^{**}	.389 ^{**}	1.000	.138	.059	.328 ^{**}	.209	.197	.302 ^{**}
		Sig. (2-tailed)	.009	.000	.	.230	.608	.004	.068	.085	.008
		N	77	77	77	77	77	77	77	77	77
	TRAFFIC_CIRCLE	Correlation Coefficient	-.023	.287 [*]	.138	1.000	-.009	.125	.154	.133	.014
		Sig. (2-tailed)	.844	.011	.230	.	.935	.280	.180	.249	.907
		N	77	77	77	77	77	77	77	77	77
DRAINAGE	Correlation Coefficient	-.044	.290 [*]	.059	-.009	1.000	.080	.041	-.021	.059	
	Sig. (2-tailed)	.705	.010	.608	.935	.	.487	.726	.855	.613	
	N	77	77	77	77	77	77	77	77	77	
WALKWAYS	Correlation Coefficient	-.257 [*]	.518 ^{**}	.328 ^{**}	.125	.080	1.000	.054	-.041	.078	
	Sig. (2-tailed)	.024	.000	.004	.280	.487	.	.640	.722	.499	
	N	77	77	77	77	77	77	77	77	77	
STREETLIGHT	Correlation Coefficient	-.226 [*]	.140	.209	.154	.041	.054	1.000	.170	.192	
	Sig. (2-tailed)	.048	.226	.068	.180	.726	.640	.	.140	.095	
	N	77	77	77	77	77	77	77	77	77	
TRAFFIC_CONGESTION	Correlation Coefficient	-.190	.009	.197	.133	-.021	-.041	.170	1.000	.352 ^{**}	
	Sig. (2-tailed)	.098	.940	.085	.249	.855	.722	.140	.	.002	
	N	77	77	77	77	77	77	77	77	77	
BUSTOP_PEDESTRAIN_BRIDGE	Correlation Coefficient	-.229 [*]	.098	.302 ^{**}	.014	.059	.078	.192	.352 ^{**}	1.000	
	Sig. (2-tailed)	.045	.396	.008	.907	.613	.499	.095	.002	.	
	N	77	77	77	77	77	77	77	77	77	

Source: SPSS 17.0

The result obtained in Table 8 shows that Road divider, Road direction, Traffic Circle, Drainage, Walkways, street light, traffic congestion and Bustop/ PD has inverse relationship with Road condition in Anambra State with the corresponding correlation coefficient -28.1%, -29.6%, -2.3%, -4.4%, -25.7%, -22.6%, -19.0% and -22.9%, respectively. This result implies that as the availability of these factors are increasing, bad road condition is expected to decrease in Anambra State. The result validates the pareto analysis; that Pareto identified the key factors that constitute the key problem facing road maintenance in Anambra state.

4.11 Time Series Analysis on Maintenance Cost

The maintenance cost of roads was analyzed using time series analysis with the main objective of designing a model that can be used in estimating the maintenance cost of roads given a time parameter. In time series analysis, the time parameter t is usually generic; in this research, time is observed as year. Hence, a trend analysis on the observed data will be performed and a corresponding model obtained. Also, the data will be tested for unit root and stationarity which will validate the use of the model for making forecasts. A five years forecast of the maintenance cost of roads using the obtained time series model will be performed with the aim of giving an idea of what maintenance of roads will cost in Anambra State all things being equal.

Table 9: Summary of maintenance cost of roads and year code

Mcr	year code (t)
57845868	1
61211163	2
83060565	3
152240042	4
201949343	5
130670316	6
182753103	7
97130327	8
141778801	9
191931676	10

Key: Mcr represents maintenance cost of roads and year code(t) represents year

Using the Table 9 the time series analysis will be performed with the maintenance cost of road being modelled over time and also tested for unit root and stationarity.

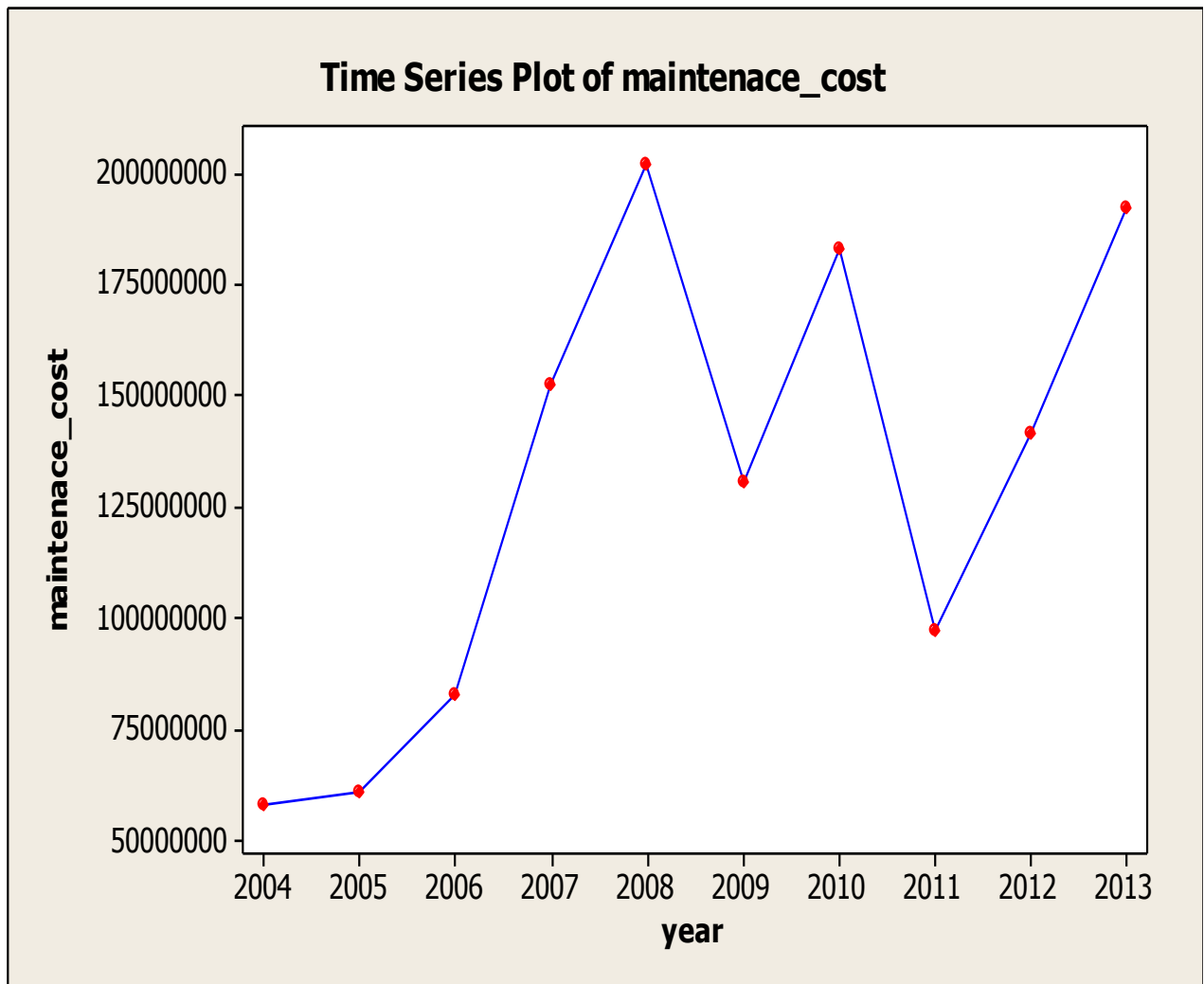


Figure 12: Distribution of Maintenance cost of roads (2004-2013)

Table 10: Trend Analysis on maintenance cost of roads in Anambra State

```
Data      Mcr
Length    10
NMissing  0
```

Fitted Trend Equation

$$Y_t = 68011964 + 11280938 * t$$

The result of the trend analysis showed an increasing trend line of the maintenance cost of roads (see Figure 12).

The trend equation Table 10 for predicting maintenance cost of roads in Anambra State in a given time is expressed as

$$Y(t) = 68011964 + 11280938*t$$

where t is time in year.

Table 11: Test of Stationarity using the Kwiatkowski-Phillips-Schmidt-Shin test and Augmented Dickey-Fuller test

Null Hypothesis: MCR is stationary

Exogenous: Constant

Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

	LM-Stat.
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.351873
Asymptotic critical values*:	
1% level	0.739000
5% level	0.463000
10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	2.57E+15
HAC corrected variance (Bartlett kernel)	3.31E+15

Source: Eview7

The Kwiatkowski-Phillips-Schmidt-Shin test displayed in Table 11 revealed that the time series process of maintenance cost of roads is stationary over the

observed time since the test statistic measure of 0.35 obtained falls on the acceptance region of the hypothesis.

Table 12: Augmented Dickey-Fuller test

Null Hypothesis: MCR has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.872082	0.3284
Test critical values:	1% level	-4.420595	
	5% level	-3.259808	
	10% level	-2.771129	

*MacKinnon (1996) one-sided p-values.

Source: Eview7

Table 13: Augmented Dickey-Fuller test at First Difference

Null Hypothesis: D(MAINTENACE_COST) has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on SIC, maxlag=1)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.640206	0.0329
Test critical values:	1% level	-4.582648	
	5% level	-3.320969	
	10% level	-2.801384	

*MacKinnon (1996) one-sided p-values.

Source: Eview7

The result of the unit root test using the Augmented Dickey-Fuller test statistic displayed in Table 13 found that the series has unit root and stationary over time since a t-statistic value of -1.87 was obtained with a p-value of 0.33 which falls on the acceptance region of the hypothesis assuming a 95% confidence level. One concludes that the time series process has unit root and then employ the result of the first difference of the Augmented Dickey-Fuller test which found a test statistic measure of -3.64 with a p-value of 0.033 which implies that the series has no unit root at the first difference I(1) and stationary overtime which implies that the model obtained can be used to make forecast for future behaviour of the process.

Table 14: Five years Forecasts of Maintenance Cost of Roads in Anambra State

Period	Forecast
2014	192102277
2015	203383215
2016	214664152
2017	225945090
2018	237226028

Source: Minitab 14.0

Also, five years forecast on the maintenance cost of roads in Anambra State was estimated and it was found that in the year 2018 all things being equal the

maintenance cost of roads in Anambra State is expected to be about N237,226,028.

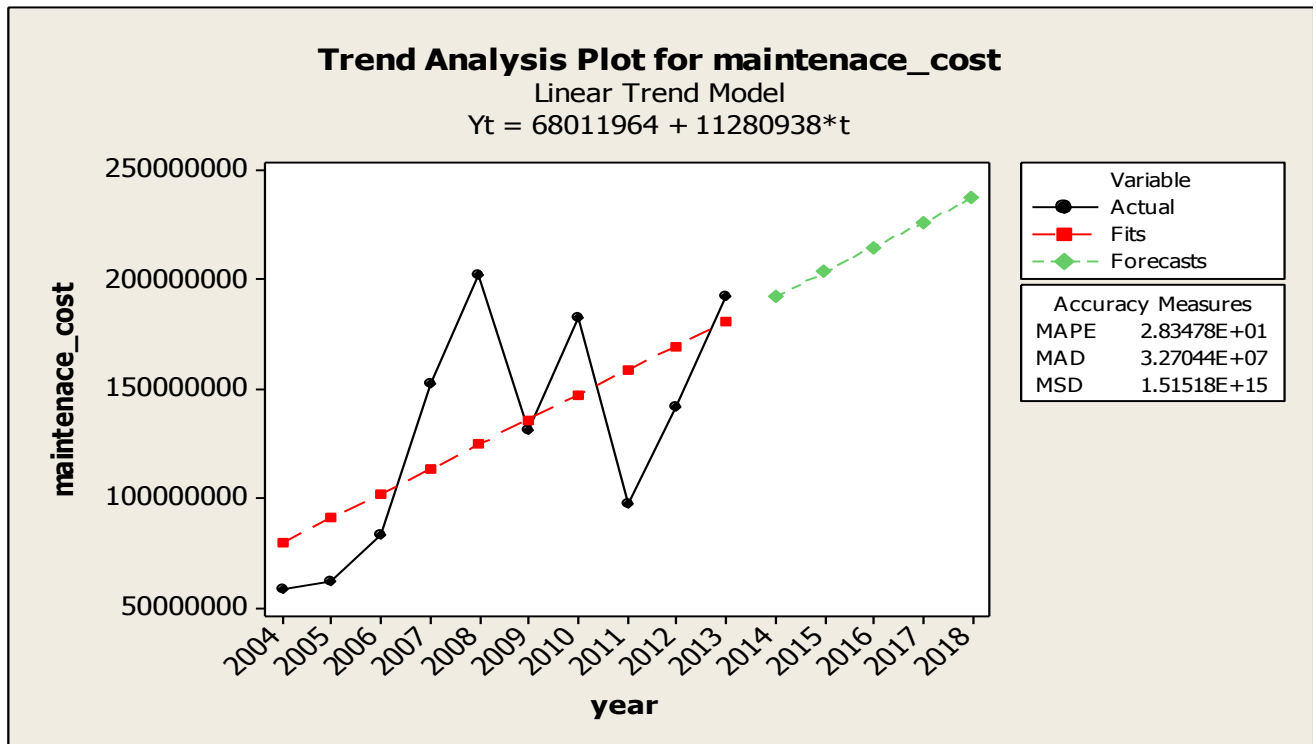


Figure 13: Trend plot of Maintenance cost of roads (2004-2013) with (2015-2018) Forecast

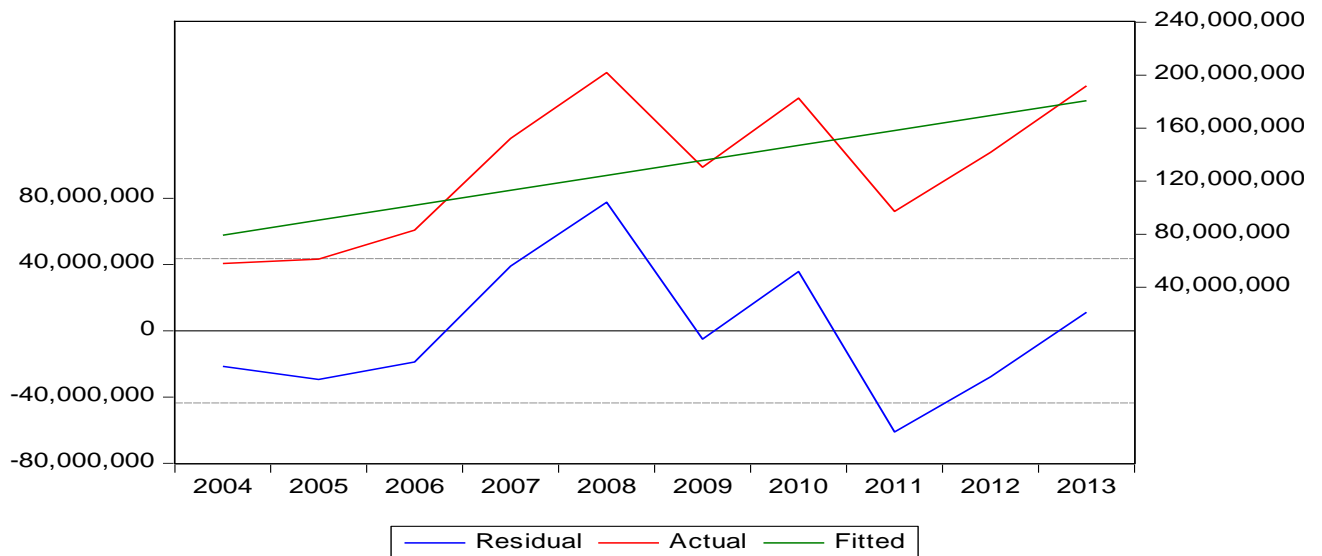


Figure 14: Distribution of Actual, Fitted & Residual for Maintenance cost of roads in Anambra State.

The result of the trend analysis and forecast showed an increasing trend line of the maintenance cost of roads (see Figures 13 and 14).

4.12 Curve Estimation Analysis between Maintenance Cost of Road on Economic Variable.

Curve estimation analysis was performed to determine the explanatory variables that contributed to the behaviour of maintenance cost of roads in Anambra state and to also asses the best type of model to employ in the estimation of maintenance cost of roads within the observed period. The models considered in this section include the linear model, Logarithmic model, inverse model, Quadratic model, cubic model, compound model, power model, S curved and logistic model.

Using details from Table 1, curve estimation analysis was done where the maintenance cost of roads (Mcr) is the dependent or response variable and Hi, Ci, IASPCA, SCRGEF, MCQCC, MCQCM, MCQCBM, CGFCFPME, CGFCFCPME, GDPCBPBC, GDPCBPBCN, LR, MMT, MRH, MRR, MF, MR, ME, VMIME, OERN, (AFEM, DAS) ERN, CIPI, CIT, ISMB, ISV, QA, MCQCAT, AND SGRBC were the explanatory parameters.

Table 15: Summary of curve fitting analysis of maintenance cost against headline inflation.

Model Summary and Parameter Estimates

Dependent Variable: maintenance
cost of road

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.021	.175	1	8	.687	1.014E8	2.688E6		
Logarithmic	.003	.026	1	8	.876	1.072E8	9.839E6		
Inverse	.001	.004	1	8	.949	1.266E8	3.426E7		
Quadratic	.310	1.575	2	7	.272	3.913E8	-5.846E7	2.986E6	
Cubic	.332	.994	3	6	.457	1.170E8	3.482E7	-6.773E6	3.198E5
Compound	.014	.114	1	8	.744	9.736E7	1.019		
Power	.001	.006	1	8	.941	1.083E8	.040		
S	.003	.025	1	8	.878	18.522	.707		
Growth	.014	.114	1	8	.744	18.394	.019		
Exponential	.014	.114	1	8	.744	9.736E7	.019		
Logistic	.014	.114	1	8	.744	1.027E-8	.981		

The independent variable is Headline Inflation.
Source: SPSS 17.0

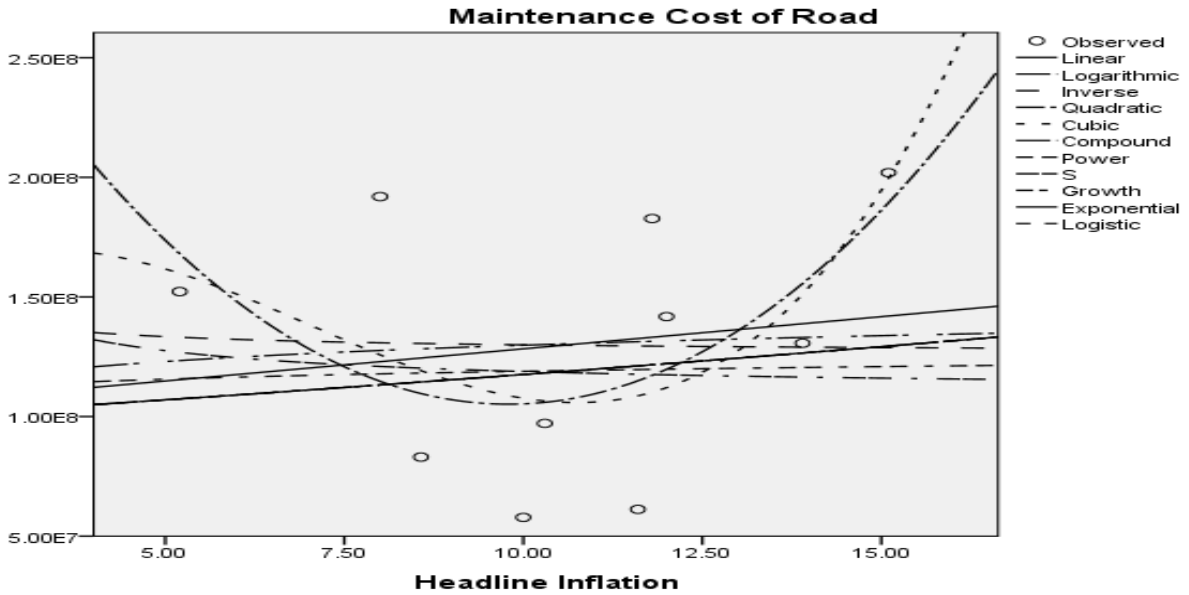


Figure 15: Curve fitting plot of maintenance cost of roads and headline inflation

From the result of the curve estimation, it was found that the cubic model performed better than the other methods since it has the highest R-squared of 33.2%. This result implies that the best model was the cubic model since the independent variable headline inflation was able to explain about 33.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.457, which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.457 > \alpha=0.05$). Hence, headline inflation does not contribute to the proposed model.

Table 16: Summary of curve fitting analysis of maintenance cost against Core inflation.

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of road

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.322	3.795	1	8	.087	4.449E7	7.003E6		
Logarithmic	.372	4.735	1	8	.061	-7.189E7	8.282E7		
Inverse	.410	5.563	1	8	.046	2.112E8	-8.647E8		
Quadratic	.416	2.490	2	7	.153	-1.000E8	3.439E7	-1.144E6	
Cubic	.441	1.578	3	6	.290	-3.807E8	1.163E8	-8.471E6	2.043E5
Compound	.346	4.229	1	8	.074	5.520E7	1.065		
Power	.418	5.748	1	8	.043	1.862E7	.761		
S	.480	7.378	1	8	.056	19.356	-8.102		
Growth	.346	4.229	1	8	.074	17.826	.063		
Exponential	.346	4.229	1	8	.074	5.520E7	.063		
Logistic	.346	4.229	1	8	.074	1.812E-8	.939		

The independent variable is Core Inflation.

Source: SPSS 17.0

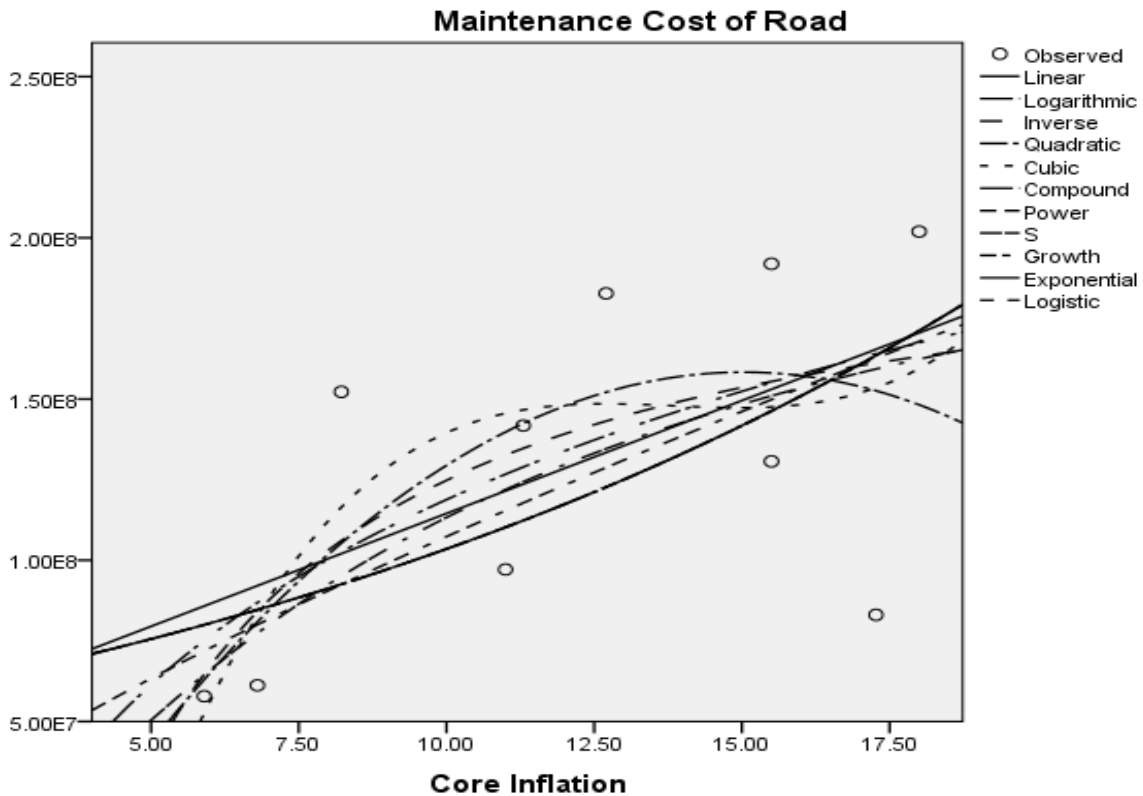


Figure 16: Curve fitting plot of maintenance cost of roads and core inflation

From the result of the curve estimation it was found that the S curve model performed better than the other methods with an R-squared of 48.0%. This result implies that the best model was the S curve model since the independent variable core inflation was able to explain about 48.0% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.056 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.056 > \alpha=0.05$). Hence, core inflation does not contribute to the proposed model.

Table 17: Summary of curve fitting analysis of maintenance cost against Sectoral Growth Rate Building & Construction

Model Summary and Parameter Estimates

Dependent Variable:

maintenance cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.085	.743	1	8	.414	-2.770E8	3.246E7		
Logarithmic	.085	.743	1	8	.414	-8.942E8	4.051E8		
Inverse	.085	.744	1	8	.413	5.335E8	-5.054E9		
Quadratic	.085	.743	1	8	.414	-7.467E7	.000	1.300E6	
Cubic	.087	.325	2	7	.733	5.483E7	-7.479E6	.000	8.533E4
Compound	.071	.614	1	8	.456	4.711E6	1.294		
Power	.072	.617	1	8	.455	3.469E4	3.220		
S	.072	.620	1	8	.454	21.808	-40.245		
Growth	.071	.614	1	8	.456	15.365	.257		
Exponential	.071	.614	1	8	.456	4.711E6	.257		
Logistic	.071	.614	1	8	.456	2.123E-7	.773		

Source: SPSS 17.0

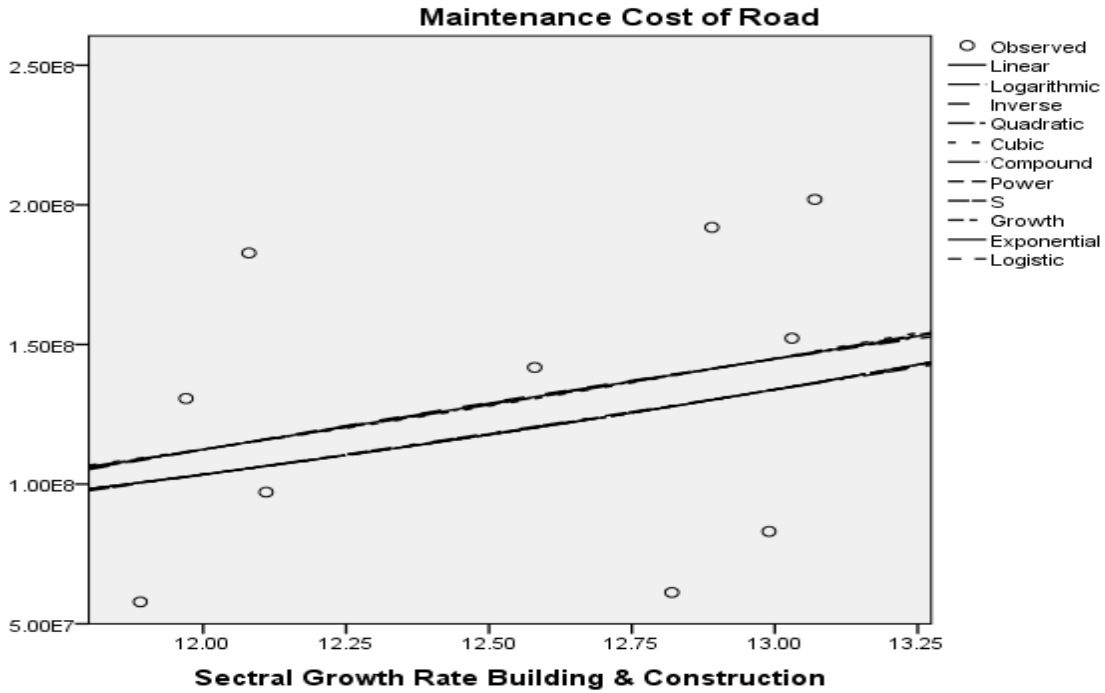


Figure 17: Curve fitting plot of maintenance cost of roads against sectoral growth rate building and construction

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 8.7%. This result implies that the best model was the S curve model since the independent variable sectoral growth rate building & construction was able to explain about 8.7% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.733 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.733 > \alpha=0.05$). Hence, sectoral growth rate building & construction does not contribute to the proposed model.

Table 18: Summary of curve fitting analysis of maintenance cost of roads against import of articles of stone, plaster, cement

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.186	1.832	1	8	.213	1.068E8	130.339		
Logarithmic	.324	3.841	1	8	.086	-1.722E8	2.618E7		
Inverse	.487	7.598	1	8	.025	1.690E8	-2.387E12		
Quadratic	.231	1.050	2	7	.399	9.131E7	413.511	.000	
Cubic	.641	3.577	3	6	.016	4.881E6	3.051E3	-.015	1.979E-8
Compound	.224	2.310	1	8	.167	9.542E7	1.000		
Power	.398	5.299	1	8	.050	6.535E6	.251		
S	.601	12.052	1	8	.008	18.970	-2.297E4		
Growth	.224	2.310	1	8	.167	18.374	1.238E-6		
Exponential	.224	2.310	1	8	.167	9.542E7	1.238E-6		
Logistic	.224	2.310	1	8	.167	1.048E-8	1.000		

The independent variable is Import of Articles of Stone, Plaster, Cement.

Source: SPSS 17.0

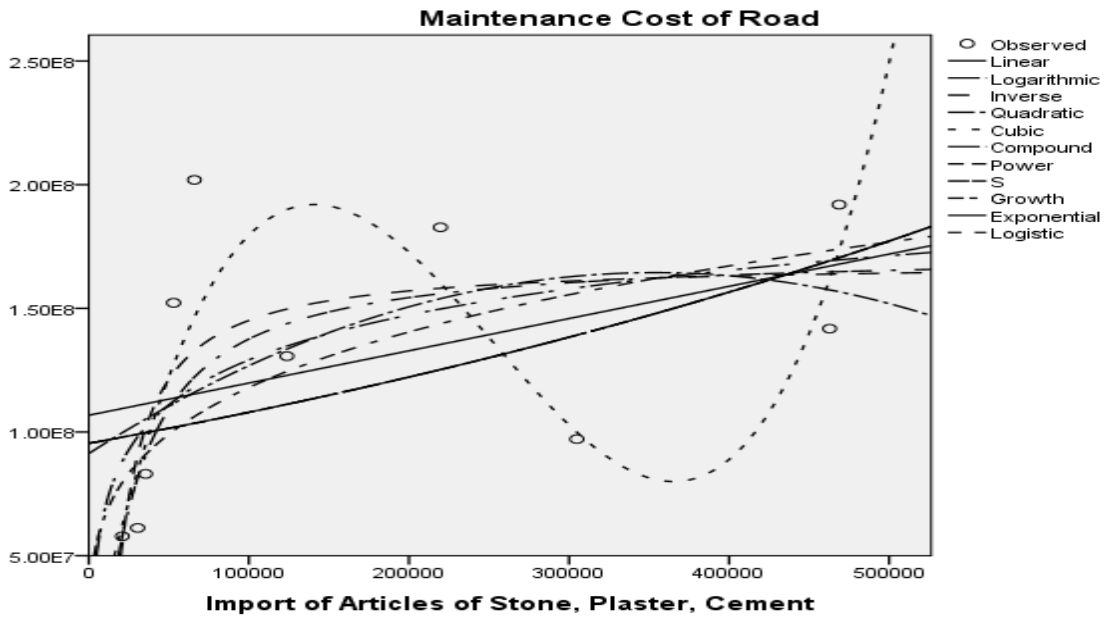


Figure 18: Curve fitting plot of maintenance cost of roads against import of articles of stone, plaster, cement

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 64.1%. This result implies that the best model was the cubic model since the independent variable import of articles of stone, plaster, cement was able to explain about 64.1% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.016 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.016 < \alpha=0.05$). Hence, the import of articles of stone, plaster, cement contribute to the proposed model.

Table 19: Summary of curve fitting analysis of maintenance cost of roads against sectoral contribution of real GDP

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.396	5.235	1	8	.051	-1.148E8	1.319E8		
Logarithmic	.422	5.844	1	8	.042	-2.066E7	2.472E8		
Inverse	.446	6.453	1	8	.035	3.796E8	-4.549E8		
Quadratic	.551	4.287	2	7	.061	-1.476E9	1.642E9	-4.113E8	
Cubic	.552	4.302	2	7	.060	-1.036E9	9.007E8	.000	-7.535E7
Compound	.480	7.380	1	8	.026	1.151E7	3.521		
Power	.512	8.389	1	8	.020	2.826E7	2.358		
S	.541	9.447	1	8	.015	20.975	-4.340		
Growth	.480	7.380	1	8	.026	16.259	1.259		
Exponential	.480	7.380	1	8	.026	1.151E7	1.259		
Logistic	.480	7.380	1	8	.026	8.689E-8	.284		

The independent variable is Sectoral Contribution of Real GDP.

Source: SPSS 17.0

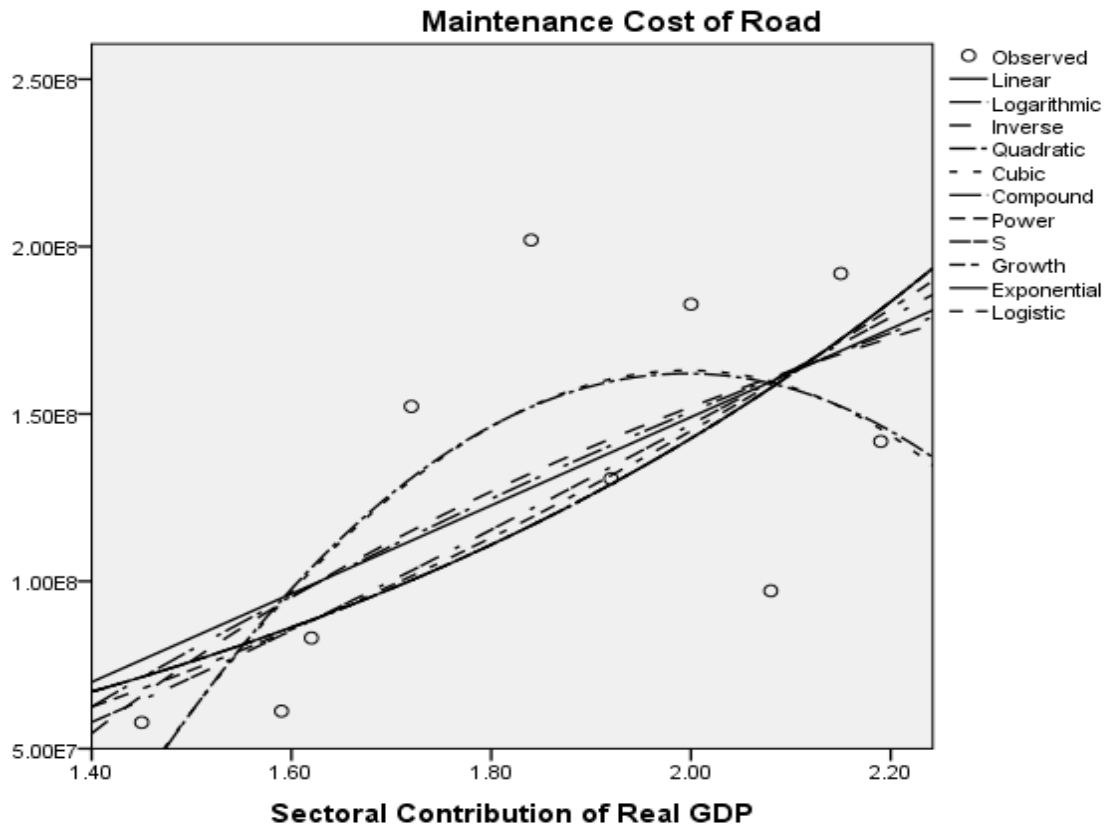


Figure 19: Curve fitting plot of maintenance cost of roads against Sectoral contribution of real GDP

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 55.2%. This result implies that the best model was the S curve model since the independent variable sectoral contribution of real GDP was able to explain about 55.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.060 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.060 > \alpha=0.05$). Hence, sectoral contribution of real GDP does not contribute to the proposed model.

Table 20: Summary of curve fitting analysis of maintenance cost of roads against market capitalization of quoted company for construction

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.651	14.898	1	8	.005	7.554E7	.001		
Logarithmic	.647	14.642	1	8	.005	-7.443E7	9.215E6		
Inverse	.227	2.345	1	8	.164	1.410E8	-1.350E14		
Quadratic	.668	7.042	2	7	.021	7.081E7	.002	-6.276E-15	
Cubic	.771	6.746	3	6	.024	6.720E7	.005	-1.119E-13	6.763E-25
Compound	.675	16.626	1	8	.004	7.357E7	1.000		
Power	.722	20.734	1	8	.002	1.832E7	.084		
S	.213	2.169	1	8	.179	18.687	-1.135E6		
Growth	.675	16.626	1	8	.004	18.114	8.450E-12		
Exponential	.675	16.626	1	8	.004	7.357E7	8.450E-12		
Logistic	.675	16.626	1	8	.004	1.359E-8	1.000		

The independent variable is Market Capitalization of Quoted Company for Construction.

Source: SPSS 17.0

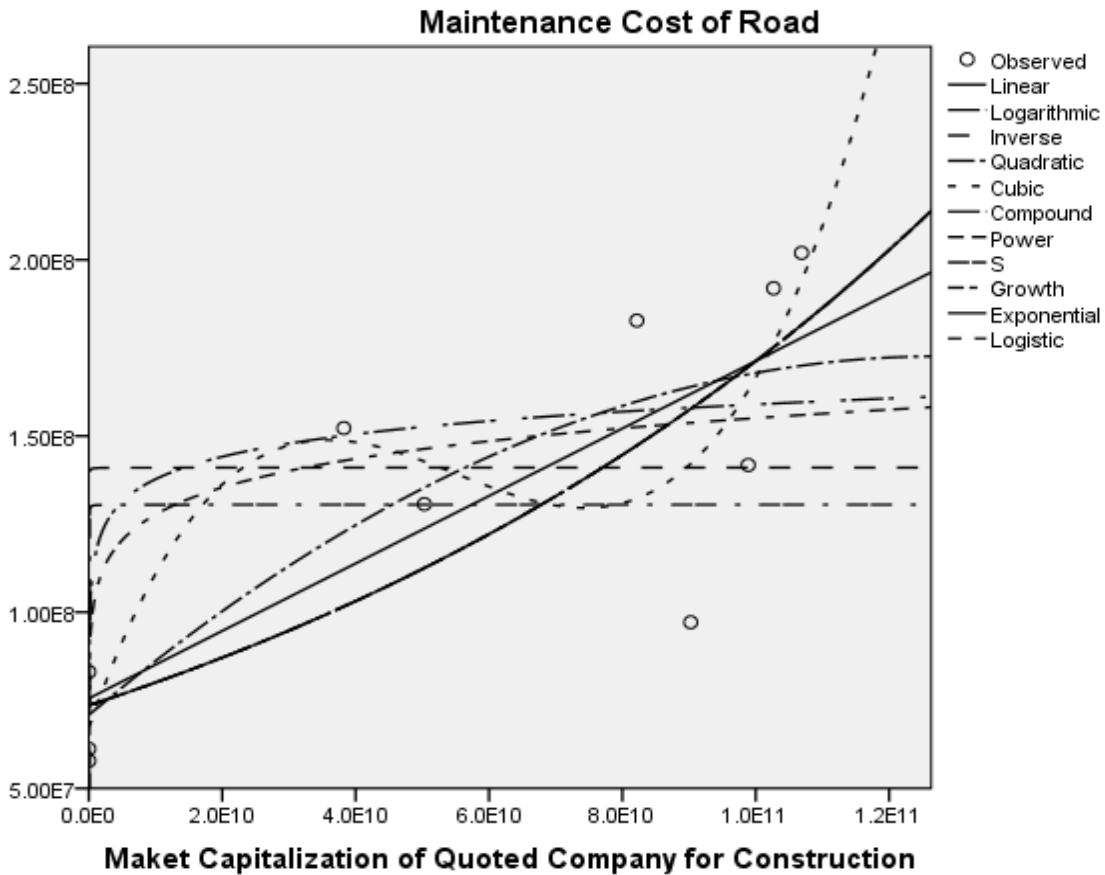


Figure 20: Curve fitting plot of maintenance cost of roads against market capitalization of quoted company for construction

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 77.1%. This result implies that the best model was the cubic model since the independent variable market capitalization of quoted company for construction was able to explain about 77.1% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.024 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.024$

< $\alpha=0.05$). Hence, market capitalization of quoted company for construction contributed to the proposed model.

Table 21: Summary of curve fitting analysis of maintenance cost of roads against market capitalization of quoted companies for machinery(marketing)

Model Summary and Parameter Estimates

Dependent Variable : maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.655	15.184	1	8	.005	6.464E7	71.567		
Logarithmic	.655	15.187	1	8	.005	-2.041E8	2.566E7		
Inverse	.652	14.981	1	8	.005	1.596E8	-3.632E12		
Quadratic	.657	6.705	2	7	.024	5.747E7	256.610	.000	
Cubic	.787	6.712	2	7	.024	6.070E7	169.179	.000	-5.688E-11
Compound	.752	24.235	1	8	.001	6.485E7	1.000		
Power	.752	24.217	1	8	.001	5.356E6	.238		
S	.746	23.548	1	8	.001	18.869	-3.367E4		
Growth	.752	24.235	1	8	.001	17.988	6.643E-7		
Exponential	.752	24.235	1	8	.001	6.485E7	6.643E-7		
Logistic	.752	24.235	1	8	.001	1.542E-8	1.000		

The independent variable is Market Capitalization of Quoted Companies for Machinery (Marketing).

Source: SPSS 17.0

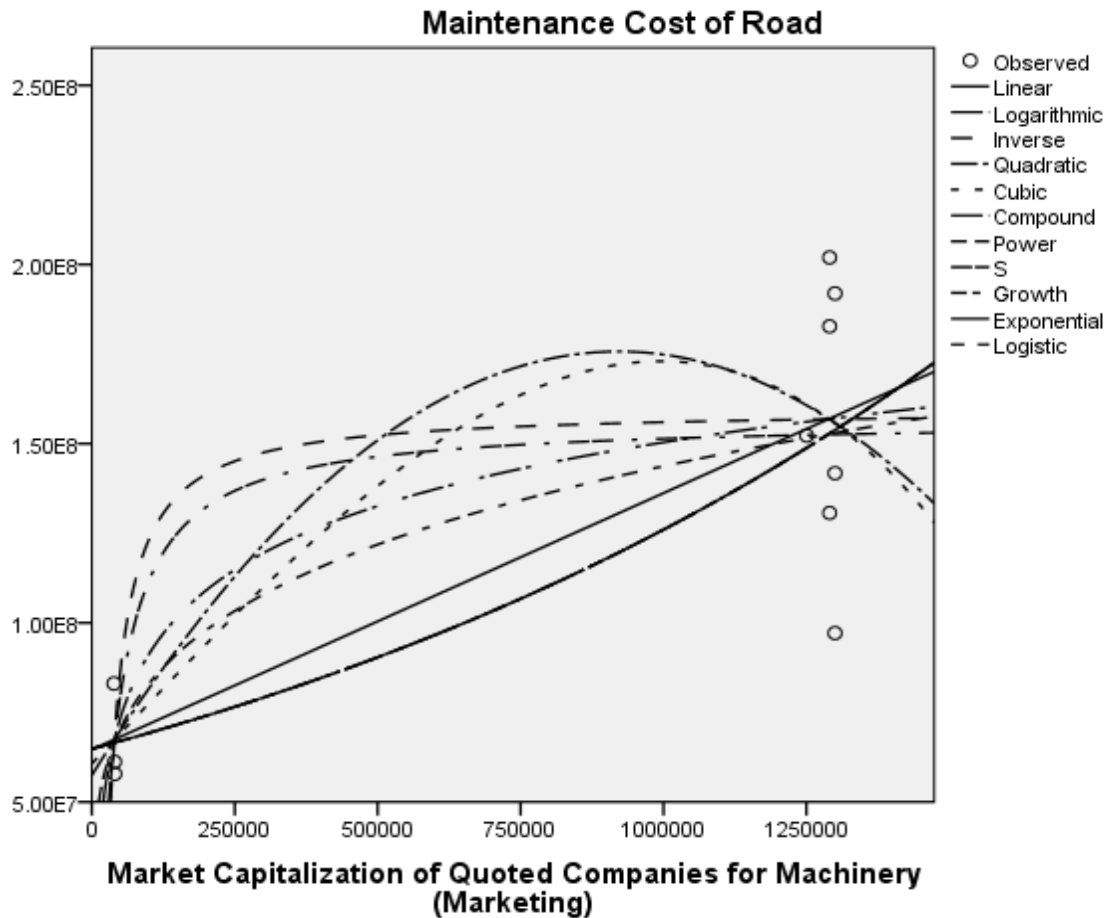


Figure 21: Curve fitting plot of maintenance cost of roads against market capitalization of quoted companies for machinery (marketing)

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 78.7%. This result implies that the best model was the cubic model since the independent variable market capitalization of quoted companies for machinery (marketing) was able to explain about 78.7% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.024 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, p-

value=0.024 < $\alpha=0.05$). Hence, market capitalization of quoted companies for machinery (marketing) contributed to the proposed model.

Table 22: Summary of curve fitting analysis of maintenance cost of roads against market capitalization of quoted companies building material

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.414	5.640	1	8	.045	8.560E7	.000		
Logarithmic	.637	14.011	1	8	.006	-1.493E8	1.150E7		
Inverse	.608	12.421	1	8	.008	1.533E8	-1.171E16		
Quadratic	.555	4.358	2	7	.059	7.341E7	.001	-8.206E-16	
Cubic	.762	6.414	3	6	.077	6.739E7	.002	-7.831E-15	9.248E-27
Compound	.518	8.608	1	8	.019	7.733E7	1.000		
Power	.752	24.213	1	8	.001	8.581E6	.108		
S	.749	23.860	1	8	.001	18.818	-1.126E8		
Growth	.518	8.608	1	8	.019	18.164	1.699E-12		
Exponential	.518	8.608	1	8	.019	7.733E7	1.699E-12		
Logistic	.518	8.608	1	8	.019	1.293E-8	1.000		

The independent variable is Market Capitalization of Quoted Companies Building Material.

Source: SPSS 17.0

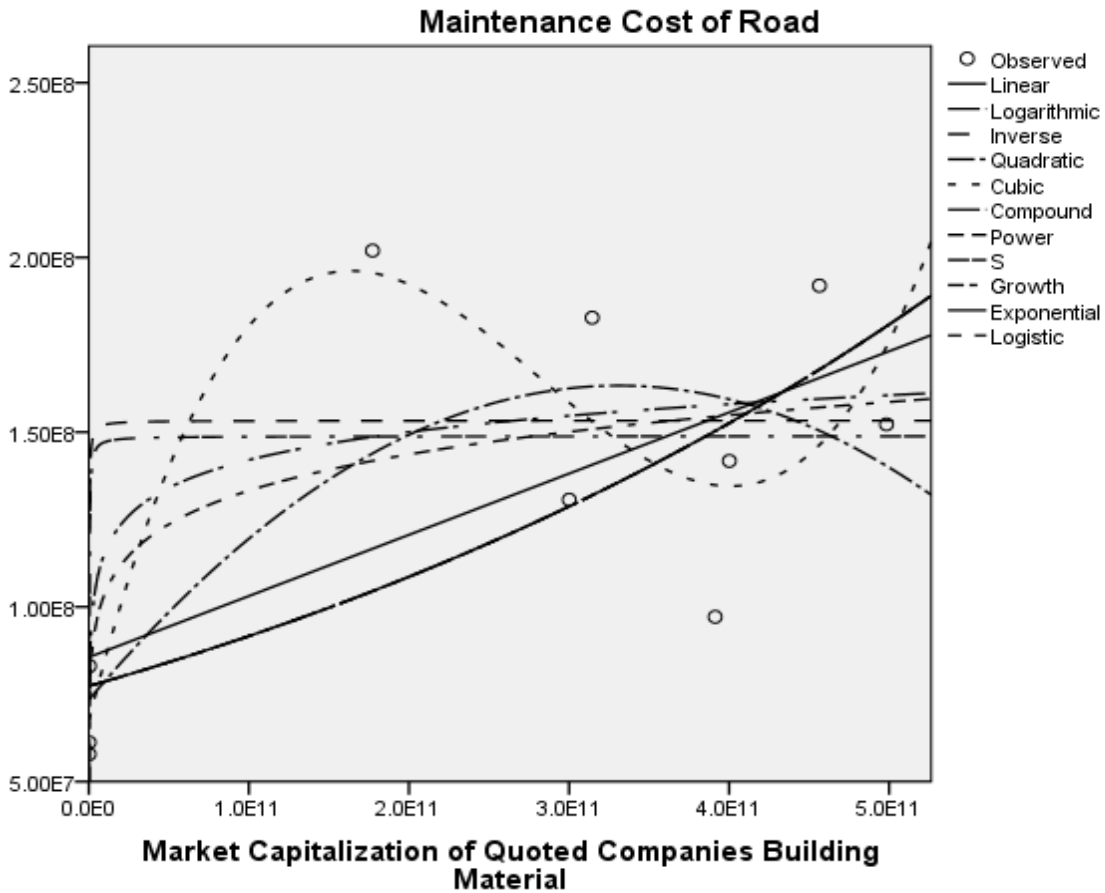


Figure 22: Curve fitting plot of maintenance cost of roads against market capitalization of quoted companies building material

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 76.2%. This result implies that the best model was the S curve model since the independent variable market capitalization of quoted companies building material was able to explain about 76.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.77 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.77 >$

$\alpha=0.05$). Hence, market capitalization of quoted companies building material does not contribute to the proposed model.

Table 24: Summary of curve fitting analysis of maintenance cost of roads against composition of Gross Fixed Capital Formation at 1990 Purchaser Value Machinery & Equipment.

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.525	8.855	1	8	.018	6.437E6	3.895E3		
Logarithmic	.497	7.893	1	8	.023	-7.675E8	8.716E7		
Inverse	.450	6.533	1	8	.034	1.919E8	-1.656E12		
Quadratic	.531	3.963	2	7	.071	3.385E7	1.313E3	.050	
Cubic	.671	2.266	3	6	.011	1.980E7	3.211E3	-.023	8.414E-7
Compound	.647	14.667	1	8	.005	3.626E7	1.000		
Power	.626	13.396	1	8	.006	1.922E4	.848		
S	.577	10.904	1	8	.011	19.202	-1.625E4		
Growth	.647	14.667	1	8	.005	17.406	3.745E-5		
Exponential	.647	14.667	1	8	.005	3.626E7	3.745E-5		
Logistic	.647	14.667	1	8	.005	2.758E-8	1.000		

The independent variable is Composition of Gross Fixed Capital Formation at 1990 Purchaser value Machinery & Equipment.

Source: SPSS 17.0

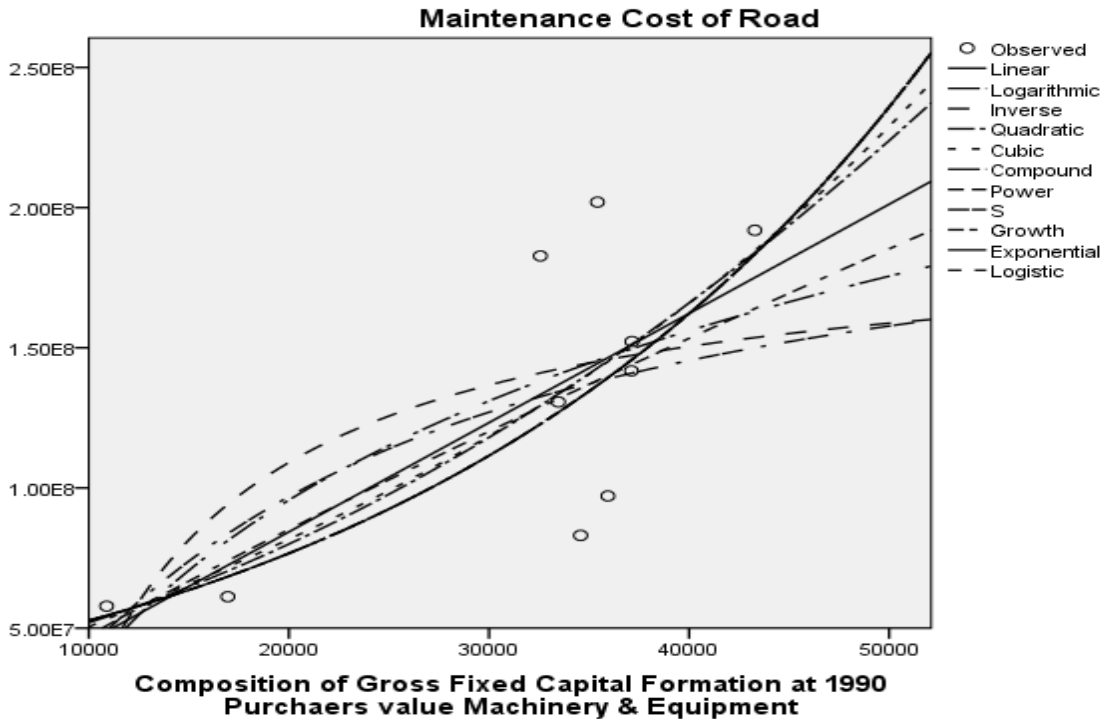


Figure 23: Curve fitting plot of maintenance cost of roads against market Composition of Gross Fixed Capital Formation at 1990 purchaser value machinery and equipment

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 67.1%. This result implies that the best model was the cubic model since the independent variable composition of gross fixed capital formation at 1990 purchasers value machinery & equipment was able to explain about 67.1% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.011 which falls on the rejection region of the hypothesis. Hence, composition of gross fixed capital formation at 1990 purchasers value machinery & equipment contribute to the proposed model.

Table 24: Summary of curve fitting analysis of maintenance cost of roads against Composition of Gross Fixed Capital Formation at current Purchaser Value Machinery & Equipment.

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.366	4.609	1	8	.064	7.202E7	47.434		
Logarithmic	.473	7.167	1	8	.028	-5.188E8	4.701E7		
Inverse	.483	7.463	1	8	.026	1.673E8	-2.661E13		
Quadratic	.470	3.103	2	7	.108	2.834E7	150.139	-4.284E-5	
Cubic	.655	14.706	3	6	.038	-4.029E7	457.187	.000	8.686E-11
Compound	.457	6.720	1	8	.032	6.786E7	1.000		
Power	.601	12.035	1	8	.008	2.104E5	.459		
S	.621	13.109	1	8	.007	18.960	-2.615E5		
Growth	.457	6.720	1	8	.032	18.033	4.592E-7		
Exponential	.457	6.720	1	8	.032	6.786E7	4.592E-7		
Logistic	.457	6.720	1	8	.032	1.474E-8	1.000		

The independent variable is Composition of Gross Fixed Capital Formation at Current Purchase value Machinery & Equipment.

Source: SPSS 17.0

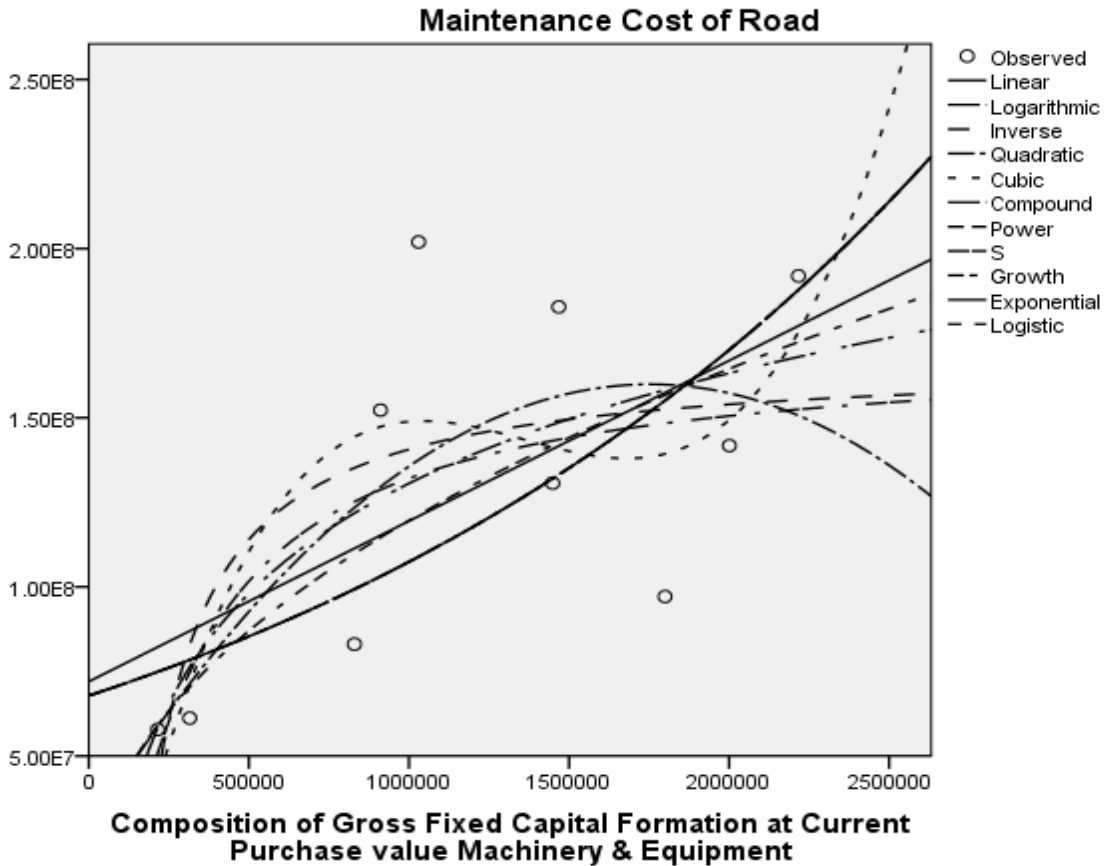


Figure 24: Curve fitting plot of maintenance cost of roads against market Composition of Gross Fixed Capital Formation at current purchaser value machinery and equipment

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 65.5%. This result implies that the best model was the cubic model since the independent variable composition of gross fixed capital formation at current purchase value machinery & equipment was able to explain about 65.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.038 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.038 < \alpha=0.05$). Hence, composition of gross fixed

capital formation at current purchase value machinery & equipment contribute to the proposed model.

Table 25: Summary of curve fitting analysis of maintenance cost of roads against GDP at Constant Basic Price for Building and Construction

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.151	1.421	1	8	.267	1.176E8	487.499		
Logarithmic	.277	3.067	1	8	.118	-1.932E8	3.359E7		
Inverse	.497	7.920	1	8	.023	2.173E8	-1.092E12		
Quadratic	.513	3.686	2	7	.081	-2.679E7	1.353E4	-.083	
Cubic	.563	10.686	2	7	.021	-2.679E7	1.353E4	-.083	.000
Compound	.138	1.285	1	8	.290	1.073E8	1.000		
Power	.280	3.105	1	8	.116	7.145E6	.292		
S	.552	9.842	1	8	.014	19.391	-9.965E3		
Growth	.138	1.285	1	8	.290	18.492	4.045E-6		
Exponential	.138	1.285	1	8	.290	1.073E8	4.045E-6		
Logistic	.138	1.285	1	8	.290	9.315E-9	1.000		

The independent variable is GDP at Constant Basic Price for Building & Construction.

Source: SPSS 17.0

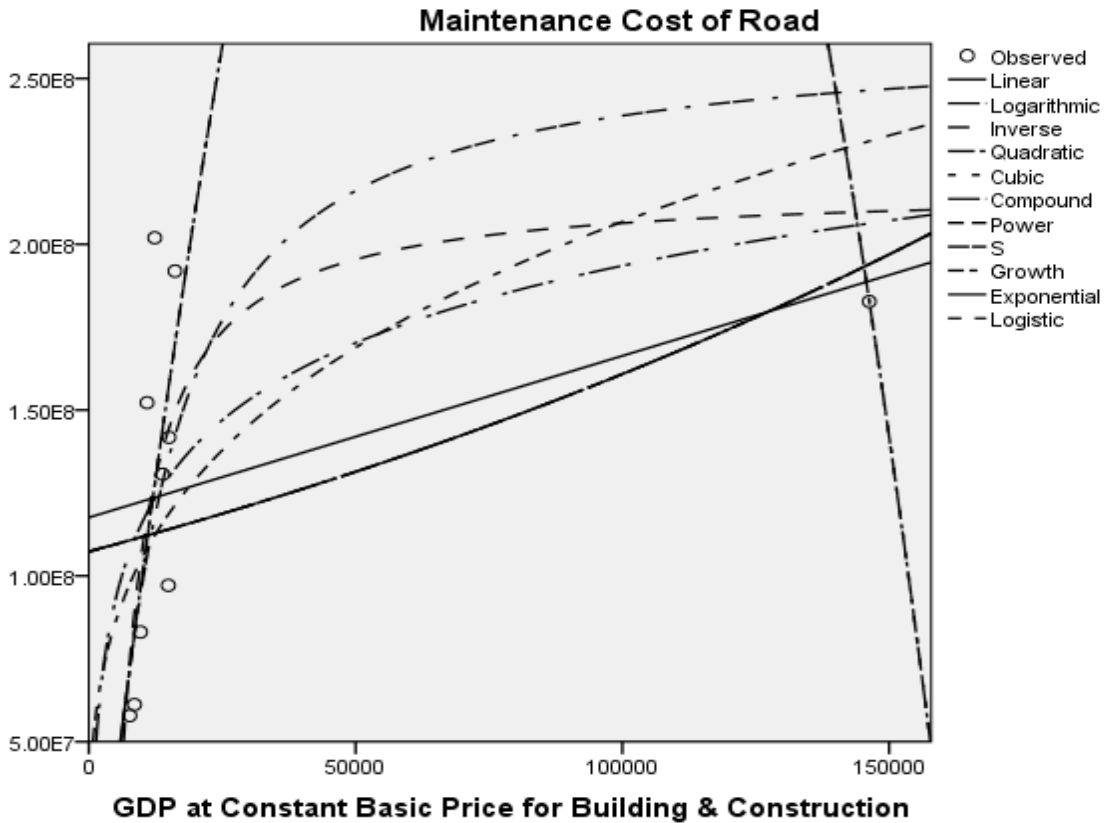


Figure 25: Curve fitting plot of maintenance cost of roads against GDP at Constant Basic Price for Building and Construction

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 56.3%. This result implies that the best model was the quadratic model since the independent variable GDP at constant basic price for building & construction was able to explain about 56.3% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.081 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.081 > \alpha=0.05$). Hence, GDP at constant basic price for building & construction does not contribute to the proposed model.

Table 26: Summary of curve fitting analysis of maintenance cost of roads against GDP at Current Basic Price for Building and Construction

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.265	2.886	1	8	.128	6.882E7	157.862		
Logarithmic	.327	3.890	1	8	.084	-7.513E8	6.897E7		
Inverse	.398	5.294	1	8	.050	2.117E8	-2.665E13		
Quadratic	.347	1.861	2	7	.225	-4.520E7	781.056	.000	
Cubic	.720	5.132	3	6	.093	-7.717E8	6.655E3	-.015	1.085E-8
Compound	.309	3.581	1	8	.095	6.711E7	1.000		
Power	.390	5.116	1	8	.054	2.851E4	.652		
S	.481	7.427	1	8	.026	19.373	-2.538E5		
Growth	.309	3.581	1	8	.095	18.022	1.477E-6		
Exponential	.309	3.581	1	8	.095	6.711E7	1.477E-6		
Logistic	.309	3.581	1	8	.095	1.490E-8	1.000		

The independent variable is GDP at Current Basic Price for Building at Construction.

Source: SPSS 17.0

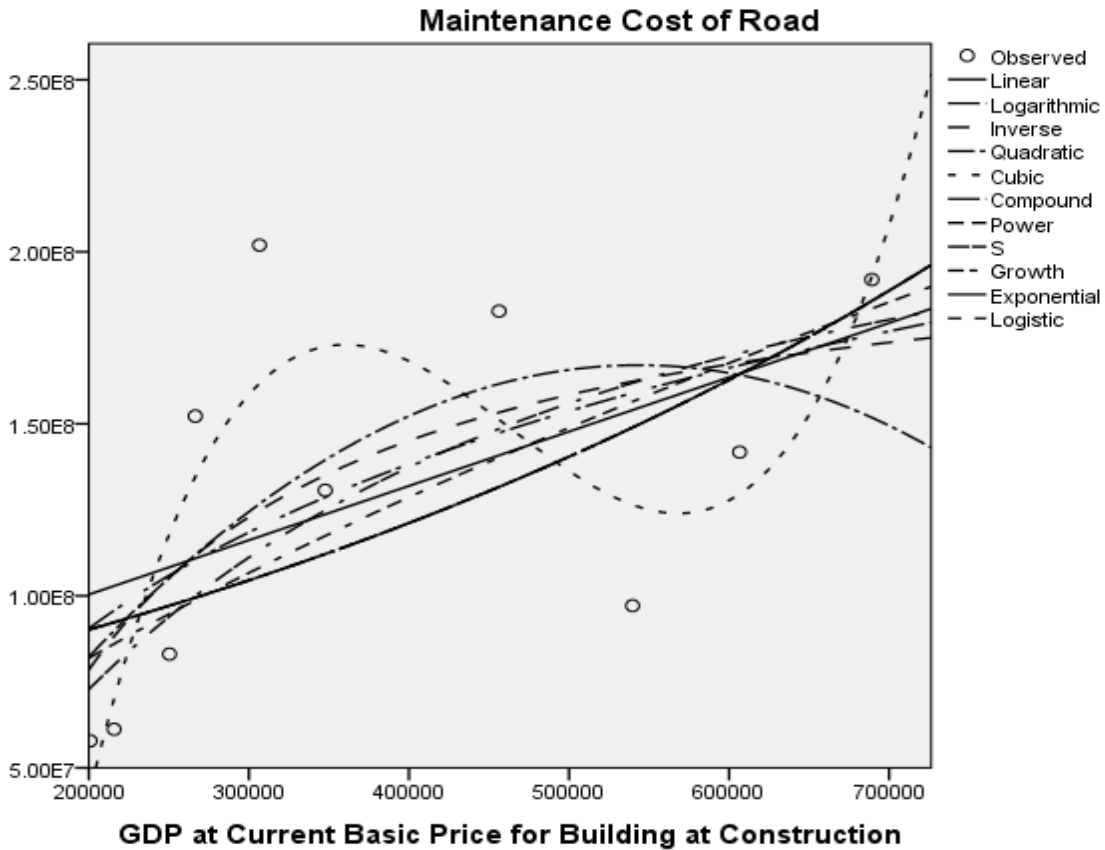


Figure 26: Curve fitting plot of maintenance cost of roads against GDP at Current Basic Price for Building and Construction

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 72.0%. This result implies that the best model was the cubic model since the independent variable GDP at current basic price for building at construction was able to explain about 72.0% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.021 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.021 < \alpha=0.05$). Hence, GDP at current basic price for building at construction contribute to the proposed model.

Table 27: Summary of curve fitting analysis of maintenance cost of roads against GDP at Current Basic Price for Crude, Petroleum & Natural Gas.

Model Summary and Parameter Estimates

Dependent Variable:

maintenance cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.325	3.849	1	8	.085	7.023E7	5.408		
Logarithmic	.394	5.205	1	8	.052	-9.321E8	6.596E7		
Inverse	.471	7.134	1	8	.028	2.084E8	6.916E14	-	
Quadratic	.397	2.305	2	7	.170	-1.907E7	23.262	-7.173E-7	
Cubic	.705	4.774	3	6	.070	-4.937E8	160.155	-1.234E-5	3.004E-13
Compound	.355	4.402	1	8	.069	6.924E7	1.000		
Power	.442	6.349	1	8	.036	6.941E3	.605		
S	.542	9.475	1	8	.015	19.323	-6.426E6		
Growth	.355	4.402	1	8	.069	18.053	4.897E-8		
Exponential	.355	4.402	1	8	.069	6.924E7	4.897E-8		
Logistic	.355	4.402	1	8	.069	1.444E-8	1.000		

The independent variable is GDP at Current Basic Price for Crude Petroleum & Natural gas.

Source: SPSS 17.0

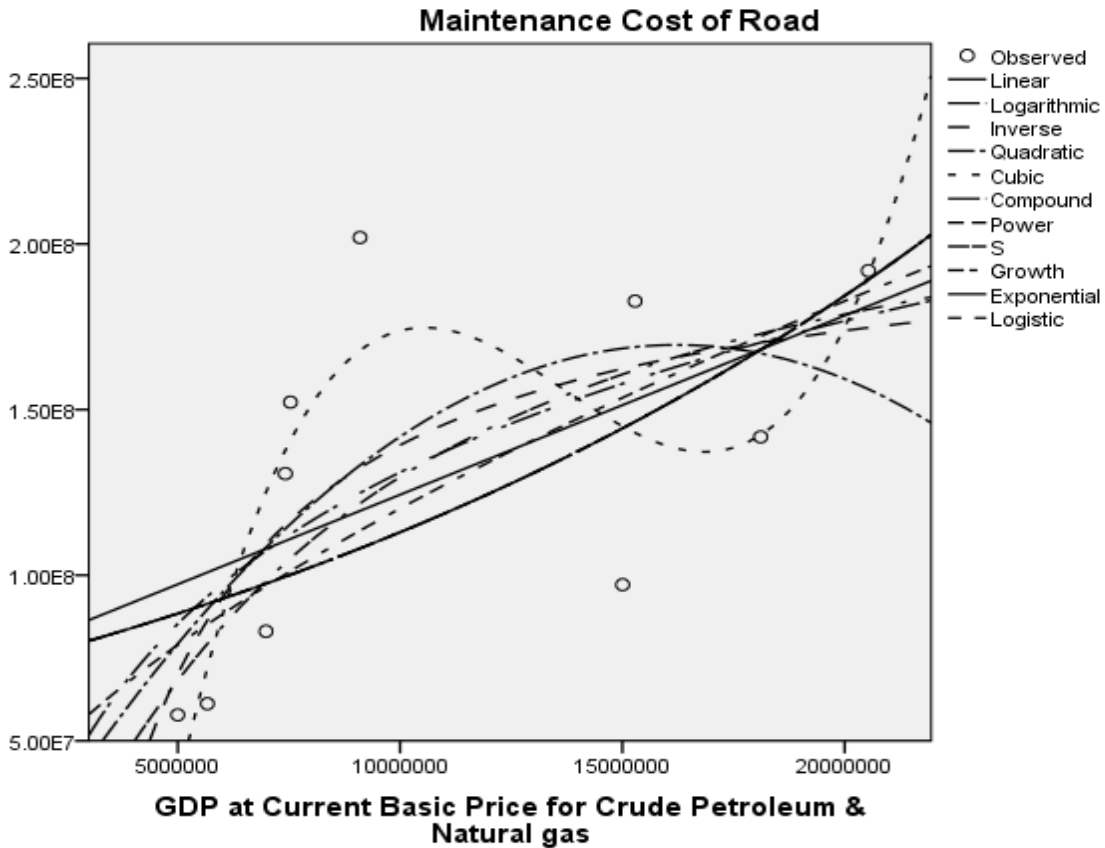


Figure 27: Curve fitting plot of maintenance cost of roads against GDP at Current Basic Price for Crude, Petroleum & Natural Gas

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 70.5%. This result implies that the best model was the cubic model since the independent variable GDP at current basic price for crude petroleum & natural gas was able to explain about 70.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.070 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.07 > \alpha=0.05$). Hence, GDP at current basic price for crude petroleum & natural gas do not contribute to the proposed model.

Table 28: Summary of curve fitting analysis of maintenance cost of roads against Total Length of Federal Government Roads in the State

Model Summary and Parameter Estimates

Dependent Variable maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.656	15.234	1	8	.005	-1.733E8	4.398E5		
Logarithmic	.657	15.320	1	8	.004	-1.718E9	2.832E8		
Inverse	.658	15.391	1	8	.004	3.976E8	-1.807E11		
Quadratic	.662	6.852	2	7	.022	-1.406E9	4.336E6	-3.002E3	
Cubic	.782	16.868	2	7	.072	-1.046E9	2.526E6	.000	-1.639
Compound	.758	25.085	1	8	.001	7.053E6	1.004		
Power	.760	25.391	1	8	.001	3.935	2.639		
S	.762	25.678	1	8	.001	21.090	-1.685E3		
Growth	.758	25.085	1	8	.001	15.769	.004		
Exponential	.758	25.085	1	8	.001	7.053E6	.004		
Logistic	.758	25.085	1	8	.001	1.418E-7	.996		

The independent variable is Total Length of Federal Government Roads in the state.

Source: SPSS 17.0

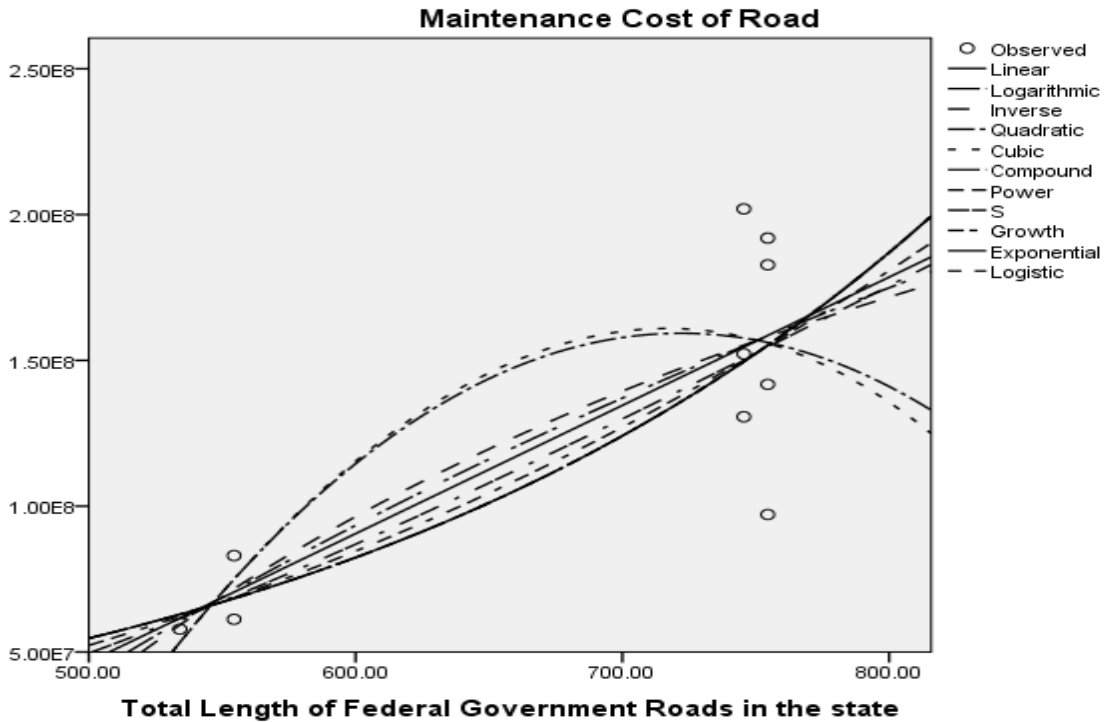


Figure 28: Curve fitting plot of maintenance cost of roads against Total Length of Federal Government Roads in the State

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 78.2%. This result implies that the best model was the cubic model since the independent variable total length of federal government roads in the state was able to explain about 78.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.072 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.072 > \alpha=0.05$). Hence, total length of federal government roads in the state does not contribute to the proposed model.

Table 29: Summary of curve fitting analysis of maintenance cost of roads against Mean Maximum Temperature

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.026	.214	1	8	.656	-6.185E7	5.732E6		
Logarithmic	.027	.224	1	8	.648	-5.760E8	2.012E8		
Inverse	.029	.236	1	8	.640	3.410E8	-7.050E9		
Quadratic	.072	.272	2	7	.769	-7.599E9	4.461E8	-6.416E6	
Cubic	.075	.272	2	7	.769	-7.599E9	4.461E8	-6.416E6	.000
Compound	.044	.367	1	8	.561	1.373E7	1.067		
Power	.046	.382	1	8	.554	4.398E4	2.252		
S	.047	.397	1	8	.546	20.944	-78.509		
Growth	.044	.367	1	8	.561	16.435	.064		
Exponential	.044	.367	1	8	.561	1.373E7	.064		
Logistic	.044	.367	1	8	.561	7.281E-8	.938		

The independent variable is Mean Maximum Temperature.

Source: SPSS 17.0

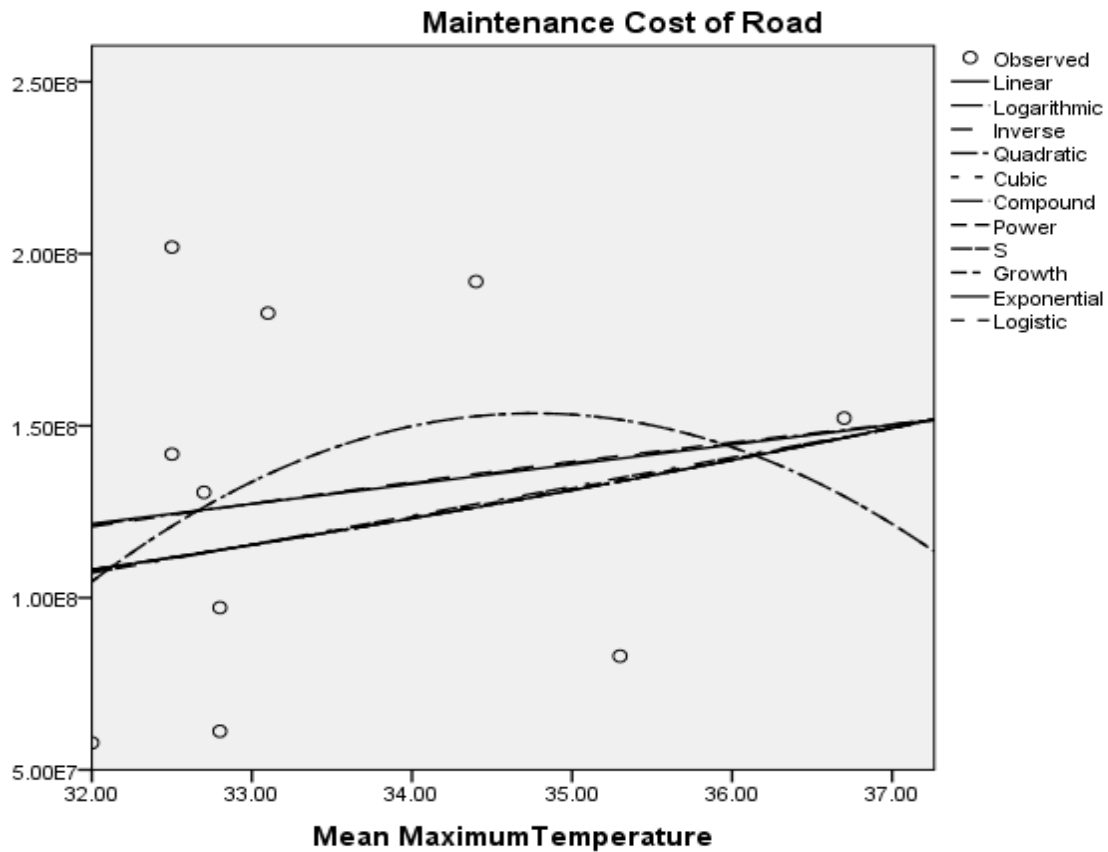


Figure 29: Curve fitting plot of maintenance cost of roads against Mean Maximum Temperature

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 7.5%. This result implies that the best model was the cubic model since the independent variable mean maximum temperature was able to explain about 7.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.769 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.769 > \alpha=0.05$). Hence, mean maximum temperature does not contribute to the proposed model.

Table 30: Summary of curve fitting analysis of maintenance cost of roads against Mean Relative Humidity

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.178	1.732	1	8	.225	-3.892E8	6.826E6		
Logarithmic	.177	1.721	1	8	.226	-2.122E9	5.201E8		
Inverse	.176	1.709	1	8	.227	6.513E8	-3.959E10		
Quadratic	.184	.790	2	7	.491	3.195E9	-8.708E7	6.141E5	
Cubic	.384	1.790	2	7	.490	9.943E8	.000	-5.335E5	5.037E3
Compound	.220	2.252	1	8	.172	8.036E5	1.068		
Power	.219	2.248	1	8	.172	.044	5.015		
S	.219	2.243	1	8	.173	23.631	-382.457		
Growth	.220	2.252	1	8	.172	13.597	.066		
Exponential	.220	2.252	1	8	.172	8.036E5	.066		
Logistic	.220	2.252	1	8	.172	1.244E-6	.936		

The independent variable is Mean Relative Humidity.

Source: SPSS 17.0

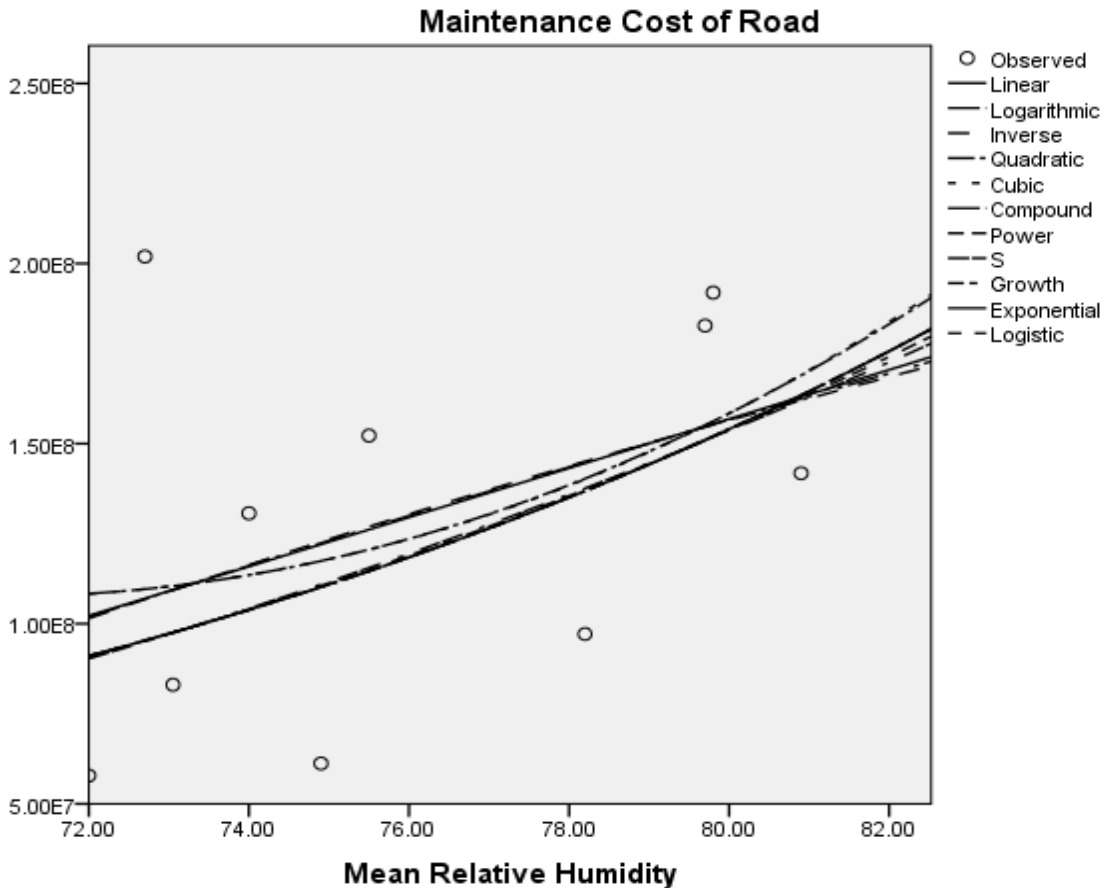


Figure 30: Curve fitting plot of maintenance cost of roads against Mean Relative Humidity

From the result of the curve estimation it was found that the cubic model performed better than the other method with an R-squared of 38.4%. This result implies that the best model was the cubic model since the independent variable mean relative humidity was able to explain about 38.4% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.490 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.490 > \alpha=0.05$). Hence, the mean relative humidity does not contribute to the proposed model.

Table 31: Summary of curve fitting analysis of maintenance cost of roads against Mean Relative Rainfall

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.382	4.951	1	8	.057	3.311E7	6.602E5		
Logarithmic	.282	3.147	1	8	.114	-4.202E7	3.563E7		
Inverse	.224	2.315	1	8	.167	1.453E8	-1.160E9		
Quadratic	.476	3.182	2	7	.104	6.697E7	-8.028E5	7.600E3	
Cubic	.614	3.175	3	6	.026	1.753E8	-9.973E6	1.112E5	-312.484
Compound	.476	7.254	1	8	.027	4.665E7	1.006		
Power	.351	4.326	1	8	.071	2.258E7	.344		
S	.279	3.095	1	8	.117	18.742	-11.202		
Growth	.476	7.254	1	8	.027	17.658	.006		
Exponential	.476	7.254	1	8	.027	4.665E7	.006		
Logistic	.476	7.254	1	8	.027	2.144E-8	.994		

The independent variable is Mean Relative Rain fall .

Source: SPSS 17.0

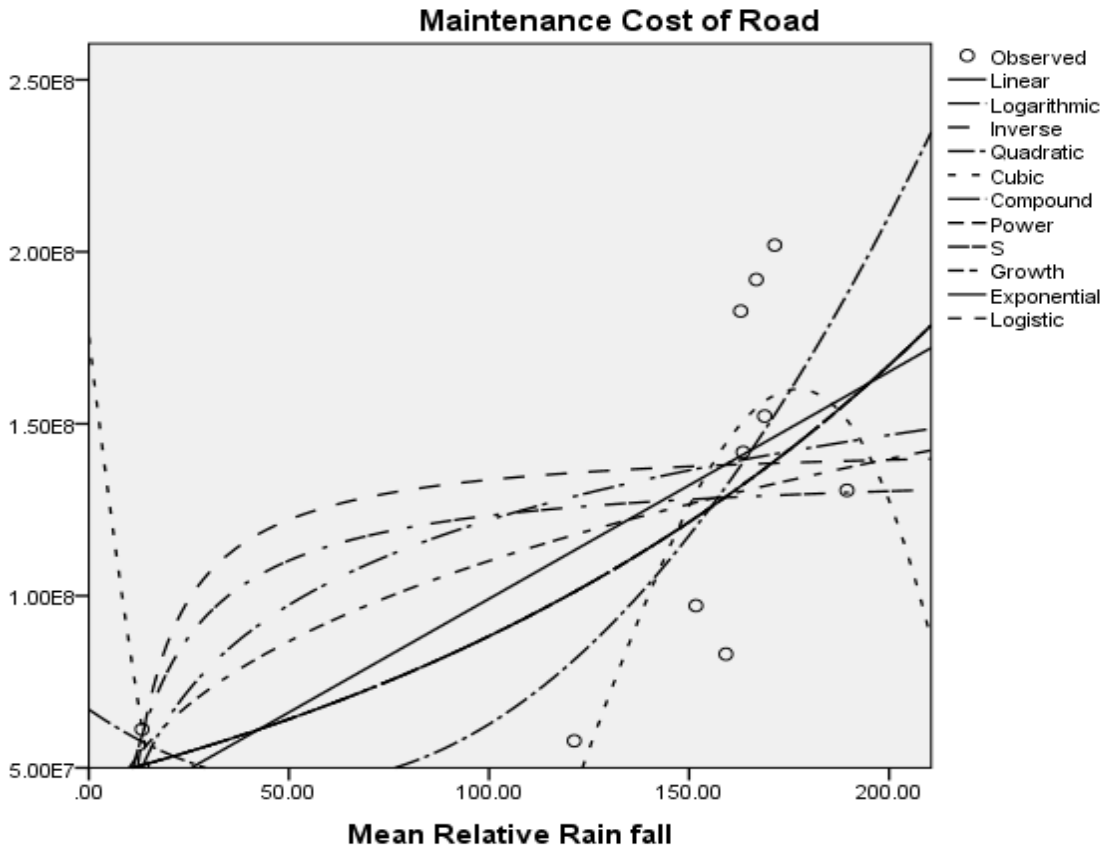


Figure 31: Curve fitting plot of maintenance cost of roads against Mean Relative Rainfall

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 61.4%. This result implies that the best model was the cubic model since the independent variable mean relative rainfall was able to explain about 61.4% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.027 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.027 < \alpha=0.05$). Hence, the mean relative rainfall contribute to the proposed model.

Table 32: Summary of curve fitting analysis of maintenance cost of roads against Mean Efficiency

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.555	9.962	1	8	.013	1.857E9	-1.901E7		
Logarithmic	.553	9.906	1	8	.014	7.990E9	-1.743E9		
Inverse	.552	9.845	1	8	.014	-1.630E9	1.598E11		
Quadratic	.556	10.015	1	8	.013	9.851E8	.000	-1.036E5	
Cubic	.769	14.622	2	7	.043	-1.083E10	1.883E8	.000	-8.188E3
Compound	.681	17.042	1	8	.003	1.867E15	.833		
Power	.678	16.872	1	8	.003	6.621E40	-16.722		
S	.676	16.695	1	8	.004	1.716	1.533E3		
Growth	.681	17.042	1	8	.003	35.163	-.182		
Exponential	.681	17.042	1	8	.003	1.867E15	-.182		
Logistic	.681	17.042	1	8	.003	5.355E-16	1.200		

The independent variable is Mean Efficiency.

Source: SPSS 17.0

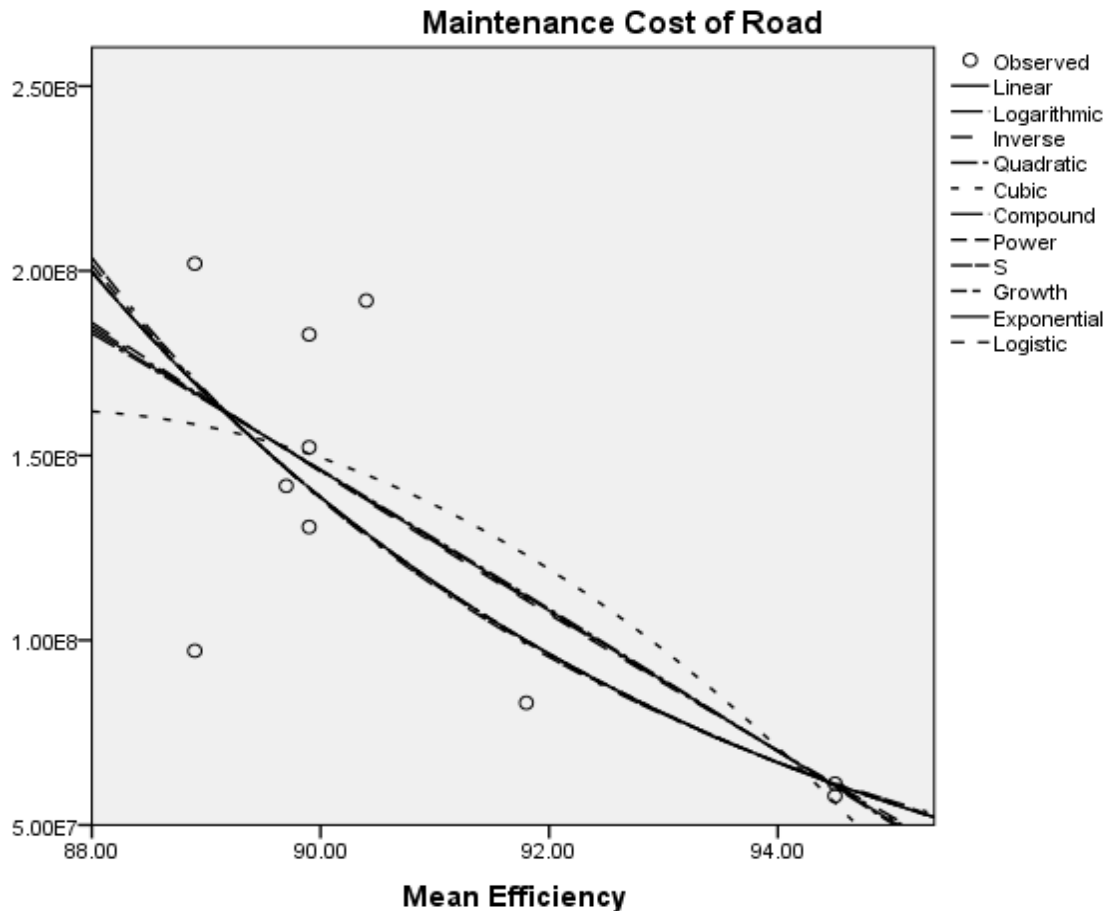


Figure 32: Curve fitting plot of maintenance cost of roads against Mean Efficiency

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 76.9%. This result implies that the best model was the cubic model since the independent variable mean efficiency was able to explain about 76.9% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.043 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.043 < \alpha=0.05$). Hence, mean efficiency contributed to the proposed model.

Table 33: Summary of curve fitting analysis of maintenance cost of roads against Mean Radiation

Model Summary and Parameter Estimates

Dependent Variable:

maintenance cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.357	4.449	1	8	.068	-1.280E9	7.666E7		
Logarithmic	.360	4.508	1	8	.066	-3.995E9	1.416E9		
Inverse	.363	4.567	1	8	.065	1.552E9	2.616E10		
Quadratic	.357	4.449	1	8	.068	-1.280E9	7.666E7	.000	
Cubic	.474	2.799	2	7	.128	-2.889E10	2.328E9	.000	-2.215E6
Compound	.428	5.985	1	8	.040	185.429	2.068		
Power	.432	6.080	1	8	.039	1.227E-9	13.431		
S	.436	6.176	1	8	.038	32.087	-248.135		
Growth	.428	5.985	1	8	.040	5.223	.727		
Exponential	.428	5.985	1	8	.040	185.429	.727		
Logistic	.428	5.985	1	8	.040	.005	.483		

The independent variable is Mean Radiation.

Source: SPSS 17.0

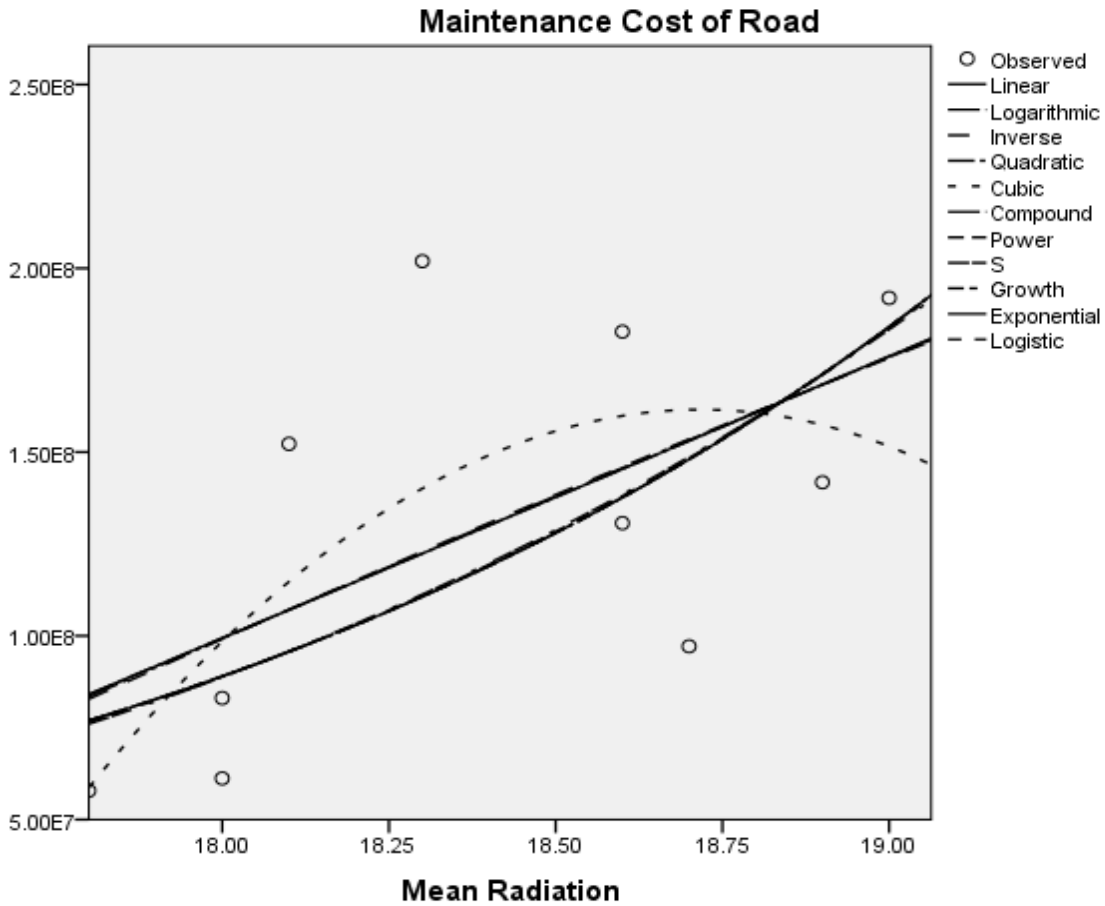


Figure 33: Curve fitting plot of maintenance cost of roads against Mean Radiation

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 47.4%. This result implies that the best model was the cubic model since the independent variable mean radiation was able to explain about 47.4% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.128 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.128 > \alpha=0.05$). Hence, mean radiation does not contribute to the proposed model.

Table 34: Summary of curve fitting analysis of maintenance cost of roads against Mean Evaporation

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.195	1.935	1	8	.202	-2.625E8	9.370E7		
Logarithmic	.198	1.972	1	8	.198	-3.966E8	3.681E8		
Inverse	.201	2.007	1	8	.194	4.747E8	-1.439E9		
Quadratic	.214	.951	2	7	.431	-2.440E9	1.216E9	-1.434E8	
Cubic	.284	.951	2	7	.431	-2.440E9	1.216E9	-1.434E8	.000
Compound	.248	2.632	1	8	.143	2.572E6	2.497		
Power	.253	2.705	1	8	.139	6.849E5	3.605		
S	.258	2.775	1	8	.134	21.978	-14.122		
Growth	.248	2.632	1	8	.143	14.760	.915		
Exponential	.248	2.632	1	8	.143	2.572E6	.915		
Logistic	.248	2.632	1	8	.143	3.887E-7	.400		

The independent variable is Mean Evaporation.

Source: SPSS 17.0

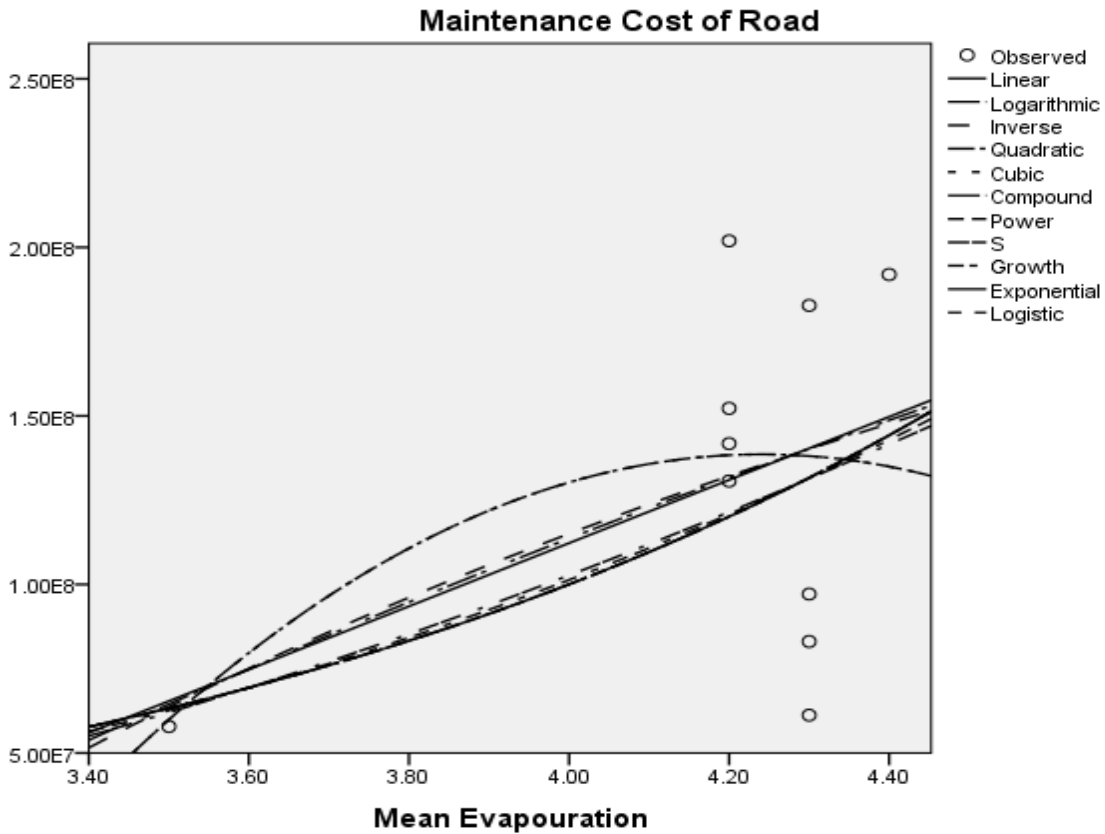


Figure 34: Curve fitting plot of maintenance cost of roads against Mean Evaporation

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 28.4%. This result implies that the best model was the cubic model since the independent variable mean evaporation was able to explain about 28.4% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.431 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.431 > \alpha=0.05$). Hence, mean evaporation does not contribute to the proposed model.

Table 35: Summary of curve fitting analysis of maintenance cost of roads against Value of Major Imports for Machinery and Transportation Equipment

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.172	1.665	1	8	.233	9.735E7	21.356		
Logarithmic	.320	3.772	1	8	.088	-4.849E8	4.383E7		
Inverse	.469	7.056	1	8	.029	1.877E8	-5.856E13		
Quadratic	.522	3.827	2	7	.075	-7.670E6	182.299	-4.268E-5	
Cubic	.662	3.920	3	6	.073	-1.594E8	552.388	.000	4.371E-11
Compound	.208	2.096	1	8	.186	8.721E7	1.000		
Power	.383	4.960	1	8	.057	3.522E5	.415		
S	.562	10.254	1	8	.013	19.141	-5.555E5		
Growth	.208	2.096	1	8	.186	18.284	2.031E-7		
Exponential	.208	2.096	1	8	.186	8.721E7	2.031E-7		
Logistic	.208	2.096	1	8	.186	1.147E-8	1.000		

The independent variable is Value of Major Imports for Machinery & Transportation Equipment.

Source: SPSS 17.0

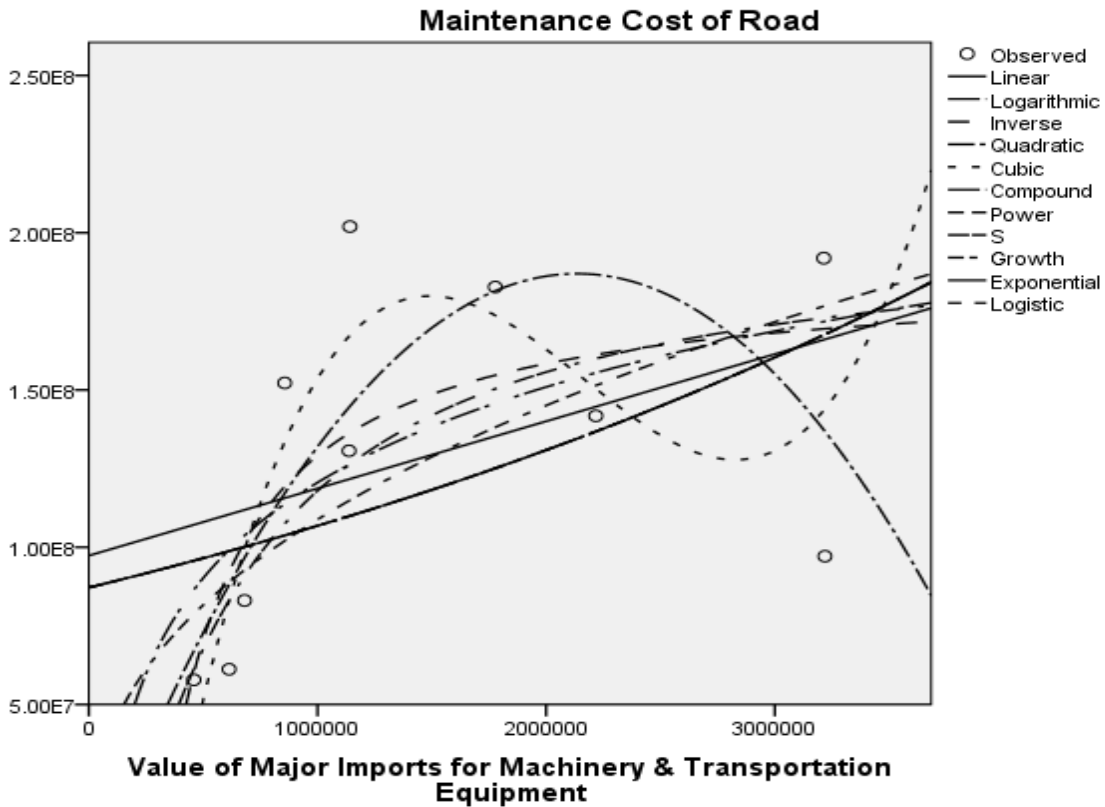


Figure 35: Curve fitting plot of maintenance cost of roads against Value of Major Imports for Machinery and Transportation Equipment

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 66.2%. This result implies that the best model was the cubic model since the independent variable value of major imports for machinery & transportation equipment was able to explain about 66.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.073 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.073 > \alpha=0.05$). Hence, value of major imports for machinery & transportation equipment does not contribute to the proposed model.

Table 36: Summary of curve fitting analysis of maintenance cost of roads against Official Exchange Rate of the Naira

Model Summary and Parameter Estimates

Dependent Variable: maintenance cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.028	.234	1	8	.642	4.391E7	6.115E5		
Logarithmic	.020	.164	1	8	.696	-2.240E8	7.163E7		
Inverse	.013	.104	1	8	.755	1.869E8	-7.929E9		
Quadratic	.564	4.533	2	7	.055	5.372E9	-7.618E7	2.739E5	
Cubic	.579	4.269	2	7	.061	3.594E9	-3.786E7	.000	649.646
Compound	.052	.440	1	8	.526	4.331E7	1.007		
Power	.041	.341	1	8	.575	1.491E6	.886		
S	.031	.252	1	8	.629	19.354	-105.940		
Growth	.052	.440	1	8	.526	17.584	.007		
Exponential	.052	.440	1	8	.526	4.331E7	.007		
Logistic	.052	.440	1	8	.526	2.309E-8	.993		

The independent variable is Official Exchange Rate of the Naira.

Source: SPSS 17.0

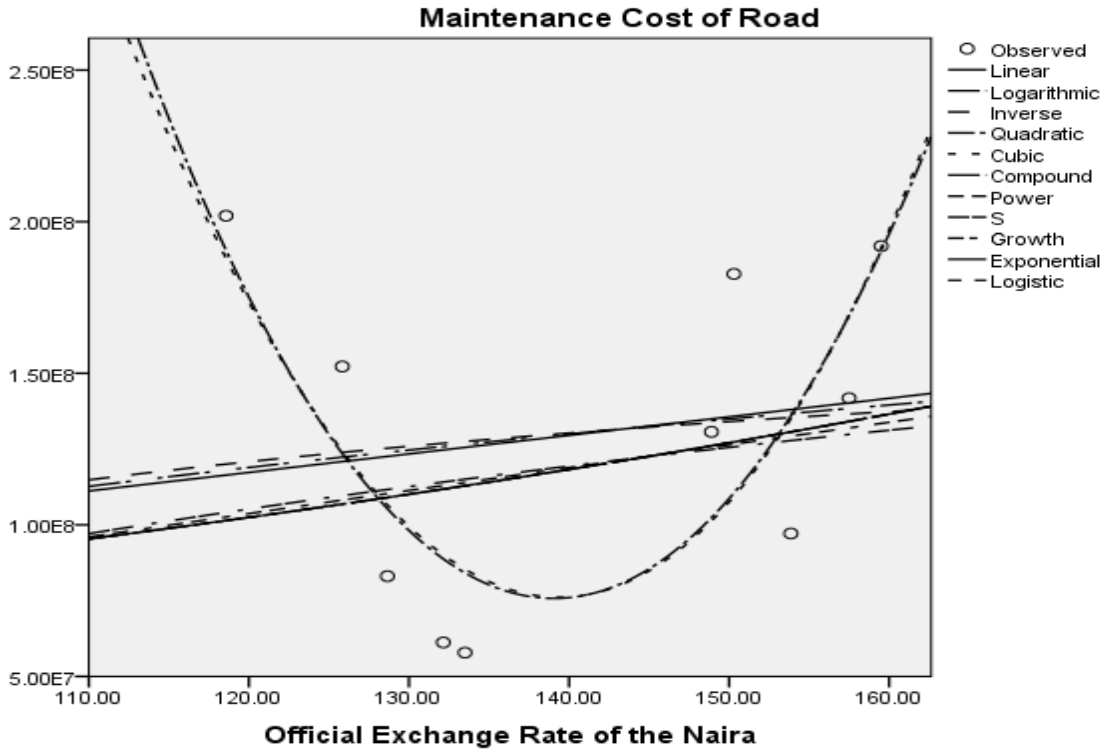


Figure 36: Curve fitting plot of maintenance cost of roads against Official Exchange Rate of the Naira

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 57.9%. This result implies that the best model was the cubic model since the independent variable official exchange rate of the Naira was able to explain about 57.9% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.061 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.061 > \alpha=0.05$). Hence, official exchange rate of the Naira does not contribute to the proposed model.

Table 37: Summary of curve fitting analysis of maintenance cost of roads against Exchange Rate of the Nigeria

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.022	.177	1	8	.685	5.147E7	5.637E5		
Logarithmic	.015	.118	1	8	.740	-1.843E8	6.372E7		
Inverse	.009	.070	1	8	.799	1.787E8	-6.713E9		
Quadratic	.564	4.520	2	7	.055	5.788E9	-8.308E7	3.021E5	
Cubic	.581	4.291	2	7	.061	3.890E9	-4.151E7	.000	728.347
Compound	.044	.364	1	8	.563	4.528E7	1.007		
Power	.033	.277	1	8	.613	1.916E6	.837		
S	.024	.199	1	8	.667	19.301	-97.531		
Growth	.044	.364	1	8	.563	17.628	.007		
Exponential	.044	.364	1	8	.563	4.528E7	.007		
Logistic	.044	.364	1	8	.563	2.208E-8	.993		

The independent variable is Exchange Rate of the Nigeria.
Source: SPSS17.0

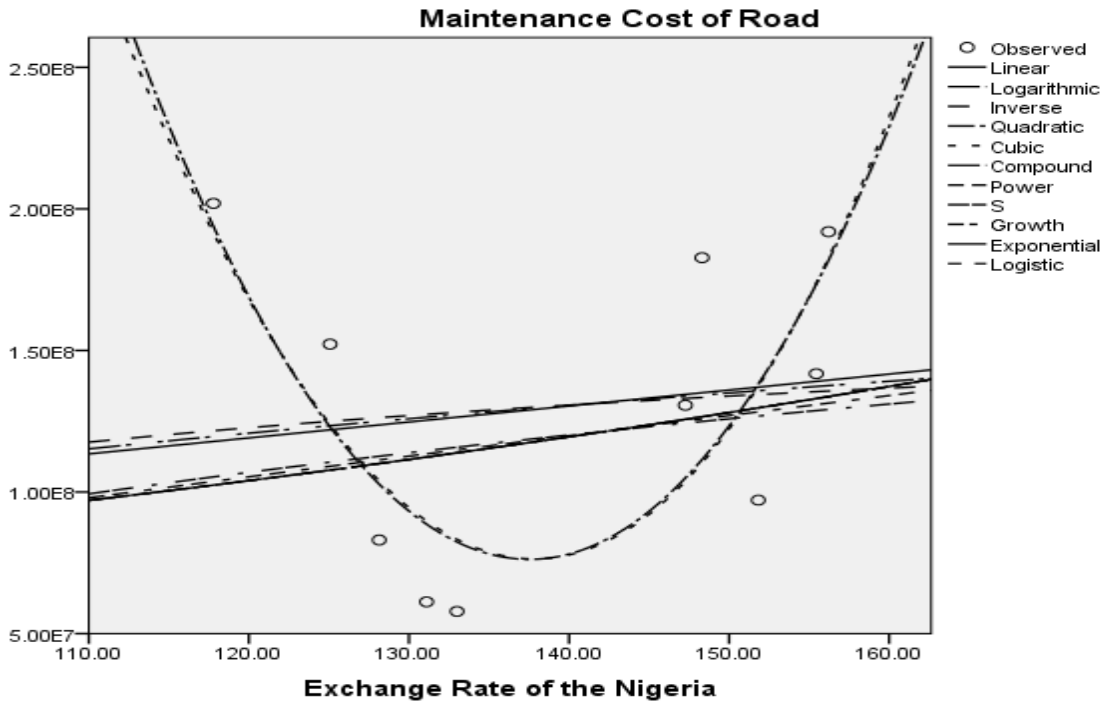


Figure 37: Curve fitting plot of maintenance cost of roads against Exchange Rate of Nigeria

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 58.1%. This result implies that the best model was the cubic model since the independent variable exchange rate of the Naira was able to explain about 58.1% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.061 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.061 > \alpha=0.05$). Hence, exchange rate of the Naira does not contribute to the proposed model.

Table 38: Summary of curve fitting analysis of maintenance cost of roads against Import Commodity Price Index

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.030	.245	1	8	.634	7.627E7	3.840E5		
Logarithmic	.029	.243	1	8	.635	-1.284E8	5.244E7		
Inverse	.029	.240	1	8	.638	1.814E8	-6.993E9		
Quadratic	.030	.108	2	7	.899	1.038E8	-2.042E4	1.444E3	
Cubic	.037	.109	2	7	.898	1.018E8	1.017E5	.000	4.715
Compound	.027	.225	1	8	.648	7.614E7	1.003		
Power	.026	.210	1	8	.659	1.480E7	.423		
S	.024	.194	1	8	.671	18.996	-54.690		
Growth	.027	.225	1	8	.648	18.148	.003		
Exponential	.027	.225	1	8	.648	7.614E7	.003		
Logistic	.027	.225	1	8	.648	1.313E-8	.997		

The independent variable is Import Commodity Price Index.

Source: SPSS 17.0

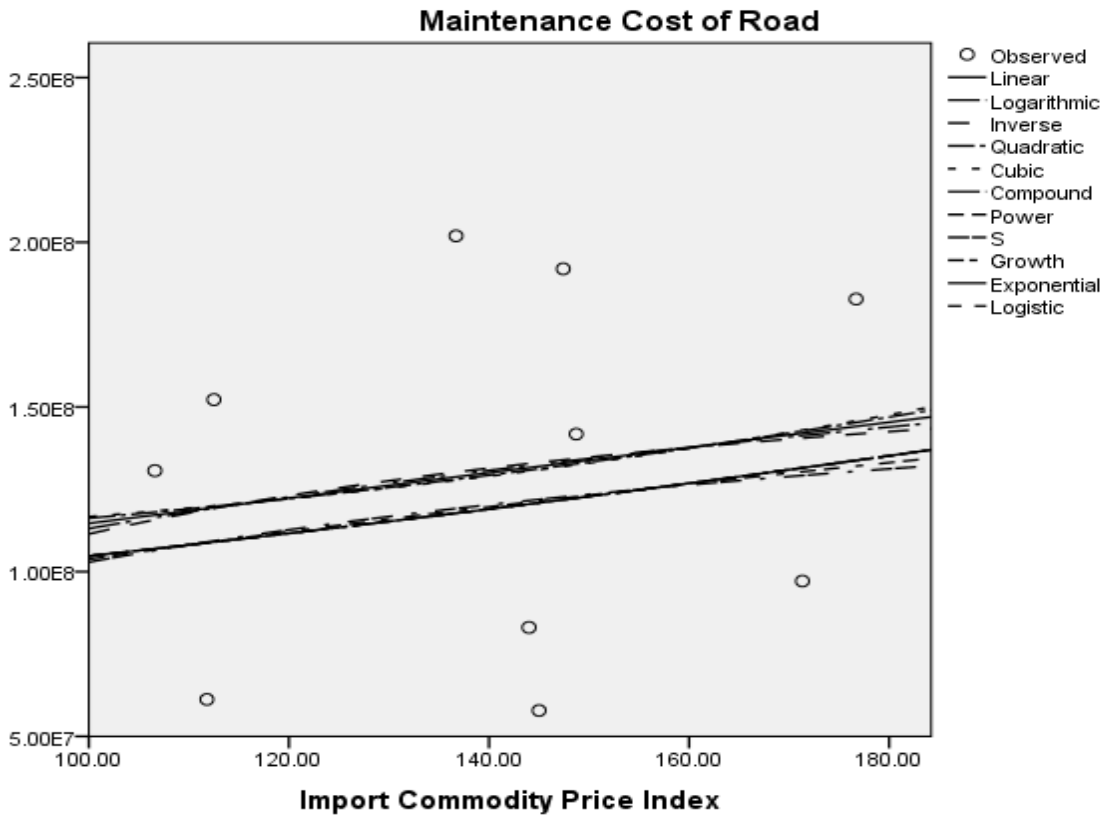


Figure 38: Curve fitting plot of maintenance cost of roads against Import Commodity Price Index

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 3.7%. This result implies that the best model was the cubic model since the independent variable import commodity price index was able to explain about 3.7% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.898 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.898 > \alpha=0.05$). Hence, import commodity price index does not contribute to the proposed model.

Table 39: Summary of curve fitting analysis of maintenance cost of roads against Commodity Terms of Trade

Model Summary and Parameter Estimates

Dependent Variable:

maintenance cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.116	1.048	1	8	.336	2.070E8	-7.690E5		
Logarithmic	.135	1.252	1	8	.296	4.918E8	-7.900E7		
Inverse	.155	1.465	1	8	.261	5.053E7	7.529E9		
Quadratic	.142	.580	2	7	.585	3.245E8	-3.224E6	1.219E4	
Cubic	.192	.980	2	7	.585	3.245E8	-3.224E6	1.219E4	.000
Compound	.067	.574	1	8	.470	1.976E8	.995		
Power	.084	.738	1	8	.415	1.415E9	-.541		
S	.103	.920	1	8	.366	18.032	53.255		
Growth	.067	.574	1	8	.470	19.102	-.005		
Exponential	.067	.574	1	8	.470	1.976E8	-.005		
Logistic	.067	.574	1	8	.470	5.061E-9	1.005		

The independent variable is Commodity Terms of Trade.

Source: SPSS 17.0

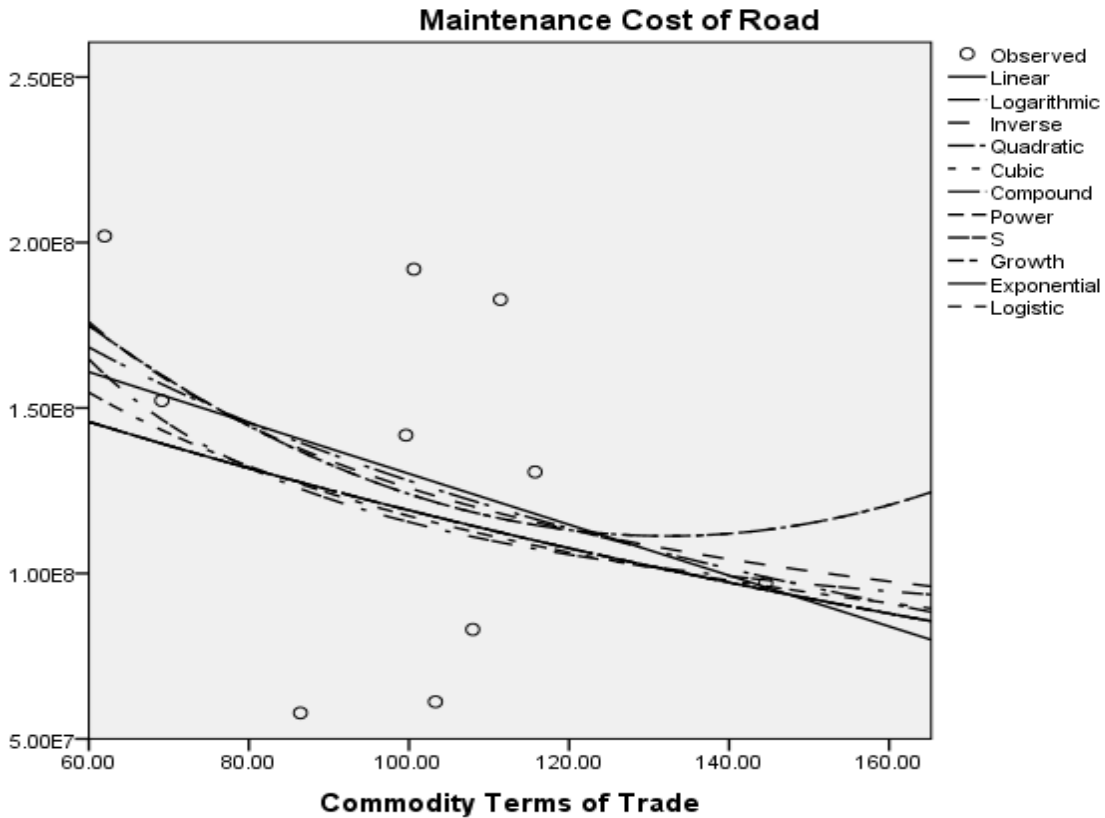


Figure 39: Curve fitting plot of maintenance cost of roads against Commodity Term of Trade

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 19.2%. This result implies that the best model was the cubic model since the independent variable commodity terms of trade was able to explain about 19.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.585 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.585 > \alpha=0.05$). Hence, commodity terms of trade does not contribute to the proposed model.

Table 40: Summary of curve fitting analysis of maintenance cost of roads against Import by Section on Boilers, Machinery Price Index
Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.255	2.744	1	8	.136	6.506E7	46.651		
Logarithmic	.285	3.186	1	8	.112	-8.100E8	6.683E7		
Inverse	.323	3.820	1	8	.086	2.054E8	-8.952E13		
Quadratic	.292	1.444	2	7	.298	-5.298E7	236.482	-6.531E-5	
Cubic	.492	6.444	2	7	.298	-5.298E7	236.482	-6.531E-5	.000
Compound	.305	3.504	1	8	.098	6.436E7	1.000		
Power	.344	4.190	1	8	.075	1.549E4	.636		
S	.392	5.153	1	8	.053	19.314	-8.538E5		
Growth	.305	3.504	1	8	.098	17.980	4.413E-7		
Exponential	.305	3.504	1	8	.098	6.436E7	4.413E-7		
Logistic	.305	3.504	1	8	.098	1.554E-8	1.000		

The independent variable is Import by Section on Boilers, Machinery price Index.

Source: SPSS 17.0

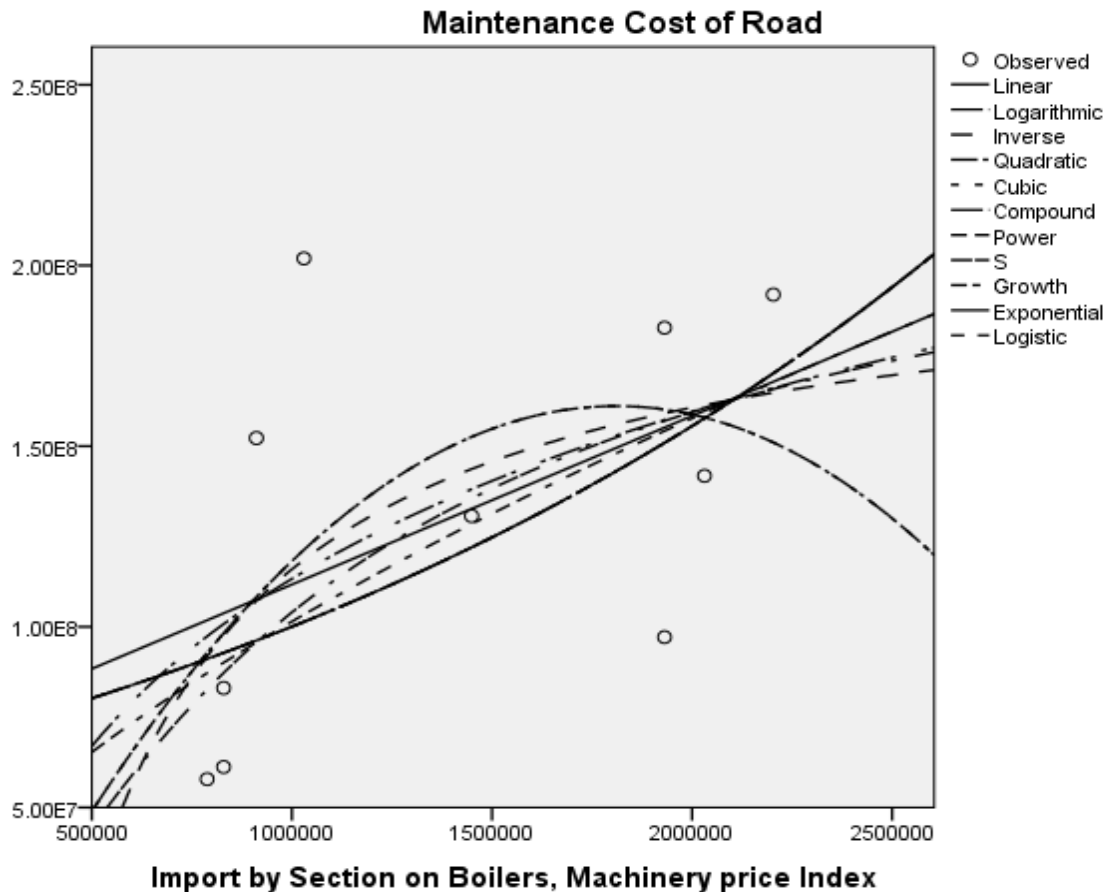


Figure 40: Curve fitting plot of maintenance cost of roads against Import by Section on Boilers, Machinery Price Index

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 49.2%. This result implies that the best model was the cubic model since the independent variable import by section on broilers, machinery price index was able to explain about 49.2% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.298 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, p-value=0.298

> $\alpha=0.05$). Hence, import by section on broilers, machinery price index does not contribute to the proposed model.

Table 41: Summary of curve fitting analysis of maintenance cost of roads against Import by Section Vehicler Price Index

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.275	3.040	1	8	.119	8.609E7	48.335		
Logarithmic	.343	4.175	1	8	.075	-4.546E8	4.330E7		
Inverse	.436	6.172	1	8	.038	1.823E8	-3.054E13		
Quadratic	.295	1.462	2	7	.295	6.138E7	122.629	-3.795E-5	
Cubic	.655	3.803	3	6	.077	-1.870E8	1.170E3	-.001	3.542E-10
Compound	.331	3.951	1	8	.082	7.841E7	1.000		
Power	.427	5.955	1	8	.041	4.183E5	.418		
S	.549	9.737	1	8	.014	19.103	-2.971E5		
Growth	.331	3.951	1	8	.082	18.177	4.588E-7		
Exponential	.331	3.951	1	8	.082	7.841E7	4.588E-7		
Logistic	.331	3.951	1	8	.082	1.275E-8	1.000		

The independent variable is Import by Section vehicler price index.

Source: SPSS 17.0

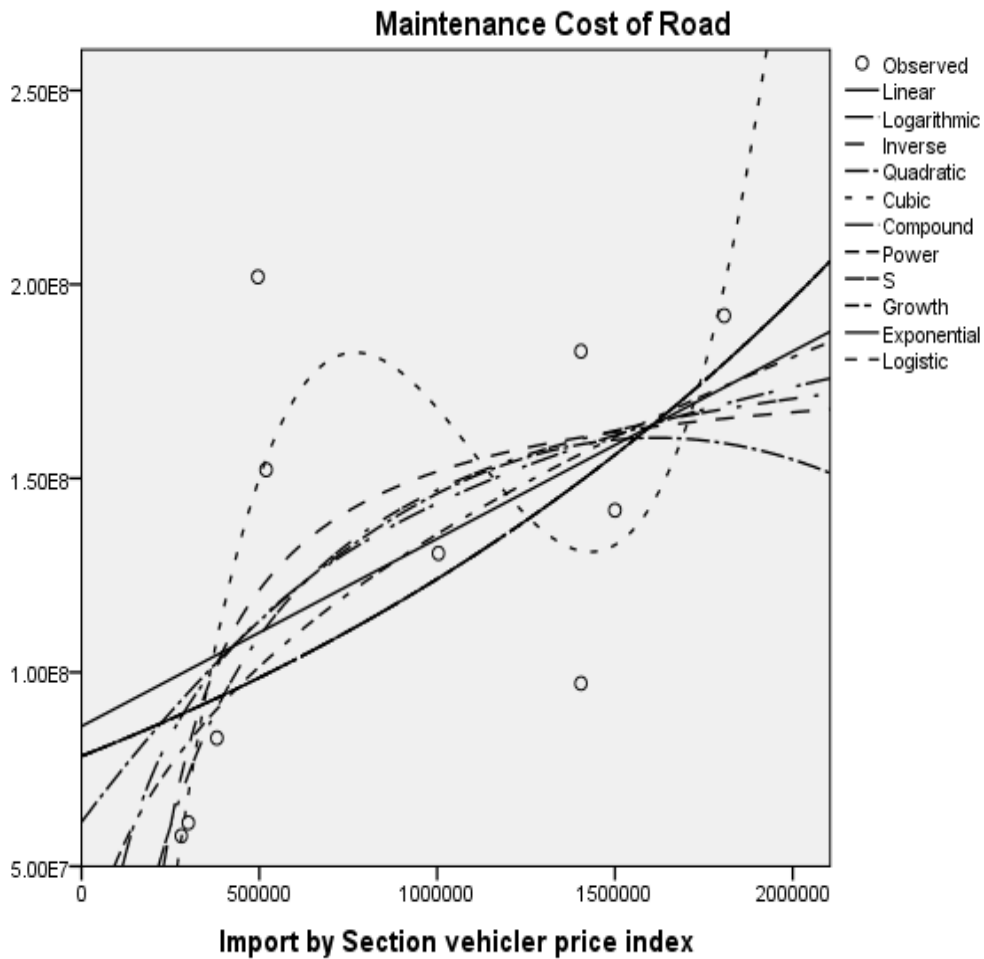


Figure 41: Curve fitting plot of maintenance cost of roads against Import by Section Vehicle Price Index

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 65.5%. This result implies that the best model was the cubic model since the independent variable import by section vehicler price index was able to explain about 65.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.077 which falls on the acceptance region of the hypothesis

assuming 95% confidence level (since, $p\text{-value}=0.077 > \alpha=0.05$). Hence, import by section vehicler price index do not contribute to the proposed model.

Table 42: Summary of curve fitting analysis of maintenance cost of roads against Quantity of Asphalt

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.032	.268	1	8	.619	9.294E8	-8.214E6		
Logarithmic	.034	.282	1	8	.610	3.873E9	-8.177E8		
Inverse	.036	.295	1	8	.602	-7.059E8	8.133E10		
Quadratic	.032	.268	1	8	.619	9.294E8	-8.214E6	.000	
Cubic	.395	2.282	2	7	.173	1.246E11	-1.917E9	.000	6.728E4
Compound	.047	.396	1	8	.547	5.053E11	.918		
Power	.049	.411	1	8	.540	8.947E24	-8.488		
S	.050	.425	1	8	.533	9.973	838.853		
Growth	.047	.396	1	8	.547	26.948	-.086		
Exponential	.047	.396	1	8	.547	5.053E11	-.086		
Logistic	.047	.396	1	8	.547	1.979E-12	1.090		

The independent variable is Quantity of Asphalt.

Source: SPSS 17.0

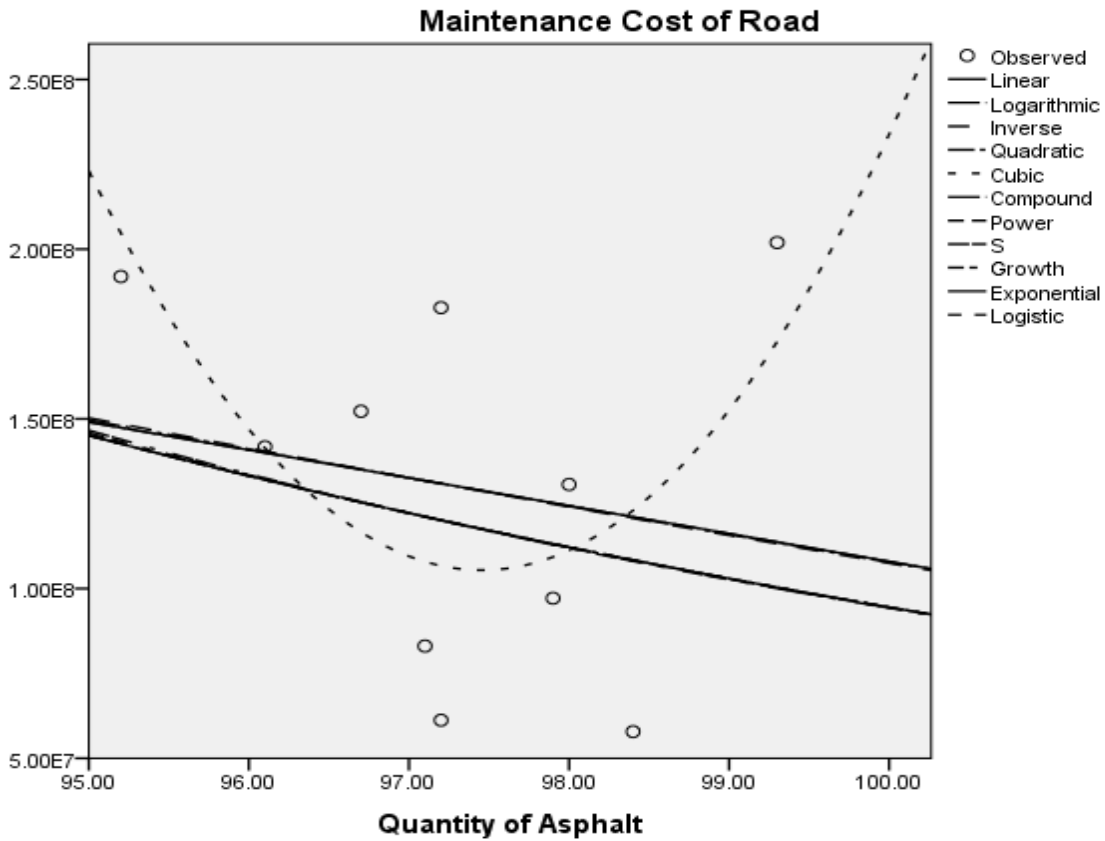


Figure 42: Curve fitting plot of maintenance cost of roads against Quantity of Asphalt

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 39.5%. This result implies that the best model was the cubic model since the independent variable quantity of asphalt was able to explain about 39.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.173 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.173 > \alpha=0.05$). Hence, quantity of asphalt does not contribute to the proposed model.

Table 43: Summary of curve fitting analysis of maintenance cost of roads against Market Capitalization of Quoted Company Automobile & Tyres

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.466	6.990	1	8	.030	8.803E7	.002		
Logarithmic	.670	16.278	1	8	.004	-1.012E8	1.081E7		
Inverse	.599	11.949	1	8	.009	1.530E8	-4.052E14		
Quadratic	.549	4.262	2	7	.062	7.724E7	.005	-7.248E-14	
Cubic	.838	10.343	3	6	.091	6.376E7	.019	-8.948E-13	1.204E-23
Compound	.514	8.450	1	8	.020	8.122E7	1.000		
Power	.773	27.178	1	8	.001	1.386E7	.100		
S	.738	22.488	1	8	.001	18.815	-3.896E6		
Growth	.514	8.450	1	8	.020	18.213	2.055E-11		
Exponential	.514	8.450	1	8	.020	8.122E7	2.055E-11		
Logistic	.514	8.450	1	8	.020	1.231E-8	1.000		

The independent variable is Market Capitalization of Quoted Company Automobile & Tyres.
Source: SPSS 17.0

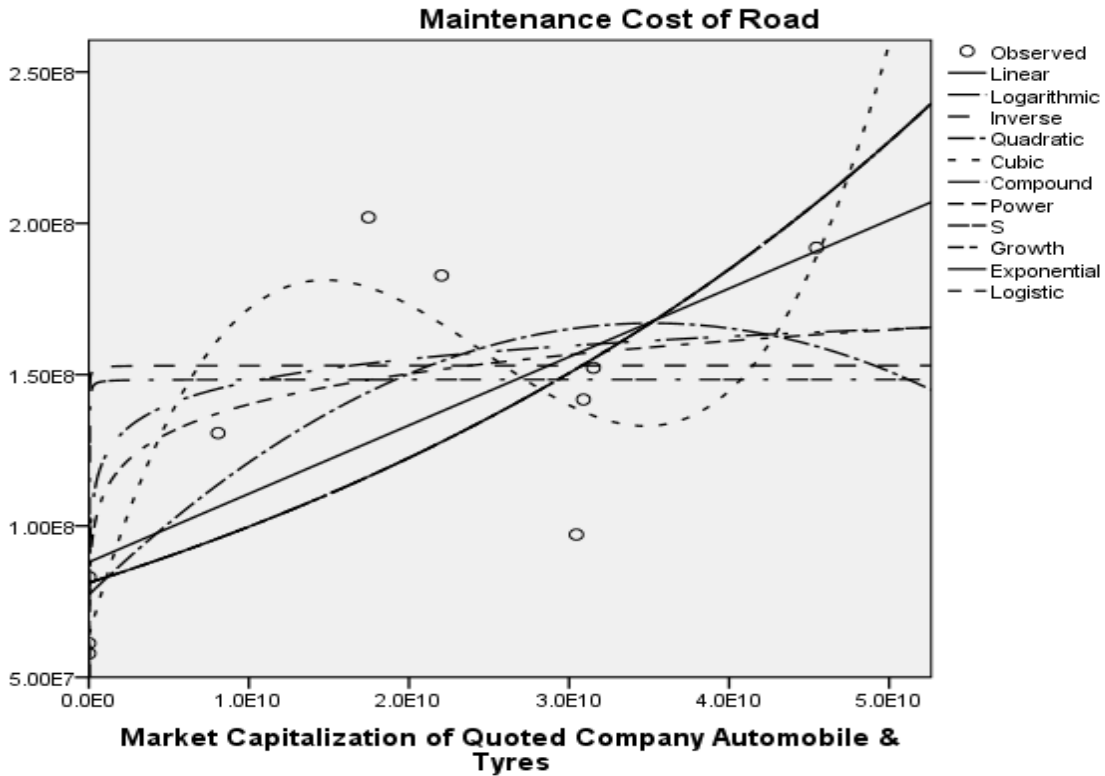


Figure 43: Curve fitting plot of maintenance cost of roads against Quoted Company Automobile & Tyres

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 83.3%. This result implies that the best model was the cubic model since the independent variable market capitalization of quoted company automobile & tyres was able to explain about 83.3% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.091 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.091 > \alpha=0.05$). Hence, market capitalization of quoted company automobile & tyres does not contribute to the proposed model.

Table 44: Summary of curve fitting analysis of maintenance cost of roads against Length of Road

Model Summary and Parameter Estimates

Dependent Variable: maintenance

cost of roads

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.000	.001	1	8	.978	1.293E8	5.493E3		
Logarithmic	.000	.001	1	8	.975	1.346E8	-9.609E5		
Inverse	.000	.001	1	8	.970	1.288E8	1.279E8		
Quadratic	.009	.030	2	7	.970	1.480E8	-2.762E5	744.050	
Cubic	.065	.139	3	6	.033	2.690E8	-3.356E6	2.231E4	-41.409
Compound	.000	.000	1	8	.996	1.189E8	1.000		
Power	.001	.009	1	8	.928	1.334E8	-.024		
S	.003	.022	1	8	.886	18.552	4.256		
Growth	.000	.000	1	8	.996	18.594	7.675E-6		
Exponential	.000	.000	1	8	.996	1.189E8	7.675E-6		
Logistic	.000	.000	1	8	.996	8.411E-9	1.000		

The independent variable is Length Of Road.

Source: SPSS 17.0

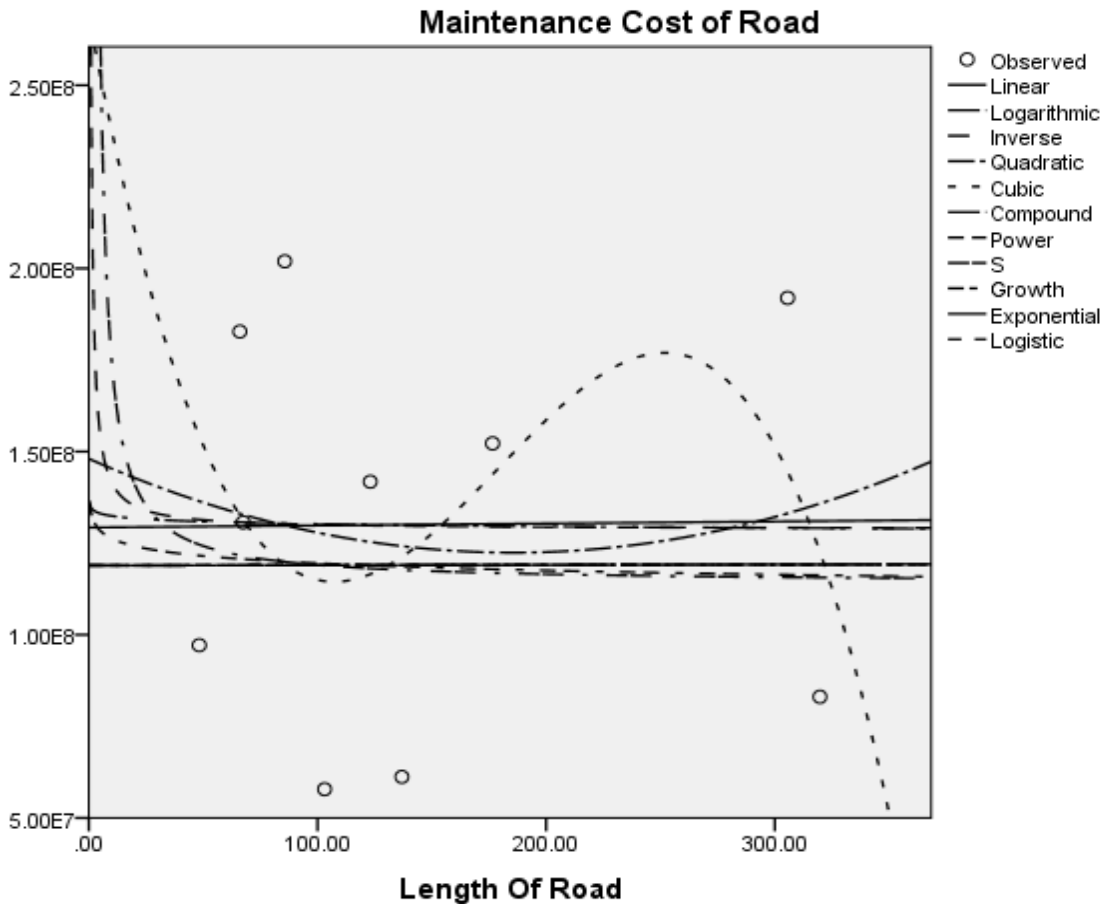


Figure 44: Curve fitting plot of maintenance cost of roads against Length of Road

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 6.5%. This result implies that the best model was the cubic model since the independent variable length of road was able to explain about 6.5% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.033 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.033 < \alpha=0.05$). Hence, length of road contributed to the proposed model.

Table 45: Summary of curve fitting analysis of maintenance cost of roads against Quantity of Wearing Produced

Model Summary and Parameter Estimates

Dependent Variable: Maintenance Cost of Road

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.843	42.857	1	8	.000	45572720.119	23064.264		
Logarithmic	.661	15.584	1	8	.004	- 232044395.686	45624481.734		
Inverse	.340	4.113	1	8	.077	148785947.161	-28916101541.050		
Quadratic	.844	18.944	2	7	.001	41029597.016	26607.998	-.483	
Cubic	.853	11.642	3	6	.007	53703091.072	3786.573	7.847	-.001
Compound	.828	38.487	1	8	.000	57620220.136	1.000		
Power	.728	21.460	1	8	.002	4417777.959	.415		
S	.423	5.873	1	8	.042	18.776	-279.727		
Growth	.828	38.487	1	8	.000	17.869	.000		
Exponential	.828	38.487	1	8	.000	57620220.136	.000		
Logistic	.828	38.487	1	8	.000	1.736E-008	1.000		

The independent variable is Quantity of Wearing Produced.

Source: SPSS 17.0

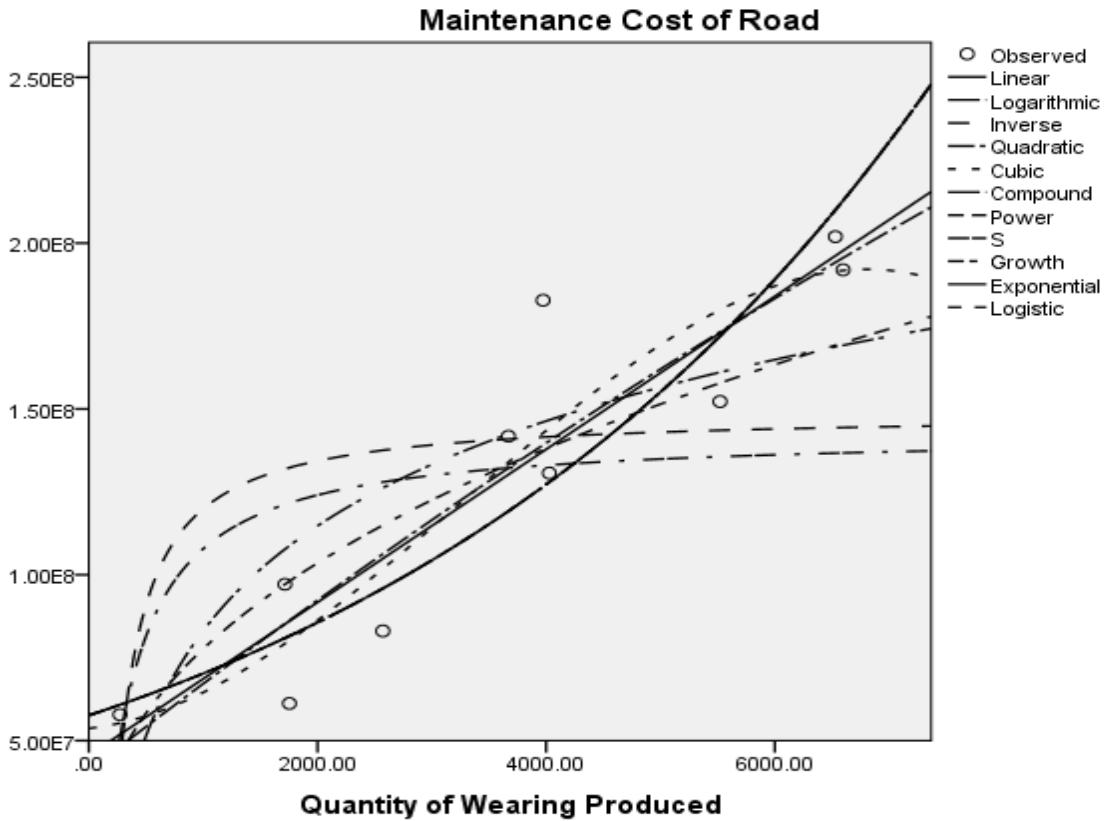


Table 45: Curve fitting plot of maintenance cost of roads against quantity of wearing produced.

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 85.3%. This result implies that the best model was the cubic model since the independent variable quantity of wearing produced was able to explain about 85.3% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.007 rejection which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.007 < \alpha=0.05$). Hence, quantity of wearing produced contributes to the proposed model.

Table 46: Summary of curve fitting analysis of maintenance cost of roads against Quantity of Binder Produced

Model Summary and Parameter Estimates

Dependent Variable: Maintenance Cost of Road

Equation	Model Summary					Parameter Estimates			
	R Square	F	df1	df2	Sig.	Constant	b1	b2	b3
Linear	.430	6.025	1	8	.040	38365546.677	33603.151		
Logarithmic	.464	6.925	1	8	.030	-578470223.654	90344577.968		
Inverse	.449	6.519	1	8	.034	211855813.074	193036624593.163		
Quadratic	.466	3.060	2	7	.111	-19715773.642	77414.056	-7.298	
Cubic	.467	1.753	3	6	.036	6527800.178	44470.660	4.815	-.001
Compound	.418	5.736	1	8	.044	54389294.115	1.000		
Power	.463	6.910	1	8	.030	257843.110	.782		
S	.462	6.859	1	8	.031	19.313	-1695.672		
Growth	.418	5.736	1	8	.044	17.812	.000		
Exponential	.418	5.736	1	8	.044	54389294.115	.000		
Logistic	.418	5.736	1	8	.044	1.839E-008	1.000		

The independent variable is Quantity of Binder Produced.

Source: SPSS 17.0

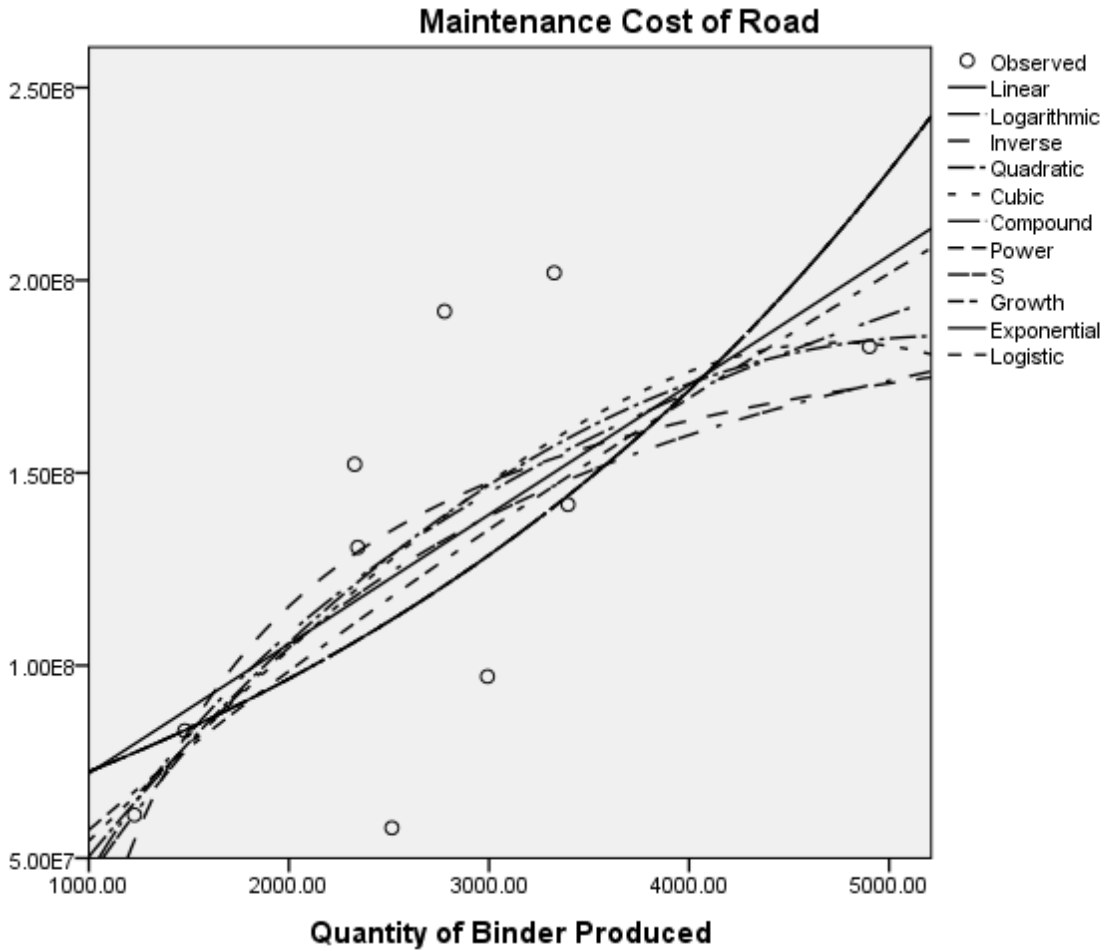


Figure 46: Curve fitting plot of maintenance cost of roads against quantity of binder produced

From the result of the curve estimation it was found that the cubic model performed better than the other methods with an R-squared of 46.7%. This result implies that the best model was the cubic model since the independent variable quantity of binder produced was able to explain about 46.7% of the total variability in the dependent variable maintenance cost of roads with a p-value of 0.036 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.036 < \alpha=0.05$). Hence, quantity of binder produced contributed to the proposed model.

4.13 Generalized Nonlinear Model Analysis on the Impact of Economic Variables on Maintenance Cost of Roads

Extracting from the curve fitting analysis obtained in section (4.12) the economic variables that contributed significantly to the fluctuations of maintenance cost of roads in Anambra State over the observed period (2004-2013), in order to design the generalize nonlinear model using the "gnm" function in R-programming.

Table 47: Summary of significant variables from curve fitting analysis of maintenance cost of roads

mcr	IASPCA	SCRGDP	MCQCC	MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF
57845868	20900	1.45	9.05E+06	40024	10890	7664	534.1	121.3	94.5
61211163	30500	1.59	1.02E+07	39900	16943	8544	554.4	13.3	94.5
83060565	35448	1.62	1.66E+06	38496	34577	9655	554.4	159.2	91.8
152240042	52911	1.72	3.82E+10	38496	37146	10913	745.5	168.9	89.9
201949343	65919	1.84	1.07E+11	1250520	35422	12339	745.5	171.4	88.9
130670316	123731	1.92	5.03E+10	1290520	33471	13816	745.5	189.45	89.9
182753103	219638	2	8.22E+10	1290520	32568	146285	745.5	162.9	89.9
97130327	304898	2.08	9.02E+10	1300024	35942	14890	745.5	151.71	88.9
141778800	462811	2.19	9.89E+10	1300024	37119	15014	745.5	163.5	89.7
191931676	469728	2.15	1.03E+11	1300024	43289	16147	745.5	166.8	90.4

The R-code for executing the generalized nonlinear model for assessing the impact of economic variables on maintenance cost of roads is written below. It should be noted that mcr represents the dependent variable while variables

IASPCA, SCRGDP, MCQCC, MCQCM, CGFCFPME, GDPCBPBC, LR, MRR and MeF represents the independent variables.

The result of the generalized nonlinear model using the extracted economic variables was found as:

Call:

```
Gnm (formula = mcr ~ IASPCA + SCRGDP + MCQCC + MCQCM +
CGFCFPME + GDPCBPBC + LR + MRR + MeF, family = gaussian, data =
NULL, method = "gnmFit", start = NULL)
```

Coefficients:

(Intercept)	IASPCA	SCRGDP	MCQCC	MCQCM	CGFCFPME
-8.417e+09	-8.887e+02	7.550e+08	2.911e-03	-1.245e+02	3.021e+03
	GDPCBPBC	LR	MRR	MeF	
	1.139e+02	1.252e+05	1.063e+06	7.592e+07	

Deviance: 3.776235e-11

Pearson chi-squared: 3.776235e-11

Residual df: 0

Call:

```
gnm(formula = mcr ~ IASPCA + SCRGDP + MCQCC + MCQCM +
CGFCFPME +
GDPCBPBC + LR + MRR + MeF, family = gaussian, data = NULL,
method = "gnmFit", start = NULL)
```

Coefficients:

	Estimate	Std. Error	z-value	Pr(> z)
(Intercept)	-8417000000	Inf	0	1
IASPCA	-889	Inf	0	1
SCRGDP	755000000	Inf	0	1
MCQCC	0	Inf	0	1
MCQCM	-125	Inf	0	1
CGFCFPME	3021	Inf	0	1
GDPCBPBC	114	Inf	0	1
LR	125200	Inf	0	1
MRR	1063000	Inf	0	1
MeF	75920000	Inf	0	1

(Dispersion parameter for gaussian family taken to be Inf)

Residual deviance: 3.7762e-11 on 0 degrees of freedom

AIC: -212.64

Number of iterations: 1

The result of generalized nonlinear model found a Pearson Chi-squared value of 3.776235e-11 and an Akakike Information Criterion value of -212.64. Also obtained was a model for estimating maintenance cost of roads in Anambra State which can be expressed as;

$$\begin{aligned} \text{mcr} = & -8417000000 - 889 * \text{IASPCA} + 755000000 * \text{SCRGDP} + -125 * \\ & \text{MCQCM} + 3021 * \text{CGFCFPME} + 114 * \text{GDPCBPBC} + 125200 * \text{LR} + \\ & 1063000 * \text{MRR} + 75920000 * \text{MeF} \end{aligned}$$

4.14 Generalized Nonlinear Model Analysis on the effect of Economic Variables and Quantity parameters on Maintenance Cost of Roads

Extracting from the curve fitting analysis of the economic variables and quantity of binder and wearing produced which contributed significantly to the fluctuations of maintenance cost of roads in Anambra State over the observed period (2004-2013), to design the generalize nonlinear model using the "gnm" function in R-programming.

mcr	Qbp	Qwp	IASPCA	SCRGDP	MCQCC	MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF
57845868	2514.7	272	20900	1.45	9.05E+06	40024	10890	7664	534	121.3	94.5
61211163	1227.9	1754	30500	1.59	1.02E+07	39900	16943	8544	554	13.3	94.5
83060565	1479.6	2571	35448	1.62	1.66E+06	38496	34577	9655	554	159.2	91.8
1.52E+08	2348.5	5521	52911	1.72	3.82E+10	38496	37146	10913	746	168.9	89.9
2.02E+08	3325.7	6529	65919	1.84	1.07E+11	1250520	35422	12339	746	171.4	88.9
1.31E+08	2344	4028	123731	1.92	5.03E+10	1290520	33471	13816	746	189.5	89.9
1.83E+08	4901.3	3973	219638	2	8.22E+10	1290520	32568	146285	746	162.9	89.9
97130327	2992.6	1715	304898	2.08	9.02E+10	1300024	35942	14890	746	151.7	88.9
1.42E+08	3394.6	3670	462811	2.19	9.89E+10	1300024	37119	15014	746	163.5	89.7
1.92E+08	2777.7	6597	469728	2.15	1.03E+11	1300024	43289	16147	746	166.8	90.4

The R-code for executing the generalized nonlinear model for estimating the estimating maintenance cost of roads using economic variables and quantity parameters as predictors is written below. It should be noted that mcr represents the dependent variable while variables Qbp, Qwp, IASPCA, SCR GDP, MCQCC, MCQCM, CGFCFPME, GDPCBPBC, LR, MRR and MeF represents the independent variables.

The result of the generalized nonlinear model using the extracted economic and quantity variables was found as:

Call:

```
gnm(formula = mcr ~ Qbp + Qwp + IASPCA + SCRGDP + MCQCC +
MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =
gaussian,
```

```
data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

(Intercept)	Qbp	Qwp	IASPCA	SCRGDP	MCQCC
7.139e+07	1.647e+04	1.959e+04	1.929e+01	-3.804e+07	7.818e-05
MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF
1.070e+01	1.517e+02	7.449e+01	-1.536e+04	NA	NA

Deviance: 1.332268e-14

Pearson chi-squared: 1.332268e-14

Residual df: 0

Call:

```
gnm(formula = mcr ~ Qbp + Qwp + IASPCA + SCRGDP + MCQCC +
MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =
gaussian, data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

	Estimate	Std. Error	z-value	Pr(> z)
(Intercept)	71390000	Inf	0	1
Qbp	16470	Inf	0	1
Qwp	19590	Inf	0	1
IASPCA	19	Inf	0	1
SCRGDP	-38040000	Inf	0	1
MCQCC	0	Inf	0	1
MCQCM	11	Inf	0	1
CGFCFPME	152	Inf	0	1
GDPCBPBC	74	Inf	0	1
LR	-15360	Inf	0	1
MRR	0	NA	NA	NA
MeF	0	NA	NA	NA

(Dispersion parameter for gaussian family taken to be Inf)

Std. Error is NA where coefficient has been constrained or is unidentified

Residual deviance: 1.3323e-14 on 0 degrees of freedom

AIC: -292.14

Number of iterations: 1

Table 48: Summary of Observed mcr and estimated mcr using economic

Variables, Qbp and Qwp

mcr	Estimated.economic	Estimated.Qbp.Qwp
57845868	57845864	57845668
61211163	61210151	61211063
83060565	83060465	83060465
152240042	152230042	152240032
201949343	201949243	201949243
130670316	130670216	130670216
182753103	182753103	182753003
97130327	97130327	97130317
141778800	141778800	141778700
191931676	191931626	191931636

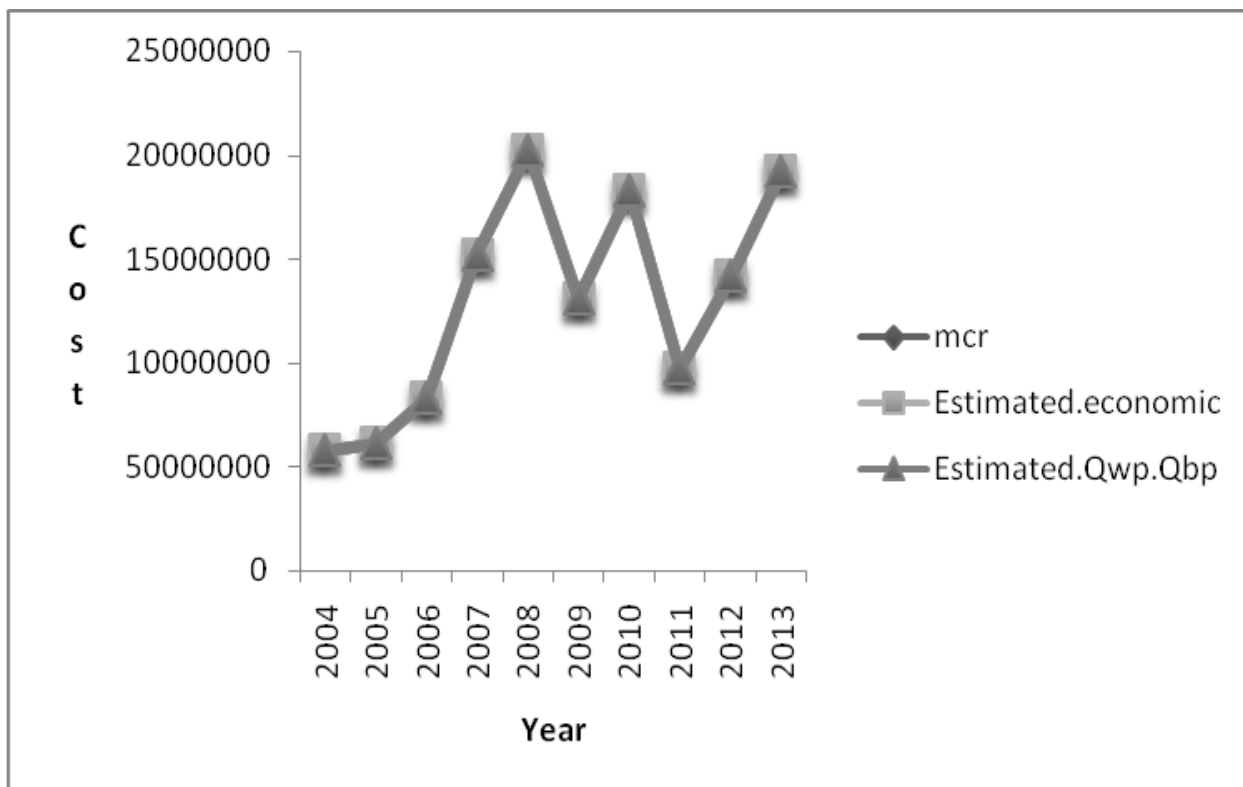


Figure 47: Graph on comparison of maintenance cost of roads and estimates

The result of generalized nonlinear model found a Pearson Chi-squared value of $1.332268e-14$ and an Akaike Information Criterion (AIC) value of -292.44 . Also obtained was a model for estimating maintenance cost of roads in Anambra State which can be expressed as;

$$mcr = 71390000 + 16470 * Qbp + 19590 * Qwp + 19 * IASPCA - 38040000 * SCRGDP + 11 * MCQCM + 152 * CGFCFPME + 74 * GDPCBPBC - 153600 * LR$$

In addition, Figure 47 showed that the estimated cost values from the economic model and quantity parameters models was able to estimate perfectly the observed maintenance cost of roads in Anambra State. This implies that the

models have the properties of generating good estimates of maintenance cost of roads in Anambra State.

4.15 Generalized Nonlinear Model Analysis on the Estimation of maintenance cost of roads using the linear maintenance cost function (CT.linear)

This section deals with estimation of the maintenance cost of roads using the cost estimated by the linear maintenance cost function. The generalized nonlinear model will be employed since it has been found that the explanatory variables have a nonlinear behaviour (see curve fitting result). Hence, we shall design the generalized nonlinear model using the "gnm" function in R-programming.

Table 49: Summary of maintenance cost of roads using the linear maintenance cost function and explanatory variables

CT.linear	Qbp	Qwp	IASPCA	SCRGDP	MCQCC	MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF
52416579	2514.7	272	20900	1.45	9.05E+06	40024	10890	7664	534.1	121.3	94.5
55474413	1227.9	1754	30500	1.59	1.02E+07	39900	16943	8544	554.4	13.3	94.5
75257320	1479.6	2571	35448	1.62	1.66E+06	38496	34577	9655	554.4	159.2	91.8
145936971	2348.5	5521	52911	1.72	3.82E+10	38496	37146	10913	745.5	168.9	89.9
182897821	3325.7	6529	65919	1.84	1.07E+11	1250520	35422	12339	745.5	171.4	88.9
118361606	2344	4028	123731	1.92	5.03E+10	1290520	33471	13816	745.5	189.5	89.9
165502471	4901.3	3973	219638	2	8.22E+10	1290520	32568	146285	745.5	162.9	89.9
87985345	2992.6	1715	304898	2.08	9.02E+10	1300024	35942	14890	745.5	151.7	88.9
131552389	3394.6	3670	462811	2.19	9.89E+10	1300024	37119	15014	745.5	163.5	89.7
173831147	2777.7	6597	469728	2.15	1.03E+11	1300024	43289	16147	745.5	166.8	90.4

The R-code for executing the generalized nonlinear model for estimation of the maintenance cost of roads using the cost estimated by the linear maintenance cost function is written below using details presented in the Table 49. Recall that CT.linear represents the dependent variable (cost values predicted from the linear maintenance cost model) while variables Qbp, Qwp, IASPCA, SCRGDP, MCQCC, MCQCM, CGFCFPME, GDPCBPBC, LR, MRR, MeF represents the independent variables.

The result of the generalized non-linear model was obtained as

Call:

```
gnm(formula = CT.linear ~ Qbp + Qwp + IASPCA + SCRGDP + MCQCC +
      MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =
      gaussian,
      data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

(Intercept)	Qbp	Qwp	IASPCA	SCRGDP	MCQCC			
5.681e+04	1.883e+04	1.841e+04	-7.994e-07	4.670e-01	-7.390e-12			
	MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF		
	1.961e-07	1.522e-05	1.334e-06	-2.173e-03	NA	NA		

Deviance: 1.054712e-14

Pearson chi-squared: 1.054712e-14

Residual df: 0

Call:

```
gnm(formula = CT.linear ~ Qbp + Qwp + IASPCA + SCRGDP + MCQCC +  
      MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =  
      gaussian,  
      data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	56810	Inf	0	1
Qbp	18830	Inf	0	1
Qwp	18410	Inf	0	1
IASPCA	-7.994e-07	Inf	0	1
SCRGDP	0.4670	Inf	0	1
MCQCC	-7.390e-12	Inf	0	1
MCQCM	-1.961e-07	Inf	0	1
CGFCFPME	1.522e-05	Inf	0	1
GDPCBPBC	1.334e-06	Inf	0	1
LR	-2.173e-03	Inf	0	1
MRR	0	NA	NA	NA
MeF	0	NA	NA	NA

(Dispersion parameter for gaussian family taken to be Inf)

Std. Error is NA where coefficient has been constrained or is unidentified

Residual deviance: 1.0547e-14 on 0 degrees of freedom

AIC: -294.48

Number of iterations: 1

Table 50 presents the observed CT.linear value with the estimated/fitted value from the gnm model analysis.

Table 50: Distribution of CT.linear and estimated values of the gnm model CT.linear

CT.linear	Estimated.CT.linear	Year
52416579	51416579	2004
55474413	55474423	2005
75257320	72257120	2006
145936971	135836971	2007
182897821	181897821	2008
118361606	107361606	2009
165502471	165502471	2010
87985345	87965345	2011
131552389	131522389	2012
173831147	173531147	2013

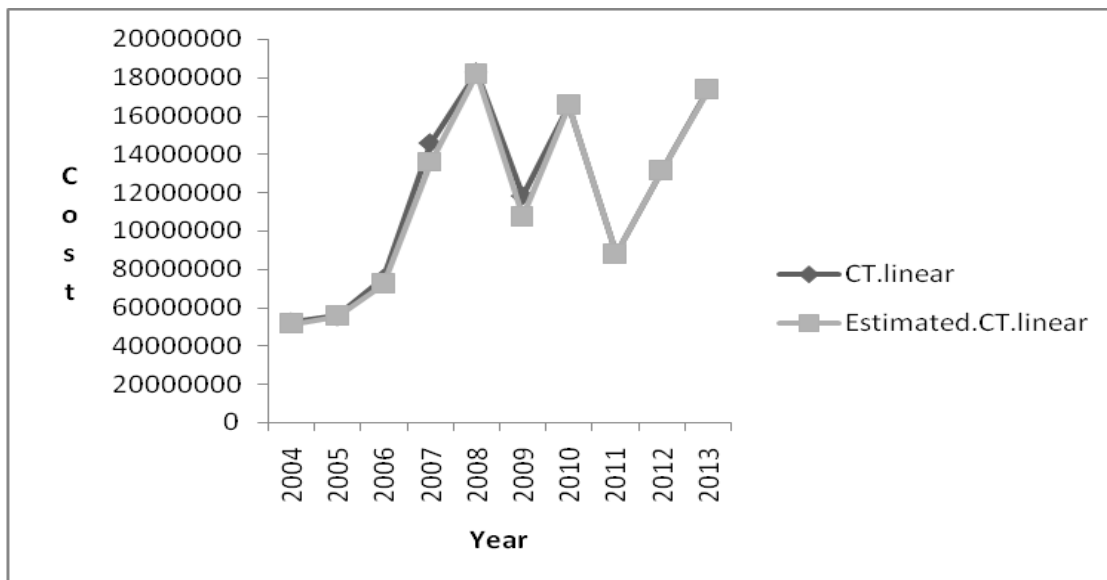


Figure 48: Distribution of CT.linear and Estimated.CT.linear over the observed years

The result of generalized nonlinear model found a Pearson Chi-squared value of $1.054712e-14$ and an Akaike Information Criterion (AIC) value of -294.48 . Also obtained was a model for estimating CT.linear which can be expressed as;

$$\text{CT.linear} = 56810 + 18830 \cdot \text{Qbp} + 18410 \cdot \text{Qwp} - 7.994 \times 10^{-7} \cdot \text{IASPCA} - 0.4670 \cdot \text{SCRGDP} - 7.390 \times 10^{-12} \cdot \text{MCQCC} - 1.961 \times 10^{-7} \cdot \text{MCQCM} + 1.522 \times 10^{-5} \cdot \text{CGFCFPME} + 1.334 \times 10^{-6} \cdot \text{GDPCBPBC} - 2.173 \times 10^{-3} \cdot \text{LR}$$

In addition, Figure 48 showed that the estimated cost values for CT.linear was able to estimate perfectly the observed maintenance cost of roads in Anambra State using the CT.linear. This implies that the models have the properties of generating good estimates of maintenance cost of roads in Anambra State using the CT.linear model.

4.16 Generalized Nonlinear Model Analysis on the Estimation of maintenance cost of roads using the nonlinear maintenance cost function (CT.nonlinear)

This section deals with estimation of the maintenance cost of roads using the non linear maintenance cost function. The generalized nonlinear model will be employed since it has been found that the explanatory variables have a nonlinear behaviour (see curve fitting result). Hence, we shall design the generalize nonlinear model using the "gnm" function in R-programming.

Table 51: Summary of maintenance cost of roads using the nonlinear maintenance cost function and explanatory variables

CT.nonlinear	Qbp	Qwp	IASPCA	SCRGDP	MCQCC	MCQCM	CGFCFPME	GDPCBPBC	LR	MRR	MeF
2697251	2514.7	272	20900	1.45	9.05E+06	40024	10890	7664	534.1	121.3	94.5
3717564	1227.9	1754	30500	1.59	1.02E+07	39900	16943	8544	554.4	13.3	94.5
4842440	1479.6	2571	35448	1.62	1.66E+06	38496	34577	9655	554.4	159.2	91.8
8880745	2348.5	5521	52911	1.72	3.82E+10	38496	37146	10913	745.5	168.9	89.9
10658702	3325.7	6529	65919	1.84	1.07E+11	1250520	35422	12339	745.5	171.4	88.9
7091646	2344	4028	123731	1.92	5.03E+10	1290520	33471	13816	745.5	189.45	89.9
8522279	4901.3	3973	219638	2	8.22E+10	1290520	32568	146285	745.5	162.9	89.9
4703539	2992.6	1715	304898	2.08	9.02E+10	1300024	35942	14890	745.5	151.71	88.9
7278052	3394.6	3670	462811	2.19	9.89E+10	1300024	37119	15014	745.5	163.5	89.7
10419397	2777.7	6597	469728	2.15	1.03E+11	1300024	43289	16147	745.5	166.8	90.4

The R-code for executing the generalized nonlinear model for estimation of the maintenance cost of roads using the cost estimated by the non-linear maintenance cost function is written below using details presented in the Table 51. Recall that CT.nonlinear represents the dependent variable (cost values predicted from the non-linear maintenance cost model) while variables Qbp, Qwp, IASPCA, SCR GDP, MCQCC, MCQCM, CGFCFPME, GDPCBPBC, LR, MRR, MeF represents the independent variables.

The result of the generalized non-linear model was obtained as

Call:

```
gnm(formula = CT.nonlinear ~ Qbp + Qwp + IASPCA + SCR GDP + MCQCC  
+ MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =  
gaussian, data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

(Intercept)	Qbp	Qwp	IASPCA	SCR GDP	MCQCC			
9.003e+05	5.852e+02	1.197e+03	1.006e-14	-1.556e-08	-1.737e-20			
MCQCM	CGFCFPME	GDPCBPBC		LR	MRR	MeF		
5.696e-16	8.527e-14	-2.983e-14	7.445e-12	NA	NA			

Deviance: 2.396087e-16

Pearson chi-squared: 2.396087e-16

Residual df: 0

Call:

```
gnm(formula = CT.nonlinear ~ Qbp + Qwp + IASPCA + SCR GDP + MCQCC  
+ MCQCM + CGFCFPME + GDPCBPBC + LR + MRR + MeF, family =  
gaussian, data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	900300	Inf	0	1
Qbp	585	Inf	0	1
Qwp	1197	Inf	0	1
IASPCA	0	Inf	0	1
SCRGDP	-1.556e-08	Inf	0	1
MCQCC	0	Inf	0	1
MCQCM	0	Inf	0	1
CGFCFPME	8.527e-14	Inf	0	1
GDPCBPBC	-2.983e-14	Inf	0	1
LR	7.445e-12	Inf	0	1
MRR	0	NA	NA	NA
MeF	0	NA	NA	NA

(Dispersion parameter for gaussian family taken to be Inf)

Std. Error is NA where coefficient has been constrained or is unidentified

Residual deviance: 2.3961e-16 on 0 degrees of freedom

AIC: -332.32

Number of iterations: 1

Table 52 presents the observed CT.nonlinear value with the estimated/fitted value from the gnm model analysis.

Table 52: Distribution of CT.nonlinear and estimated values of the model.CT.nonlinear

year	CT.nonlinear	Estimated.CT.nonlinear
2004	2676267	2654755
2005	3696002	3660066
2006	4820560	4861506
2007	8857715	8782701
2008	10635280	10611122
2009	7069198	7167488
2010	8499852	8524412
2011	4681992	4749222
2012	7255744	7120940
2013	10395949	10456345

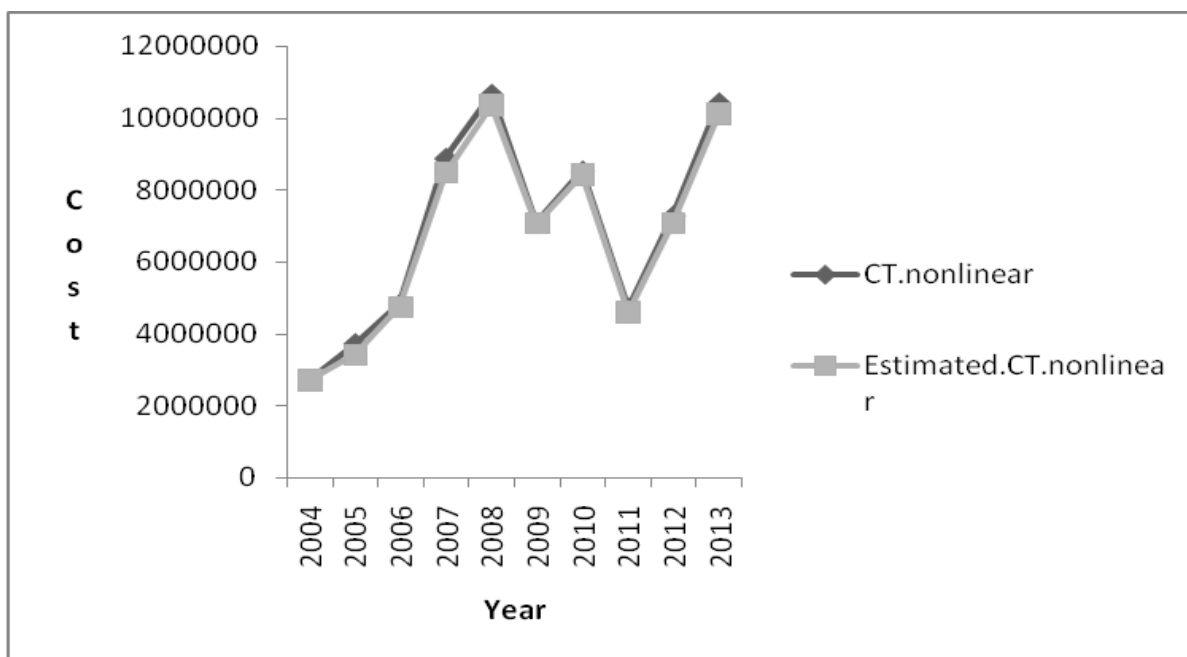


Figure 49: Distribution of CT.nonlinear and Estimated.CT.nonlinear over the observed years

The result of generalized nonlinear model found a Pearson Chi-squared value of $2.396087e-16$ and an Akaike Information Criterion (AIC) value of -332.32 . Also obtained was a model for estimating CT.nonlinear which can be expressed as;

$$\text{CT.nonlinear} = 900300 + 585 * Q_{wp} + 1197 * Q_{bp} - 1.556e-08 * \text{SCRGDP} + 8.527e-14 * \text{CGFCFPME} - 2.983e-14 * \text{GDPCBPBC} + 7.445e-12 * \text{LR}$$

In addition, Figure 49 showed that the estimated cost values for CT.nonlinear was able to estimate perfectly the observed maintenance cost of roads in Anambra State using the CT.nonlinear since there exist no significant dispersion from the trend of the two variables. This implies that the models have the

properties of generating good estimates of maintenance cost of roads in Anambra State using the CT.nonlinear model.

4.17 Curve Estimation Analysis between Quantity of Binder Produced (QbP) for Road maintenance in Anambra State

Table 53: Summary of quantity of binder produced and explanatory parameter

Qbp	MMT	MRH	MRR	MeF	MR	ME	S	C5	C10	B	C15
2514.7	32	72	121.3	94.5	17.8	3.5	1169.3	286.7	455.2	125.7	447.8
1227.9	32.8	74.9	13.3	94.5	18	4.3	571	139.9	222.2	61.4	233.3
1479.6	35.3	73.05	159.2	91.8	18	4.3	688	168.7	267.8	74	281.1
2348.5	36.7	75.5	168.9	89.9	18.1	4.2	1082.8	265.4	421.5	116.4	442.4
3325.7	32.5	72.7	171.4	88.9	18.3	4.2	1546.5	379.1	601.9	166.3	6232
2344	32.7	74	189.45	89.9	18.6	4.2	1089.9	267.2	424.3	117.2	445.4
4901.3	33.1	79.7	162.9	89.9	18.6	4.3	2279.1	558.7	887.1	245.1	931.2
2992.6	32.8	78.7	151.71	88.9	18.7	4.3	1391.6	341.1	541.7	149.6	568.6
3394.6	32.5	80.9	163.5	89.7	18.9	4.2	1578.5	386.9	614.4	169.7	644.9
2777.7	34.4	79.8	166.8	90.4	19	4.4	1291.6	316.7	502.8	138.9	527.8

Curve estimation analysis was performed to determine the explanatory variables that contributed to the attributes of quantity of binder produced for road maintenance in Anambra State and to also assess the best type of model to employ in the estimation of the Quantity of binder produced with the observed period. The models considered in this section includes the linear model, Logarithmic model, Inverse model, Quadratic model, Cubic model, Compound

model, Power model, S curve model, Growth model, Exponential model and Logistic model.

Using details from the Table 53 the curve estimation analysis was performed where quantity of wearing produced (Qwp) is the dependent or response variable and MMT, MRH, MRR, MeF, MR, ME, S, C5, C10 and B are the explanatory parameters.

Table 54: Summary of Curve Fitting Analysis between Qbp and MMT

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.083	.726	1	8	.419	9417.890	-199.738
Logarithmic	.082	.719	1	8	.421	26649.471	-6814.341
Inverse	.082	.711	1	8	.424	-4209.179	231944.228
Quadratic	.087	.334	2	7	.727	-33559.674	2310.994
Cubic	.088	.332	2	7	.023	-17136.553	964.417
Compound	.075	.650	1	8	.443	29773.048	.929
Power	.075	.652	1	8	.443	17640682.279	-2.519
S	.075	.653	1	8	.442	5.263	86.246
Growth	.075	.650	1	8	.443	10.301	-.073
Exponential	.075	.650	1	8	.443	29773.048	-.073
Logistic	.075	.650	1	8	.443	3.359E-005	1.076

The independent variable is MMT.

Source: SPSS 17.0

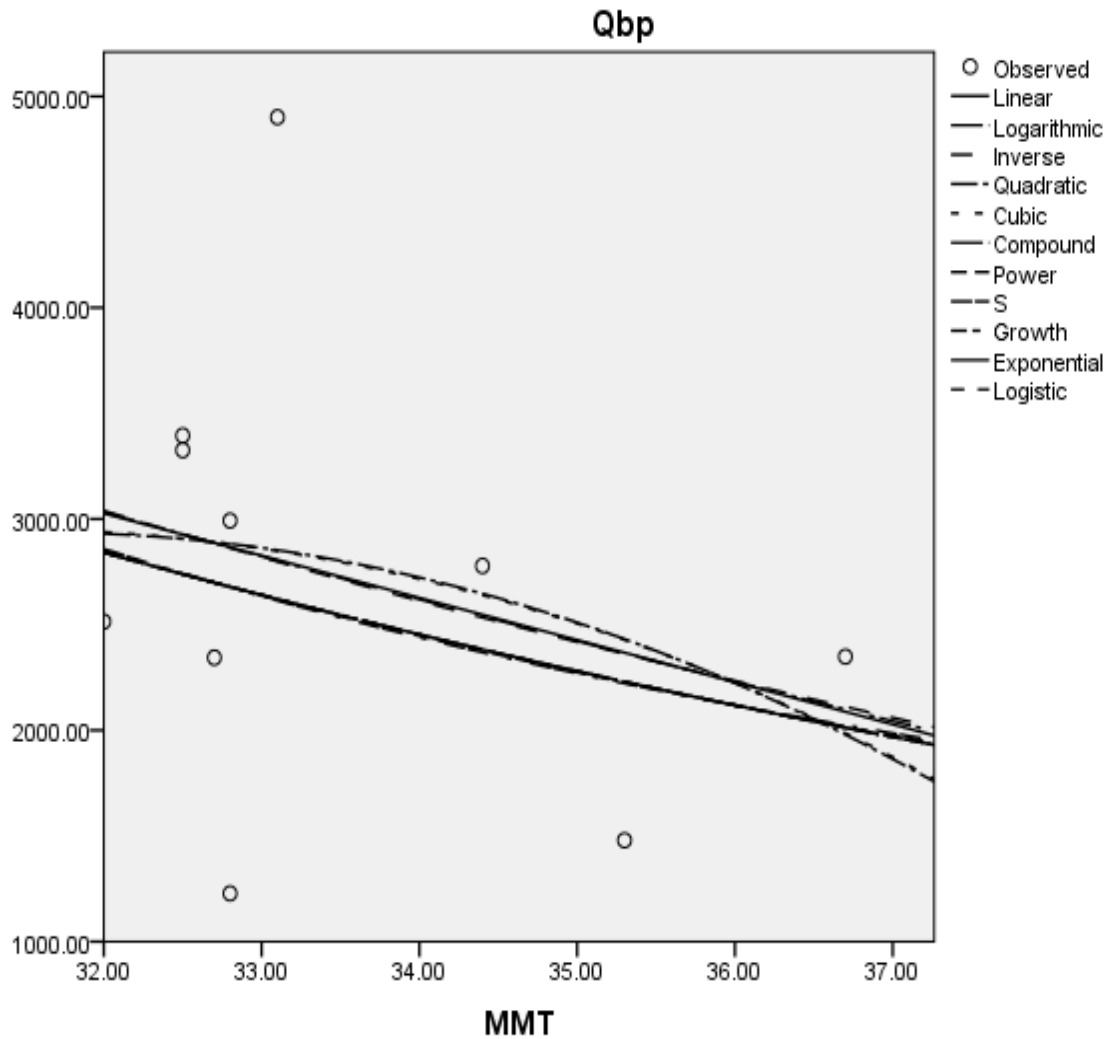


Figure 50: Curve fitting plot of quantity of binder against mean maximum Temperature

The result of the curve estimation analysis found that the cubic model performed better than the other methods with an R-squared of 8.8%. This result implies that the best model was the cubic model since the independent variable MMT was able to explain about 8.8% of the total variability in the dependent variable Qbp with a p-value of 0.023 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.023 < \alpha=0.05$). Hence, MMT contributes to the proposed model.

Table 55: Summary of Curve Fitting Analysis between quantity of binder produce against mean relative humidity

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.309	3.577	1	8	.095	-10456.033	173.224
Logarithmic	.304	3.496	1	8	.098	-54142.038	13129.977
Inverse	.299	3.412	1	8	.102	15808.171	-993816.523
Quadratic	.418	2.512	2	7	.151	292728.516	-7769.593
Cubic	.426	2.490	2	7	.015	190305.018	-3773.269
Compound	.278	3.083	1	8	.117	20.198	1.066
Power	.273	3.003	1	8	.121	2.282E-006	4.810
S	.268	2.922	1	8	.126	12.627	-363.496
Growth	.278	3.083	1	8	.117	3.006	.064
Exponential	.278	3.083	1	8	.117	20.198	.064
Logistic	.278	3.083	1	8	.117	.050	.938

The independent variable is MRH

Source: SPSS 17.0

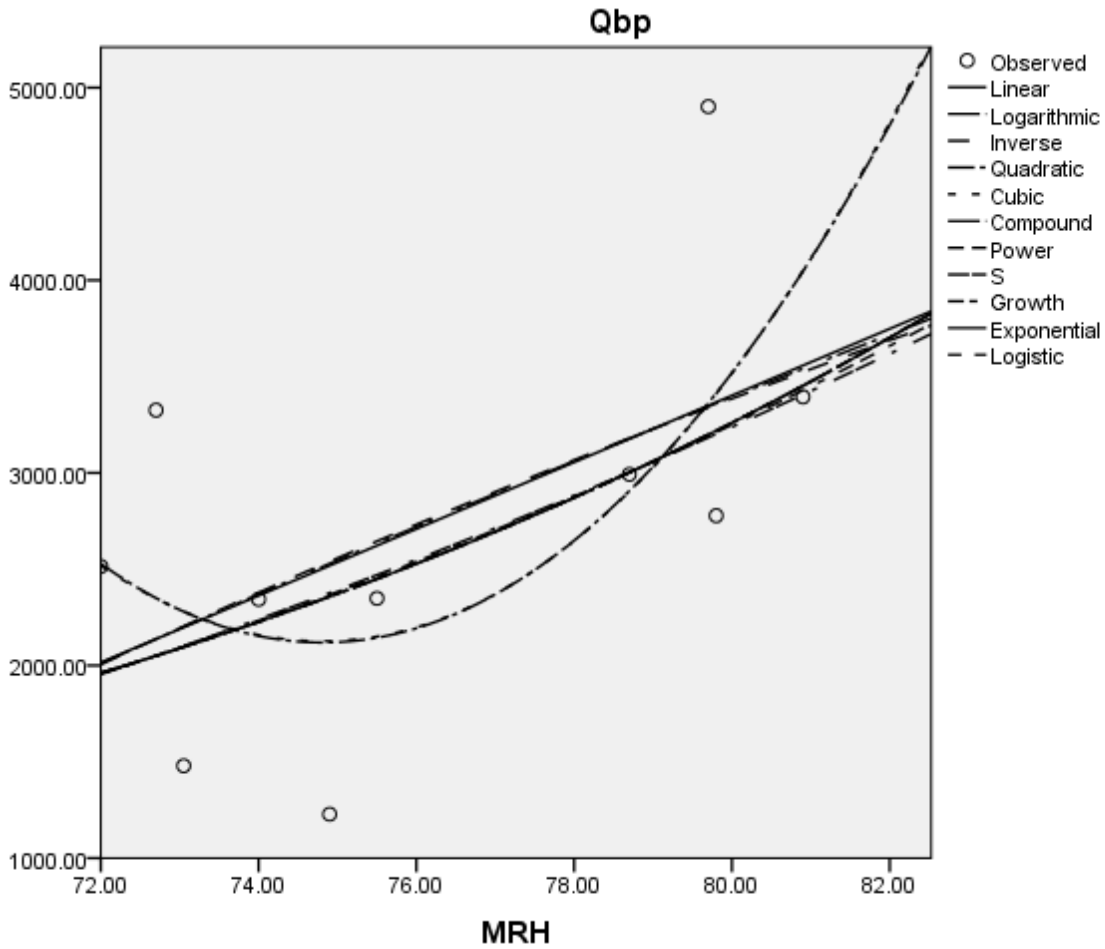


Figure 51: Curve fitting plot of quantity of binder against mean Relative Humidity

The result of the curve estimation analysis found that the cubic model performed better than the other methods with an R-squared of 42.6%. This result implies that the best model was the cubic model since the independent variable MRH was able to explain about 42.6% of the total variability in the dependent variable Qbp with a p-value of 0.015 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.015 < \alpha=0.05$). Hence, MRH contributes to the proposed model.

Table 56: Summary of Curve Fitting Analysis between quantity of binder produce against mean relative rainfall

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.238	2.503	1	8	.152	1238.933	10.158
Logarithmic	.260	2.808	1	8	.132	-486.695	666.087
Inverse	.260	2.806	1	8	.132	3050.570	-24311.405
Quadratic	.273	1.316	2	7	.327	836.807	27.536
Cubic	.315	.920	3	6	.486	2002.597	-71.127
Compound	.370	4.693	1	8	.062	1242.573	1.005
Power	.405	5.456	1	8	.048	538.754	.322
S	.409	5.525	1	8	.047	7.999	-11.790
Growth	.370	4.693	1	8	.062	7.125	.005
Exponential	.370	4.693	1	8	.062	1242.573	.005
Logistic	.370	4.693	1	8	.062	.001	.995

The independent variable is Mean Relative Rainfall.

Source: SPSS 17.0

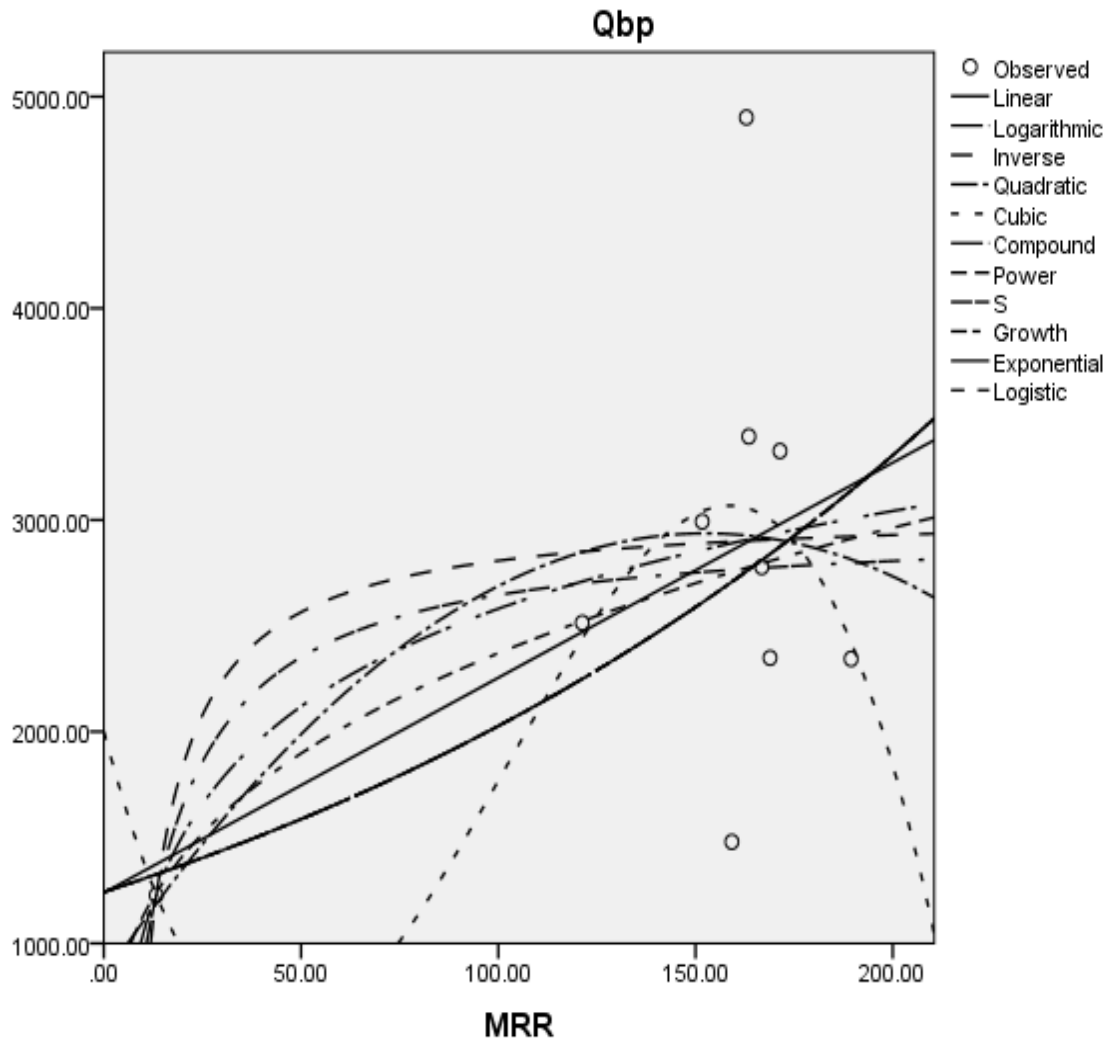


Figure 52: Curve fitting plot of quantity of binder against mean Relative Rainfall

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 40.9%. This result implies that the best model was the S curve model since the independent variable MRR was able to explain about 40.9% of the total variability in the dependent variable Qbp with a p-value of 0.047 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.047 < \alpha=0.05$). Hence, MRR contributes to the proposed model.

Table 57: Summary of Curve Fitting Analysis between quantity of binder produce against mean efficiency

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.330	3.937	1	8	.083	28677.571	-285.633
Logarithmic	.331	3.959	1	8	.082	121227.388	-26280.836
Inverse	.332	3.981	1	8	.081	-23889.918	2417084.281
Quadratic	.330	3.937	1	8	.083	28677.571	-285.633
Cubic	.354	1.915	2	7	.217	346305.190	-5476.179
Compound	.418	5.739	1	8	.043	204221935.349	.883
Power	.420	5.781	1	8	.043	6389240180486 0480000000000 .000	-11.439
S	.421	5.822	1	8	.042	-3.745	1052.237
Growth	.418	5.739	1	8	.043	19.135	-.124
Exponential	.418	5.739	1	8	.043	204221935.349	-.124
Logistic	.418	5.739	1	8	.043	4.897E-009	1.132

The independent variable is MeF.
Source: SPSS 17.0

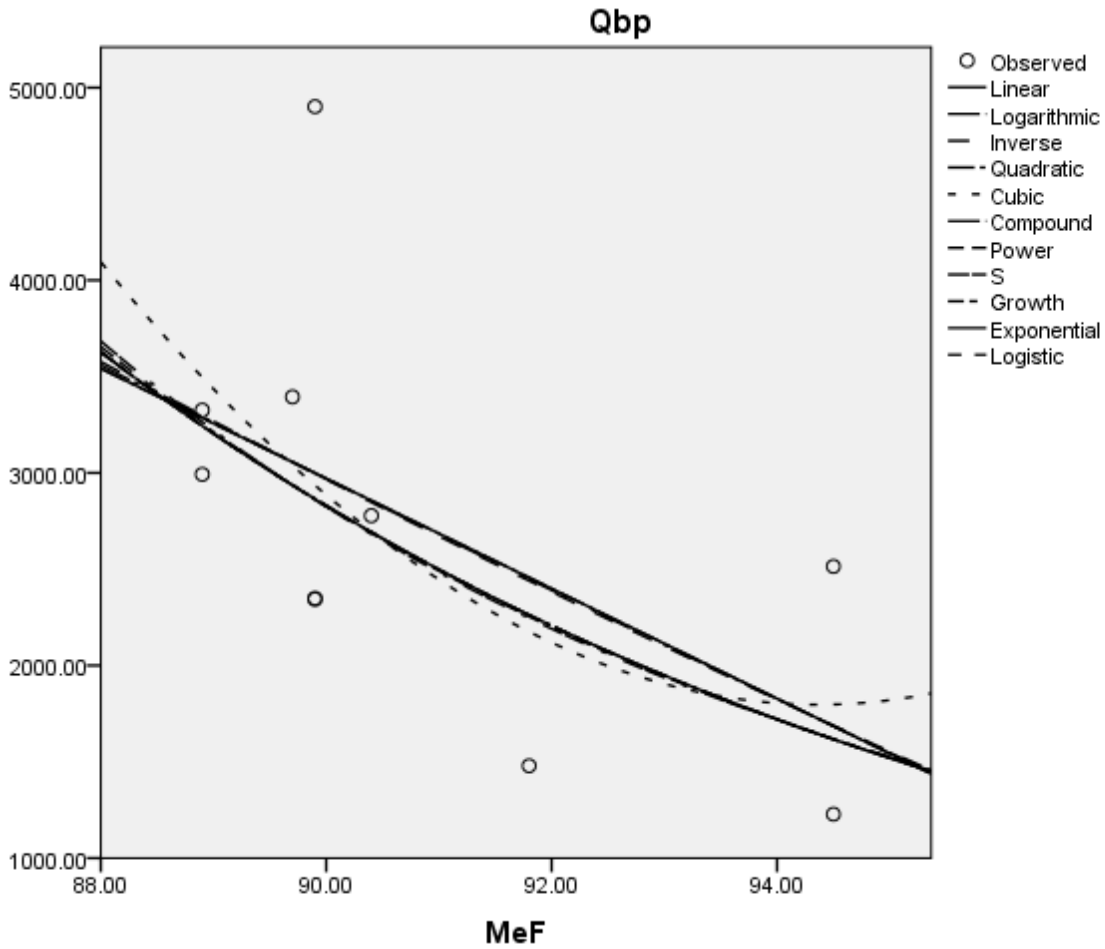


Figure 53: Curve fitting plot of quantity of binder produce against mean efficiency

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with a R-squared of 42.1%. This result implies that the best model was the S curve model since the independent variable MeF was able to explain about 42.1% of the total variability in the dependent variable Qbp with a p-value of 0.042 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.042 < \alpha=0.05$). Hence, MeF contributes to the proposed model.

Table 58: Summary of Curve Fitting Analysis between quantity of binder produce against Mean Radiation

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.285	3.191	1	8	.112	-21824.140	1334.500
Logarithmic	.287	3.223	1	8	.110	-69028.139	24641.427
Inverse	.289	3.255	1	8	.109	27458.453	-454781.777
Quadratic	.285	3.191	1	8	.112	-21824.140	1334.500
Cubic	.342	1.821	2	7	.231	-457909.316	36897.659
Compound	.335	4.034	1	8	.079	.086	1.750
Power	.337	4.063	1	8	.079	2.276E-010	10.318
S	.338	4.090	1	8	.078	18.185	-190.197
Growth	.335	4.034	1	8	.079	-2.451	.559
Exponential	.335	4.034	1	8	.079	.086	.559
Logistic	.335	4.034	1	8	.079	11.597	.572

The independent variable is MR.
Source: SPSS 17.0

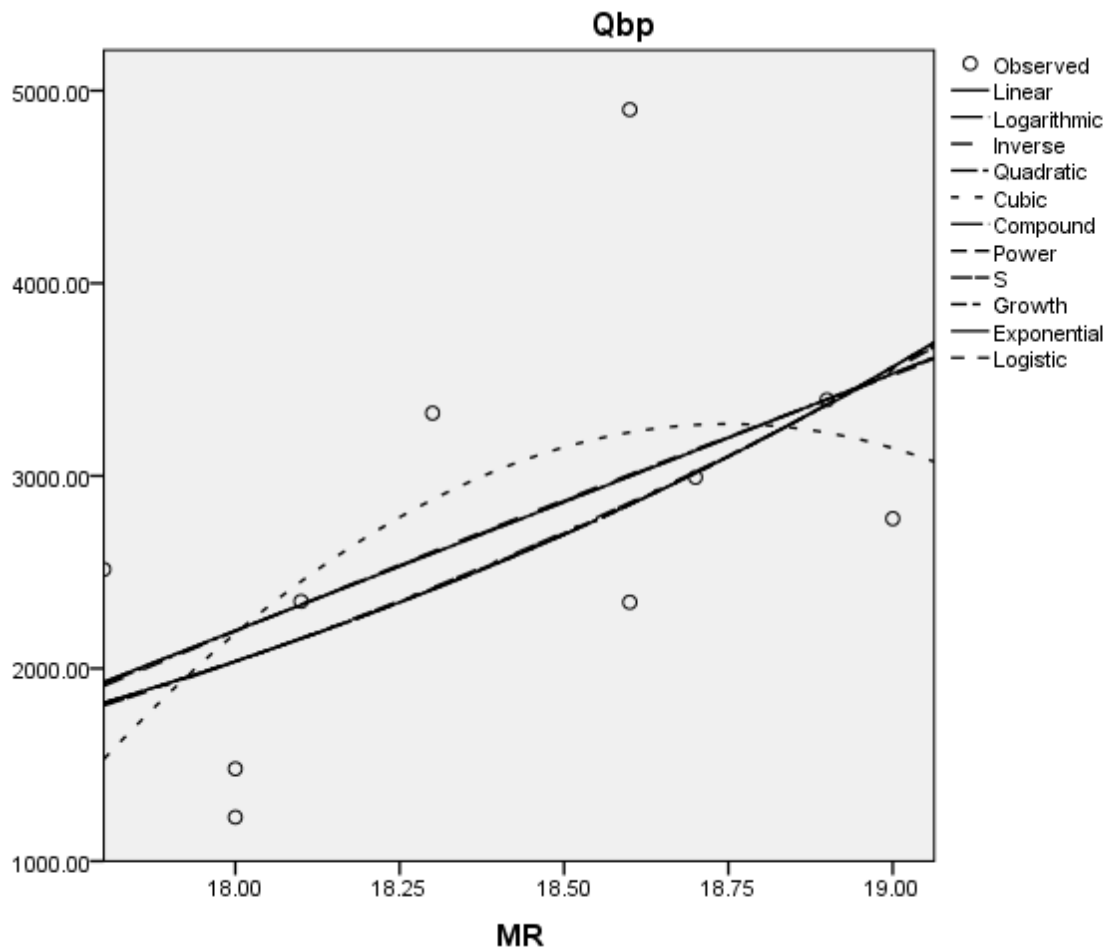


Figure 54: Curve fitting plot of quantity of binder produce against mean Radiation

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 34.1%. This result implies that the best model was the cubic model since the independent variable MR was able to explain about 34.1% of the total variability in the dependent variable Qbp with a p-value of 0.231 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.231 > \alpha=0.05$). Hence, MR does not contribute to the proposed model.

Table 59: Summary of Curve Fitting Analysis between quantity of binder produce against mean maximum Evaporation

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.003	.024	1	8	.881	1784.736	225.757
Logarithmic	.003	.025	1	8	.877	1431.300	908.062
Inverse	.003	.027	1	8	.874	3599.339	-3626.143
Quadratic	.008	.028	2	7	.973	-19878.873	11392.078
Cubic	.009	.028	2	7	.973	-19878.873	11392.078
Compound	.000	.004	1	8	.954	2939.076	.967
Power	.000	.003	1	8	.959	3011.160	-.117
S	.000	.002	1	8	.965	7.749	.392
Growth	.000	.004	1	8	.954	7.986	-.034
Exponential	.000	.004	1	8	.954	2939.076	-.034
Logistic	.000	.004	1	8	.954	.000	1.035

The independent variable is ME.

Source: SPSS 17.0

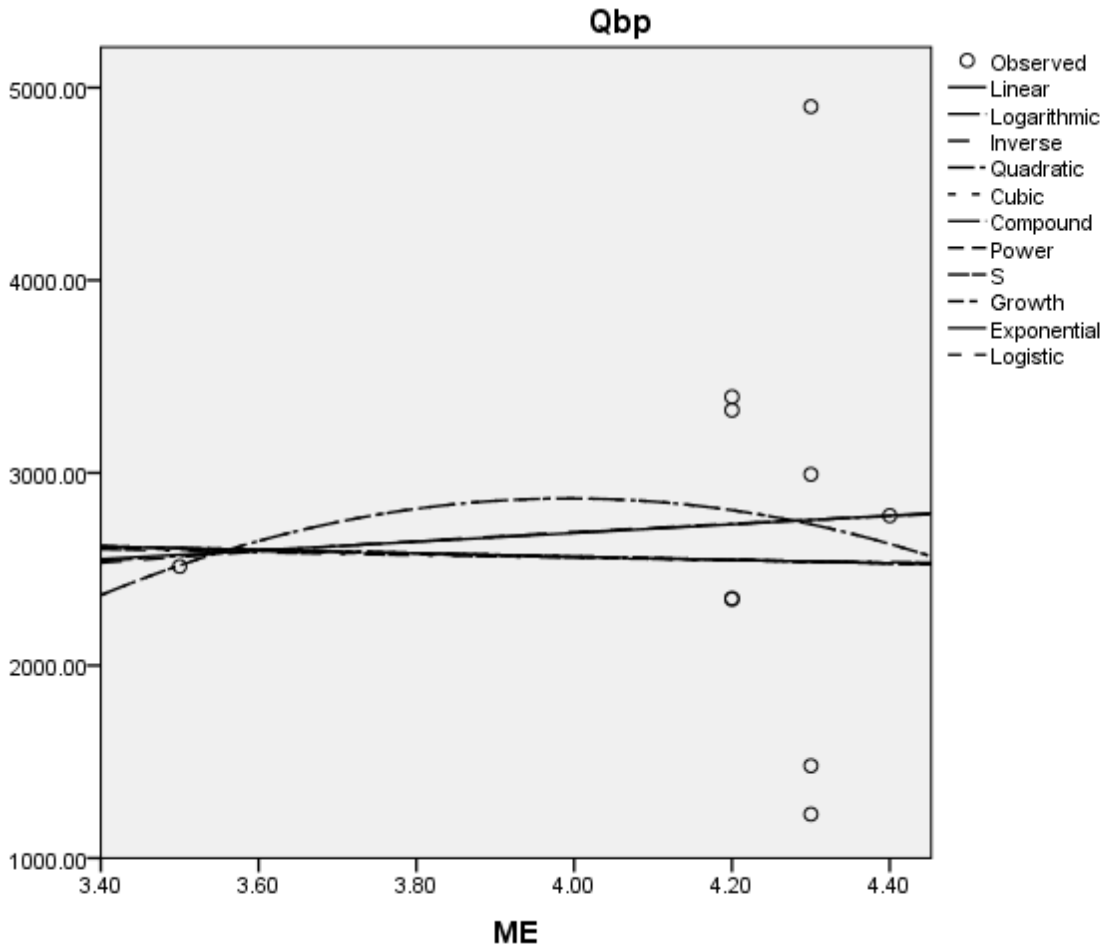


Figure 55: Curve fitting plot of quantity of binder produce against Mean Evaporation

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 0.9%. This result implies that the best model was the cubic model since the independent variable ME was able to explain about 0.9% of the total variability in the dependent variable Qbp with a p-value of 0.973 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.973 > \alpha=0.05$). Hence, ME does not contribute to the proposed model.

Table 60: Summary of Curve Fitting Analysis between quantity of binder Produce against stone-dust

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.962	222951.096	1	8	.000	4.246	2.149
Logarithmic	.944	134.393	1	8	.000	-15041.191	2511.289
Inverse	.811	34.272	1	8	.000	4872.921	-2350827.451
Quadratic	.942	99836.627	2	7	.000	-1.111	2.157
Cubic	.995	69625.540	3	6	.000	-51.425	2.293
Compound	.942	130.889	1	8	.000	915.936	1.001
Power	.944	179972.650	1	8	.000	2.160	.999
S	.956	173.789	1	8	.000	8.743	-987.044
Growth	.942	130.889	1	8	.000	6.820	.001
Exponential	.942	130.889	1	8	.000	915.936	.001
Logistic	.942	130.889	1	8	.000	.001	.999

The independent variable is S.

Source: SPSS 17.0

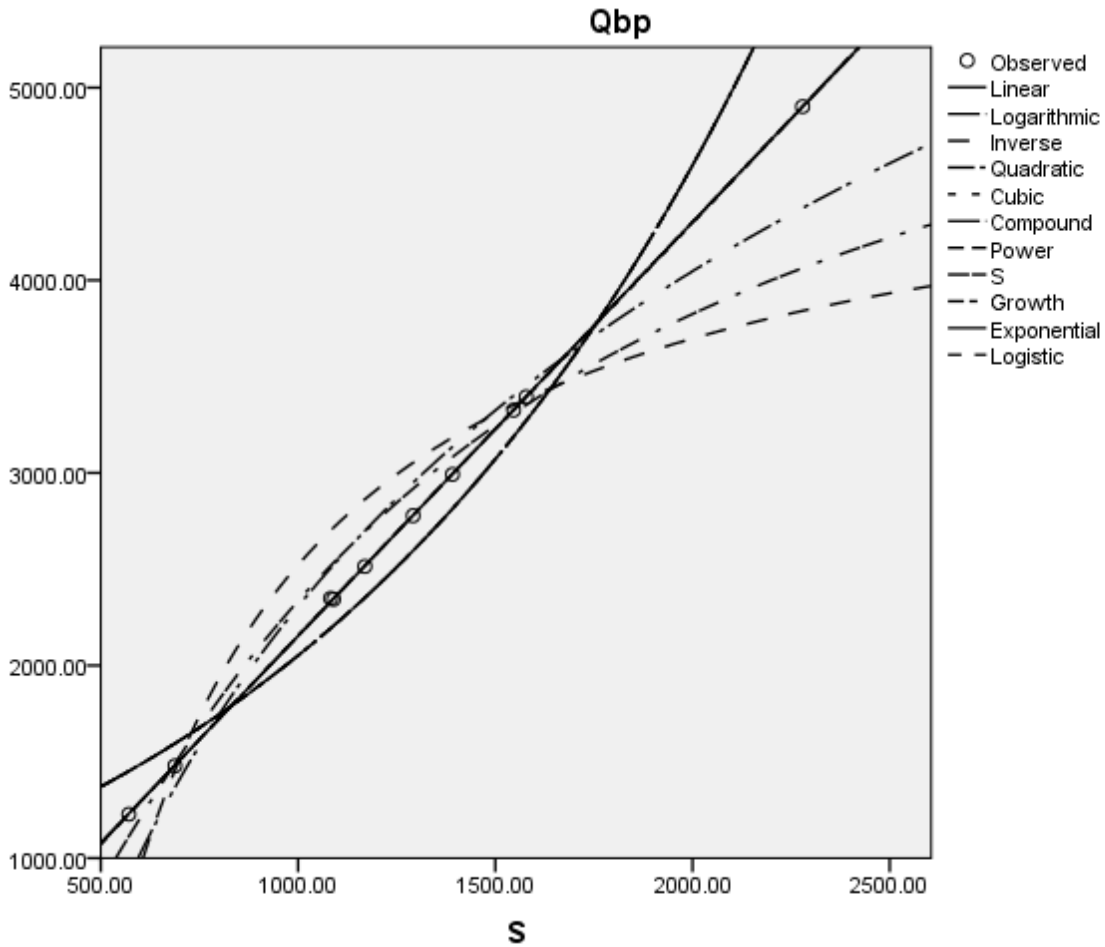


Figure 56: Curve fitting plot of quantity of binder produced against stone-dust (s)

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.5%. This result implies that the best model was the cubic model since the independent variable S was able to explain about 99.5% of the total variability in the dependent variable Qbp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, S contributes to the proposed model.

Table 61: Summary of Curve Fitting Analysis between quantity of binder produce against chipping c5

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.958	214362.769	1	8	.000	4.277	8.765
Logarithmic	.944	134.143	1	8	.000	-11507.640	2510.791
Inverse	.811	34.217	1	8	.000	4871.830	-575960.854
Quadratic	.952	95541.407	2	7	.000	-.608	8.798
Cubic	.967	63681.617	3	6	.000	-46.294	9.301
Compound	.942	131.022	1	8	.000	915.919	1.003
Power	.953	173814.572	1	8	.000	8.813	.999
S	.956	173.159	1	8	.000	8.742	-241.847
Growth	.942	131.022	1	8	.000	6.820	.003
Exponential	.942	131.022	1	8	.000	915.919	.003
Logistic	.942	131.022	1	8	.000	.001	.997

The independent variable is C5.

Source: SPSS 17.0

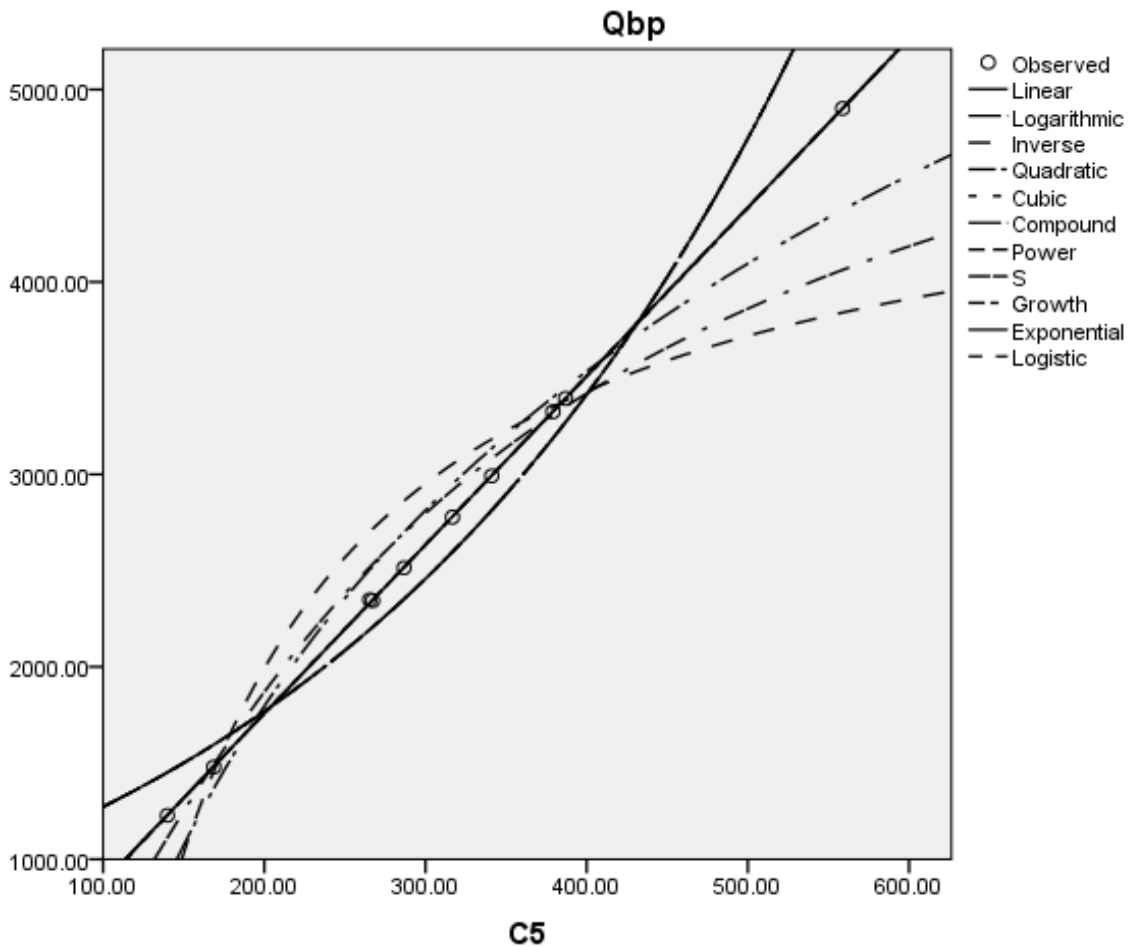


Figure 57: Curve fitting plot o quantity of binder produce against chippings c5

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 96.7%. This result implies that the best model was the cubic model since the independent variable c5 was able to explain about 96.7% of the total variability in the dependent variable Qbp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, c5 contributes to the proposed model.

Table 62: Summary of Curve Fitting Analysis between Quantity of Binder Produce against Chipping c10

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.936	225365.068	1	8	.000	4.123	5.521
Logarithmic	.944	134.163	1	8	.000	-12669.561	2510.943
Inverse	.811	34.233	1	8	.000	4872.156	-914703.987
Quadratic	.901	100346.960	2	7	.000	-.516	5.540
Cubic	.969	67902.106	3	6	.000	-47.079	5.863
Compound	.942	131.061	1	8	.000	915.858	1.002
Power	.944	182919.101	1	8	.000	5.550	.999
S	.956	173.366	1	8	.000	8.743	-384.079
Growth	.942	131.061	1	8	.000	6.820	.002
Exponential	.942	131.061	1	8	.000	915.858	.002
Logistic	.942	131.061	1	8	.000	.001	.998

The independent variable is C10.

Source: SPSS 17.0

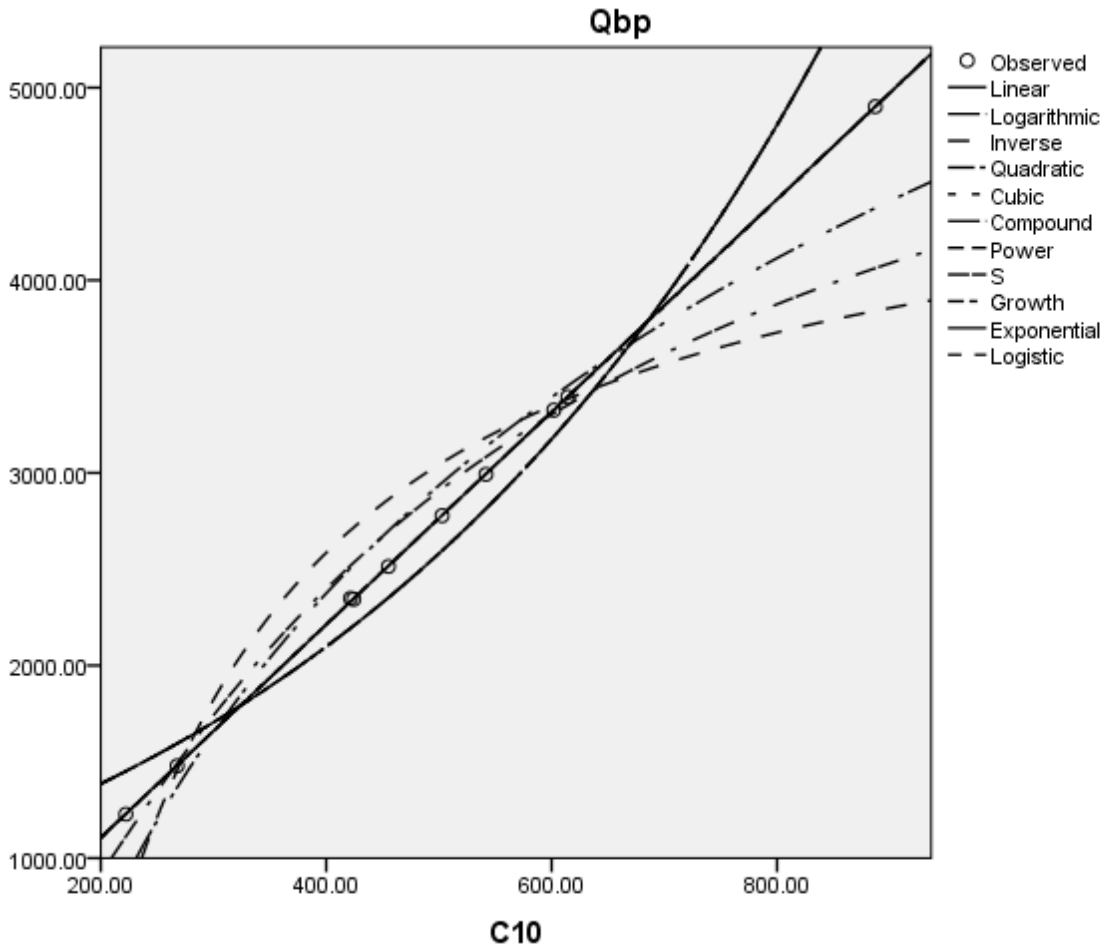


Figure 58: Curve fitting plot of quantity of binder produced against chippings c10

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 96.9%. This result implies that the best model was the cubic model since the independent variable c10 was able to explain about 96.9% of the total variability in the dependent variable Qbp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, c10 contributes to the proposed model.

Table 63: Summary of Curve Fitting Analysis between quantity of binder produced against Bitumen

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.956	209631.471	1	8	.000	4.540	19.982
Logarithmic	.944	134.672	1	8	.000	-9442.721	2511.659
Inverse	.811	34.299	1	8	.000	4873.527	-252848.756
Quadratic	.976	95362.917	2	7	.000	-2.587	20.089
Cubic	.987	65410.969	3	6	.000	-52.076	21.332
Compound	.942	130.565	1	8	.000	916.103	1.008
Power	.956	168289.218	1	8	.000	20.059	1.000
S	.956	174.014	1	8	.000	8.743	-106.159
Growth	.942	130.565	1	8	.000	6.820	.008
Exponential	.942	130.565	1	8	.000	916.103	.008
Logistic	.942	130.565	1	8	.000	.001	.993

The independent variable is B.

Source: SPSS 17.0

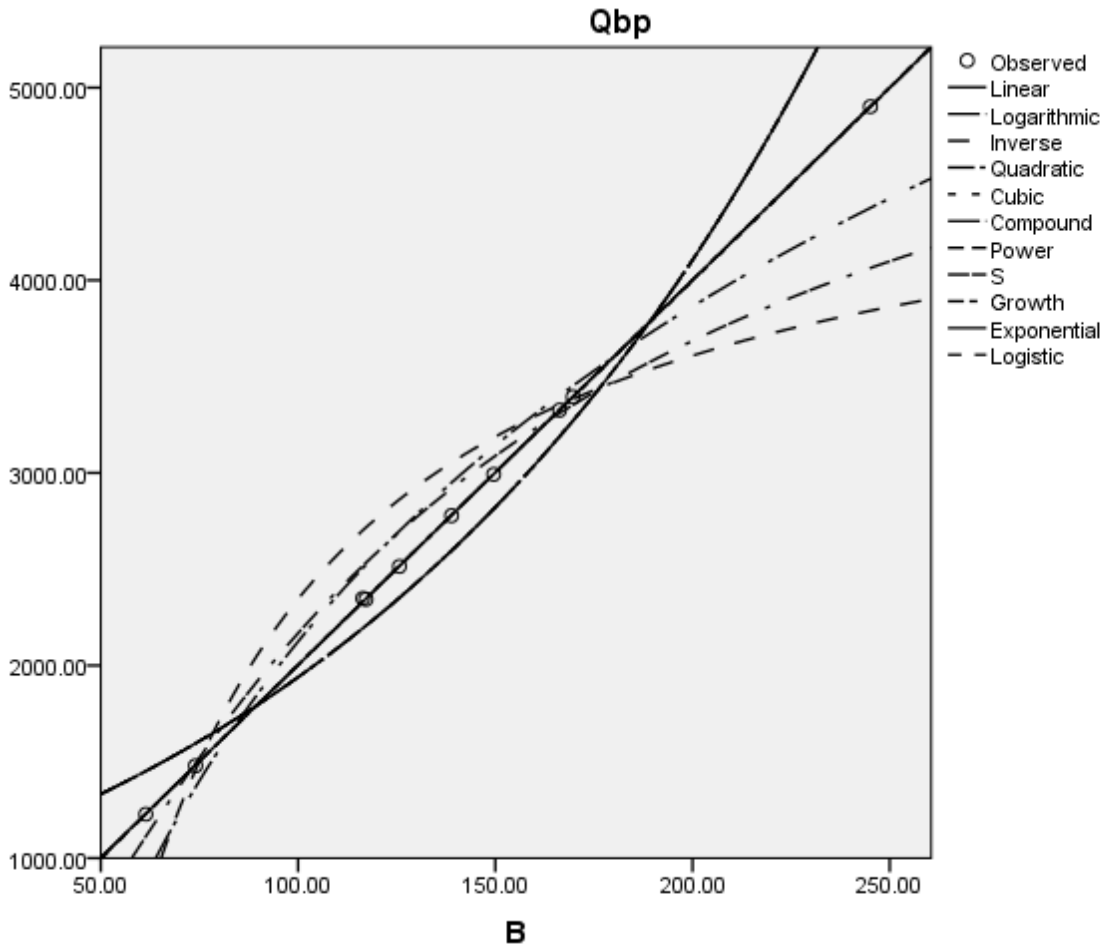


Figure 59: Curve fitting plot of quantity of binder against Bitumen

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 98.7%. This result implies that the best model was the cubic model since the independent variable B was able to explain about 98.7% of the total variability in the dependent variable Qbp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, B contributes to the proposed model.

Table 6\$: Summary of Curve Fitting Analysis between Quantity of Binder Produced against Chipping c15

Model Summary and Parameter Estimates

Dependent Variable: Qbp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.093	.816	1	8	.393	2543.842	.174
Logarithmic	.351	4.319	1	8	.071	-1611.577	678.035
Inverse	.694	18.163	1	8	.003	4293.045	-743255.488
Quadratic	.997	1099.566	2	7	.000	-227.991	6.286
Cubic	.998	1637.811	2	7	.000	-11.482	5.372
Compound	.110	.986	1	8	.350	2355.934	1.000
Power	.395	5.220	1	8	.052	429.007	.278
S	.824	37.425	1	8	.000	8.501	-313.079
Growth	.110	.986	1	8	.350	7.765	7.314E-005
Exponential	.110	.986	1	8	.350	2355.934	7.314E-005
Logistic	.110	.986	1	8	.350	.000	1.000

The independent variable is c15.

Source: SPSS 17.0

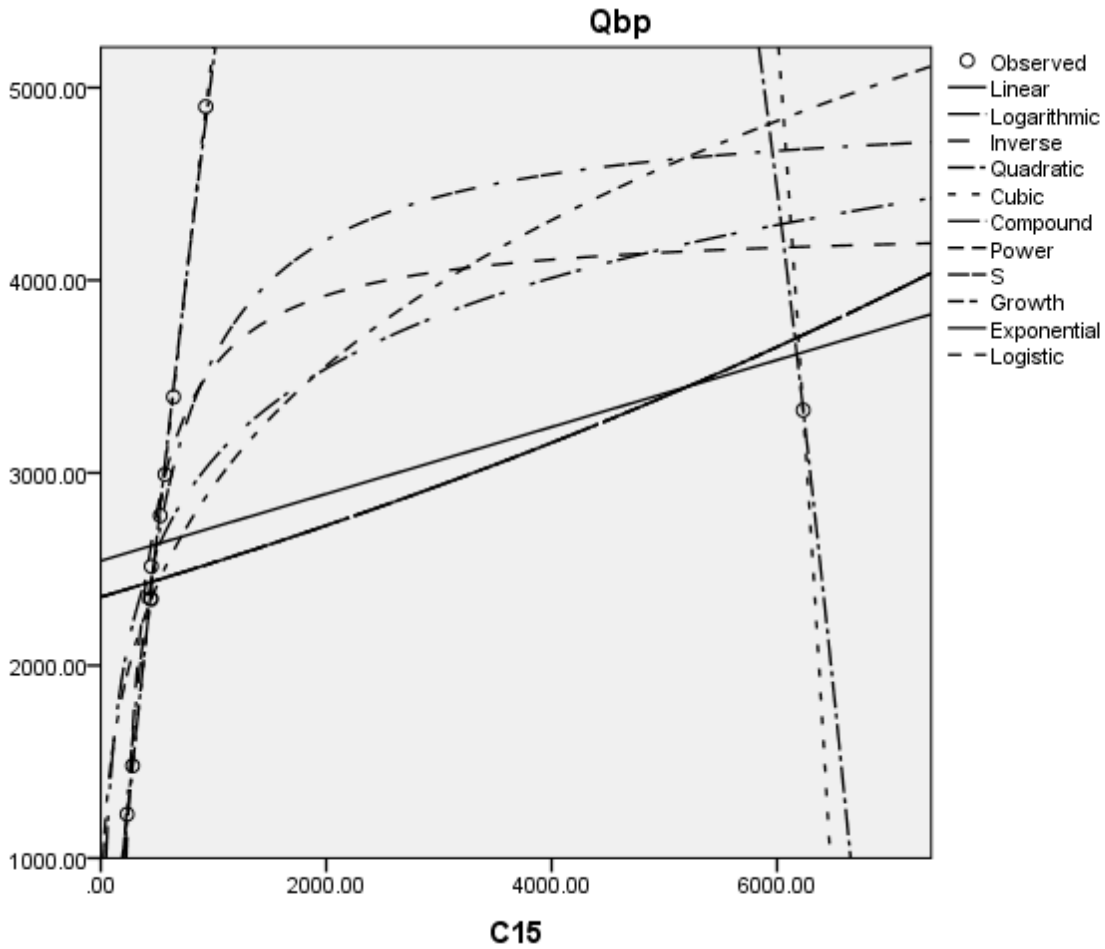


Figure 60: Curve fitting plot of a quantity of binder produced against chipping c15

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.8%. This result implies that the best model was the cubic model since the independent variable c15 was able to explain about 99.8% of the total variability in the dependent variable Qbp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, c15 contributes to the proposed model.

4.18 Generalized Nonlinear Model Analysis on the Estimation of Quantity of Binder produced for maintenance of roads in Anambra State

This section deals with estimation of the quantity of binder produced for the maintenance of roads in Anambra State. The generalized nonlinear model was used because it was found from the curve fitting analysis that the explanatory variables follow a nonlinear characteristic model (e.g. Cubic model). Hence, we shall design the generalize nonlinear model using the "gnm" function in R-programming.

Table 65: Summary of Quantity of Binder Produced and Explanatory Parameters

Qbp	MMT	MRH	MRR	MeF	MR	ME	S	C5	C10	B	C15
2514.7	32	72	121.3	94.5	17.8	3.5	1169.3	286.7	455.2	125.7	447.8
1227.9	32.8	74.9	13.3	94.5	18	4.3	571	139.9	222.2	61.4	233.3
1479.6	35.3	73.05	159.2	91.8	18	4.3	688	168.7	267.8	74	281.1
2348.5	36.7	75.5	168.9	89.9	18.1	4.2	1082.8	265.4	421.5	116.4	442.4
3325.7	32.5	72.7	171.4	88.9	18.3	4.2	1546.5	379.1	601.9	166.3	6232
2344	32.7	74	189.45	89.9	18.6	4.2	1089.9	267.2	424.3	117.2	445.4
4901.3	33.1	79.7	162.9	89.9	18.6	4.3	2279.1	558.7	887.1	245.1	931.2
2992.6	32.8	78.7	151.71	88.9	18.7	4.3	1391.6	341.1	541.7	149.6	568.6
3394.6	32.5	80.9	163.5	89.7	18.9	4.2	1578.5	386.9	614.4	169.7	644.9
2777.7	34.4	79.8	166.8	90.4	19	4.4	1291.6	316.7	502.8	138.9	527.8

The R-code for executing the generalized nonlinear model for estimation of the quantity of binder produced is written below using details presented in the Table 65. It should be noted that Qbp represents the dependent variable while variables MMT, MRH, MRR, MeF, S, C5, C10, B and C15 represents the independent variables.

The result of the generalized nonlinear model for estimating quantity of binder produced was obtained as

Call:

```
gnm(formula = Qbp ~ MMT + MRH + MRR + MeF + S + C5 + C10 + B +
     C15, family = gaussian, data = NULL, method = "gnmFit", start = NULL)
```

Coefficients:

(Intercept)	MMT	MRH	MRR	MeF	S
-4.631e+03	-1.704e+00	-2.008e+01	7.586e-02	6.551e+01	5.656e+01
C5	C10	B	C15		
1.685e+03	6.054e+00	-4.442e+03	1.944e+01		

Deviance: 4.546375e-19

Pearson chi-squared: 4.546375e-19

Residual df: 0

Call:

```
gnm(formula = Qbp ~ MMT + MRH + MRR + MeF + S + C5 + C10 + B +
```

C15, family = gaussian, data = NULL, method = "gnmFit", start = NULL)

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-4631	Inf	0	1
MMT	-1.7	Inf	0	1
MRH	-20.08	Inf	0	1
MRR	0.08	Inf	0	1
MeF	65.51	Inf	0	1
S	56.56	Inf	0	1
C5	1685	Inf	0	1
C10	6.05	Inf	0	1
B	-4442	Inf	0	1
C15	19.44	Inf	0	1

(Dispersion parameter for gaussian family taken to be Inf)

Residual deviance: 4.5464e-19 on 0 degrees of freedom

AIC: -394.99

Number of iterations: 1

Table 66: Distribution of Observed Quantity of Binder Produced and Estimated Quantity of Binder Produced for maintenance of Roads in Anambra State

Year	Qbp	Estimated.Qbp
2004	2514.7	2504.7
2005	1227.9	1226.9
2006	1479.6	1459.6
2007	2348.5	2328.5
2008	3325.7	3125.7
2009	2344	2342
2010	4901.3	4900.3
2011	2992.6	2982.6
2012	3394.6	3394.6
2013	2777.7	2737.7

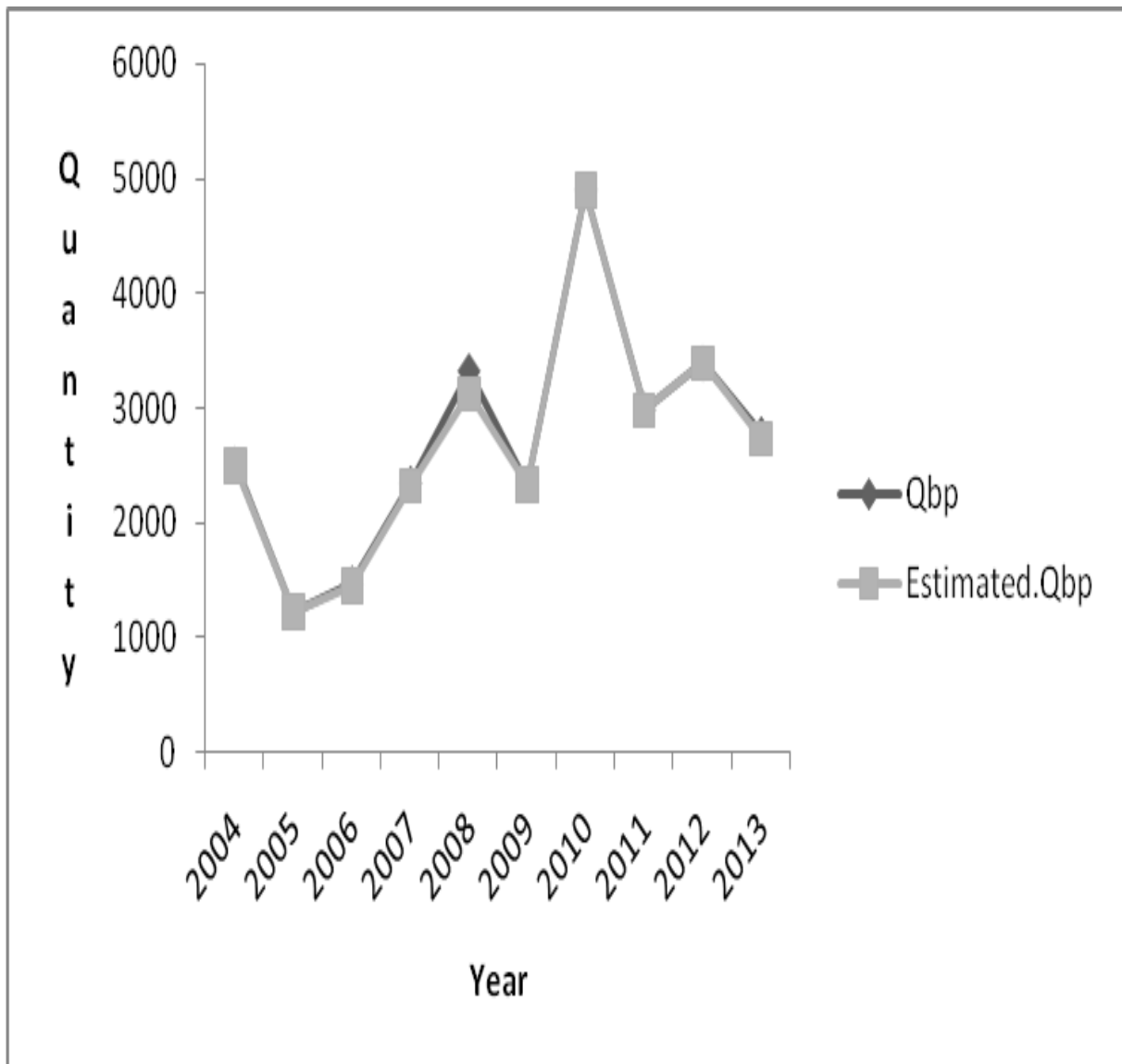


Figure 61: Distribution of Quantity of Binder Produced (Qbp) and Estimated quantity produced using the model (Estimated.Qbp) over the observed years

The result of generalized nonlinear model found a Pearson Chi-squared value of $4.546375e-19$ and an Akaike Information Criterion (AIC) value of -394.99 .

Also obtained was a model for estimating Qbp which can be expressed as;

$$Qbp = -4631 - 1.7 * MMT - 20.08 * MRH + 0.08 * MRR + 65.51 * MeF + 56.56 * S + 1685 * C5 + 6.05 * C10 - 4442 * B + 19.44 * C15$$

In addition, Figure 61 showed that the obtained model was able to estimate the quantity of binder produced with less variation since the variation between the estimated quantity of binder produced using the model and the observed appears insignificant. This implies that the models have the properties of generating good estimates of quantity of binder produced for the maintenance of roads in Anambra State.

4:19 Curve Estimation Analysis between Quantity of Wearing Produced (QwP) for Road maintenance in Anambra State

Curve estimation analysis was performed to determine the explanatory variables that contributed to the attributes of quantity of wearing produced for road maintenance in Anambra State and to also assess the best type of model to employ in the estimation of the Quantity of wearing produced with the observed period. The models considered in this section includes the linear model, Logarithmic model, Inverse model, Quadratic model, Cubic model, Compound model, Power model, S curve model, Growth model, Exponential model and Logistic model.

Table 67: Summary of Quantity of wearing Produced and Explanatory Parameters

Qwp	MMT	MRH	MRR	MeF	MR	ME	S	C5	C10	B
272	32	72	121.3	94.5	17.8	3.5	176.8	26.7	51.7	16.9
1754	32.8	74.9	13.3	94.5	18	4.3	1140.1	171.9	333.3	108.7
2571	35.3	73.05	159.2	91.8	18	4.3	1671.2	251.9	488.5	159.4
5521	36.7	75.5	168.9	89.9	18.1	4.2	3588.7	541.1	1048.9	342.3
6529	32.5	72.7	171.4	88.9	18.3	4.2	4243.9	639.9	1240.5	391.7
4028	32.7	74	189.45	89.9	18.6	4.2	2618.2	394.7	765.3	249.7
3973	33.1	79.7	162.9	89.9	18.6	4.3	2582.5	389.4	754.9	246.3
1715	32.8	78.7	151.71	88.9	18.7	4.3	1114.8	168.1	325.9	106.3
3670	32.5	80.9	163.5	89.7	18.9	4.2	2385.5	359.7	697.3	227.5
6597	34.4	79.8	166.8	90.4	19	4.4	4288.1	1646.5	1253.4	409

Using details from the Table 67, the curve estimation analysis was performed where quantity of wearing produced (Qwp) is the dependent or response variable and MMT, MRH, MRR, MeF, MR, ME, S, C5, C10 and B are the explanatory parameters.

Table 68: Summary of Curve Fitting Analysis Between quantity of wearing produce against mean maximum Temperature

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.150	1.409	1	8	.269	-14659.044	547.253
Logarithmic	.152	1.439	1	8	.265	-62750.430	18920.829
Inverse	.155	1.469	1	8	.260	23207.198	-653208.797
Quadratic	.187	.806	2	7	.484	-284605.115	16317.395
Cubic	.189	.806	2	7	.041	-284605.115	16317.395
Compound	.177	1.720	1	8	.226	.376	1.305
Power	.183	1.787	1	8	.218	2.065E-011	9.270
S	.188	1.857	1	8	.210	17.579	-322.257
Growth	.177	1.720	1	8	.226	-.979	.266
Exponential	.177	1.720	1	8	.226	.376	.266
Logistic	.177	1.720	1	8	.226	2.661	.766

The independent variable is MMT

Source: SPSS 17.0

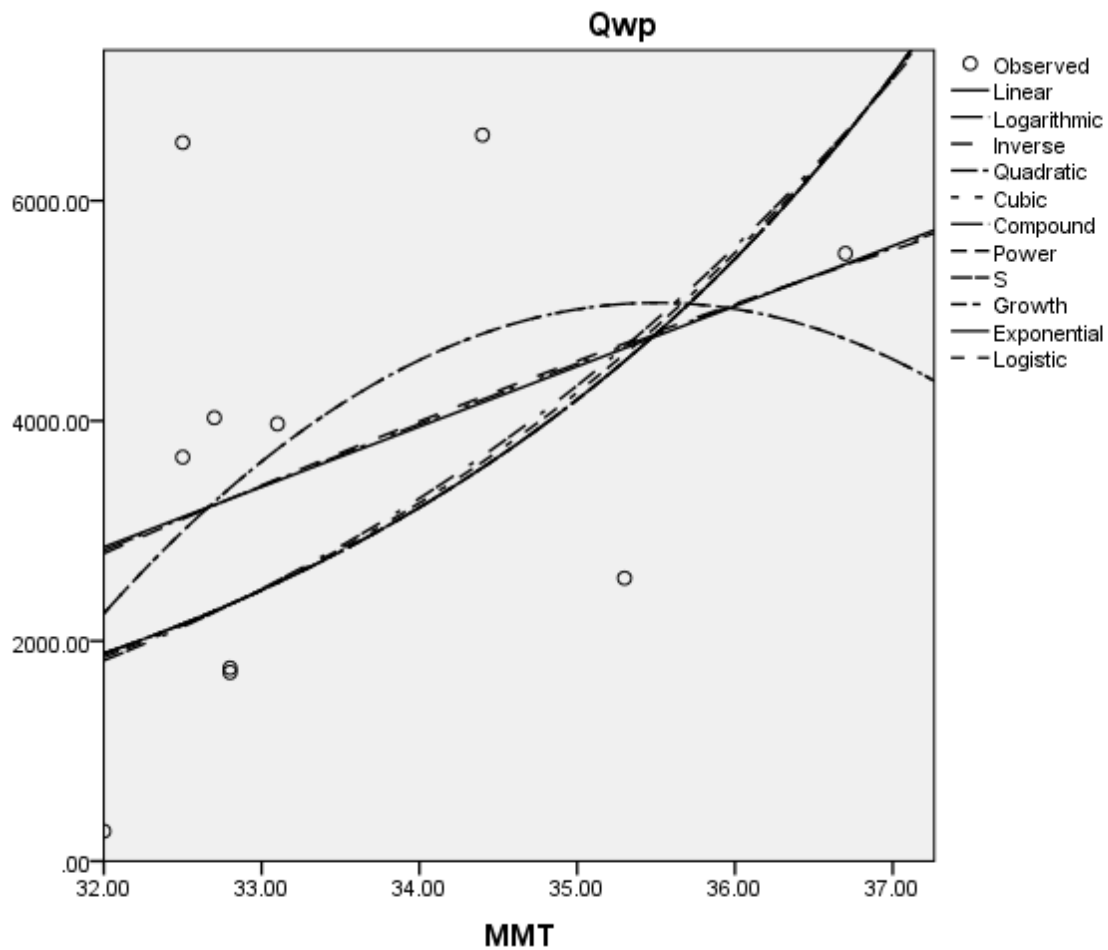


Figure 62: Curve fitting plot of quantity of wearing produced against Mean maximum Temperature

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 18.9%. This result implies that the best model was the cubic model since the independent variable MMT was able to explain about 18.9% of the total variability in the dependent variable Qwp with a p-value of 0.041 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.041 < \alpha=0.05$). Hence, MMT contributes to the proposed model.

Table 69: Summary of Curve Fitting Analysis between quantity of wearing produce against mean relative humidity

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.054	.457	1	8	.518	-7596.758	147.911
Logarithmic	.055	.463	1	8	.515	-45612.838	11376.120
Inverse	.055	.470	1	8	.512	15166.550	-874204.486
Quadratic	.067	.252	2	7	.784	-221949.288	5763.511
Cubic	.069	.252	2	7	.049	-221949.288	5763.511
Compound	.142	1.329	1	8	.282	.781	1.114
Power	.146	1.363	1	8	.277	6.635E-013	8.306
S	.149	1.400	1	8	.271	16.373	-641.133
Growth	.142	1.329	1	8	.282	-.248	.108
Exponential	.142	1.329	1	8	.282	.781	.108
Logistic	.142	1.329	1	8	.282	1.281	.898

The independent variable is MRH.

Source: SPSS 17.0

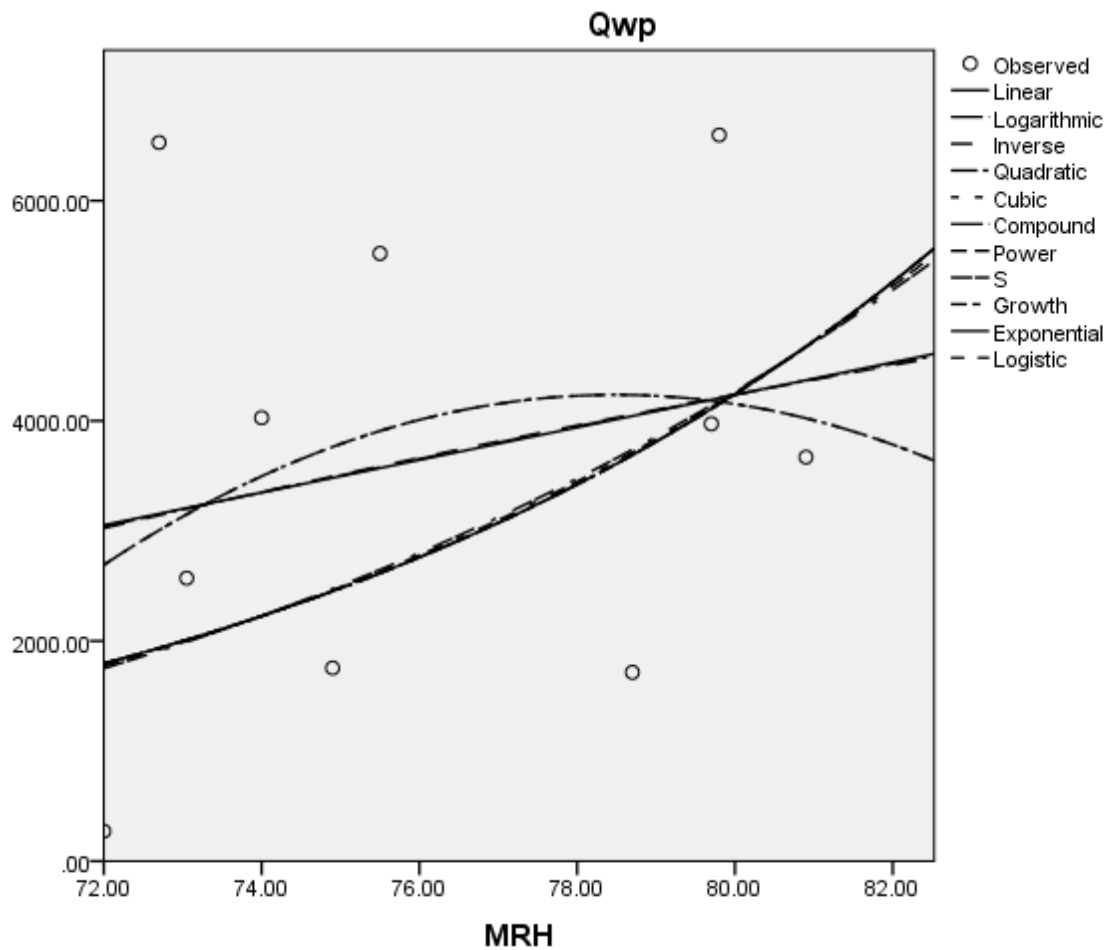


Figure 63: Curve fitting plot of quantity of wearing produced against Mean relative humidity

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 6.9%. This result implies that the best model was the cubic model since the independent variable MRH was able to explain about 6.9% of the total variability in the dependent variable Qwp with a p-value of 0.049 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.049 < \alpha=0.05$). Hence, the MRH contributes to the proposed model.

Table 70: Summary of Curve Fitting Analysis between Quantity of wearing produced and mean relative rainfall

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.284	3.166	1	8	.113	340.276	22.627
Logarithmic	.170	1.642	1	8	.236	-1656.893	1101.374
Inverse	.116	1.049	1	8	.336	4099.539	-33174.539
Quadratic	.510	3.643	2	7	.082	2433.164	-67.817
Cubic	.647	3.670	3	6	.042	6743.953	-432.649
Compound	.212	2.152	1	8	.181	773.156	1.009
Power	.089	.785	1	8	.401	498.376	.357
S	.042	.350	1	8	.570	8.054	-8.931
Growth	.212	2.152	1	8	.181	6.650	.009
Exponential	.212	2.152	1	8	.181	773.156	.009
Logistic	.212	2.152	1	8	.181	.001	.991

The independent variable is MRR
Source: SPSS 17.0

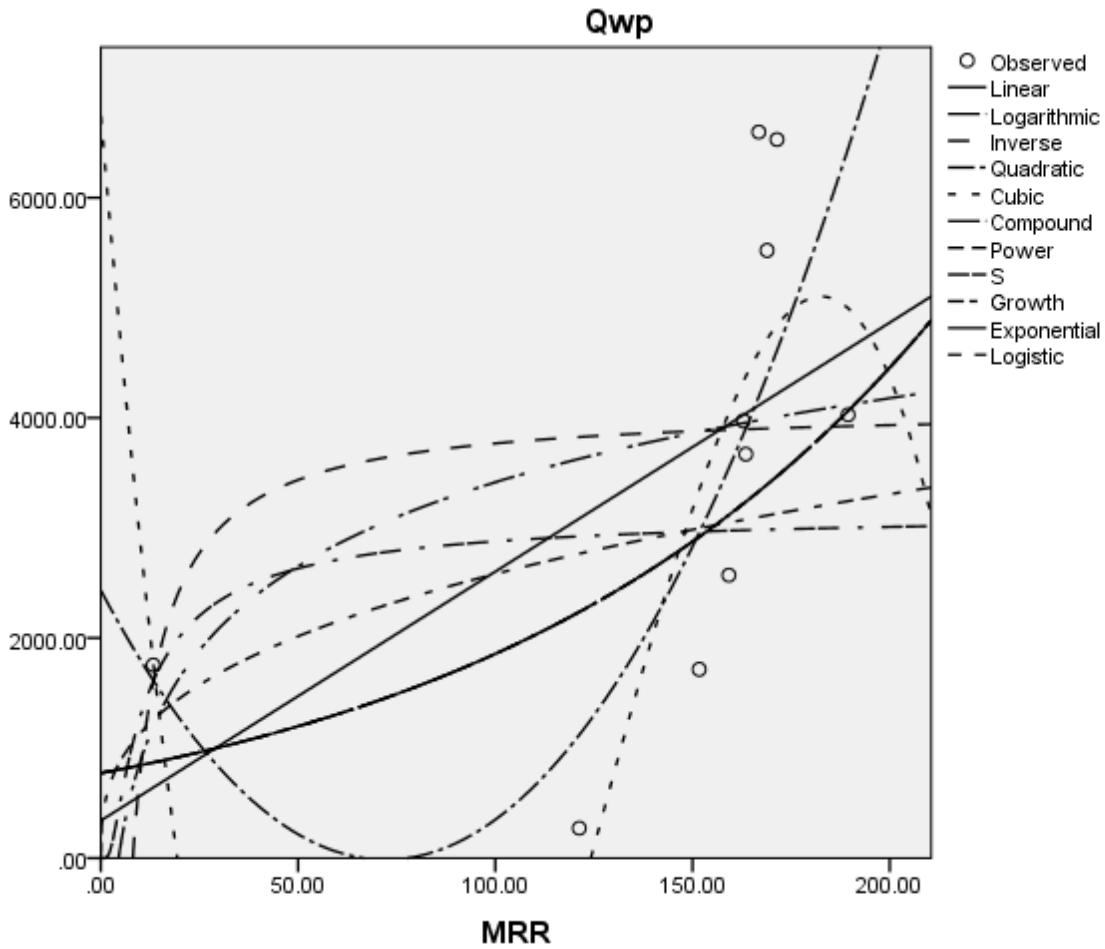


Figure 64: Curve fitting plot of quantity of wearing produced against Mean relative rainfall

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 64.7%. This result implies that the best model was the S curve model since the independent variable MRR was able to explain about 64.7% of the total variability in the dependent variable Qwp with a p-value of 0.042 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.042 < \alpha=0.05$). Hence, MRR contributes to the proposed model.

Table 71: Summary of Curve Fitting Analysis between Quantity of wearing produced and Mean efficiency

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.419	5.779	1	8	.043	63418.486	-657.810
Logarithmic	.417	5.724	1	8	.044	275274.992	-60239.555
Inverse	.415	5.667	1	8	.045	-57066.468	5514089.109
Quadratic	.422	5.833	1	8	.042	33301.980	.000
Cubic	.475	3.167	2	7	.105	-927449.788	15534.571
Compound	.528	8.951	1	8	.017	3036083590596 3764.000	.719
Power	.524	8.824	1	8	.018	4.601E+062	-30.240
S	.541	8.696	1	8	.018	-22.532	2766.433
Growth	.528	8.951	1	8	.017	37.952	-.330
Exponential	.528	8.951	1	8	.017	3036083590596 3764.000	-.330
Logistic	.528	8.951	1	8	.017	3.294E-017	1.392

The independent variable is MeF.

Source: SPSS 17.0

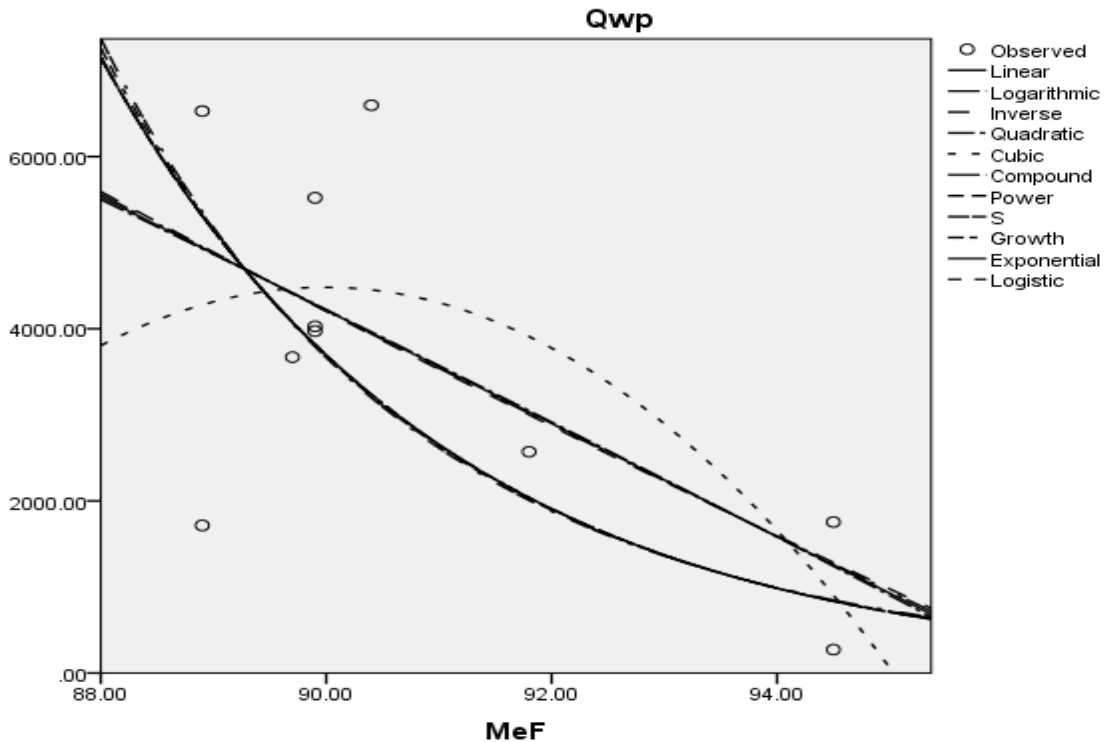


Figure 65: Curve fitting plot of quantity of wearing produced against Mean efficiency

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 54.1%. This result implies that the best model was the S curve model since the independent variable MeF was able to explain about 54.1% of the total variability in the dependent variable Qwp with a p-value of 0.018 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.018 < \alpha=0.05$). Hence, MeF contributes to the proposed model.

Table 72: Summary of Curve Fitting Analysis between Quantity of Wearing Produced and Mean Radiation

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.217	2.212	1	8	.175	-40042.897	2375.321
Logarithmic	.219	2.239	1	8	.173	-124200.250	43907.270
Inverse	.221	2.266	1	8	.171	47780.980	-811396.841
Quadratic	.217	2.212	1	8	.175	-40042.897	2375.321
Cubic	.279	1.353	2	7	.318	-969735.414	78192.626
Compound	.308	3.555	1	8	.096	2.089E-007	3.551
Power	.312	3.629	1	8	.093	5.605E-027	23.482
S	.317	3.705	1	8	.090	31.587	-434.975
Growth	.308	3.555	1	8	.096	-15.381	1.267
Exponential	.308	3.555	1	8	.096	2.089E-007	1.267
Logistic	.308	3.555	1	8	.096	4786407.854	.282

The independent variable is MR.

Source: SPSS 17.0

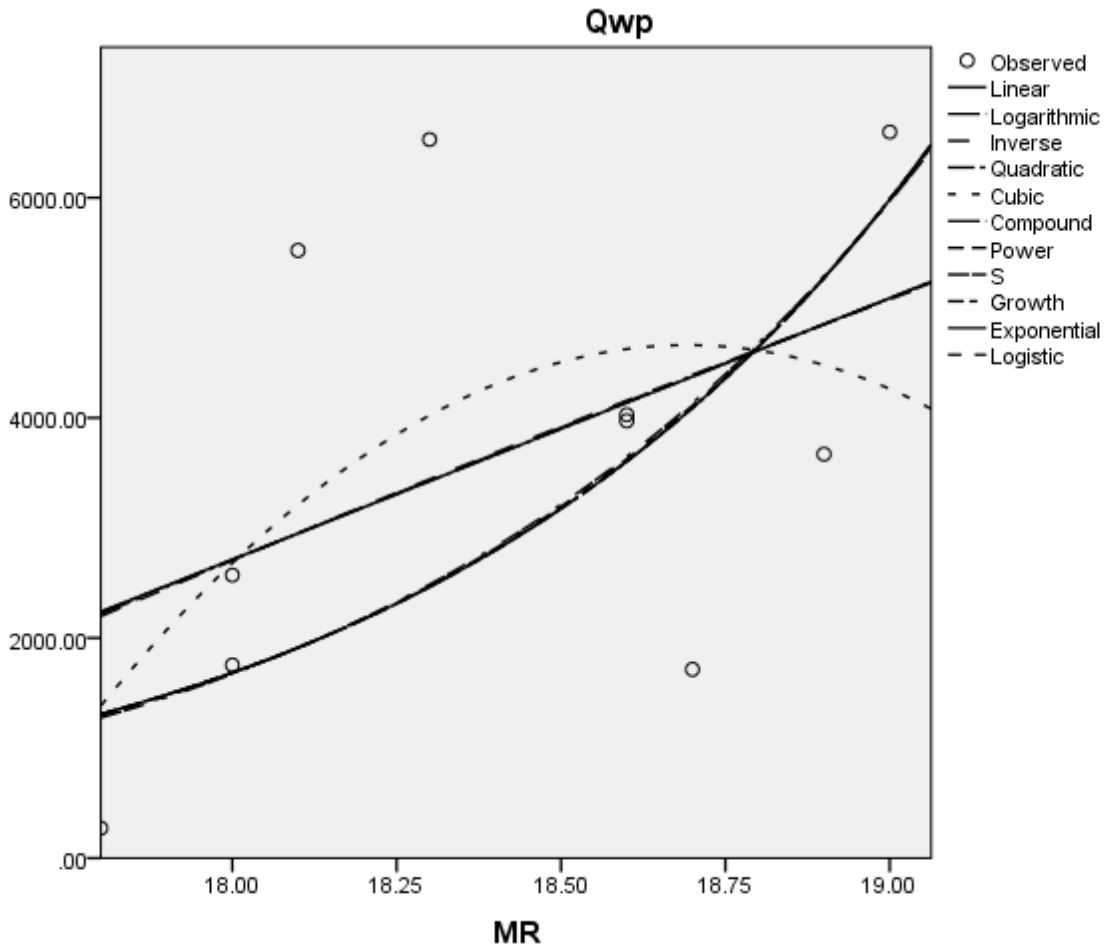


Figure 66: Curve fitting plot of quantity of wearing produced against Mean Radiation

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 31.7%. This result implies that the best model was the S curve model since the independent variable MR was able to explain about 31.7% of the total variability in the dependent variable Qwp with a p-value of 0.090 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.09 > \alpha=0.05$). Hence, MR does not contribute to the proposed model.

Table 73: Summary of Curve Fitting Analysis between Quantity of Wearing Produced and Mean Evaporation

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.270	2.953	1	8	.124	-14721.453	4387.698
Logarithmic	.274	3.018	1	8	.121	-21006.394	17240.274
Inverse	.278	3.079	1	8	.117	19808.810	-67397.758
Quadratic	.297	1.481	2	7	.291	-119659.703	58477.213
Cubic	.297	1.481	2	7	.291	-119659.703	58477.213
Compound	.649	14.794	1	8	.005	.008	21.065
Power	.660	15.532	1	8	.004	.000	11.980
S	.670	16.239	1	8	.004	19.159	-46.845
Growth	.649	14.794	1	8	.005	-4.833	3.048
Exponential	.649	14.794	1	8	.005	.008	3.048
Logistic	.649	14.794	1	8	.005	125.572	.047

The independent variable is ME

Source: SPSS 17.0

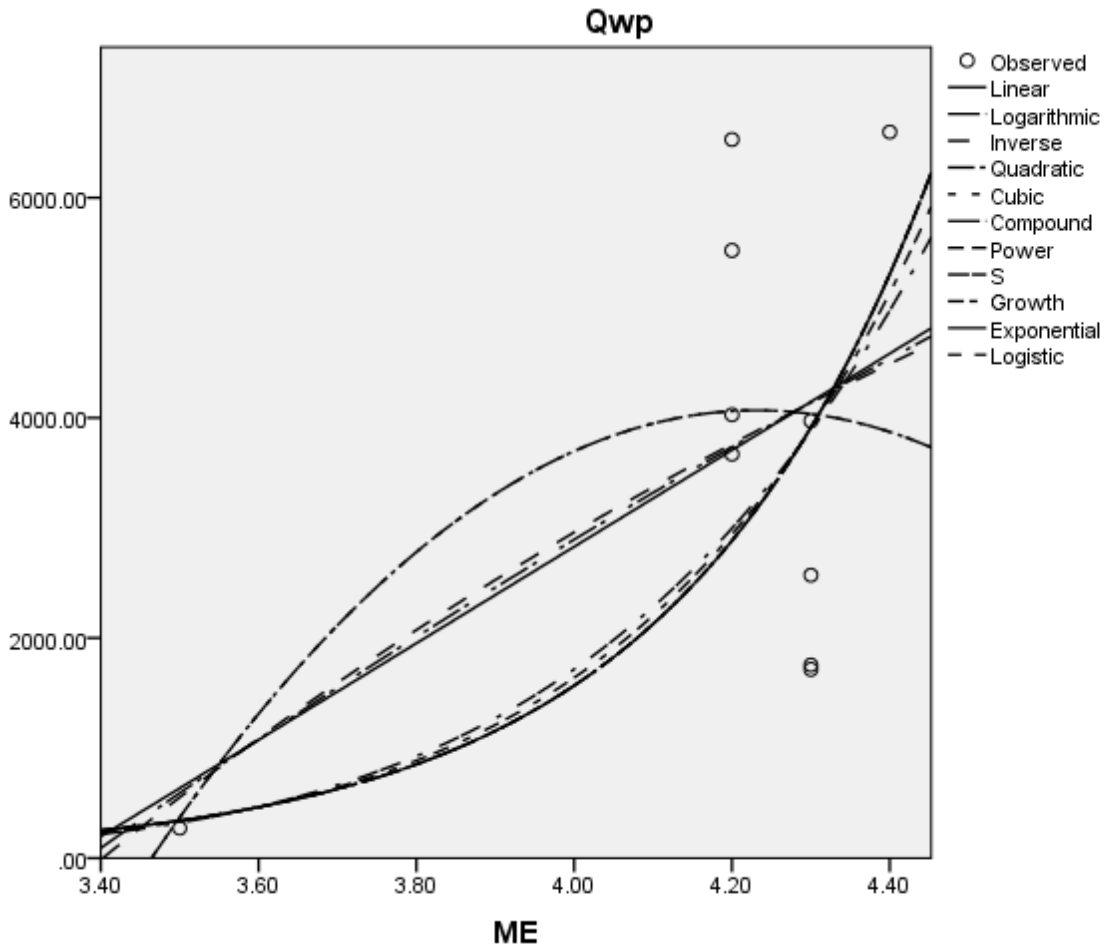


Figure 67: Curve fitting plot of quantity of wearing produced against Mean Evaporation

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 67.0%. This result implies that the best model was the S curve model since the independent variable ME was able to explain about 67.0% of the total variability in the dependent variable Qwp with a p-value of 0.004 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.004 < \alpha=0.05$). Hence, ME contributed to the proposed model.

Table 74: Summary of Curve Fitting Analysis between Quantity of Wearing Produced and Stone-dust

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.992	.825	1	8	.390	1960.207	1.342
Logarithmic	.958	1.163	1	8	.312	-9645.678	1880.611
Inverse	.854	1.370	1	8	.275	5520.962	-2038849.912
Quadratic	.992	.652	2	7	.550	-1076.432	6.268
Cubic	.993	.374	3	6	.025	-293.756	4.155
Compound	.966	.547	1	8	.481	1489.477	1.000
Power	.989	.524	1	8	.490	44.290	.586
S	.935	.448	1	8	.522	8.437	-549.483
Growth	.966	.547	1	8	.481	7.306	.000
Exponential	.966	.547	1	8	.481	1489.477	.000
Logistic	.966	.547	1	8	.481	.001	1.000

The independent variable is S

Source: SPSS 17.0

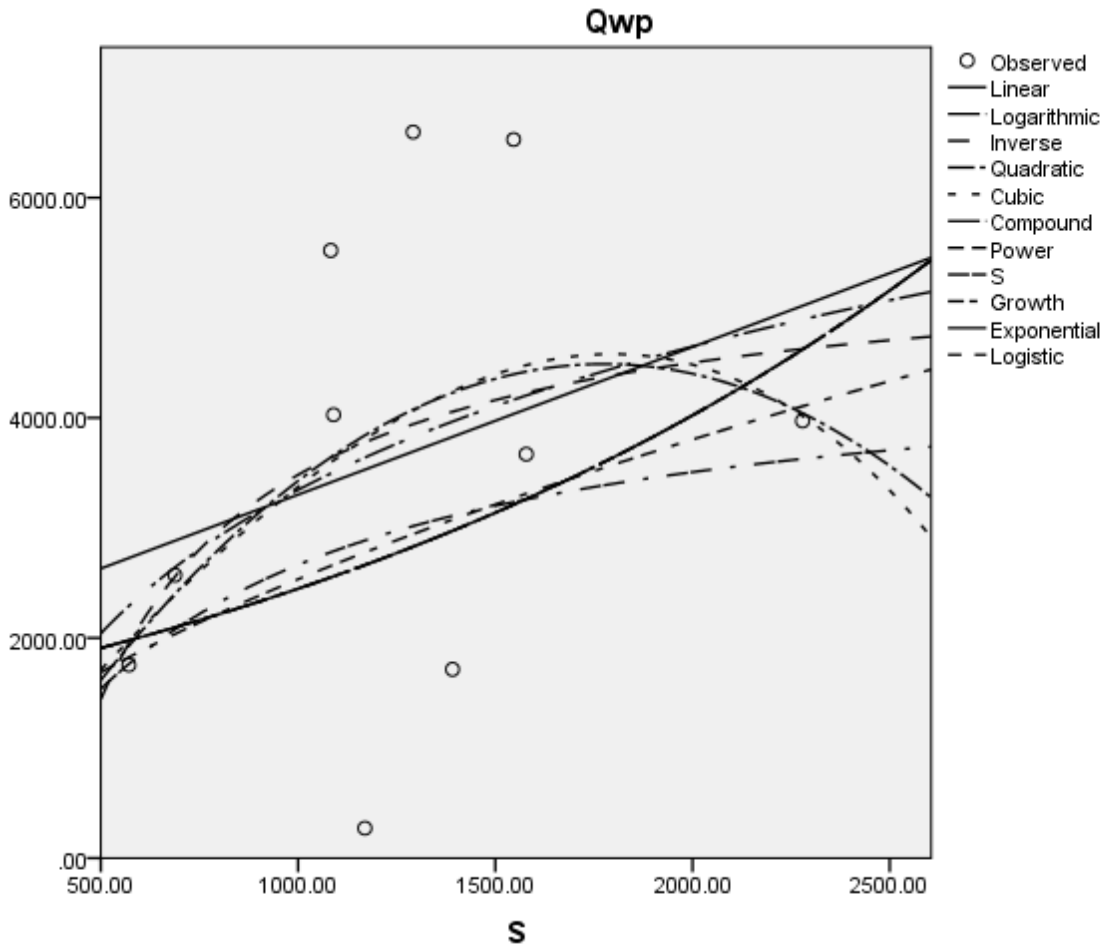


Figure 68: Curve fitting plot of quantity of wearing produced against Stone-dust

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.3%. This result implies that the best model was the cubic model since the independent variable S was able to explain about 99.3% of the total variability in the dependent variable Qwp with a p-value of 0.025 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.025 < \alpha=0.05$). Hence, S contributes to the proposed model.

Table 75: Summary of Curve Fitting Analysis between Quantity of wearing produced and Chipping c5

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.996	.826	1	8	.390	1959.969	5.475
Logarithmic	.975	1.163	1	8	.312	-7001.178	1880.528
Inverse	.910	1.370	1	8	.275	5520.339	-499612.002
Quadratic	.996	.652	2	7	.550	-1074.679	25.558
Cubic	.998	.374	3	6	.026	-283.974	16.849
Compound	.972	.546	1	8	.481	1489.707	1.002
Power	.997	.524	1	8	.490	101.067	.586
S	.977	.447	1	8	.522	8.437	-134.610
Growth	.972	.546	1	8	.481	7.306	.002
Exponential	.972	.546	1	8	.481	1489.707	.002
Logistic	.972	.546	1	8	.481	.001	.998

The independent variable is c5.

Source: SPSS 17.0

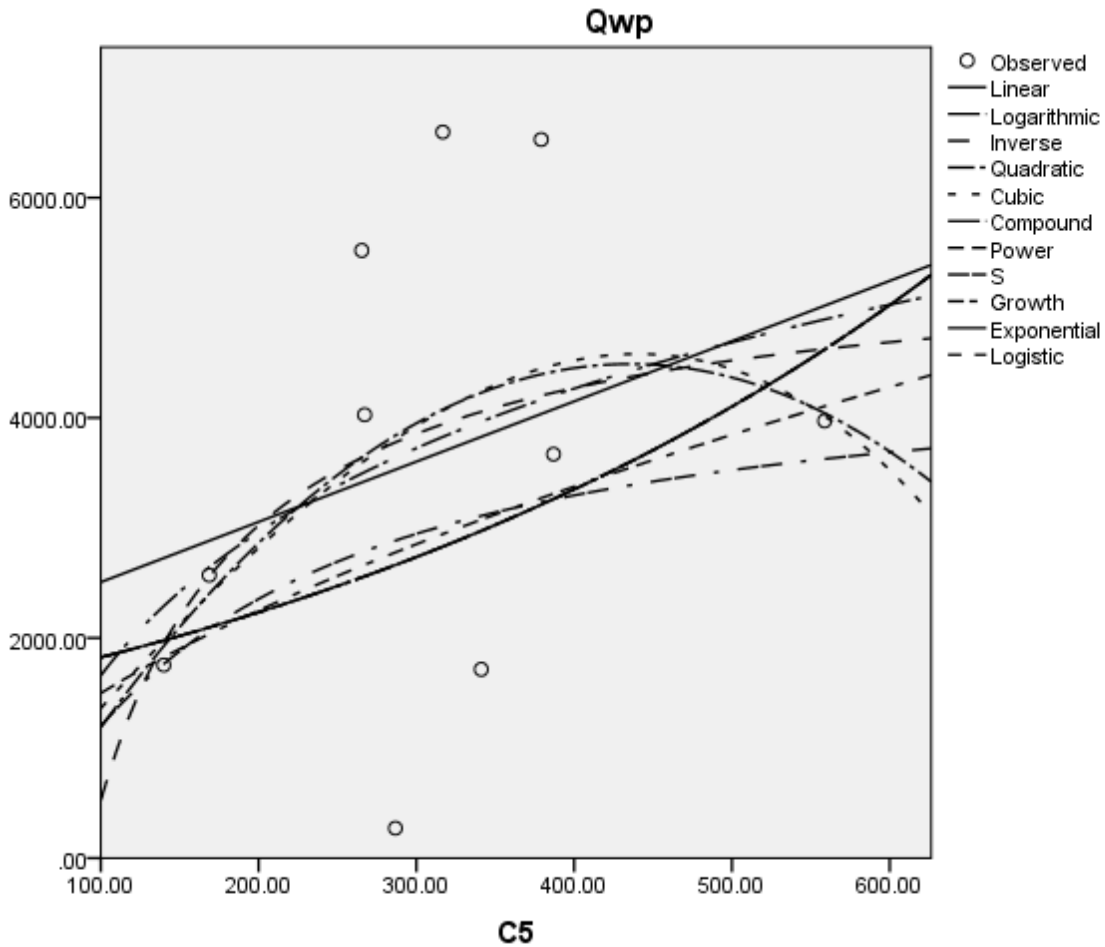


Figure 69: Curve fitting plot of quantity of wearing produced against Chippings c5

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.8%. This result implies that the best model was the cubic model since the independent variable c5 was able to explain about 99.8% of the total variability in the dependent variable Qwp with a p-value of 0.026 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.026 > \alpha=0.05$). Hence, c5 contributes to the proposed model.

Table 76: Summary of Curve Fitting Analysis between Quantity of wearing produced and chipping c10

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.961	.825	1	8	.000	1960.238	3.448
Logarithmic	.974	1.163	1	8	.000	-7869.720	1880.363
Inverse	.899	1.370	1	8	.000	5520.412	-793362.304
Quadratic	.920	.652	2	7	.000	-1075.320	16.099
Cubic	.993	.374	3	6	.000	-295.092	10.687
Compound	.974	.546	1	8	.000	1489.642	1.001
Power	.912	.524	1	8	.000	77.067	.586
S	.972	.448	1	8	.000	8.437	-213.780
Growth	.974	.546	1	8	.000	7.306	.001
Exponential	.974	.546	1	8	.000	1489.642	.001
Logistic	.974	.546	1	8	.000	.001	.999

The independent variable is C10.

Source: SPSS 17.0

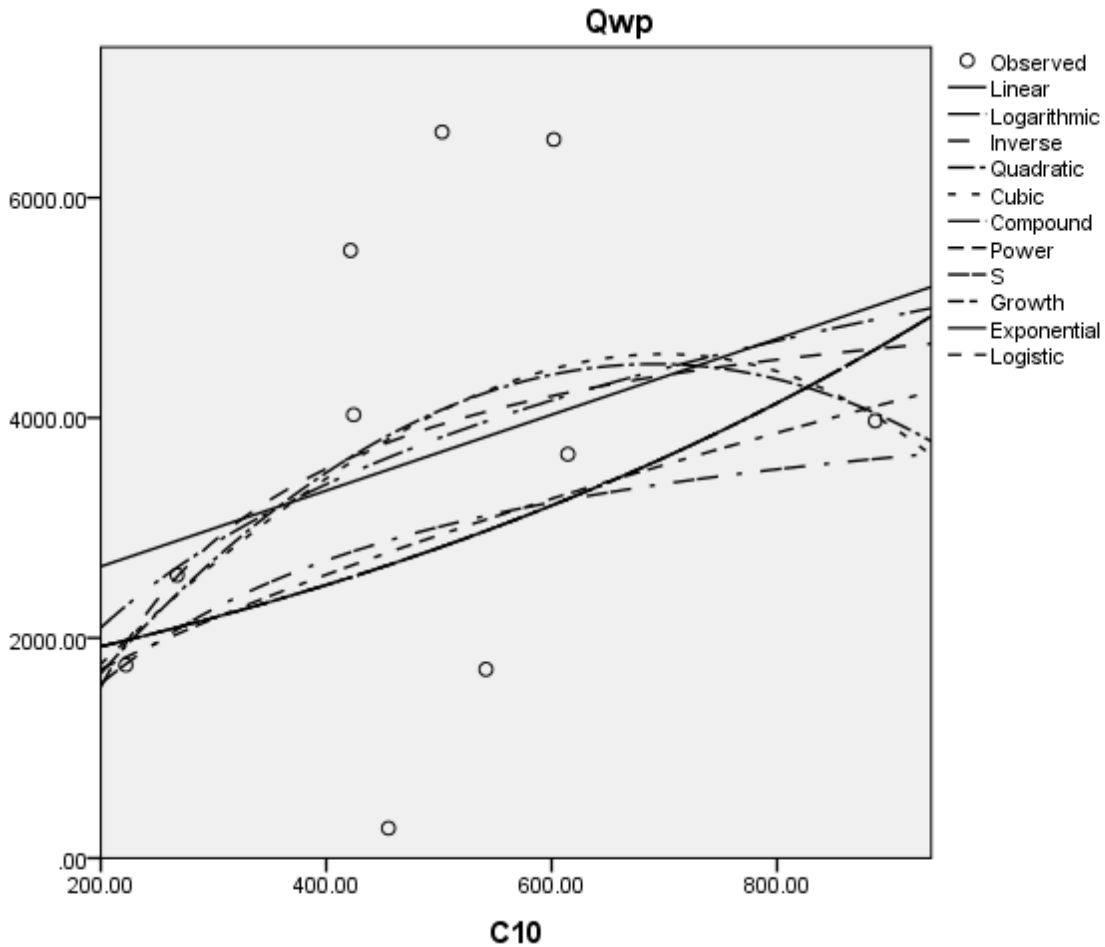


Figure 70: Curve fitting plot of quantity of wearing produced against chipping c10

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 99.3%. This result implies that the best model was the cubic model since the independent variable c10 was able to explain about 99.3% of the total variability in the dependent variable Qwp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 > \alpha=0.05$). Hence, c10 contributes to the proposed model.

Table 77: Summary of Curve Fitting Analysis between Quantity of Wearing Produced and Bitumen

Model Summary and Parameter Estimates

Dependent Variable: Qwp

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.996	.826	1	8	.000	1959.501	12.486
Logarithmic	.964	1.164	1	8	.000	-5456.932	1881.659
Inverse	.874	1.371	1	8	.000	5522.037	-219358.079
Quadratic	.996	.653	2	7	.000	-1078.983	58.317
Cubic	.998	.374	3	6	.000	-272.028	38.060
Compound	.974	.548	1	8	.000	1488.851	1.005
Power	.995	.525	1	8	.000	163.122	.586
S	.953	.449	1	8	.000	8.438	-59.145
Growth	.974	.548	1	8	.000	7.306	.005
Exponential	.974	.548	1	8	.000	1488.851	.005
Logistic	.974	.548	1	8	.000	.001	.995

The independent variable is B

Source: SPSS 17.0

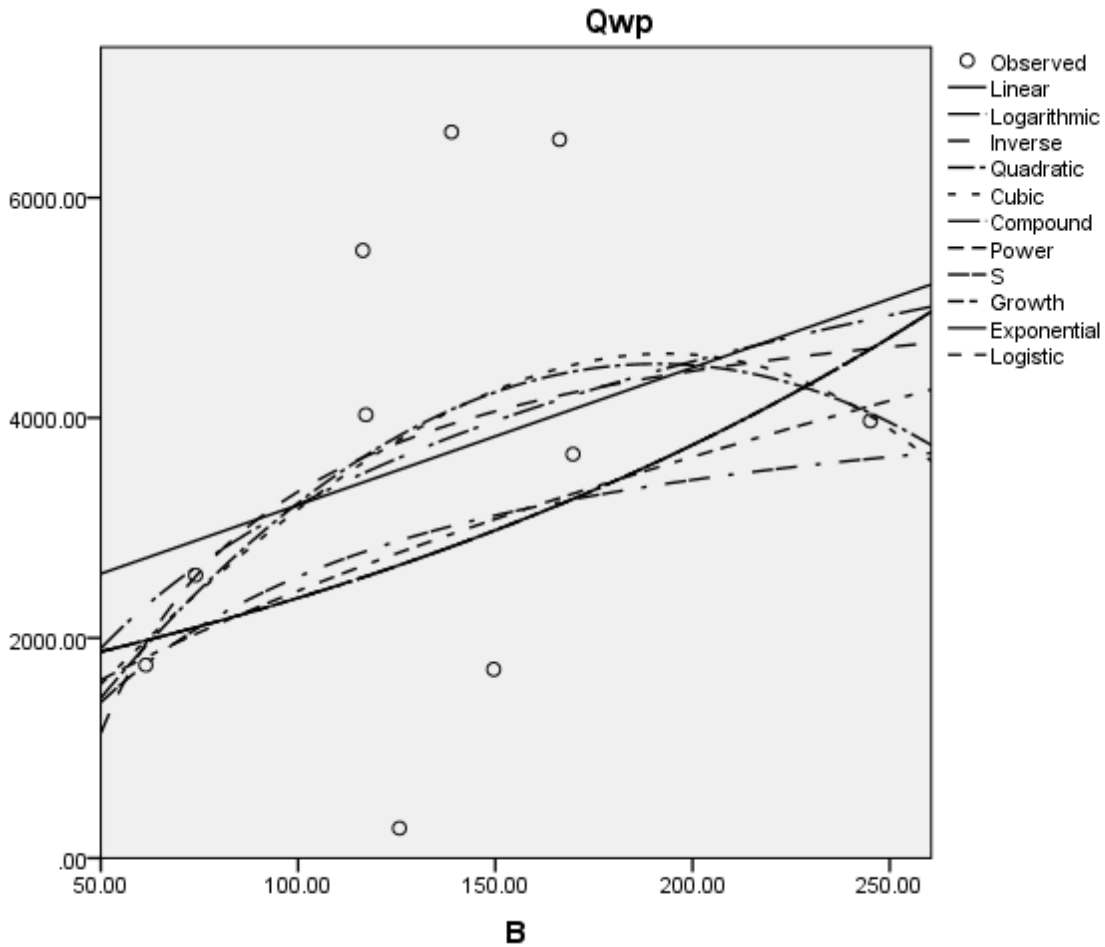


Figure 71: Curve fitting plot of quantity of wearing produced against Bitumen

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.8%. This result implies that the best model was the cubic model since the independent variable B was able to explain about 99.8% of the total variability in the dependent variable Qwp with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, B contributes to the proposed model.

4.20 Generalized Nonlinear Model Analysis on the Estimation of Quantity of Wearing Produced for Maintenance of Roads in Anambra State

This section deals with estimation of the quantity of wearing produced for the maintenance of roads in Anambra State. The generalized nonlinear model was used because it was found from the curve fitting analysis that the explanatory variables follow a nonlinear characteristic model (e.g. Cubic model). Hence, we shall design the generalize nonlinear model using the "gnm" function in R-programming.

Extracting the parameters that contributed to the attributes of the response variable in the curve estimation analysis and summarizing then in Table 78

Table 78: Summary of Quantity of wearing Produced and Extracted Explanatory Parameters

Qwp	MMT	MRH	MRR	MeF	ME	S	C5	C10	B
272	32	72	121.3	94.5	3.5	176.8	26.7	51.7	16.9
1754	32.8	74.9	13.3	94.5	4.3	1140.1	171.9	333.3	108.7
2571	35.3	73.05	159.2	91.8	4.3	1671.2	251.9	488.5	159.4
5521	36.7	75.5	168.9	89.9	4.2	3588.7	541.1	1048.9	342.3
6529	32.5	72.7	171.4	88.9	4.2	4243.9	639.9	1240.5	391.7
4028	32.7	74	189.45	89.9	4.2	2618.2	394.7	765.3	249.7
3973	33.1	79.7	162.9	89.9	4.3	2582.5	389.4	754.9	246.3
1715	32.8	78.7	151.71	88.9	4.3	1114.8	168.1	325.9	106.3
3670	32.5	80.9	163.5	89.7	4.2	2385.5	359.7	697.3	227.5
6597	34.4	79.8	166.8	90.4	4.4	4288.1	1646.5	1253.4	409

The R-code for executing the generalized nonlinear model for estimation of the quantity of wearing produced is written below using details presented in the Table 78. Recall that Qwp represents the dependent variable while variables MMT, MRH, MRR, MeF, ME, S, c5, c10 and B represents the independent variables.

The result of the generalized nonlinear model on the R console window for estimating quantity of wearing produced was obtained as

Call:

```
gnm(formula = Qwp ~ MMT + MRH + MRR + MeF + ME + S + c5 +
     c10 + B, family = gaussian, data = NULL, method = "gnmFit",
     start = NULL)
```

Coefficients:

(Intercept)	MMT	MRH	MRR	MeF	ME
-6.604396	-0.093002	0.004485	0.001999	0.072331	0.642684
S	c5	c10	B		
2.693796	0.919407	-4.424416	-0.008201		

Deviance: 1.458229e-23

Pearson chi-squared: 1.458229e-23

Residual df: 0

Call:

```
gnm(formula = Qwp ~ MMT + MRH + MRR + MeF + ME + S + C5 +
     C10 + B, family = gaussian, data = NULL, method = "gnmFit",
     start = NULL)
```

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)_1
(Intercept)	-6.6044	Inf	0	1
MMT	-0.093	Inf	0	1
MRH	0.00449	Inf	0	1
MRR	0.002	Inf	0	1
MeF	0.07233	Inf	0	1
ME	0.64268	Inf	0	1
S	2.6938	Inf	0	1
c5	0.91941	Inf	0	1
c10	-4.42442	Inf	0	1
B	-0.0082	Inf	0	1

(Dispersion parameter for gaussian family taken to be Inf)

Residual deviance: 1.4582e-23 on 0 degrees of freedom

AIC: -498.47

Number of iterations: 1

Table 79: Distribution of Observed Quantity of Wearing Produced and Estimated Quantity of Wearing Produced for Maintenance of Roads in Anambra State

Year	Qwp	Estimated.Qwp
2004	272	270
2005	1754	1724
2006	2571	2521
2007	5521	5501
2008	6529	6522
2009	4028	4018
2010	3973	3273
2011	1715	1615
2012	3670	3370
2013	6597	6297

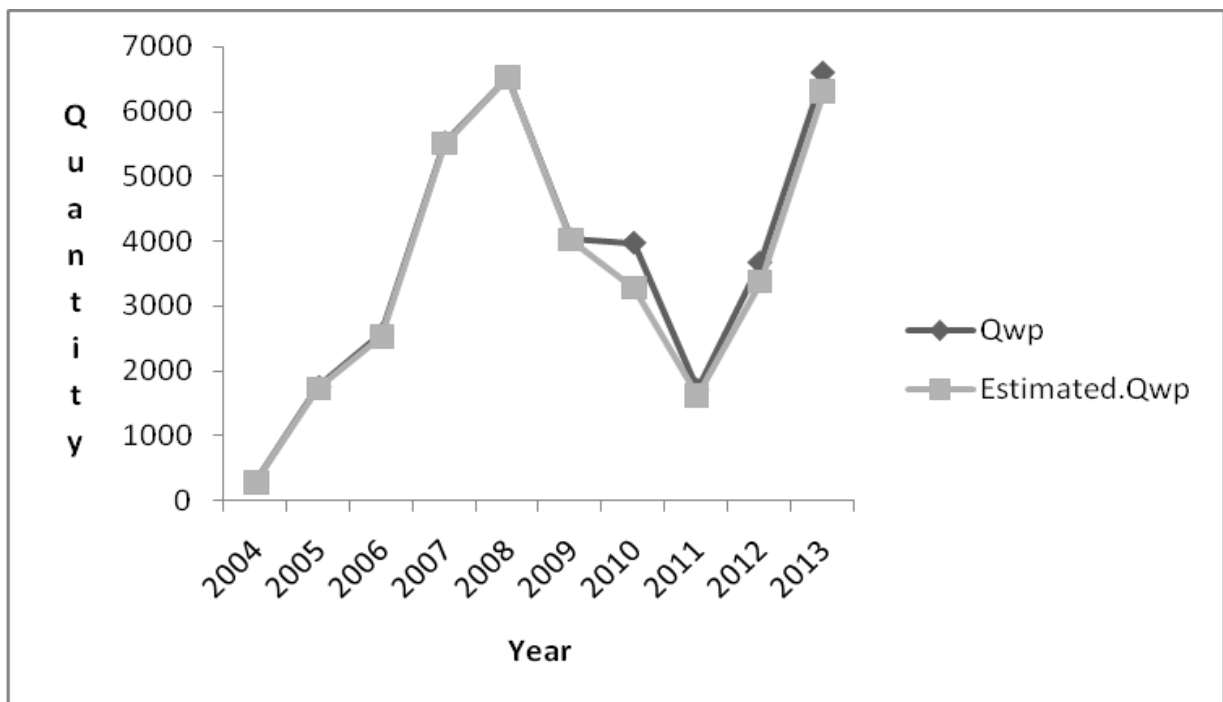


Figure 72: Distribution of Quantity of Wearing Produced (Qwp) and estimated quantity of wearing produced using the model (Estimated.Qwp) over the observed years

The result of generalized nonlinear model found a Pearson Chi-squared value of $1.458229e-23$ and an Akakike Information Criterion (AIC) value of -498.47 .

Also obtained was a model for estimating Qwp which can be expressed as;

$$Qwp = -6.6044 - 0.093 * MMT + 0.00449 * MRH + 0.002 * MRR + 0.07233 * MeF + 0.64268 * ME + 2.6938 * S + 0.91941 * c5 - 4.42442 * c10 - 0.0082 * B$$

In addition, Figure 72 showed that the obtained model was able to estimate the quantity of wearing produced with less variation since the variation between the estimated quantity of wearing produced using the model and the observed appears insignificant. This implies that the models have the properties of

generating good estimates of quantity of wearing produced for the maintenance of roads in Anambra State.

4.21 Curve Estimation Analysis between Total Quantity of Asphalt produced for Road maintenance in Anambra State

Curve estimation analysis was performed to determine the explanatory variables that contributed to the attributes of Total quantity of Asphalt produced for road maintenance in Anambra State and to also assess the best type of model to employ in the estimation of the total Quantity of Asphalt produced with the observed period. The models considered in this section includes the linear model, Logarithmic model, Inverse model, Quadratic model, Cubic model, Compound model, Power model, S curve model, Growth model, Exponential model and Logistic model.

Table 80: Summary of Total Quantity of Asphalt Produced and Explanatory Parameters

TQAP	TMMT	TMRH	TMRR	TMeF	TMR	TME	TS	Tc5	Tc10	TB	Tc15
2786.7	32	72	121.3	94.5	17.8	3.5	1346.1	313.4	506.9	142.6	447.8
2981.9	32.8	74.9	13.3	94.5	18	4.3	1711.1	311.8	555.5	170.1	233.3
4050.6	35.3	73.05	159.2	91.8	18	4.3	2359.2	420.6	756.3	233.4	281.1
7869.5	36.7	75.5	168.9	89.9	18.1	4.2	4671.5	806.5	1470.4	458.7	442.4
9854.7	32.5	72.7	171.4	88.9	18.3	4.2	5790.4	1019	1842.4	558	631.9
6372	32.7	74	189.45	89.9	18.6	4.2	3708.1	661.9	1189.6	366.9	445.4
8874.3	33.1	79.7	162.9	89.9	18.6	4.3	4861.6	948.1	1642	491.4	931.2
4707.6	32.8	78.7	151.71	88.9	18.7	4.3	2506.4	509.2	867.6	255.9	568.6
7064.6	32.5	80.9	163.5	89.7	18.9	4.2	3964	746.6	1311.7	397.2	644.9
9374.7	34.4	79.8	166.8	90.4	19	4.4	5579.7	963.2	1756.2	547.9	527.8

Using details from the Table 80, the curve estimation analysis was done where total quantity of asphalt produced (TQAP) is the dependent or response variable and TMMT, TMRH, TMRR, TMeF, TMR, TME, TS, Tc5, Tc10, TB and Tc15 are the explanatory parameters.

Table 81: Summary of Curve Fitting Analysis Between Total Quantity of Asphalt Produced and Total Mean Maximum Temperature

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.039	.326	1	8	.584	-5241.154	347.515
Logarithmic	.040	.338	1	8	.577	-36100.958	12106.488
Inverse	.042	.350	1	8	.571	18998.019	-421264.569
Quadratic	.072	.271	2	7	.771	-318164.789	18628.389
Cubic	.172	.271	2	7	.017	-318164.789	18628.389
Compound	.056	.474	1	8	.511	491.017	1.077
Power	.058	.489	1	8	.504	.702	2.572
S	.059	.505	1	8	.497	11.345	-89.326
Growth	.056	.474	1	8	.511	6.196	.074
Exponential	.056	.474	1	8	.511	491.017	.074
Logistic	.056	.474	1	8	.511	.002	.929

The independent variable is TMMT

Source: SPSS 17.0

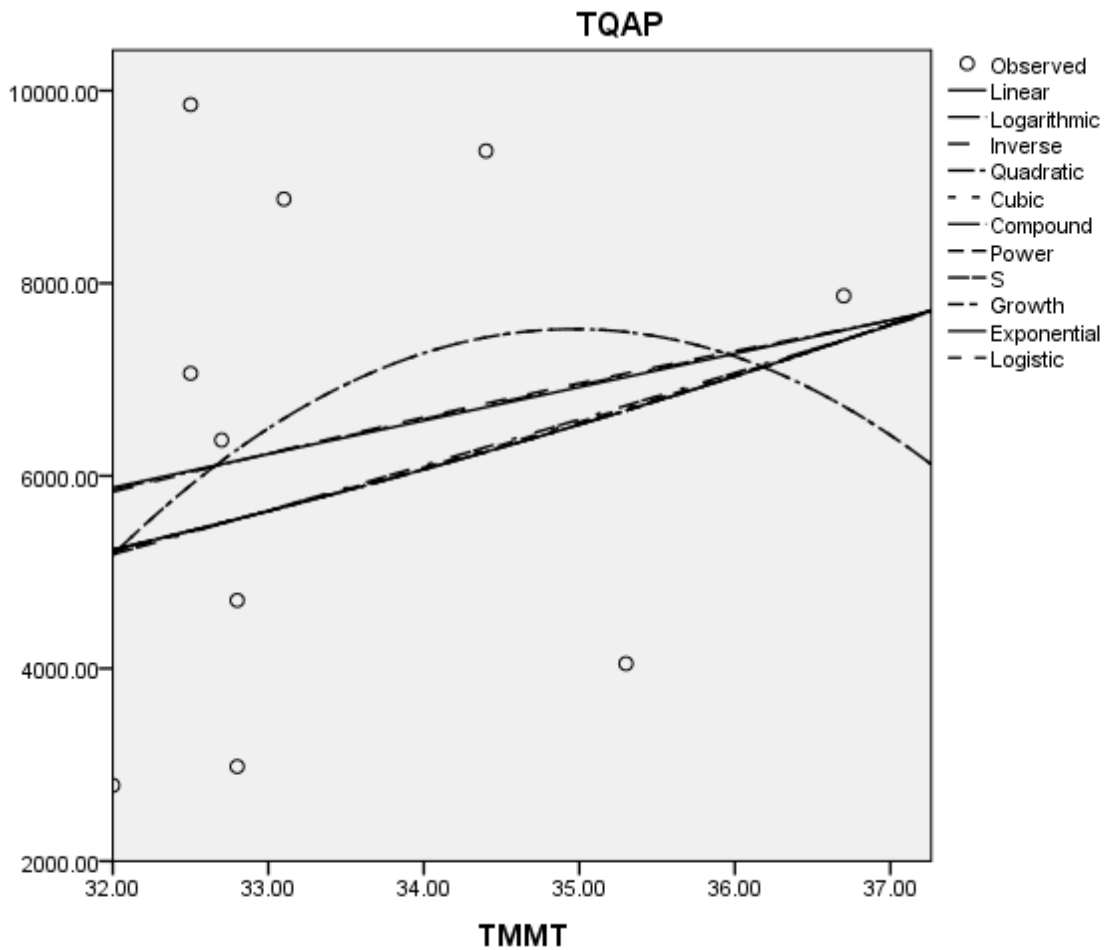


Figure 73: Curve fitting plot of quantity of wearing produced against total mean maximum temperature

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 17.2%. This result implies that the best model was the cubic model since the independent variable TMMT was able to explain about 17.2% of the total variability in the dependent variable TQAP with a p-value of 0.017 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.017 < \alpha=0.05$). Hence, TMMT contributes to the proposed model.

Table 82: Summary of Curve Fitting Analysis Between Total quantity of Asphalt Produced and Total Maximum Relative Humidity.

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.165	1.583	1	8	.244	-18052.791	321.136
Logarithmic	.165	1.578	1	8	.244	-99754.876	24506.097
Inverse	.164	1.573	1	8	.245	30974.721	-1868021.009
Quadratic	.167	.700	2	7	.528	70779.228	-2006.082
Cubic	.167	.700	2	7	.528	21013.904	.000
Compound	.207	2.092	1	8	.186	44.542	1.066
Power	.207	2.094	1	8	.186	3.615E-006	4.895
S	.216	2.094	1	8	.016	13.590	-373.695
Growth	.207	2.092	1	8	.186	3.796	.064
Exponential	.207	2.092	1	8	.186	44.542	.064
Logistic	.207	2.092	1	8	.186	.022	.938

The independent variable is TMRH

Source: SPSS 17.0

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 21.6%. This result implies that the best model was the S curve model since the independent variable TMRH was able to explain about 21.6% of the total variability in the dependent variable TQAP with a p-value of 0.016 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.016 < \alpha=0.05$). Hence, TMRH contributes to the proposed model.

Table 83: Summary of Curve Fitting Analysis Between Total Quantity of Asphalt Produced and Total Mean Relative Rainfall

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.386	5.033	1	8	.055	1579.209	32.786
Logarithmic	.285	3.182	1	8	.112	-2143.587	1767.460
Inverse	.226	2.334	1	8	.165	7150.109	-57485.944
Quadratic	.482	3.258	2	7	.100	3269.971	-40.280
Cubic	.626	3.345	3	6	.067	8746.550	-503.776
Compound	.474	7.220	1	8	.028	2257.928	1.006
Power	.349	4.285	1	8	.072	1085.127	.348
S	.277	3.057	1	8	.118	8.821	-11.324
Growth	.474	7.220	1	8	.028	7.722	.006
Exponential	.474	7.220	1	8	.028	2257.928	.006
Logistic	.474	7.220	1	8	.028	.000	.994

The independent variable is TMRR

Source: SPSS 17.0

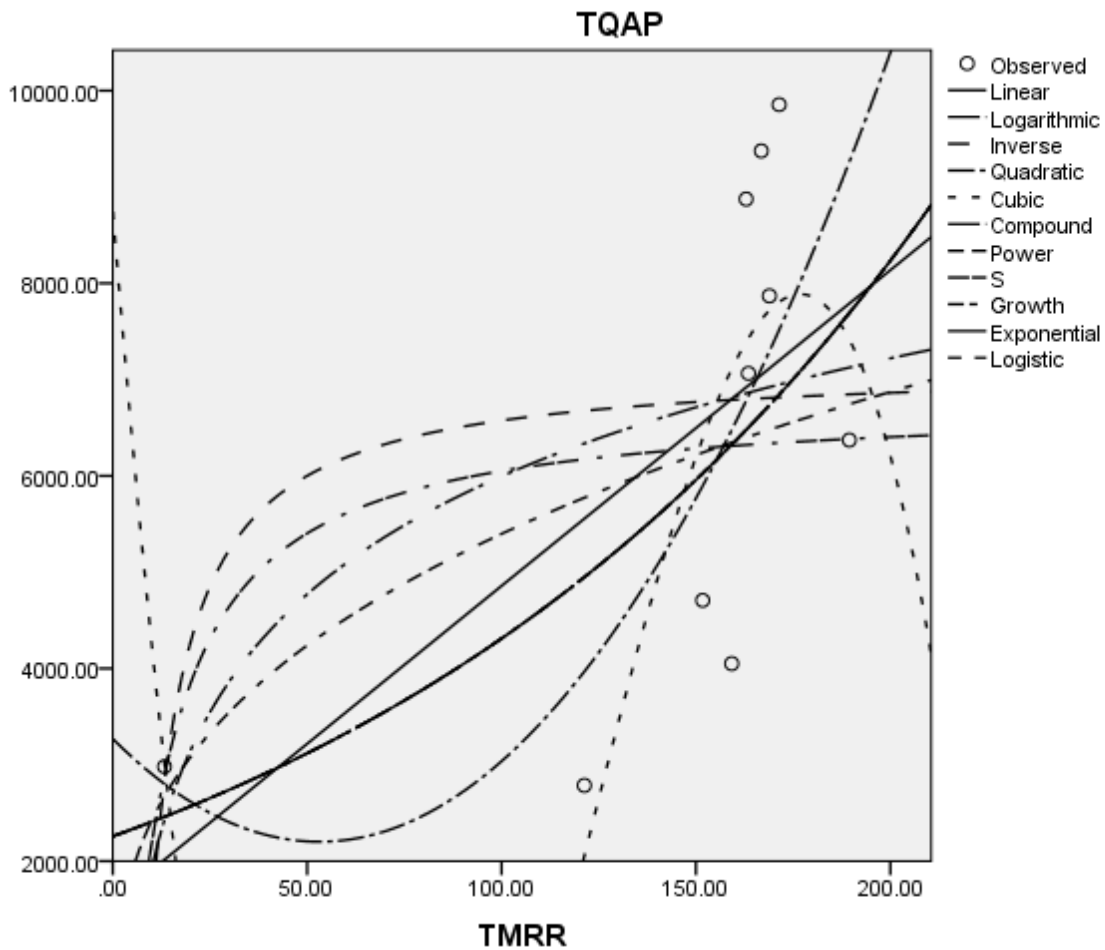


Figure 74: Curve fitting plot of quantity of wearing produced against total mean relative rainfall

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 62.6%. This result implies that the best model was the cubic model since the independent variable TMRR was able to explain about 62.6% of the total variability in the dependent variable TQAP with a p-value of 0.067 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.067 > \alpha=0.05$). Hence, TMRR does not contribute to the proposed model.

Table 84: Summary of Curve Fitting Analysis Between Total quantity of asphalt produced and Total mean efficiency

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.560	10.170	1	8	.013	92096.056	-943.443
Logarithmic	.558	10.107	1	8	.013	396502.380	-86520.391
Inverse	.557	10.041	1	8	.013	-80956.386	7931173.389
Quadratic	.561	10.229	1	8	.013	48842.167	.000
Cubic	.689	4.762	2	7	.049	-581144.598	10058.392
Compound	.687	17.082	1	8	.003	119082636772.904	.831
Power	.679	16.904	1	8	.003	1.067E+037	-16.986
S	.676	16.719	1	8	.003	-8.471	1556.593
Growth	.681	17.082	1	8	.003	25.503	-.185
Exponential	.681	17.082	1	8	.003	119082636772.904	-.185
Logistic	.681	17.082	1	8	.003	8.398E-012	1.204

The independent variable is TMeF

Source: SPSS 17.0

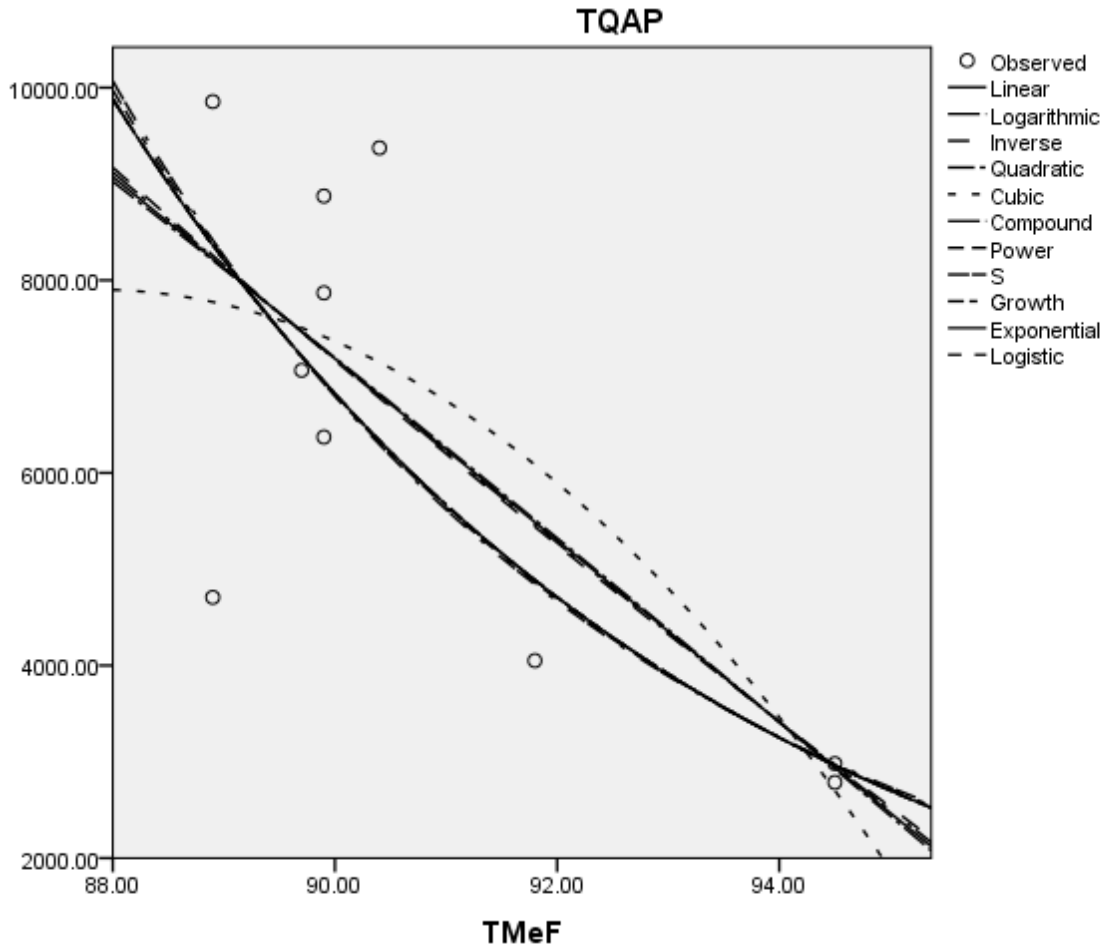


Figure 76: Curve fitting plot of quantity of wearing produced against total mean efficiency

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 68.9%. This result implies that the best model was the cubic model since the independent variable TMeF was able to explain about 68.9% of the total variability in the dependent variable TQAP with a p-value of 0.049 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.049 < \alpha=0.05$). Hence, TMeF contributes to the proposed model.

Table 85: Summary of Curve Fitting Analysis between Total quantity of asphalt produced and Total mean radiation

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.343	4.173	1	8	.075	-61867.037	3709.821
Logarithmic	.346	4.228	1	8	.074	-193228.389	68548.697
Inverse	.349	4.283	1	8	.072	75239.433	-1266178.618
Quadratic	.343	4.173	1	8	.075	-61867.037	3709.821
Cubic	.472	2.640	2	7	.140	-1427644.731	115090.286
Compound	.414	5.663	1	8	.045	.009	2.067
Power	.418	5.752	1	8	.043	6.165E-014	13.423
S	.462	5.842	1	8	.142	22.157	-248.005
Growth	.414	5.663	1	8	.045	-4.691	.726
Exponential	.414	5.663	1	8	.045	.009	.726
Logistic	.414	5.663	1	8	.045	108.934	.484

The independent variable is TMR

Source: SPSS 17.0

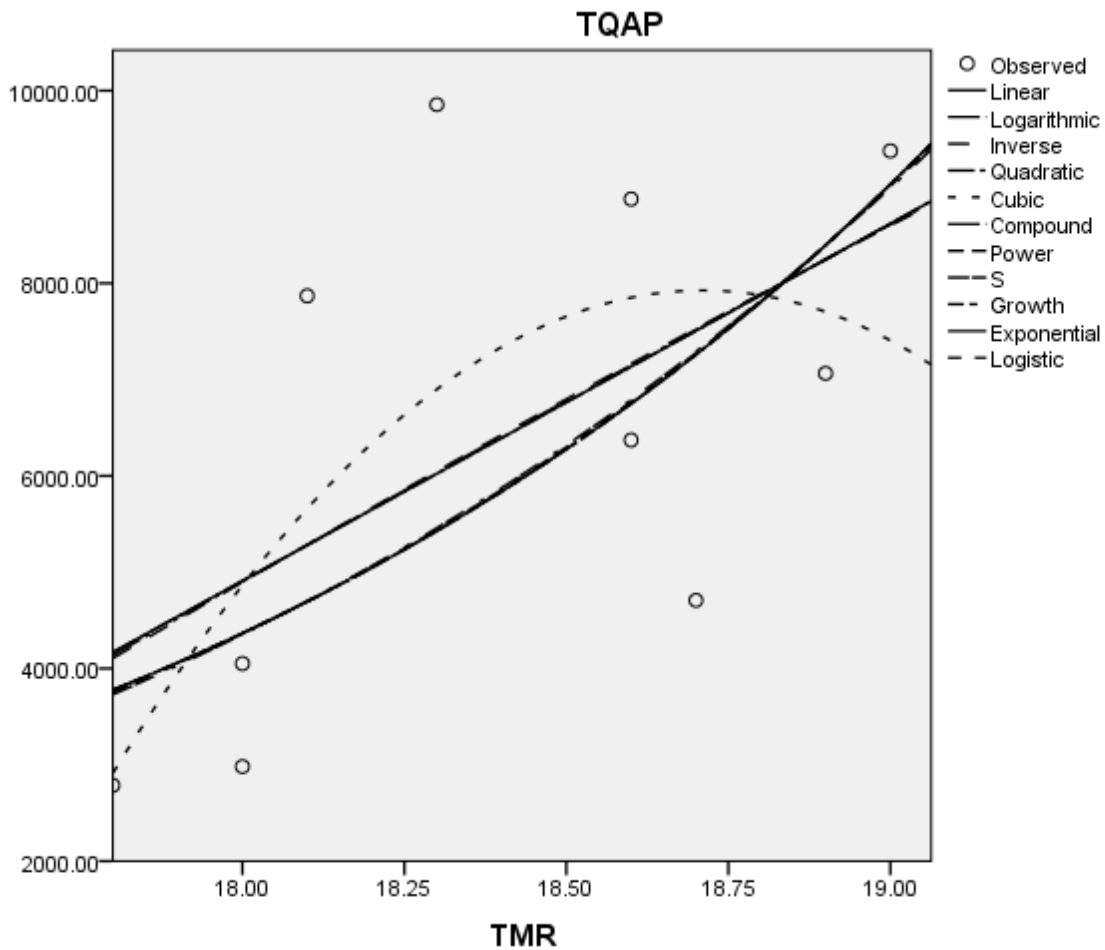


Figure 77: Curve fitting plot of quantity of wearing produced against total mean radiation

From the result of the curve estimation, it was found that the cubic model performed better than the other method with an R-squared of 47.2%. This result implies that the best model was the cubic model since the independent variable TMR was able to explain about 47.2% of the total variability in the dependent variable TQAP with a p-value of 0.140 which falls on the acceptance region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.140 > \alpha=0.05$). Hence, TMR does not contribute to the proposed model.

Table 86: Summary of Curve Fitting Analysis Between Total Quantity of Asphalt Produced and Total Mean Evaporation

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.193	1.918	1	8	.203	-12936.717	4613.455
Logarithmic	.197	1.962	1	8	.199	-19575.094	18148.336
Inverse	.200	2.003	1	8	.195	23408.149	-71023.901
Quadratic	.220	.985	2	7	.420	-139538.576	69869.291
Cubic	.220	.985	2	7	.020	-139538.576	69869.291
Compound	.248	2.635	1	8	.143	118.698	2.534
Power	.253	2.715	1	8	.138	30.802	3.665
S	.259	2.791	1	8	.033	12.115	-14.371
Growth	.248	2.635	1	8	.143	4.777	.930
Exponential	.248	2.635	1	8	.143	118.698	.930
Logistic	.248	2.635	1	8	.143	.008	.395

The independent variable is TME

Source: SPSS 17.0

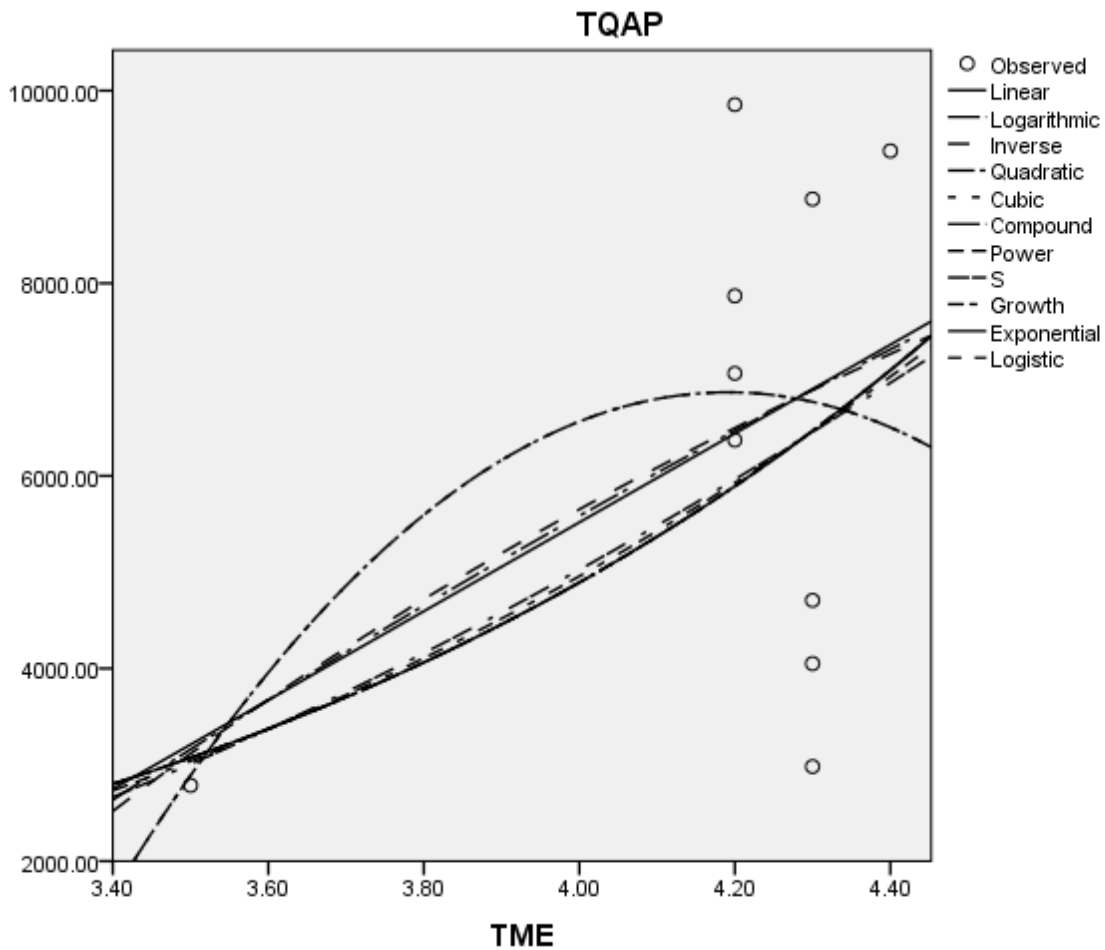


Figure 78: Curve fitting plot of quantity of wearing produced against total mean evaporation

From the result of the curve estimation it was found that the S curve model performed better than the other methods with an R-squared of 25.9%. This result implies that the best model was the S curve model since the independent variable TME was able to explain about 25.9% of the total variability in the dependent variable TQAP with a p-value of 0.033 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.033 < \alpha=0.05$). Hence, TME contributes to the proposed model.

Table 87: Summary of Curve Fitting Analysis between Total quantity of asphalt produced and Total Stone-dust

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.992	942.176	1	8	.000	390.990	1.645
Logarithmic	.958	181.376	1	8	.000	-34659.803	5069.892
Inverse	.854	46.637	1	8	.000	10758.686	-12675079.961
Quadratic	.992	417.549	2	7	.000	238.376	1.749
Cubic	.993	274.395	3	6	.000	1531.428	.389
Compound	.966	228.971	1	8	.000	2033.004	1.000
Power	.989	724.141	1	8	.000	3.472	.917
S	.935	115.425	1	8	.000	9.486	-2362.021
Growth	.966	228.971	1	8	.000	7.617	.000
Exponential	.966	228.971	1	8	.000	2033.004	.000
Logistic	.966	228.971	1	8	.000	.000	1.000

The independent variable is TS

Source: SPSS 17.0

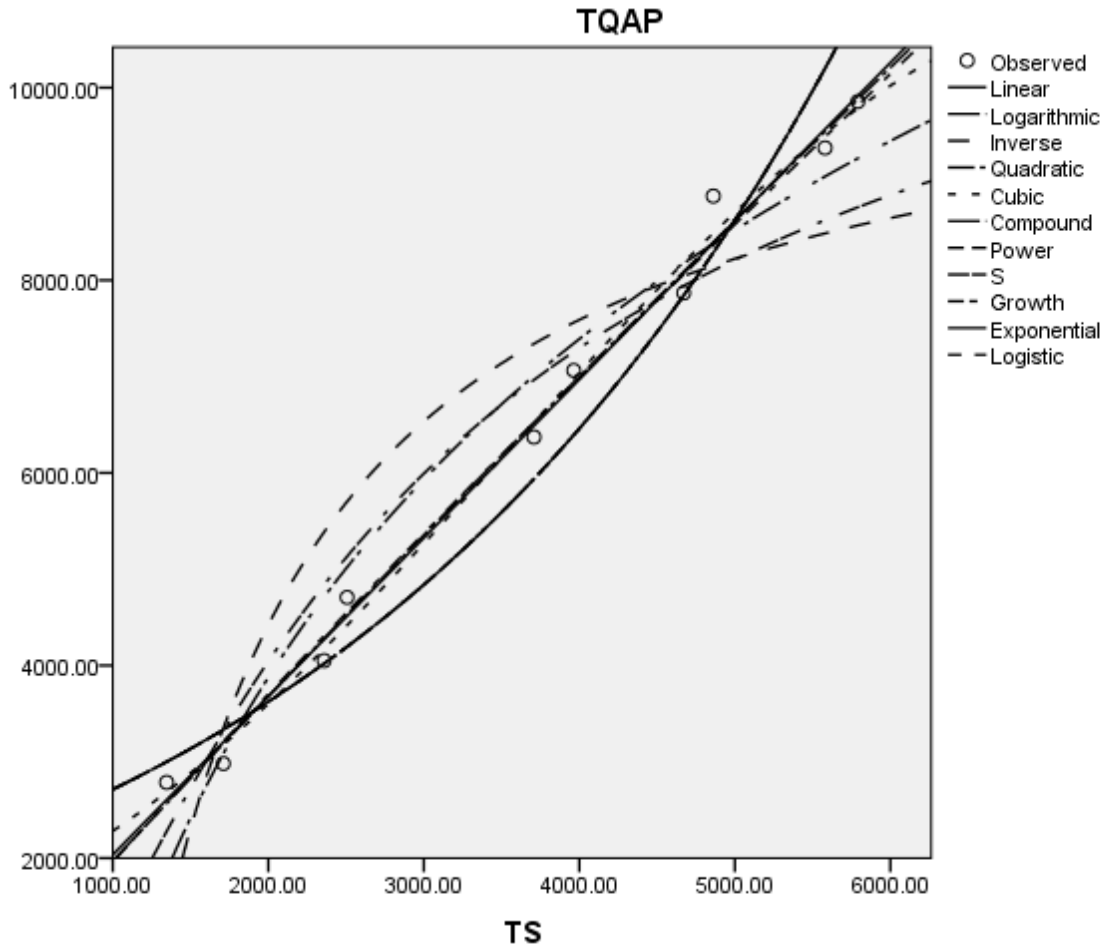


Figure 79: Curve fitting plot of quantity of wearing produced against total stone-dust

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.3%. This result implies that the best model was the cubic model since the independent variable TS was able to explain about 99.3% of the total variability in the dependent variable TQAP with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, TS contributes to the proposed model.

Table 88: Summary of Curve Fitting Analysis Between Total quantity of asphalt produced and Total chipping c5

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.996	3415.024	1	8	.000	-159.589	9.781
Logarithmic	.975	310.055	1	8	.000	-30439.838	5735.607
Inverse	.910	81.232	1	8	.000	11620.623	-2919463.192
Quadratic	.996	1494.484	2	7	.000	-174.961	9.836
Cubic	.998	854.352	3	6	.000	-242.546	10.205
Compound	.972	280.575	1	8	.000	1845.383	1.002
Power	.997	2949.790	1	8	.000	7.687	1.033
S	.977	341.659	1	8	.000	9.636	-538.493
Growth	.972	280.575	1	8	.000	7.520	.002
Exponential	.972	280.575	1	8	.000	1845.383	.002
Logistic	.972	280.575	1	8	.000	.001	.998

The independent variable is Tc5.

Source: SPSS 17.0

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.8%. This result implies that the best model was the cubic model since the independent variable Tc5 was able to explain about 99.8% of the total variability in the

dependent variable TQAP with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, Tc5 contributes to the proposed model.

Table 89: Summary of Curve Fitting Analysis Between Total quantity of asphalt produced and Total chipping c10

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.961	41654.791	1	8	.000	53.156	5.329
Logarithmic	.974	295.294	1	8	.000	-31926.317	5482.938
Inverse	.899	70.818	1	8	.000	11318.217	-4803481.764
Quadratic	.920	18415.641	2	7	.000	28.550	5.379
Cubic	.993	11588.525	3	6	.000	256.912	4.667
Compound	.974	303.794	1	8	.000	1915.719	1.001
Power	.912	32588.308	1	8	.000	5.806	.989
S	.972	278.858	1	8	.000	9.584	-889.532
Growth	.974	303.794	1	8	.000	7.558	.001
Exponential	.974	303.794	1	8	.000	1915.719	.001
Logistic	.974	303.794	1	8	.000	.001	.999

The independent variable is Tc10

Source: SPSS 17.0

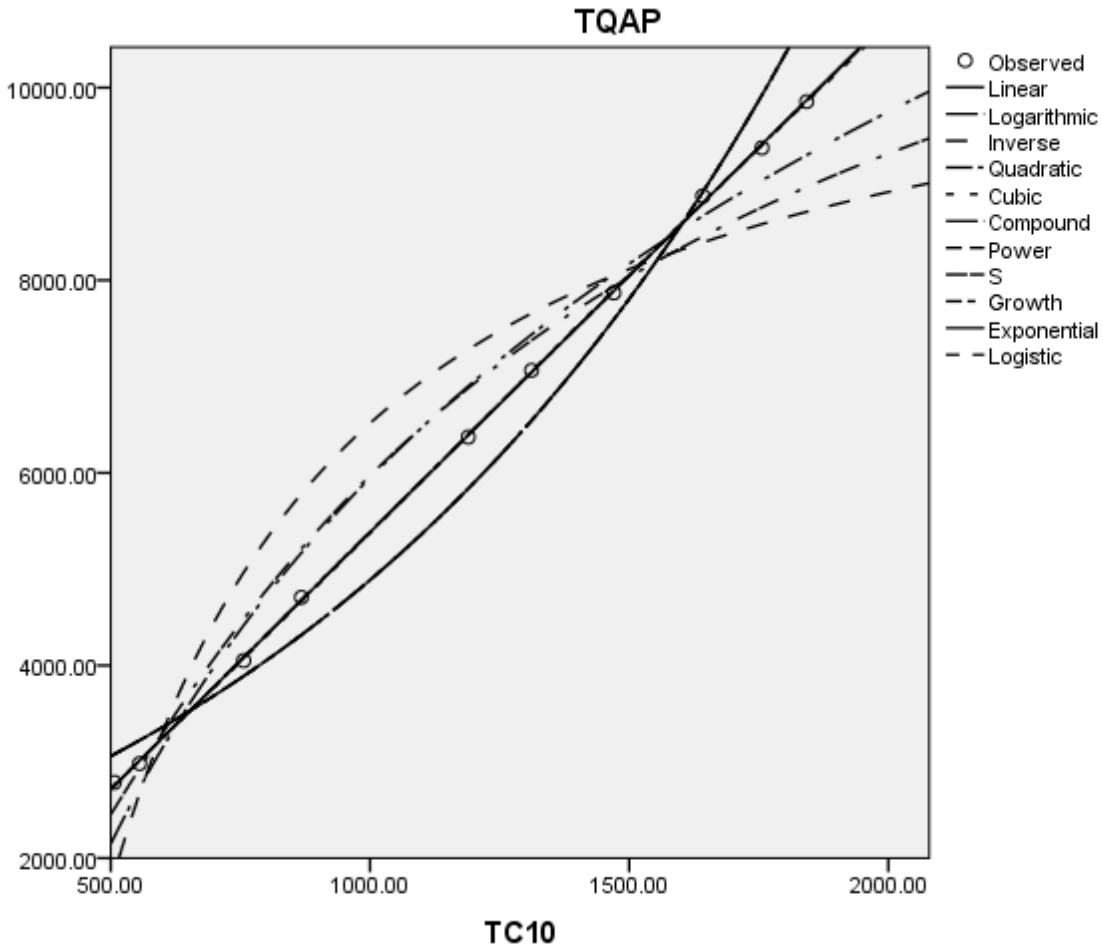


Figure 80: Curve fitting plot of quantity of wearing produced against total chipping c10

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.3%. This result implies that the best model was the cubic model since the independent variable Tc10 was able to explain about 99.3% of the total variability in the dependent variable TQAP with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, Tc10 contributes to the proposed model.

Table 90: Summary of Curve Fitting Analysis between Total Quantity of Asphalt Produced and Total Mean Maximum Temperature

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.996	2034.357	1	8	.000	196.104	17.110
Logarithmic	.964	212.687	1	8	.000	-24142.559	5270.353
Inverse	.874	55.378	1	8	.000	11016.221	-1353237.026
Quadratic	.996	897.900	2	7	.000	291.498	16.457
Cubic	.998	532.514	3	6	.000	848.586	10.611
Compound	.974	299.582	1	8	.000	1960.851	1.003
Power	.995	1619.821	1	8	.000	23.290	.953
S	.953	163.555	1	8	.000	9.532	-251.658
Growth	.974	299.582	1	8	.000	7.581	.003
Exponential	.974	299.582	1	8	.000	1960.851	.003
Logistic	.974	299.582	1	8	.000	.001	.997

The independent variable is TB.

Source: SPSS 17.0

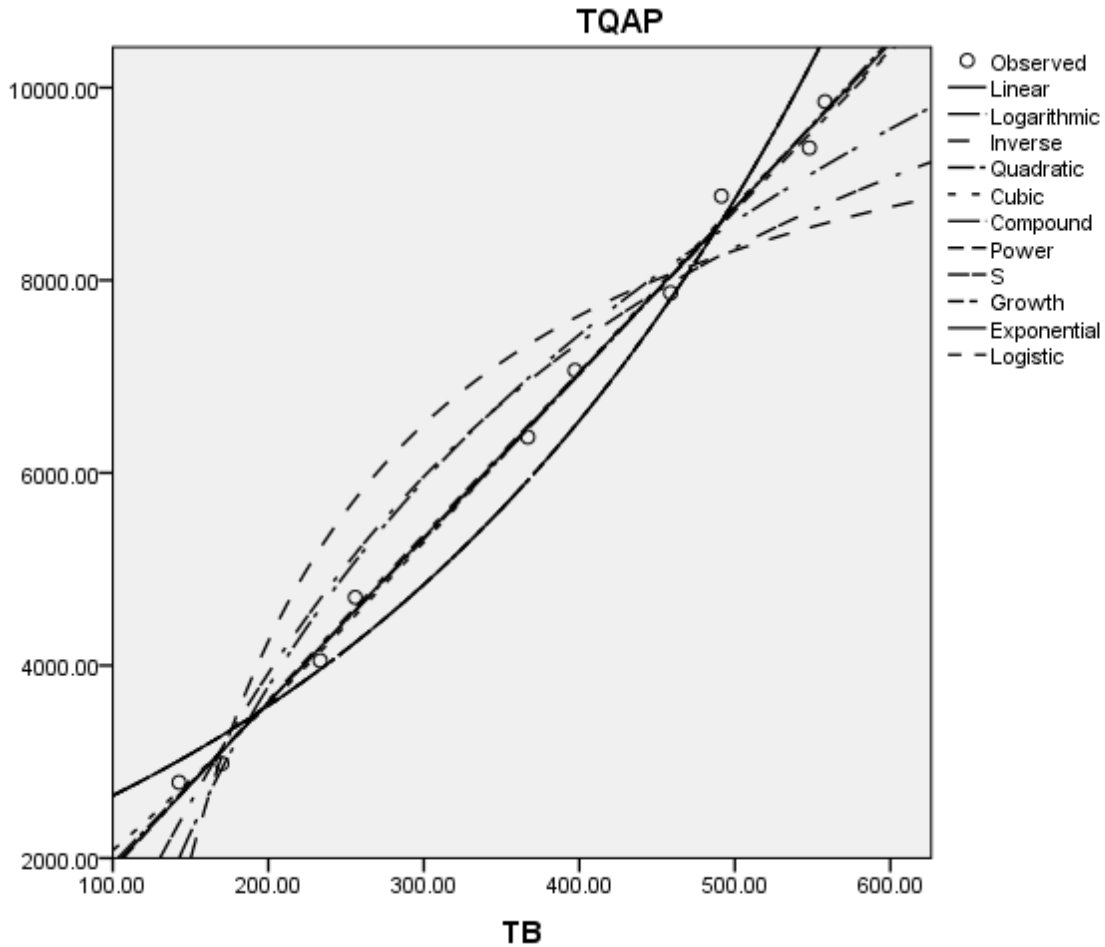


Figure 81: Curve fitting plot of quantity of wearing produced against Total bitumen

From the result of the curve estimation, it was found that the cubic model performed better than the other methods with an R-squared of 99.8%. This result implies that the best model was the cubic model since the independent variable TB was able to explain about 99.8% of the total variability in the dependent variable TQAP with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, TB contributes to the proposed model.

Table 91: Summary of Curve Fitting Analysis Between Total Quantity of Asphalt Produced and Total Chipping c15

Model Summary and Parameter Estimates

Dependent Variable: TQAP

Equation	Model Summary					Parameter Estimates	
	R Square	F	df1	df2	Sig.	Constant	b1
Linear	.437	6.200	1	8	.038	1872.964	8.771
Logarithmic	.481	7.405	1	8	.026	-21614.547	4535.539
Inverse	.470	7.104	1	8	.029	10561.458	-1857068.206
Quadratic	.488	3.342	2	7	.096	-1555.977	22.399
Cubic	.490	1.921	3	6	.227	399.627	9.523
Compound	.431	6.058	1	8	.039	2624.420	1.002
Power	.485	7.533	1	8	.025	39.004	.811
S	.495	7.544	1	8	.025	9.426	-335.852
Growth	.431	6.058	1	8	.039	7.873	.002
Exponential	.431	6.058	1	8	.039	2624.420	.002
Logistic	.431	6.058	1	8	.039	.000	.998

The independent variable is Tc15.

Source: SPSS 17.0

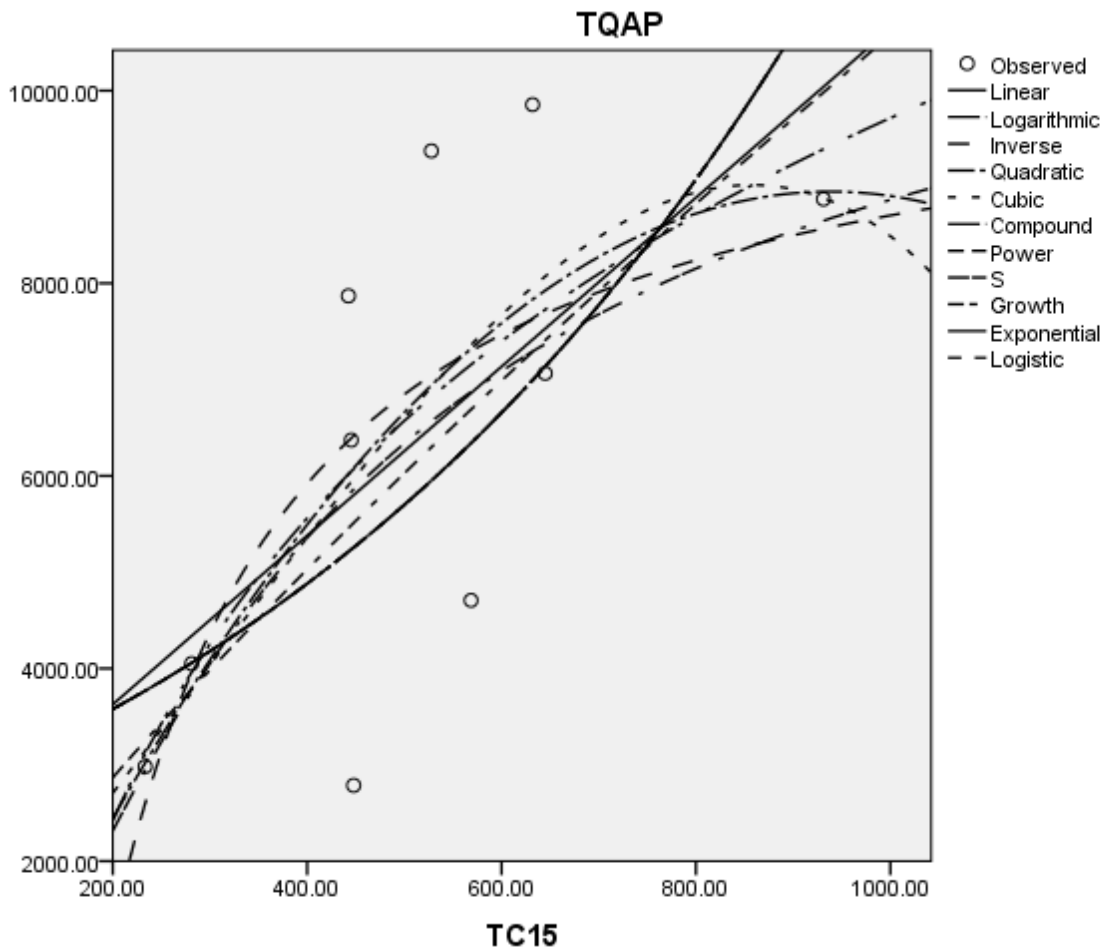


Figure 82: Curve fitting plot of quantity of wearing produced against Total chipping c15

From the result of the curve estimation, it was found that the S curve model performed better than the other methods with an R-squared of 49.5%. This result implies that the best model was the S curve model since the independent variable Tc15 was able to explain about 49.5% of the total variability in the dependent variable TQAP with a p-value of 0.00 which falls on the rejection region of the hypothesis assuming 95% confidence level (since, $p\text{-value}=0.00 < \alpha=0.05$). Hence, Tc15 contributes to the proposed model.

4.22 Generalized Nonlinear Model Analysis on the Estimation of Total Quantity of Asphalt produced for maintenance of roads in Anambra State

This section deals with estimation of the total quantity of asphalt produced for the maintenance of roads in Anambra State. The generalized nonlinear model was used because it was found from the curve fitting analysis that the explanatory variables follow a nonlinear characteristic model (e.g. Cubic model and the S curve model). Hence, we shall design the generalize nonlinear model using the "gnm" function in R-programming.

Extracting parameters that contributed to the attributes of the response variable in the curve estimation analysis and presenting in Table 92.

Table 92: Summary of Total Quantity of Asphalt Produced and Extracted Explanatory Parameters

TQAP	TMMT	TMRH	TMeF	TME	TS	TC5	TC10	TB	TC15
2786.7	32	72	94.5	3.5	1346.1	313.4	506.9	142.6	447.8
2981.9	32.8	74.9	94.5	4.3	1711.1	311.8	555.5	170.1	233.3
4050.6	35.3	73.05	91.8	4.3	2359.2	420.6	756.3	233.4	281.1
7869.5	36.7	75.5	89.9	4.2	4671.5	806.5	1470.4	458.7	442.4
9854.7	32.5	72.7	88.9	4.2	5790.4	1019	1842.4	558	631.9
6372	32.7	74	89.9	4.2	3708.1	661.9	1189.6	366.9	445.4
8874.3	33.1	79.7	89.9	4.3	4861.6	948.1	1642	491.4	931.2
4707.6	32.8	78.7	88.9	4.3	2506.4	509.2	867.6	255.9	568.6
7064.6	32.5	80.9	89.7	4.2	3964	746.6	1311.7	397.2	644.9
9374.7	34.4	79.8	90.4	4.4	5579.7	963.2	1756.2	547.9	527.8

The R-code for executing the generalized nonlinear model for estimation of the total asphalt produced using details presented in the table 93 is written below. Recall that TQAP represents the dependent variable while variables TMMT, TMRH, TMeF, TME, TS, TC5, TC10, TB and TC15 represents the independent variables.

The result of the generalized nonlinear model for estimating total asphalt produced was obtained in the R-command window as given

Call:

```
gnm(formula = TQAP ~ TMMT + TMRH + TMeF + TME + TS + TC5 + TC10
+ TB + TC15, family = gaussian, data = NULL, method = "gnmFit", start =
NULL)
```

Coefficients:

(Intercept)	TMMT	TMRH	TMeF	TME	TS
-3333.225	37.023	9.747	23.064	-215.327	-161.691
Tc5	Tc10	TB	Tc15		
-1224.891	1195.341	-15.476	1.404		

Deviance: 9.177153e-19

Pearson chi-squared: 9.177153e-19

Residual df: 0

Call:

gnm(formula = TQAP ~ TMMT + TMRH + TMeF + TME + TS + TC5 + TC10 + TB + TC15, family = gaussian, data = NULL, method = "gnmFit", start = NULL)

Coefficients:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-3333.23	Inf	0	1
TMMT	37.02	Inf	0	1
TMRH	9.75	Inf	0	1
TMeF	23.06	Inf	0	1
TME	-215.33	Inf	0	1
TS	-161.69	Inf	0	1
Tc5	-1224.89	Inf	0	1
Tc10	1195.34	Inf	0	1
TB	-15.48	Inf	0	1
Tc15	1.4	Inf	0	1

(Dispersion parameter for gaussian family taken to be Inf)

Residual deviance: 9.1772e-19 on 0 degrees of freedom

AIC: -387.97

Number of iterations: 1

Table 93: Distribution of Observed Total Quantity of Asphalt Produced and Estimated Total Quantity of Asphalt Produced for Maintenance of Roads in Anambra State

Year	TQAP	Estimated.QAP
2004	2786.7	2736.7
2005	2981.9	2921.9
2006	4050.6	4020.6
2007	7869.5	7369.5
2008	9854.7	9554.7
2009	6372	6072
2010	8874.3	8374.3
2011	4707.6	4507.6
2012	7064.6	7024.6
2013	9374.7	9334.7

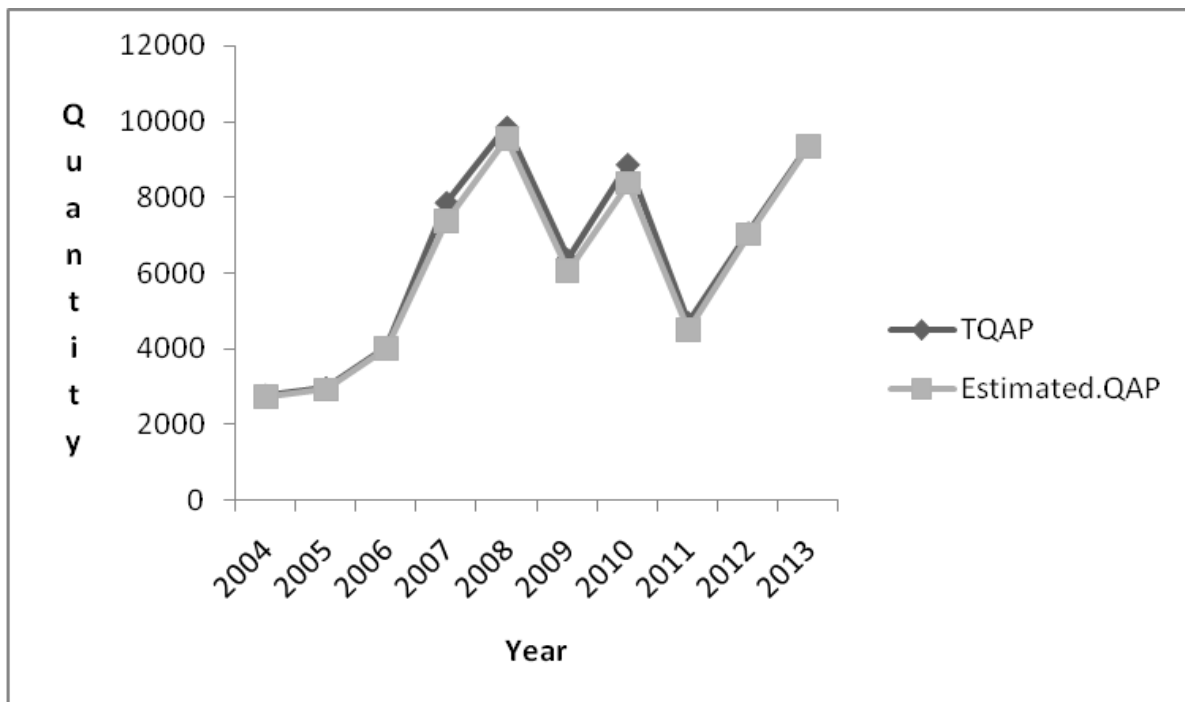


Figure 83: Distribution of total quantity produced and estimated total quantity of asphalt over the years

The result of generalized nonlinear model found a Pearson Chi-squared value of $9.177153e-19$ and an Akaike Information Criterion (AIC) value of -387.97 .

Also obtained was a model for estimating TQAP which can be expressed as;

$$\text{TQAP} = -3333.23 + 37.02 \cdot \text{TMMT} + 9.75 \cdot \text{TMRH} + 23.06 \cdot \text{TMeF} - 215.33 \cdot \text{TME} - 161.69 \cdot \text{TS} - 1224.89 \cdot \text{Tc5} + 1195.34 \cdot \text{Tc10} - 15.48 \cdot \text{TB} + 1.40 \cdot \text{Tc15}$$

In addition, Figure 83 showed that the obtained model was able to estimate the quantity of wearing produced with less variation since the variation between the estimated quantity of wearing produced using the model and the observed appears insignificant. This implies that the models have the properties of generating good estimates of quantity of wearing produced for the maintenance of roads in Anambra State.

4.23: Regression Analysis for Estimating Maintenance Cost of Roads per Kilometre in Anambra State

Table 94: Distribution of Length of Roads and Maintenance Cost of Roads per Kilometre

Year	mcr	LR	MCRPKM
2004	57845868	534.1	108305.3
2005	61211163	554.4	110409.7
2006	83060565	554.4	149820.6
2007	152240042	745.5	204212
2008	201949343	745.5	270891.1
2009	130670316	745.5	175278.8
2010	182753103	754.5	242217.5
2011	97130327	754.5	128734.7
2012	141778801	754.5	187910.9
2013	191931676	754.5	254382.6

using data obtained presented in Table 94, a linear regression analysis was performed with the aim of assessing the impact of length of road on maintenance cost of roads per kilometre. It is expected that the model from this analysis will be useful in estimating maintenance cost of roads per kilometre with respect to length of roads.

Table 95: Model Summary for assessing the relationship between Maintenance Cost of Road per kilometre and Length of Road

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.701 ^a	.592	.428	44909.61567

a. Predictors: (Constant), LR

The result obtained in Table 96 found an R-square of 59.2% which implies that length of road can only explain about 59.2% of total variation in maintenance cost of road per kilometre. This result implies positive coefficient of determination.

Table 96: ANOVA for assessing the impact of Length of Road (LR) on Maintenance Cost of Road per kilometre

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.562E10	1	1.562E10	7.744	.024 ^a
	Residual	1.613E10	8	2.017E9		
	Total	3.175E10	9			

a. Predictors: (Constant), LR

b. Dependent Variable: MCRPKM

The result displayed in Table 96 showed an F-value of 7.74 and p-value of 0.024 which falls on the rejection region of the hypothesis. This result implies that length of road has significant impact on maintenance cost of road per kilometre.

Table 97: Coefficient result on assessing the impact of Length of Road (LR) on Maintenance Cost of Road per kilometre

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-109103.127	105997.803		-1.029	.333
	LR	423.811	152.292	.701	2.783	.024

a. Dependent Variable: MCRPKM

It was found in Table 97 that the independent variable length of road has significant impact on determining maintenance cost of roads per kilometre since an t-value of 2.78 and a corresponding p-value of 0.024 was obtained assuming 95% confidence level (since, p-value=0.024 < α =0.05). Also, the model for estimating maintenance cost of roads per kilometre can be expressed as given

$$\text{MCRPKM} = -109103.13 + 423.81 * \text{LR}$$

where, MCRPKM is maintenance cost of roads per kilometre and LR represents length of road.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMMENDATIONS

5.1 Summary of Findings

The findings from the present research are discussed in details in this chapter.

Two maintenance cost models of roads in Anambra State were evaluated per title in this study, they include a linear maintenance cost equation (3.4) and a nonlinear maintenance cost model equation (3.8).

The linear maintenance cost model was optimized using the general-purpose unconstrained optimization method, general purpose optimization method and the quasi-Newton and conjugate-gradient method. Also, the nonlinear maintenance cost model was optimized using the Barzilai-Borwein (BB) Steplengths method, the nonlinear optimization with multi start values and the spectral projected gradient method for large-scale optimization.

The result of optimizing the linear maintenance cost function using a general-purpose unconstrained optimization method found the value of the estimated annual minimum as N52,416,540 with estimated points at which the minimum value of the function as 60.33 and 19.22 for cost of binder and cost of wearing, respectively. This result implies that the annual minimum maintenance cost of

roads using the linear cost function is N52,416,540. Hence, the linear cost function was expressed as equation (4.1)

The result of optimizing the linear maintenance cost function using a general-purpose optimization method found the value of the estimated minimum as N52,416,579.36 with estimated points at which the minimum value of the function as 59.34 and 21.27 for cost of binder and cost of wearing, respectively. This result implies that the annual minimum maintenance cost of roads using the linear cost function is N52,416,579.36. Hence, the linear cost function was written as equation (4.2).

The result of optimizing the linear maintenance cost function using a general-purpose optimization method based on quasi-Newton and Conjugate-gradient algorithms found the value of the estimated annual minimum as N52,416,579.36 with estimated points at which the minimum value of the function as 59.34 and 21.27 for cost of binder and cost of wearing respectively. This result implies that the minimum production cost of asphalt using the linear cost function is N52,416,579.36. Hence, the linear cost function was written as equation (4.3).

The result of optimizing the non-linear cost function using the Barzilai-Borwein (BB) Steplengths algorithm found the value of the estimated minimum as N2697251.47 with estimated points at which the minimum value of the function

as 1037.03 and 237.26 for cost of binder and cost of wearing, respectively. This result implies that the annual minimum maintenance cost of roads using the non-linear cost function is N2697251.47. Hence nonlinear maintenance cost function was expressed equation (4.4)

Also, the result of optimizing the non-linear cost function using the nonlinear optimization with multi start values found the value of the estimated minimum as N2697251.47 while the estimated points at which the minimum value of the function as 1037.03 and 237.26 for cost of binder and cost of wearing, respectively. This result implies that the annual minimum maintenance cost of roads using the non-linear cost function is N2697251.47. Hence the nonlinear maintenance cost function was rewritten as equation (4.5).

In addition, the result of optimizing the non-linear cost function using the spectral projected gradient method for large-scale optimization found the value of the estimated minimum as N2697251.47 while the estimated points at which the minimum value of the function as 1037.03 and 237.26 for cost of binder and cost of wearing, respectively. This result implies that the annual minimum maintenance cost of roads using the nonlinear cost function was N2697251.47. Hence the nonlinear maintenance cost function was written as equation (4.6).

It was revealed from the findings of this study that the minimum cost and other cost values estimated using the various optimization method have no variation

except for the minimal variation between the estimated point generated by the generalized unconstrained optimization method and the general-purpose optimization method and general-purpose optimization method based on quasi-Newton and Conjugate-gradient. However, the estimated points obtained using the generalized unconstrained optimization method and the general-purpose optimization method and general-purpose optimization method based on quasi-Newton and Conjugate-gradient are the same.

The result of validating the estimated cost by the optimization model of the linear cost function using the bivariate regression analysis revealed minimum dispersion. This result connotes that the bivariate regression fitted values were able to fit perfectly to the resemblance of the cost values obtained by the linear maintenance cost model.

Findings of the study showed that annual minimum cost and other cost values estimated using the various nonlinear optimization methods have no variation. Also, the result of the cost values generated by the response surface method was found to have has a perfect fit on the cost values of nonlinear maintenance cost model. This result connotes that the fitted values obtained using the response surface analysis were able to fit perfectly to the resemblance of the cost values obtained by the nonlinear maintenance cost model.

The findings from the Pareto analysis showed that unavailability of Street lights, Bustop/PD, Traffic Congestion, traffic circle and road direction constitute 80% of factors affecting roads in Anambra State.

Moreover, findings showed that that Road divider, Road direction, Traffic Circle, Drainage, Walkways, street light, traffic congestion and Bustop/ PD has inverse relationship with Road condition in Anambra State. This result implies that as the availability of these factors are increasing, bad road condition is expected to decrease in Anambra State. This result validates the result obtained by the Pareto analysis that truly these factors constitute the key problem facing the quality of roads in Anambra state.

It was found that the maintenance cost of roads has an increasing trend over time. The obtained trend equation for predicting maintenance cost of roads in Anambra State given time can be expressed as equation (4.7).

The series was found to be stationary using the Kwiatkowski-Phillips-Schmidt-Shin test. Also, it was found that the series has no unit root at the first difference using the Augmented Dickey-Fuller test. Hence we concluded that the series was stationary overtime which implies that the model obtained can be used to make forecast for future behaviour of the process.

Also, five years forecast on the maintenance cost of roads in Anambra State was made and it was found that in the year 2018 all things being equal the

maintenance cost of roads in Anambra State is expected to be about N237,226,028.

The result of the curve estimation analysis of maintenance cost of roads economic parameter revealed that a nonlinear model will best fit the data set observed. Hence, it was found that IASPCA, SCRGDP, MCQCM, MCQCM, CGFCFPME, GDPCBPBC MRR, MeF and LR were the variables that contributed significantly to determining the behaviour of the response variables mcr. In addition, the result of generalized nonlinear model found a Pearson Chi-squared value of $3.776235e-11$ and an Akaike Information Criterion value of -212.64. Also obtained was a model for estimating maintenance cost of roads in Anambra State given some economic variables that were found to contribute to the fluctuations observed in the maintenance cost of roads in Anambra State equation (4.8).

The obtained model was found to have the properties of generating good estimates of maintenance cost of roads in Anambra State since its fitted or estimated values have no significant variation from the observed maintenance cost of roads over the years.

The result of the curve estimation analysis of maintenance cost of roads and quantity of binder produced, quantity of wearing produce and economic parameter revealed that a nonlinear model will best fit the data set observed.

Hence, it was found that Qbp, Qwp, IASPCA, SCRGDP, MCQCM, CGFCFPME, GDPCBPBC and LR were the variables that contributed significantly to determining the behaviour of the response variables mcr.

The result of generalized nonlinear model found a Pearson Chi-squared value of $1.332268e-14$ and an Akaike Information Criterion (AIC) value of -292.44. Also obtained was a model for estimating maintenance cost of roads in Anambra State which can be expressed as equation (4.9).

It was found that the obtained model has the properties of generating good estimates of maintenance cost of roads in Anambra State since its fitted or estimated values have no significant variation from the observed maintenance cost of roads over the years.

The result of the curve estimation analysis of maintenance cost of roads using the linear maintenance cost model and quantity of binder produced, quantity of wearing produce and economic parameter revealed that a nonlinear model will best fit the data set observed. Hence, it was found that Qbp, Qwp, IASPCA, SCRGDP, MCQCM, MCQCM, CGFCFPME, GDPCBPBC and LR were the variables that contributed significantly to determining the behaviour of the response variables maintenance cost of roads using the linear maintenance cost model (CT.linear).

The result of generalized nonlinear model found a Pearson Chi-squared value of $1.054712e-14$ and an Akaike Information Criterion (AIC) value of -294.48 . Also obtained was a model for estimating CT.linear which can be expressed as equation (4.10).

It was found that the obtained model has the ability of producing good estimates of maintenance cost of roads using the linear maintenance cost model in Anambra State since its fitted or estimated values have no significant variation from the observed maintenance cost of roads using the CT.linear model over the years.

The result of the curve estimation analysis of maintenance cost of roads using the nonlinear maintenance cost model and quantity of binder produced, quantity of wearing produce and economic parameter revealed that a nonlinear model will best fit the data set observed. Hence, it was found that Qbp, Qwp, SCRGDP, CGFCFPME, GDPCBPBC and LR were the variables that contributed significantly to determining the behaviour of the response variables maintenance cost of roads using the linear maintenance cost model (CT.nonlinear).

The result of generalized nonlinear model found a Pearson Chi-squared value of $2.396087e-16$ and an Akaike Information Criterion (AIC) value of -332.32 .

Also obtained was a model for estimating CT.nonlinear which can be expressed as equation (4.11).

It was found that the obtained model has the ability of producing good estimates of maintenance cost of roads using the nonlinear maintenance cost model in Anambra State since its fitted or estimated values have no significant variation from the observed maintenance cost of roads using the CT.nonlinear model over the years.

The result of the curve estimation analysis of quantity of binder produced and explanatory parameters revealed that a nonlinear model will best fit the data set observed. Hence, it was found that MMT, MRR, MeF, S, C5, C10, B, and C15 were the variables that contributed significantly to determining the behaviour of the response variables quantity of binder produced.

The result of generalized nonlinear model for quantity of binder produced found a Pearson Chi-squared value of $4.546375e-19$ and an Akaike Information Criterion (AIC) value of -394.99 . Also obtained was a model for estimating Qbp which can be expressed as equation (4.12).

It was found that the obtained quantity of binder produced model have the ability of producing good estimates of quantity of binder produced in Anambra State since its fitted or estimated values have no significant variation from the over the years.

The result of the curve estimation analysis of quantity of wearing produced and explanatory parameters revealed that a nonlinear model will best fit the data set observed. Hence, it was found that MMT, MRH, MRR, MeF, ME, S, C5, C10, and B, were the variables that contributed significantly to determining the behaviour of the response variables quantity of binder produced. The result of generalized nonlinear model found a Pearson Chi-squared value of $1.458229e-23$ and an Akaike Information Criterion (AIC) value of -498.47 . Also obtained was a model for estimating Qwp which can be expressed as equation (4.13).

It was found that the obtained quantity of binder produced model have the ability of producing good estimates of quantity of binder produced in Anambra State since its fitted or estimated values have no significant variation from the over the years.

The result of the curve estimation analysis of the total quantity of asphalt produced and explanatory parameters revealed that a nonlinear model will best fit the data set observed. Hence, it was found that TMMT, TMRH, TMeF, TME, TS, TC5, TC10, TB, and TC15 were the variables that contributed significantly to determining the behaviour of the response variables maintenance cost of roads using the linear maintenance cost model (CT.nonlinear).

The result of generalized nonlinear model found a Pearson Chi-squared value of $9.177153e-19$ and an Akaike Information Criterion (AIC) value of -387.97 . Also obtained was a model for estimating TQAP which can be expressed as equation (4.14).

It was found that the obtained total quantity of asphalt produced for the maintenance of roads in Anambra State have the ability of producing good estimates of total quantity of asphalt produced in Anambra State since its fitted or estimated values have no significant variation from the over the years.

The result of assessing the impact of length of road on maintenance cost of roads per kilometre found a positive coefficient of determination which implies that length of road has significant impact on maintenance cost of road per kilometre.

The designed model for estimating maintenance cost of roads per kilometre was expressed as equation (4.15).

5.2 Conclusion

This study evaluated government involvement on road maintenance in Nigeria using Anambra State as case study. The main objective of this study was to design a linear and nonlinear maintenance cost model for estimating the maintenance cost of roads in Anambra State.

The findings of this study revealed that the researcher was able to design a linear and nonlinear maintenance cost model for estimating the maintenance cost of roads in Anambra State. Also, the linear maintenance cost model was optimized using the general-purpose unconstrained optimization method, general purpose optimization method and the quasi-Newton and conjugate-gradient algorithms and the three methods employed obtained the same annual minimum cost of road maintenance of N52,416,579.36. Also, the bivariate regression analysis was used to validate the cost estimate obtained by the three linear optimization methods and it was found to fit best to the cost estimated using the linear optimization methods with minimum variations.

Furthermore, the nonlinear maintenance cost model was optimized using the the Barzilai-Borwein (BB) Steplengths method, the nonlinear optimization with multi start values method and the spectral projected gradient method for large-scale optimization and the three methods employed obtained the same annual minimum cost of road maintenance of N2697251.47. Also, the response surface

analysis was used to validate the cost estimate obtained by the three nonlinear optimization methods and it was found to fit best to the cost estimated using the nonlinear optimization methods with minimum dispersions.

In addition, it was found that the linear maintenance cost model performed better than the nonlinear maintenance model in estimating the observed maintenance cost of roads over the time period. This is because the cost estimates generated by the linear model have little variations towards the behaviour of the observed maintenance cost of roads over the period of ten years (2004-2013). While the cost estimates generated by the nonlinear model were far below the observed maintenance cost of roads over the observed period.

The findings of the study found that unavailability of Street lights, Bustop/PD, Traffic Congestion, traffic circle and road direction constitute 80% of factors affecting road maintenance in Anambra State.

It was revealed that Road divider, Road direction, Traffic Circle, Drainage, Walkways, street light, traffic congestion and Bustop/ PD has inverse relationship with Road condition in Anambra State. This result implies that as the availability of these factors are increasing, bad road condition is expected to decrease in Anambra State.

The researcher also modelled a time series model for estimating the maintenance cost of roads in Anambra State. It was found that the maintenance cost of roads has an increasing trend over time. Also, five years forecast on the maintenance cost of roads in Anambra State was made and it was found that in the year 2018 all things being equal the maintenance cost of roads in Anambra State is expected to be about N237,226,028.

The generalized nonlinear model was used to model the maintenance cost of roads on the economic variables and it was found that variables such as import of Articles of Stones, Plaster & Cement, sectoral contribution to real GDP, market capitalization of quoted company for construction, market capitalization of quoted companies for machinery (Marketing), composition of gross fixed capital formation at current purchase value machinery and equipment, GDP at constant basic price for building and construction, total length of federal government and construction, mean relative rain fall and mean efficiency has significant impact on the maintenance cost of roads in Anambra State.

It was found that the all the models designed for estimating maintenance cost of roads, quantity of binder produced for maintenance of road, quantity of wearing produced for maintenance of roads and total quantity of asphalt produced for maintenance of roads have properties of generating good estimates for the corresponding response variables with regards to maintenance cost of roads in Anambra state over the years.

It was found that the obtained total quantity of asphalt produced for the maintenance of roads in Anambra State have the ability of producing good estimates of total quantity of asphalt produced in Anambra State since its fitted or estimated values have no significant variation from the over the years.

Also, findings showed that length of road has significant impact on maintenance cost of road per kilometre.

5.3 Contribution to Knowledge

1. Since there exist no literature on a suitable maintenance cost model for estimating the cost of road maintenance in Anambra State, this study has established a linear and non-linear maintenance cost models for effective estimation of the maintenance cost of road in Anambra State this would enable government to have proper knowledge of cost of maintenance of roads and to also check-mate over estimation of cost of maintenance of roads from contractors.
2. Designed a generalize non-linear model for estimating maintenance cost of roads in Anambra State with the consideration of economic parameters, thereby enabling the government to properly budget, estimate cost of roads maintenance at any given economic condition and time.

5.4 Recommendations

This study developed the linear and non linear maintenance cost models for estimating the annual maintenance cost of roads in Anambra State and it was found that the linear cost model estimated better the maintenance cost in Anambra State, hence we recommend that government should employ the use of the linear cost model in other to checkmate the excesses of contractors in the maintenance of roads in Anambra state. All other constructing companies can equally used the model to estimate the maintenance cost of roads at any point in time.

It is recommended also that government should either supervise the production of the production process of asphalt and materials been used by them on the site so as to ascertain the exact durability of the materials before using on roads to avoid failure in the long run.

In addition, the present study dealt with modelling and estimating the maintenance cost of roads in Anambra state. Thus we recommend studies on assessing the quality and standard of maintenance of roads as fruitful area for future research.

Further work on the evaluation of percentage contributions of aggregate (stone dust) in binder coarse and wearing coarse mix design to the overall maintenance cost of road.

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APPENDIX I

R-programming code for the methods

The R-code for the general-purpose unconstrained optimization method is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R>ucminf(par, fn, gr = NULL, ..., control = list(), hessian=0)
```

The R-code for the general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R> optimx(par, fn, gr = gradient, ..., control = list(), hessian=0, Inf,  
method=c("Nelder-Mead","BFGS"))
```

The R-code for the general-purpose optimization method is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R> optim(par, fn, gr = gradient, ..., control = list(), hessian=0, Inf, method= "L-  
BFGS-B"))
```

The R-code for the Barzilai-Borwein steplength methods is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R> BBOptim(par, fn, gr = gradient, ..., control = list(), hessian=0, Inf,  
method=c(2,3,1))
```

The R-code for the optimization method with Multi-start values is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R> multiStart(par, fn, gr = gradient, ..., action = "optimize", method=c(2,3,1))
```

The R-code for the Spectral Projected Gradient (SPG) method is written as;

```
R> objective.function <- function(x)( input model)
```

```
R> function(x) c(gradient)
```

```
R> spg (par, fn, gr = gradient, ..., method=3)
```

The R-code to fit a linear model with a response-surface component, and produce appropriate analyses and summaries is written as;

```
R> Y=dependent variable
```

```
R> X1,..., Xn=independent variables
```

```
R>rsm(Y~SO(X1,..., Xn))
```

The R-code used to fit linear models. It can be used to carry out regression, single stratum analysis of variance and analysis of covariance is written as;

```
R>Y=dependent variable
```

```
R>X1,..., Xn=independent variables
```

```
R>lm(Y~X1+ X1+...+ Xn)
```

The R-code used to run the Pareto analysis is written as:

```
R> factors=c(input the values for factors)
```

```
R> names(list factors name)=c("factor name 1", "factor name 2",..., factor name  
nth")
```

```
R> pareto.chart(factor name)
```

The R-code used to fits generalised nonlinear models using an over-parameterised representation and where nonlinear terms are specified by calls to functions of class "nonlin" is written as

```
R>Y=dependent variable
```

```
R>X1,..., Xn=independent variables
```

```
R>lm(Y~X1+ X1+...+ Xn)
```

```
R>gnm(Y~ X1+ X1+...+ Xn, family = gaussian, data = NULL, method =  
"gnmFit", start = NULL)
```

APPENDIX II

The algorithm for the General-Purpose Unconstrained Optimization Method

```
R> objective.function <- function(x)( 710.65*x[1] + 688.30*x[2]+  
(2514700/x[1]) + 14213*2514.7+ 2000*2514.7 + 2000*2514.7 + 600*2514.7 +  
(272000/x[2]) + 13766*272 + 2000*272 + 2000*272 + 600*272)
```

```
R> function(x) c(710.65-(2514700/x[1]^2),  
+ 600.3 - (272000/x[2]^2))
```

```
R> CT.linear.uncmin <- ucminf(par = c(0.595, 0.213), fn = objective.function,  
gr = gradient, control = list(trace = 1))
```

```
R> CT.linear.uncmin
```

The result of optimizing the linear cost function using the general-purpose unconstrained optimization method on R-command console window was obtained as:

```
$par
```

```
[1] 60.33361 19.22233
```

```
$value
```

```
[1] 52416540
```

```
$convergence
```

```
[1] 4
```

\$message

[1] "Stopped by zero step from line search"

\$invhessian.lt

[1] 0.030375750 0.009672183 0.003080241

\$info

Optimization has converged

Stopped by zero step from line search

maxgradient	laststep	stepmax	neval
135.8343	0.0000	9.4500	22.0000

APPENDIX III

The algorithm for the General-Purpose Optimization Method

```
R> objective.function <- function(x)( 710.65*x[1] + 688.30*x[2]+
(2514700/x[1]) + 14213*2514.7+ 2000*2514.7 + 2000*2514.7 + 600*2514.7 +
(272000/x[2]) + 13766*272 + 2000*272 + 2000*272 + 600*272)

R> function(x) c(710.65-(2514700/x[1]^2),
+ 600.3 - (272000/x[2]^2))

R > CT.linear.optimx <- optimx(par = c(0.595, 0.213), fn = objective.function,
gr = gradient, hess=NULL,Inf, method= c("Nelder-Mead","BFGS"))

R> CT.linear.optimx
```

The result of optimizing the linear cost function using the general purpose optimization method on R-command console window was obtained as;

	p1	p2	value	fevals	gevals	niter	convcode
Nelder-Mead	59.34	21.27	52416579.356	38	38	NA	0
TRUE	NA	0					
BFGS	59.34	21.27	52416579.356	38	38	NA	0
TRUE	NA	0					

APPENDIX IV

The algorithm for the Quasi-Newton and Conjugate-Gradient Optimization Method

To optimize the linear cost function using the quasi-Newton and conjugate-gradient algorithms on R-command window the following algorithm were written to obtain the desired result;

```
R> objective.function <- function(x)( 710.65*x[1] + 688.30*x[2]+  
(2514700/x[1]) + 14213*2514.7+ 2000*2514.7 + 2000*2514.7 + 600*2514.7 +  
(272000/x[2]) + 13766*272 + 2000*272 + 2000*272 + 600*272)
```

```
R> function(x) c(710.65-(2514700/x[1]^2),  
+ 600.3 - (272000/x[2]^2))
```

```
R> CT.linear.optim <- optim(par = c(0.595, 0.213), fn = objective.function, gr  
= gradient, method= "L-BFGS-B")
```

```
R> CT.linear.optim
```

The result of optimizing the linear cost function using the quasi-Newton and conjugate-gradient algorithms on R-command console window was obtained as;

```
$par
```

```
[1] 59.3420308160 21.2741816626
```

```
$value
```

```
[1] 52416579.3566
```

```
$counts
```

```
function gradient
```

```
38 38
```

```
$convergence
```

```
[1] 0
```


APPENDIX V

The algorithm for the BB Steplength Optimization Method

To run the nonlinear cost function using the BB steplengths algorithm on R-command window the following algorithm were written to obtain the desired result;

```
R> objective.function <- function(x) (710.65*x[1] + 688.30*x[2] +
(2514700*x[1]^(-1)) + (14213*2514.7*x[1]^(-1/2)) + (2000*2514.7*x[1]^(-1/2))
+ (2000*2514.7*x[1]^(-1/2)) + (600*2514.7*x[1]^(-1/2)) + (272000*x[2]^(-1)) +
(13766*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) +
(600*272*x[2]^(-1/2)))
```

```
R> gradient <- function(x) c(710.65 - 2514700*x[1]^(-2) -
1/2*14213*2514.7*x[1]^(-3/2) - 1/2*2000*2514.7*x[1]^(-3/2) -
1/2*2000*2514.7*x[1]^(-3/2) - 1/2*600*2514.7*x[1]^(-3/2),
+ 688.30 - 272000*x[2]^(-2) - 1/2*13766*272*x[2]^(-3/2) -
1/2*2000*272*x[2]^(-3/2) - 1/2*2000*272*x[2]^(-3/2) - 1/2*600*272*x[2]^(-
(3/2))
```

```
R> CT.nolinear.BB <- BBoptim(par= c(0.0002, 0.0215), fn= objective.function,
gr= gradient, method=c(2,3,1))
```

```
iter: 0 f-value: 15965475644 pgrad: 71230637710367
```

```
iter: 10 f-value: 55670865.2663 pgrad: 20990569.86
```

```
iter: 20 f-value: 10167242.2303 pgrad: 144627.632437
```

```
iter: 30 f-value: 2754068.37672 pgrad: 452.889071432
```

iter: 40 f-value: 2697251.47321 pgrad: 0.137396101619

Successful convergence.

R> CT.nolinear.BB

The result of optimizing the non-linear cost function using the BB steplengths algorithm on R-command console window was obtained as;

\$par

[1] 1037.034506329 237.259445641

\$value

[1] 2697251.47104

\$gradient

[1] 2.58641819073e-08

\$fn.reduction

[1] 15962778392.6

\$iter

[1] 44

\$feval

[1] 45

\$convergence

[1] 0

\$message

[1] "Successful convergence"

\$cpair

method	M
2	50

APPENDIX VI

The algorithm for the Multi Start Values Optimization Method

To run the nonlinear cost function using the nonlinear optimization method with multi start values on R-command window the following algorithm were written to obtain the desired result;

```
R> objective.function <- function(x) (710.65*x[1] + 688.30*x[2] +
(2514700*x[1]^(-1)) + (14213*2514.7*x[1]^(-1/2)) + (2000*2514.7*x[1]^(-1/2))
+ (2000*2514.7*x[1]^(-1/2)) + (600*2514.7*x[1]^(-1/2)) + (272000*x[2]^(-1)) +
(13766*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) +
(600*272*x[2]^(-1/2)))
```

```
R> gradient <- function(x) c(710.65 - 2514700*x[1]^(-2) -
1/2*14213*2514.7*x[1]^(-3/2) - 1/2*2000*2514.7*x[1]^(-3/2) -
1/2*2000*2514.7*x[1]^(-3/2) - 1/2*600*2514.7*x[1]^(-3/2),
+ 688.30 - 272000*x[2]^(-2) - 1/2*13766*272*x[2]^(-3/2) -
1/2*2000*272*x[2]^(-3/2) - 1/2*2000*272*x[2]^(-3/2) - 1/2*600*272*x[2]^(-
(3/2))
```

```
R> CT.nonlinear.multi.start <- multiStart(par= c(0.0002, 0.0215), fn=
objective.function, gr= gradient, action = "optimize", method=c(2,3,1))
```

Parameter set : 1 ...

iter: 0 f-value: 15965475644 pgrad: 71230637710367

iter: 10 f-value: 55670865.2663 pgrad: 20990569.86

```
iter: 20 f-value: 10167242.2303 pgrad: 144627.632437
iter: 30 f-value: 2754068.37672 pgrad: 452.889071432
iter: 40 f-value: 2697251.47321 pgrad: 0.137396101619
```

Successful convergence.

```
R> CT.nonlinear.multi.start
```

The result of optimizing the non-linear cost function using the optimization method with multi start values on R-command console window was obtained as;

```
$par
```

```
      [,1]      [,2]
```

```
[1,] 1037.03450633 237.259445641
```

```
$fvalue
```

```
[1] 2697251.47104
```

```
$converged
```

```
[1] TRUE
```

The result of optimizing the non-linear cost function using the nonlinear optimization with multi start values obtained the value of the estimated minimum as N2697251.47 while the estimated points at which the minimum

value of the function were 1037.03 and 237.26 for cost of binder (x[1]) and cost of wearing (x[2]) respectively. This result implies that the minimum maintenance cost of roads using the non-linear cost function was N2697251.47. Hence, after substituting the estimated points for cost binder and wearing the non-linear maintenance cost function can be rewritten as

$$\begin{aligned}
 \text{CT.nonlinear.multi.start} = & k_1 * 1037.03 + k_2 * 237.26 + (k_3 * Q_1 * 1037.03^{-1}) + \\
 & (k_4 * Q_1 * 1037.03^{-(1/2)}) + (k_5 * Q_1 * 1037.03^{-(1/2)}) + (k_6 * Q_1 * 1037.03^{-(1/2)}) \\
 & + (k_7 * Q_1 * 1037.03^{-(1/2)}) + (k_8 * Q_2 * 237.26^{-1}) + (k_9 * Q_2 * 237.26^{-(1/2)}) + \\
 & (k_{10} * Q_2 * 237.26^{-(1/2)}) + (k_{11} * Q_2 * 237.26^{-(1/2)}) + (k_{12} * Q_2 * 237.26^{-(1/2)})
 \end{aligned}$$

APPENDIX VII

The algorithm for the Spectral Projected Gradient Optimization Method

To optimize the nonlinear cost function using the spectral projected gradient (spg) method for large-scale optimization the following algorithm were written to obtain the desired result;

```
R> objective.function <- function(x) (710.65*x[1] + 688.30*x[2] +
(2514700*x[1]^(-1)) + (14213*2514.7*x[1]^(-1/2)) + (2000*2514.7*x[1]^(-1/2))
+ (2000*2514.7*x[1]^(-1/2)) + (600*2514.7*x[1]^(-1/2)) + (272000*x[2]^(-1)) +
(13766*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) + (2000*272*x[2]^(-1/2)) +
(600*272*x[2]^(-1/2)))
```

```
R> gradient <- function(x) c(710.65 - 2514700*x[1]^(-2) -
1/2*14213*2514.7*x[1]^(-3/2) - 1/2*2000*2514.7*x[1]^(-3/2) -
1/2*2000*2514.7*x[1]^(-3/2) - 1/2*600*2514.7*x[1]^(-3/2),
+ 688.30 - 272000*x[2]^(-2) - 1/2*13766*272*x[2]^(-3/2) -
1/2*2000*272*x[2]^(-3/2) - 1/2*2000*272*x[2]^(-3/2) - 1/2*600*272*x[2]^(-
(3/2))
```

```
R> CT.nonlinear.spg <- spg(par= c(0.0002, 0.0215), fn= objective.function, gr=
gradient, method=3)
```

```
iter: 0 f-value: 15965475644 pgrad: 71230637710367
```

```
iter: 10 f-value: 55141177.9744 pgrad: 20582040.3642
```

```
iter: 20 f-value: 9833036.31903 pgrad: 130681.958792
```

iter: 30 f-value: 2741626.23214 pgrad: 386.966976293

iter: 40 f-value: 2697251.47121 pgrad: 0.0378981831472

R> CT.nonlinear.spg

The result of optimizing the non-linear cost function using the spectral projected gradient (spg) method for large-scale optimization on R-command console window was obtained as;

\$par

[1] 1037.034527165 237.259445424

\$value

[1] 2697251.47104

\$gradient

[1] 9.40100079561e-07

\$fn.reduction

[1] 15962778392.6

\$iter

[1] 41

\$convergence

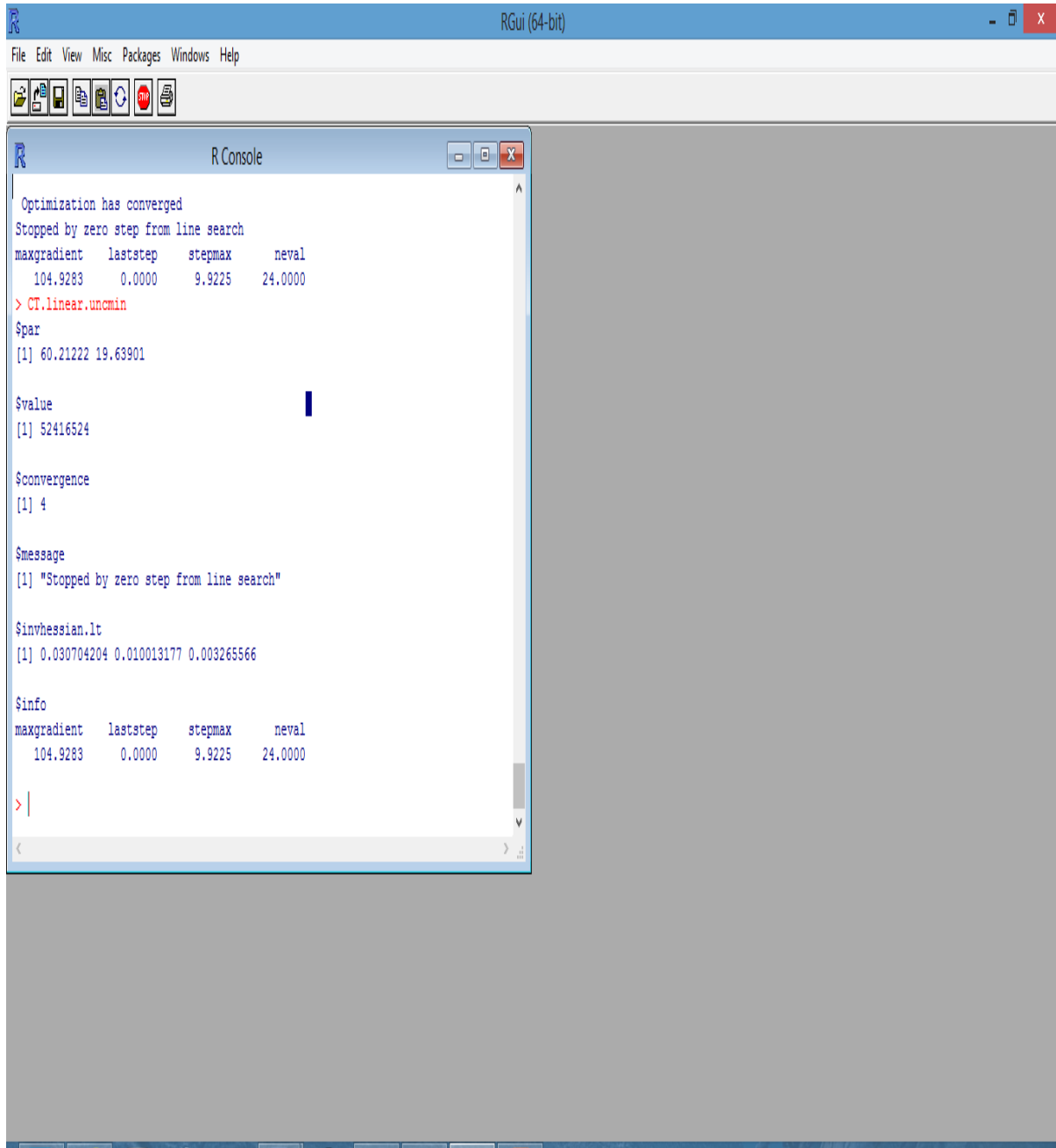
[1] 0

\$message

[1] "Successful convergence"

APPENDIX VIII

Output of the general-purpose unconstrained optimization method in R-3.1.2 window



```
RGui (64-bit)
File Edit View Misc Packages Windows Help
[Icons]

R Console
Optimization has converged
Stopped by zero step from line search
maxgradient  laststep  stepmax  neval
  104.9283    0.0000    9.9225   24.0000
> CT.linear.uncmin
$par
[1] 60.21222 19.63901

$value
[1] 52416524

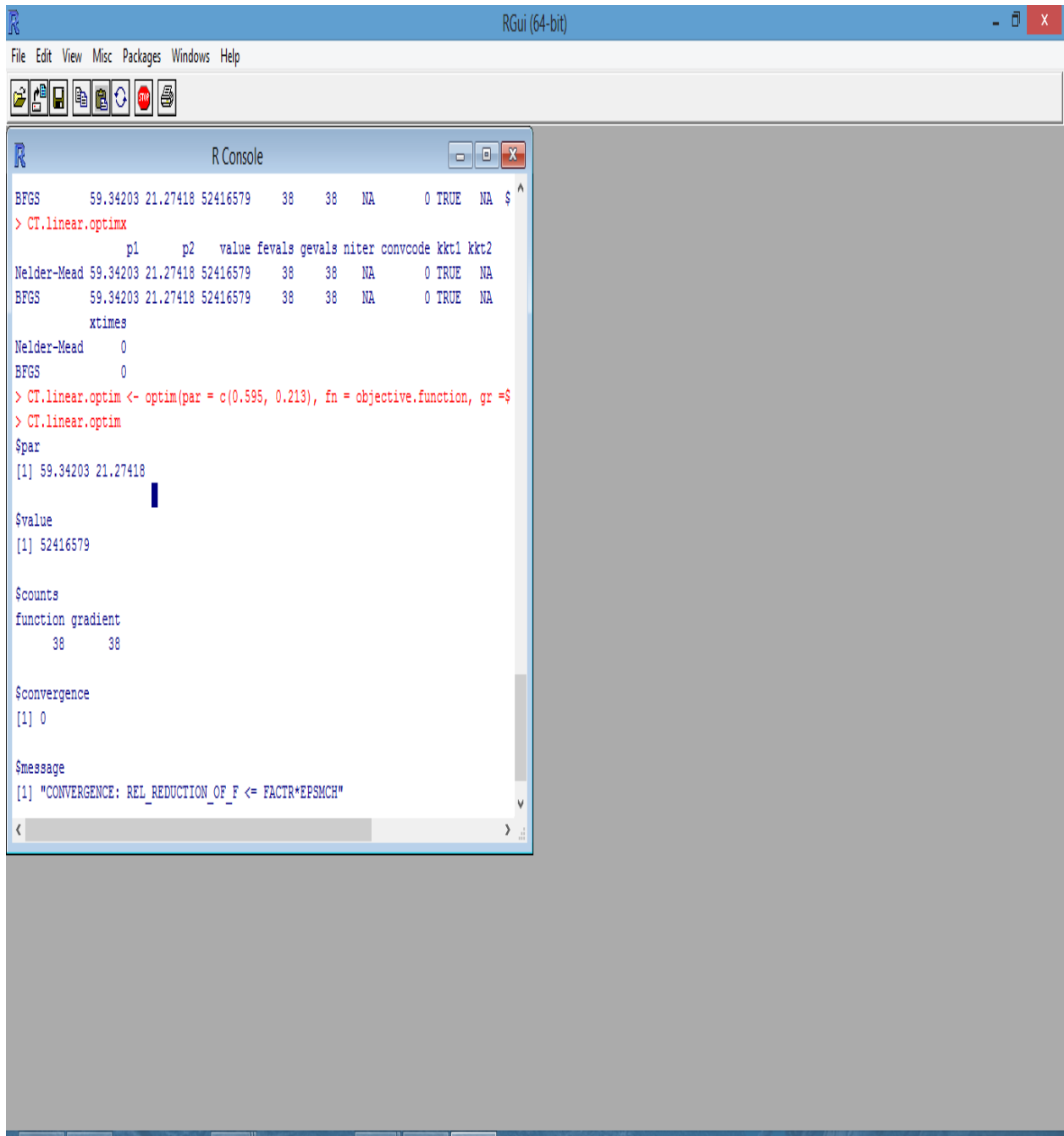
$convergence
[1] 4

$message
[1] "Stopped by zero step from line search"

$invhessian.lt
[1] 0.030704204 0.010013177 0.003265566

$info
maxgradient  laststep  stepmax  neval
  104.9283    0.0000    9.9225   24.0000
> |
```

Output of the general-purpose optimization based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms and general-purpose optimization method in R-3.1.2 window



The screenshot shows the R GUI (64-bit) window with the R Console open. The console displays the output of the `CT.linear.optimx` function, which compares the Nelder-Mead and BFGS optimization algorithms. The output includes a table of results, the number of iterations (xtimes), and the convergence status.

```
BFGS      59.34203 21.27418 52416579   38   38   NA   0 TRUE  NA  $  
> CT.linear.optimx  
      p1      p2  value fevals gevals niter convcode kkt1 kkt2  
Nelder-Mead 59.34203 21.27418 52416579   38   38   NA   0 TRUE  NA  
BFGS      59.34203 21.27418 52416579   38   38   NA   0 TRUE  NA  
      xtimes  
Nelder-Mead    0  
BFGS          0  
> CT.linear.optim <- optim(par = c(0.595, 0.213), fn = objective.function, gr = $  
> CT.linear.optim  
$par  
[1] 59.34203 21.27418  
$value  
[1] 52416579  
$counts  
function gradient  
      38      38  
$convergence  
[1] 0  
$message  
[1] "CONVERGENCE: REL_REDUCTION_OF_F <= FACTR*EPSMCH"
```

Output of the Barzilai-Borwein steplength methods in R-3.1.2 window

```
RGui (64-bit) - [R Console]
File Edit View Misc Packages Windows Help
[Icons]

> objective.function <- function(x) (710.65*x[1] + 688.30*x[2] + (2514700*x[1]^(-1) + (14213*2514.7*x[1]^(-1/2)) + (2000*2514.7*x[1]^(-1/2)) + (2000*2514.7*x[1]^(-1/2)
> gradient <- function(x) c(710.65 - 2514700*x[1]^(-2) - 1/2*14213*2514.7*x[1]^(-3/2) - 1/2*2000*2514.7*x[1]^(-3/2) - 1/2*2000*2514.7*x[1]^(-3/2) - 1/2*600*2514.7*x[1]^
+ 688.30 - 272000*x[2]^(-2) - 1/2*13766*272*x[2]^(-3/2) - 1/2*2000*272*x[2]^(-3/2) - 1/2*2000*272*x[2]^(-3/2) - 1/2*600*272*x[2]^(-3/2))
> CT.nonlinea.BB <- BBoptim(par= c(0.0002, 0.0215), fn= objective.function, gr= gradient, method=c(2,3,1))
Error: could not find function "BBoptim"
> local({pkg <- select.list(sort(.packages(all.available = TRUE)),graphics=TRUE)
+ if(nchar(pkg)) library(pkg, character.only=TRUE)})
> CT.nonlinea.BB <- BBoptim(par= c(0.0002, 0.0215), fn= objective.function, gr= gradient, method=c(2,3,1))
iter: 0 f-value: 15965475644 pgrad: 7.123064e+13
iter: 10 f-value: 55670865 pgrad: 20990570
iter: 20 f-value: 10167242 pgrad: 144627.6
iter: 30 f-value: 2754068 pgrad: 452.8891
iter: 40 f-value: 2697251 pgrad: 0.1373961
Successful convergence.
> CT.nonlinea.BB
$par
[1] 1037.0345 237.2594

$value
[1] 2697251

$gradient
[1] 2.586418e-08

$fn.reduction
[1] 15962778393

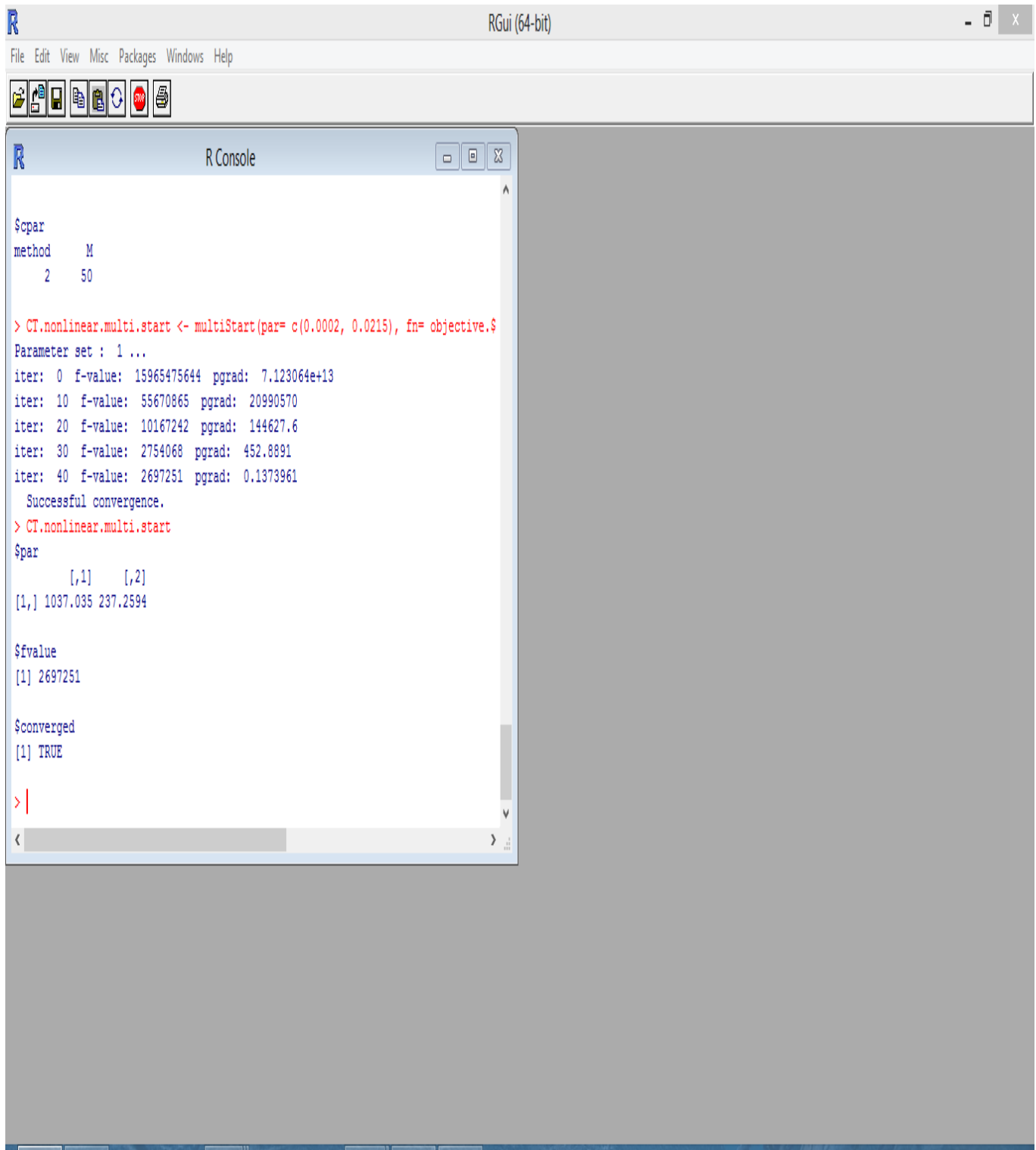
$iter
[1] 44

$feval
[1] 45

$convergence
[1] 0

$message
[1] "Successful convergence"
```

Output of the optimization method with Multi-start values in R-3.1.2 window



The screenshot shows the R GUI (64-bit) with the R Console window open. The console displays the output of the `multiStart` function. The output includes the parameter set, iteration details, and the final results.

```
R Console

$par
method      M
      2      50

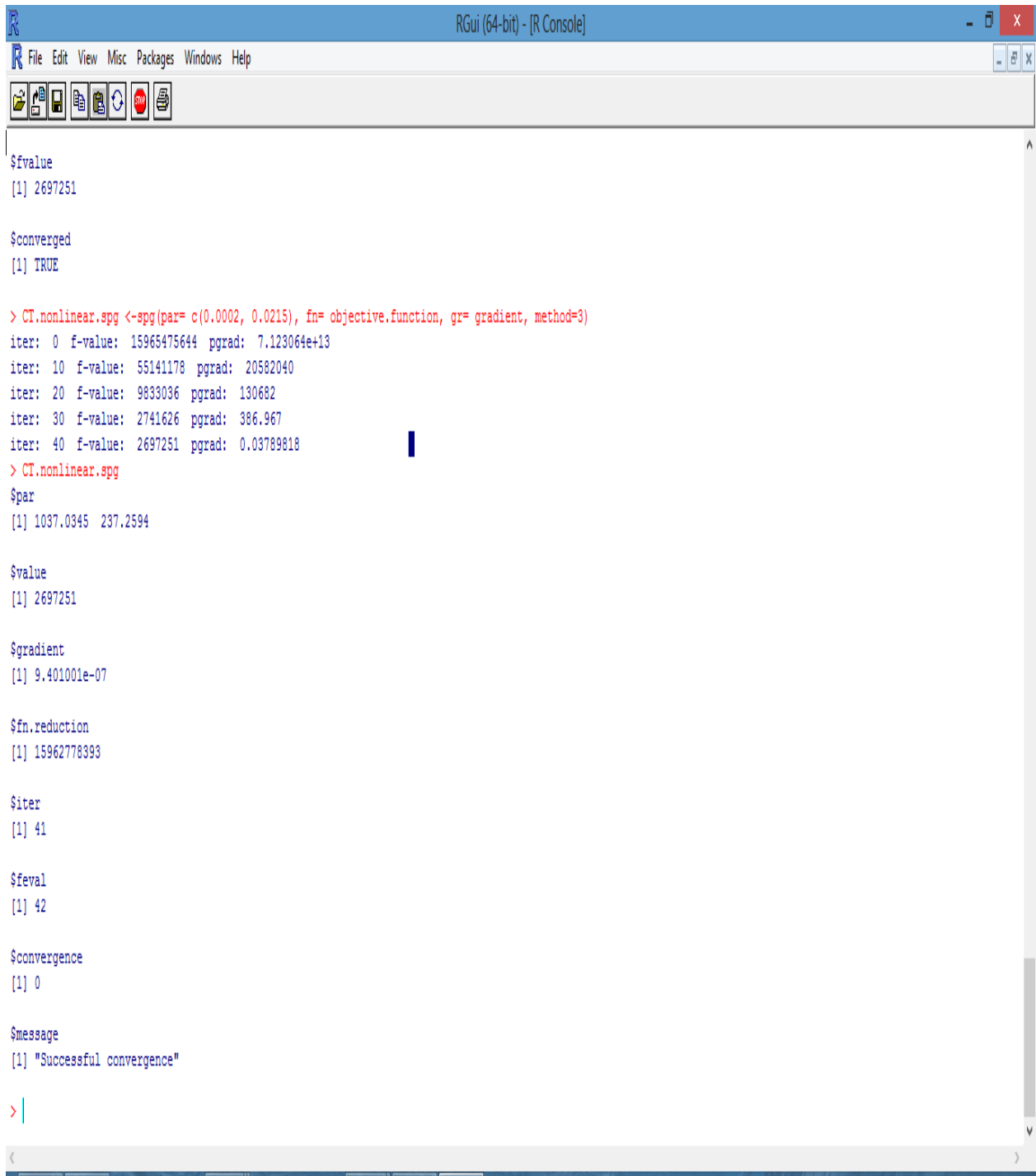
> CT.nonlinear.multi.start <- multiStart(par= c(0.0002, 0.0215), fn= objective.$
Parameter set : 1 ...
iter: 0 f-value: 15965475644 pgrad: 7.123064e+13
iter: 10 f-value: 55670865 pgrad: 20990570
iter: 20 f-value: 10167242 pgrad: 144627.6
iter: 30 f-value: 2754068 pgrad: 452.8891
iter: 40 f-value: 2697251 pgrad: 0.1373961
  Successful convergence.
> CT.nonlinear.multi.start
$par
      [,1] [,2]
[1,] 1037.035 237.2594

$fvalue
[1] 2697251

$converged
[1] TRUE

> |
```

Output of the Spectral Projected Gradient (SPG) method in R-3.1.2 window



```
RGui (64-bit) - [R Console]
File Edit View Misc Packages Windows Help

$fvale
[1] 2697251

$converged
[1] TRUE

> CT.nonlinear.spg <-spg(par= c(0.0002, 0.0215), fn= objective.function, gr= gradient, method=3)
iter: 0 f-value: 15965475644 pgrad: 7.123064e+13
iter: 10 f-value: 55141178 pgrad: 20582040
iter: 20 f-value: 9833036 pgrad: 130682
iter: 30 f-value: 2741626 pgrad: 386.967
iter: 40 f-value: 2697251 pgrad: 0.03789818
> CT.nonlinear.spg
$par
[1] 1037.0345 237.2594

$value
[1] 2697251

$gradient
[1] 9.401001e-07

$fn.reduction
[1] 15962778393

$iter
[1] 41

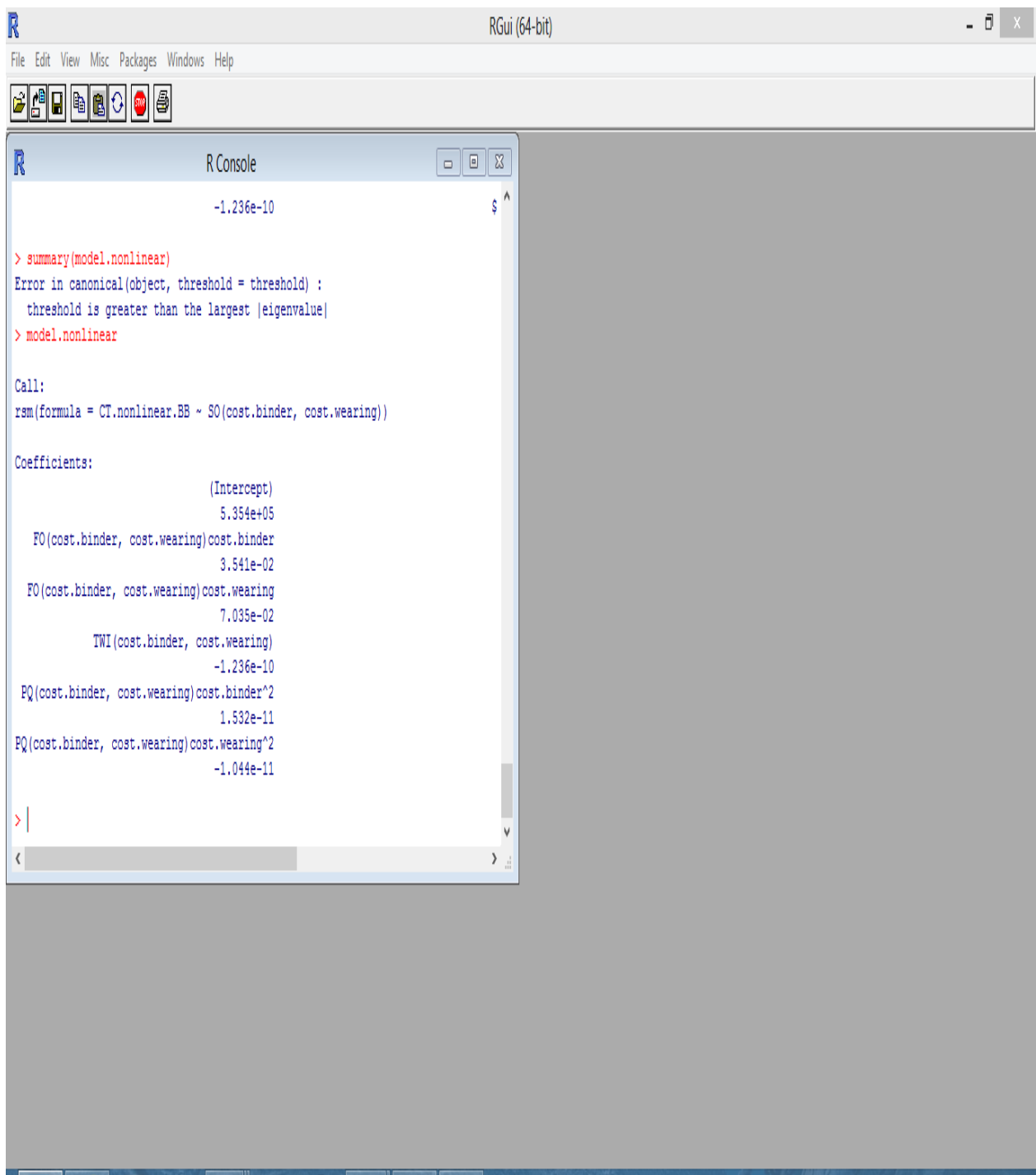
$feval
[1] 42

$convergence
[1] 0

$message
[1] "Successful convergence"

> |
```

Output of response surface method in R-3.1.2 window



```
RGui (64-bit)
File Edit View Misc Packages Windows Help
[Icons]

R Console
-1.236e-10 $ ^

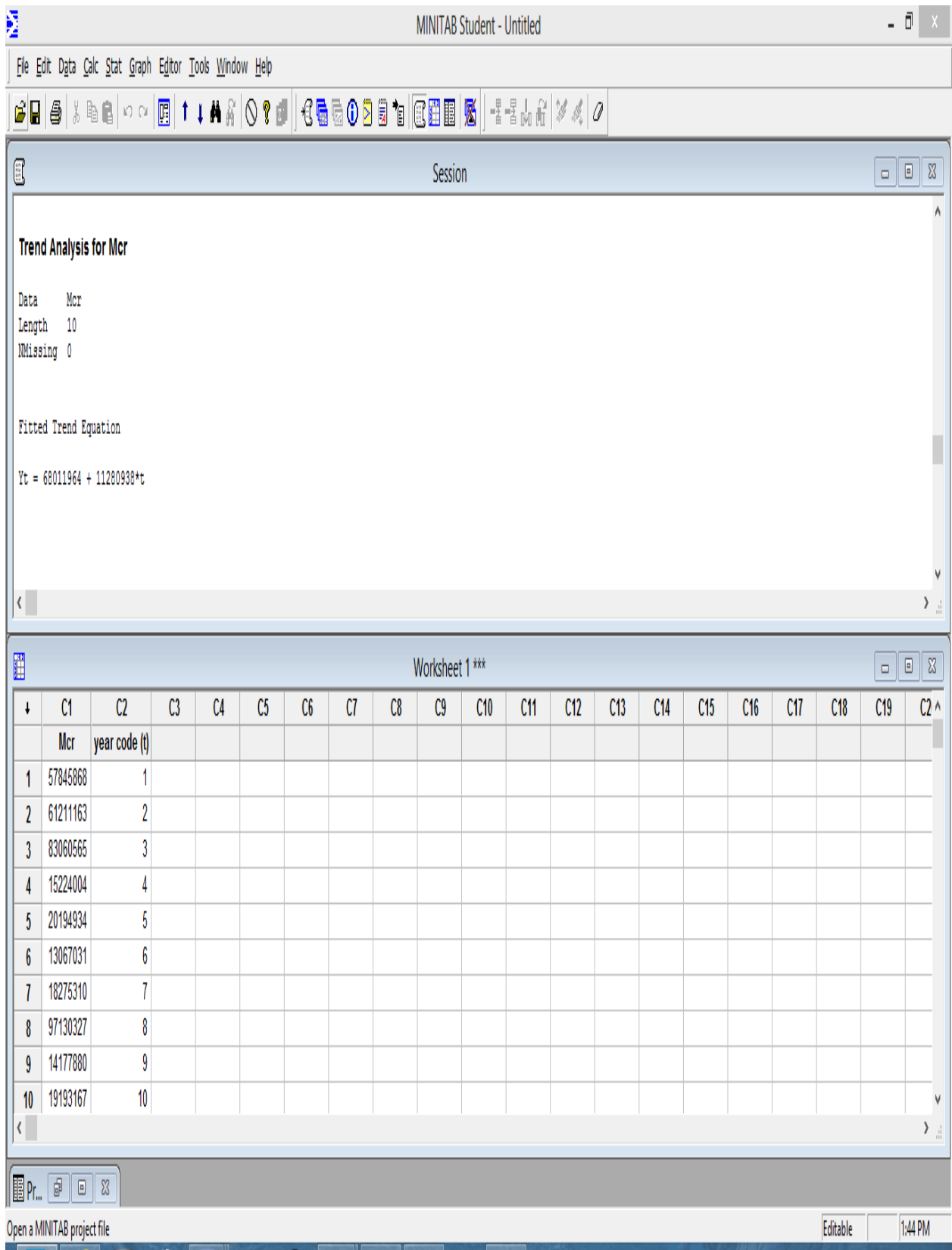
> summary(model.nonlinear)
Error in canonical(object, threshold = threshold) :
  threshold is greater than the largest |eigenvalue|
> model.nonlinear

Call:
rsm(formula = CT.nonlinear.BB ~ S0(cost.binder, cost.wearing))

Coefficients:
              (Intercept)
              5.354e+05
FO(cost.binder, cost.wearing)cost.binder
              3.541e-02
FO(cost.binder, cost.wearing)cost.wearing
              7.035e-02
              TWI(cost.binder, cost.wearing)
              -1.236e-10
EQ(cost.binder, cost.wearing)cost.binder^2
              1.532e-11
EQ(cost.binder, cost.wearing)cost.wearing^2
              -1.044e-11

> |
< > ...
```

Output of Time series analysis in Minitab 14.0 Window



The screenshot displays the Minitab 14.0 interface. The top window, titled "Session", shows the results of a trend analysis for the variable "Mcr". The data has a length of 10 and no missing values. The fitted trend equation is $Y_t = 68011964 + 11280938 \cdot t$.

The bottom window, titled "Worksheet 1 ***", shows a data table with 20 columns (C1 to C20) and 10 rows. The first two columns are labeled "Mcr" and "year code (t)". The data points are as follows:

Row	Mcr	year code (t)
1	57845868	1
2	61211163	2
3	83060565	3
4	15224004	4
5	20194934	5
6	13067031	6
7	18275310	7
8	97130327	8
9	14177880	9
10	19193167	10

Test of Stationarity using the Kwiatkowski-Phillips-Schmidt-Shin test and Augmented Dickey-Fuller test in the Eview7 window

Augmented Dickey-Fuller test in the Eview7 window

EViews - [Series: MCR Workfile: DATA EKWUEME:Untitled]

File Edit Object View Proc Quick Options Window Help

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats Ident

Augmented Dickey-Fuller Unit Root Test on MCR

Null Hypothesis: MCR has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-1.872082	0.3284
Test critical values:		
1% level	-4.420595	
5% level	-3.259808	
10% level	-2.771129	

*MacKinnon (1996) one-sided p-values.
 Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 9

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(MCR)
 Method: Least Squares
 Date: 01/06/16 Time: 13:50
 Sample (adjusted): 2 10
 Included observations: 9 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MCR(-1)	-0.629092	0.336039	-1.872082	0.1034
C	92391332	44518824	2.075332	0.0766

R-squared	0.333631	Mean dependent var	14898423
Adjusted R-squared	0.238435	S.D. dependent var	56326329
S.E. of regression	49154672	Akaike info criterion	38.45197
Sum squared resid	1.69E+16	Schwarz criterion	38.49580
Log likelihood	-171.0339	Hannan-Quinn criter.	38.35739
F-statistic	3.504691	Durbin-Watson stat	2.183289
Prob(F-statistic)	0.103361		

Path - c:\users\pabre\documents DB = ekwueme WF = data ekwueme

Augmented Dickey-Fuller test at First Difference in the Eview7 window

EViews - [Series: MCR Workfile: DATA EKWUEME:Untitled]

File Edit Object View Proc Quick Options Window Help

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats Ident

Augmented Dickey-Fuller Unit Root Test on D(MCR)

Null Hypothesis: D(MCR) has a unit root
 Exogenous: Constant
 Lag Length: 0 (Automatic - based on SIC, maxlag=1)

	t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic	-3.640206	0.0329
Test critical values:		
1% level	-4.582648	
5% level	-3.320969	
10% level	-2.801384	

*MacKinnon (1996) one-sided p-values.
 Warning: Probabilities and critical values calculated for 20 observations and may not be accurate for a sample size of 8

Augmented Dickey-Fuller Test Equation
 Dependent Variable: D(MCR,2)
 Method: Least Squares
 Date: 01/06/16 Time: 13:50
 Sample (adjusted): 3 10
 Included observations: 8 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(MCR(-1))	-1.402215	0.385202	-3.640206	0.0108
C	20559955	21474633	0.957407	0.3753

R-squared	0.688330	Mean dependent var	5848448.
Adjusted R-squared	0.636384	S.D. dependent var	98928028
S.E. of regression	59654137	Akaike info criterion	38.85834
Sum squared resid	2.14E+16	Schwarz criterion	38.87820
Log likelihood	-153.4334	Hannan-Quinn criter.	38.72439
F-statistic	13.25110	Durbin-Watson stat	1.962059
Prob(F-statistic)	0.010832		

Path = c:\users\pabre\documents DB = ekwueme WF = data ekwueme

Kwiatkowski-Phillips-Schmidt-Shin test in the Eview7 window

EViews - [Series: MCR Workfile: DATA EKWUEME:Untitled]

File Edit Object View Proc Quick Options Window Help

View Proc Object Properties Print Name Freeze Sample Genr Sheet Graph Stats Ident

KPSS Unit Root Test on MCR

Null Hypothesis: MCR is stationary
 Exogenous: Constant
 Bandwidth: 1 (Newey-West automatic) using Bartlett kernel

	LM-Stat
Kwiatkowski-Phillips-Schmidt-Shin test statistic	0.351873
Asymptotic critical values*:	
1% level	0.739000
5% level	0.463000
10% level	0.347000

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

Residual variance (no correction)	2.57E+15
HAC corrected variance (Bartlett kernel)	3.31E+15

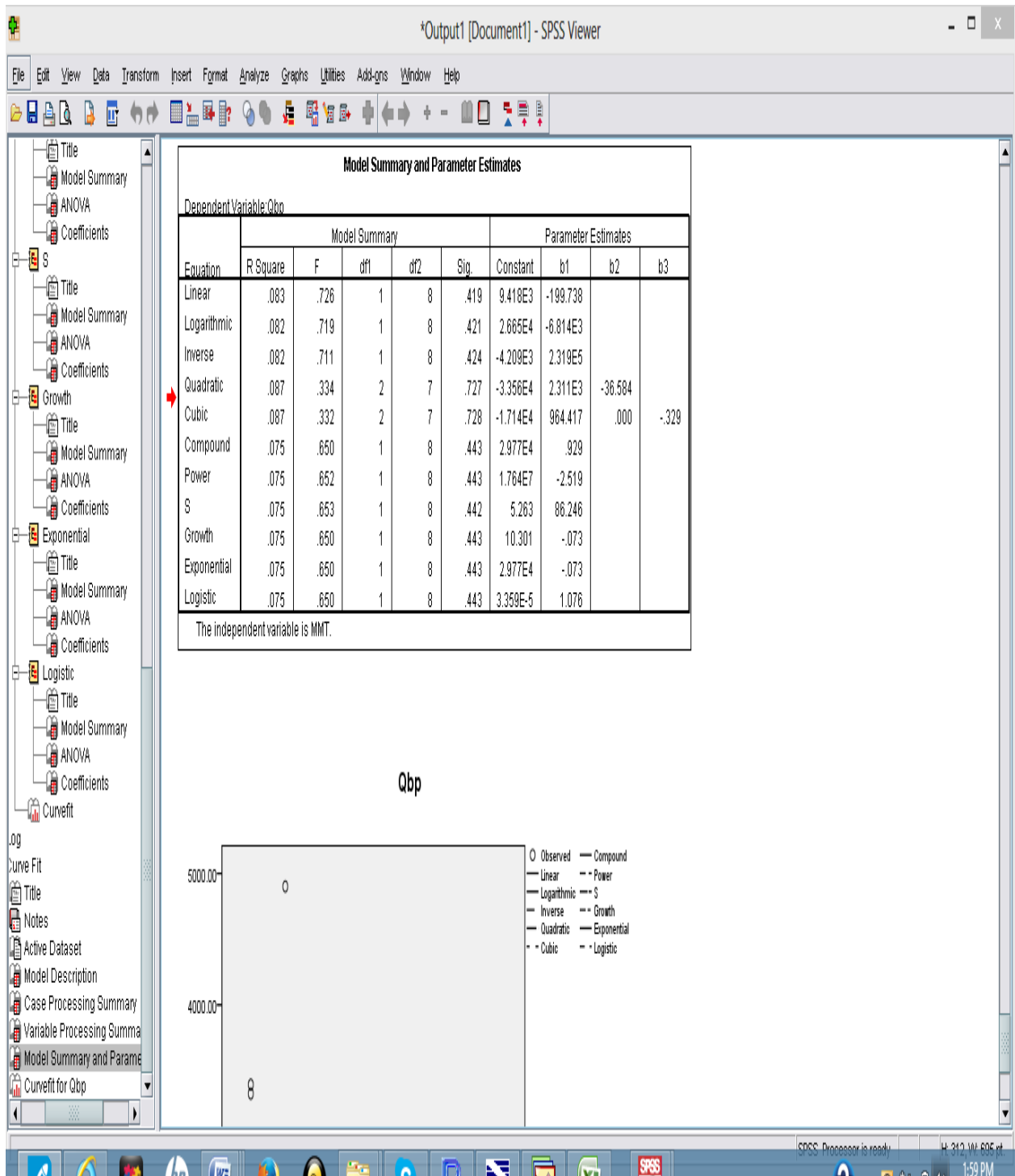
KPSS Test Equation
 Dependent Variable: MCR
 Method: Least Squares
 Date: 01/06/16 Time: 13:52
 Sample: 1 10
 Included observations: 10

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.30E+08	16882192	7.703805	0.0000

R-squared	0.000000	Mean dependent var	1.30E+08
Adjusted R-squared	0.000000	S.D. dependent var	53386177
S.E. of regression	53386177	Akaike info criterion	38.51864
Sum squared resid	2.57E+16	Schwarz criterion	38.54890
Log likelihood	-191.5932	Hannan-Quinn criter.	38.48545
Durbin-Watson stat	1.067372		

Path = c:\users\pabre\documents DB = ekwueme WF = data ekwueme

Output of curve fitting Analysis in SPSS 17.0 Window



Data set input of curve fitting Analysis in SPSS 17.0 Window

mcr data qbp qwp.sav [DataSet1] - SPSS Data Editor

File Edit View Data Transform Analyze Graphs Utilities Add-ons Window Help

1: Qbp 2514.7 Visible: 13 of 13 Variables

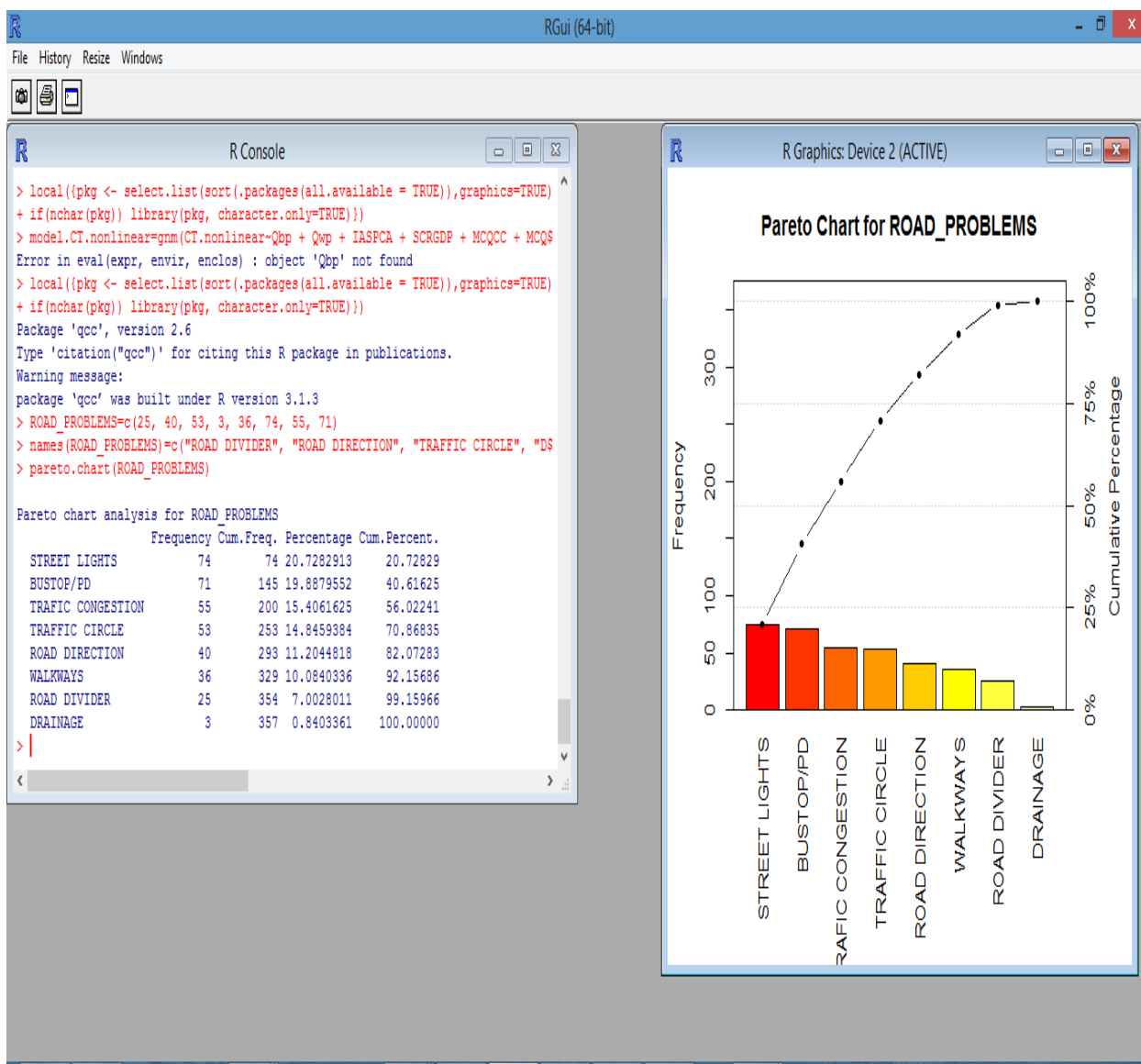
	Qbp	MMT	MRH	MRR	MeF	MR	ME	S	C5	C10	B	C15	Qwp	var	var	va
1	2514.70	32.00	72.00	121.30	94.50	17.80	3.50	1169.30	286.70	455.20	125.70	447.80	272.00			
2	1227.90	32.80	74.90	13.30	94.50	18.00	4.30	571.00	139.90	222.20	61.40	233.30	1754.00			
3	1479.60	35.30	73.05	159.20	91.80	18.00	4.30	688.00	168.70	267.80	74.00	281.10	2571.00			
4	2349.50	36.70	75.50	168.90	89.90	18.10	4.20	1082.80	265.40	421.50	116.40	442.40	5521.00			
5	3325.70	32.50	72.70	171.40	88.90	18.30	4.20	1546.50	379.10	601.90	166.30	6231.90	6529.00			
6	2344.00	32.70	74.00	189.45	89.90	18.60	4.20	1089.90	267.20	424.30	117.20	445.40	4028.00			
7	4901.30	33.10	79.70	162.90	89.90	18.60	4.30	2279.10	568.70	887.10	245.10	931.20	3973.00			
8	2992.60	32.80	78.70	151.71	88.90	18.70	4.30	1391.60	341.10	541.70	149.60	568.60	1715.00			
9	3394.60	32.50	80.90	163.50	89.70	18.90	4.20	1578.50	386.90	614.40	169.70	644.90	3670.00			
10	2777.70	34.40	79.80	166.80	90.40	19.00	4.40	1291.60	316.70	502.80	138.90	527.80	6597.00			
11																
12																
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23																
24																
25																

Data View Variable View

SPSS Processor is ready

7:27 PM

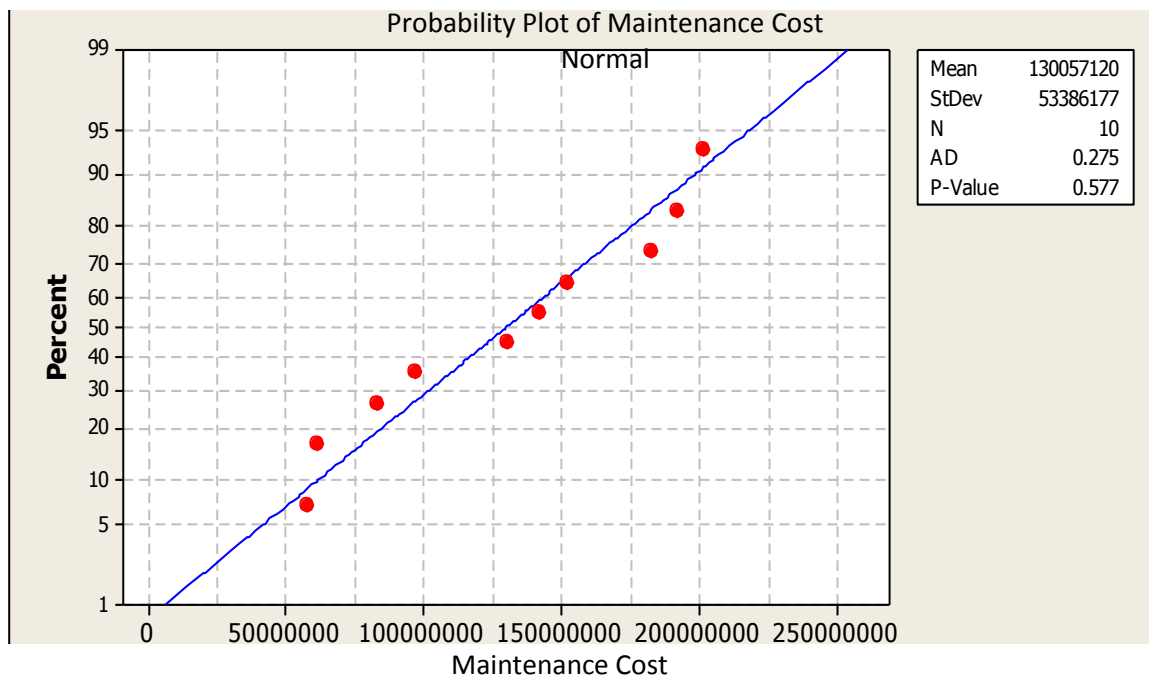
Output of Pareto Chart Analysis in R-3.1.2 Window



APPENDIX IX

Summary of Test of Normality and Randomness

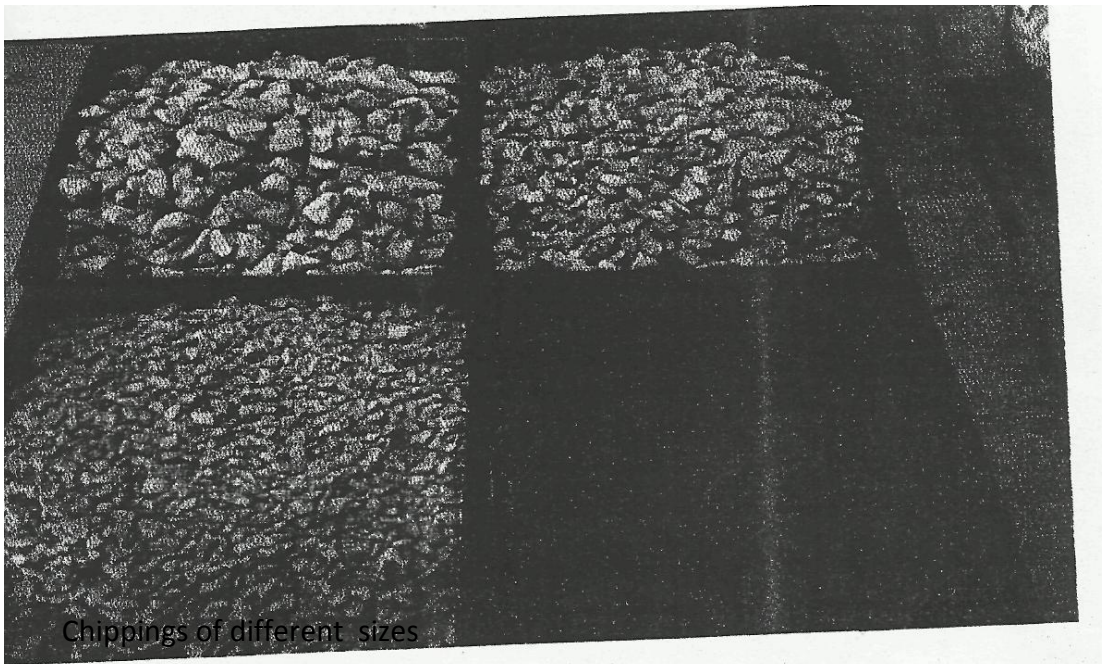
sktest Maintenance_Cost					
Skewness/Kurtosis tests for Normality					
----- joint -----					
Variable	Pr(Skewness)	Pr(Kurtosis)	adj chi2(2)	Prob>chi2	
Maintenance_Cost	0.918	0.158	2.39	0.3032	
. swilk Maintenance_Cost					
Shapiro-Wilk W test for normal data					
Variable	Obs	W	V	z	Prob>z
Maintenance_Cost	10	0.92768	1.114	0.188	0.42548
. sfrancia Maintenance_Cost					
Shapiro-Francia W' test for normal data					
Variable	Obs	W'	V'	z	Prob>z
Maintenance_Cost	10	0.95306	0.785	-0.385	0.64999
. runtest Maintenance_Cost					
N(Maintenance_Cost <= 136224558.5) = 5					
N(Maintenance_Cost > 136224558.5) = 5					
obs = 10					
N(runs) = 6					
z = 0					
Prob>z = 1					

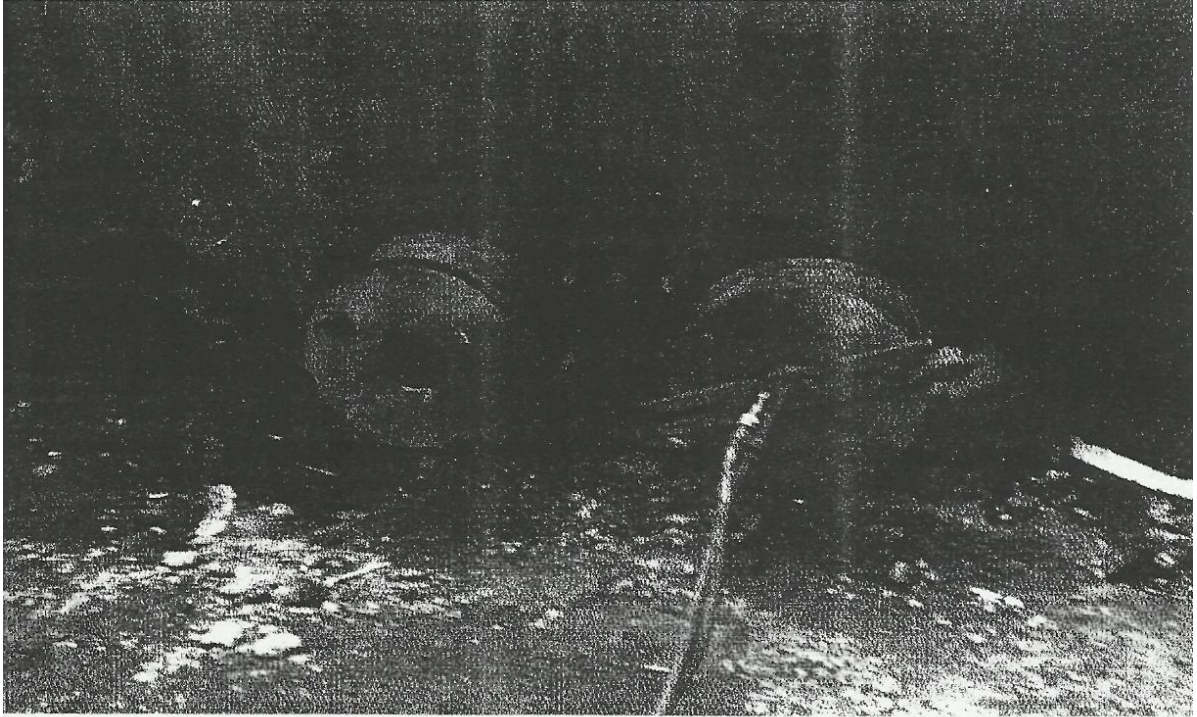


Normality distribution of Maintenance Cost

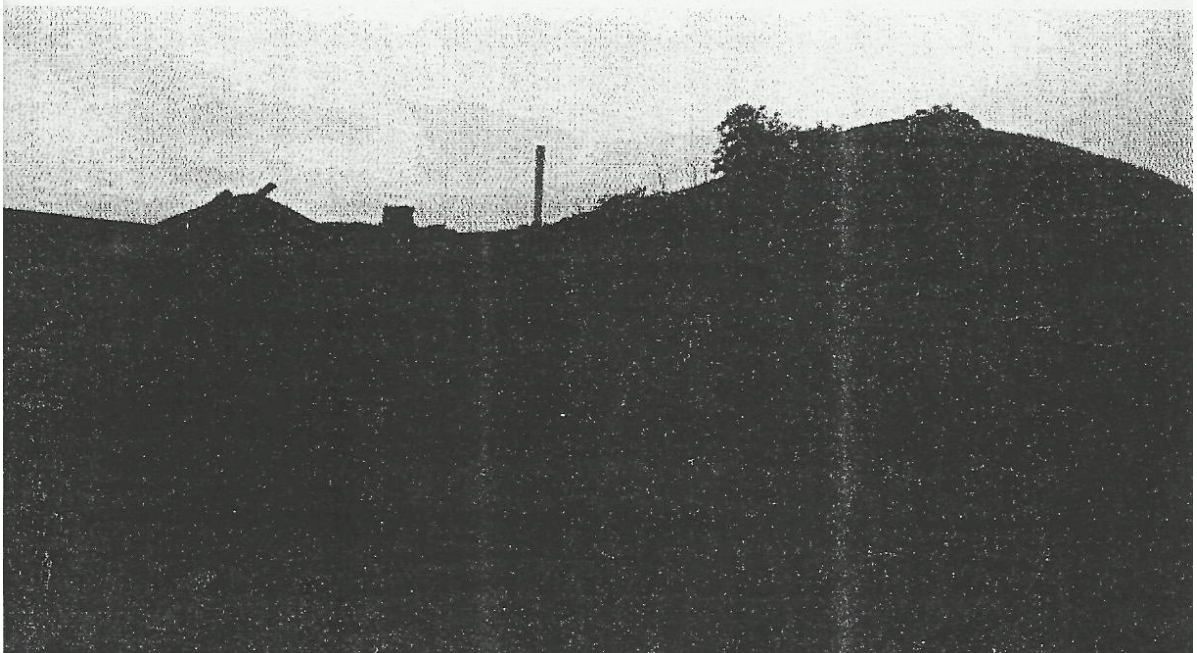
The result of the normality test using the Skewness/Kurtosis test of normality found a Chi-square of 2.39 with a p-value of 0.30 which falls on the acceptance region of the hypothesis. Also, the result revealed the probability of Skewness value of 0.92 and Probability of Kurtosis value of 0.16. Also, the Shapiro- Wilk W test of normality obtained a z score of 0.19 and a corresponding p-value of 0.43 while the Shapiro -Francia W test revealed a z score of -0.39 and a p-value of 0.65. This result implies that the response variable maintenance cost is approximately normally distributed and fit for regression analysis.

APPENDIX X

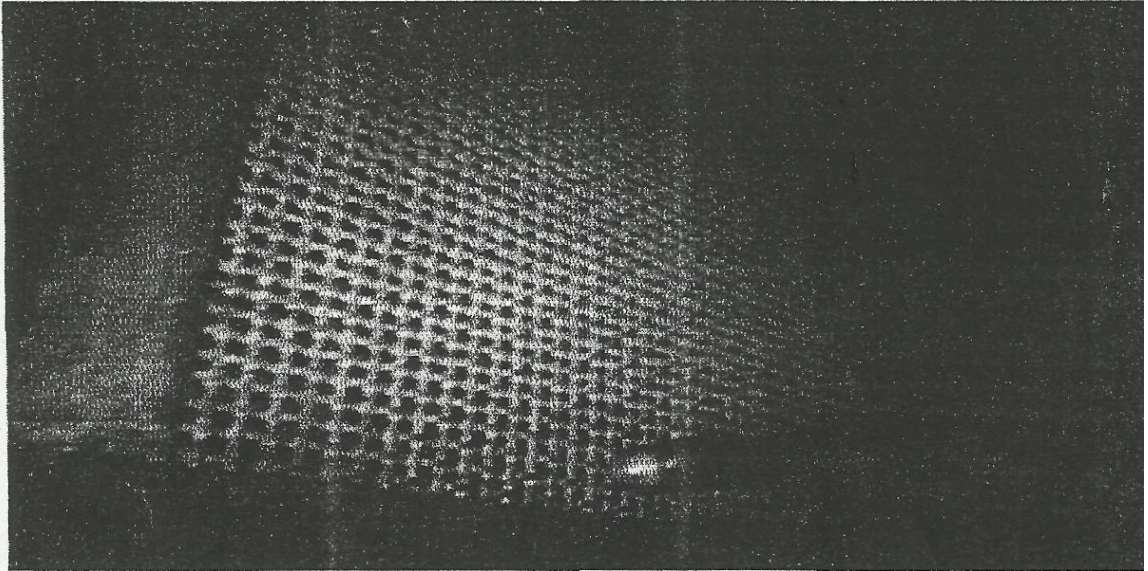




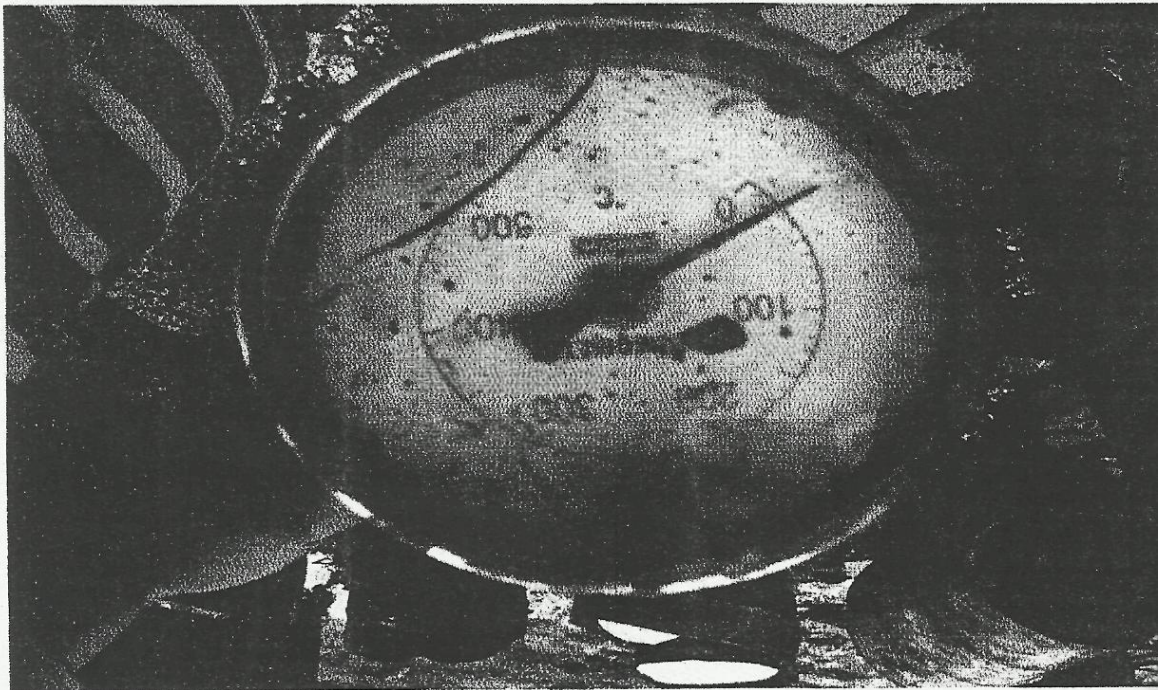
Tank boiler



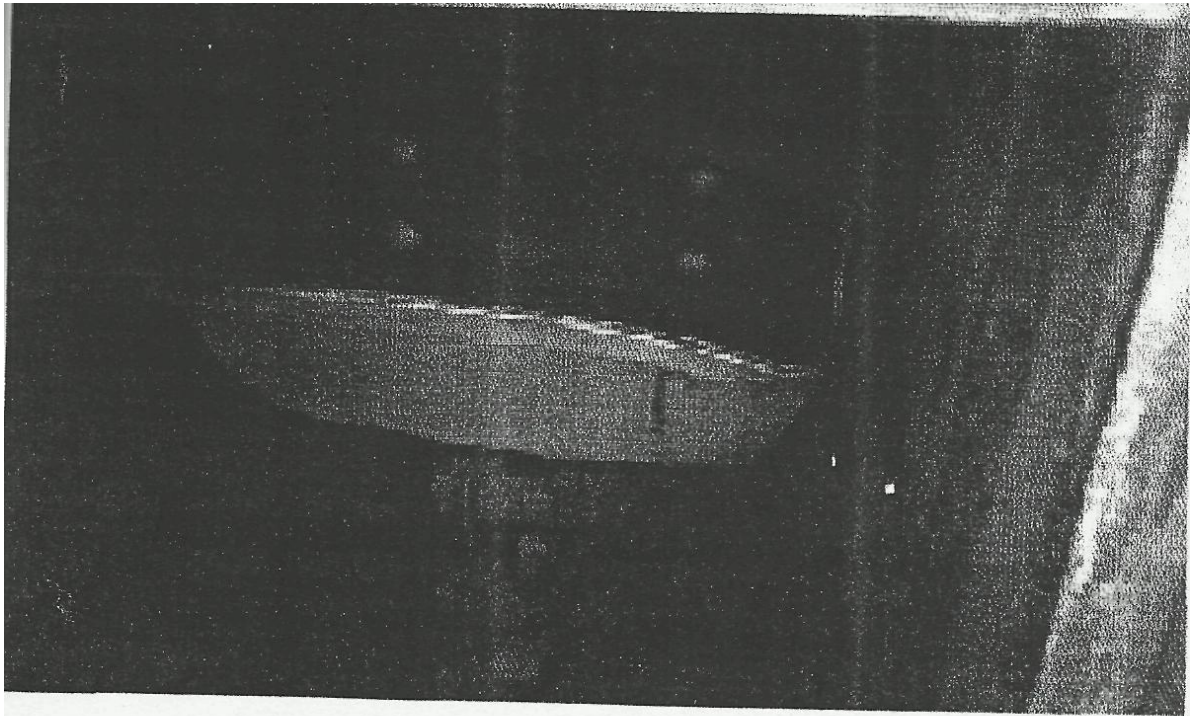
Silos



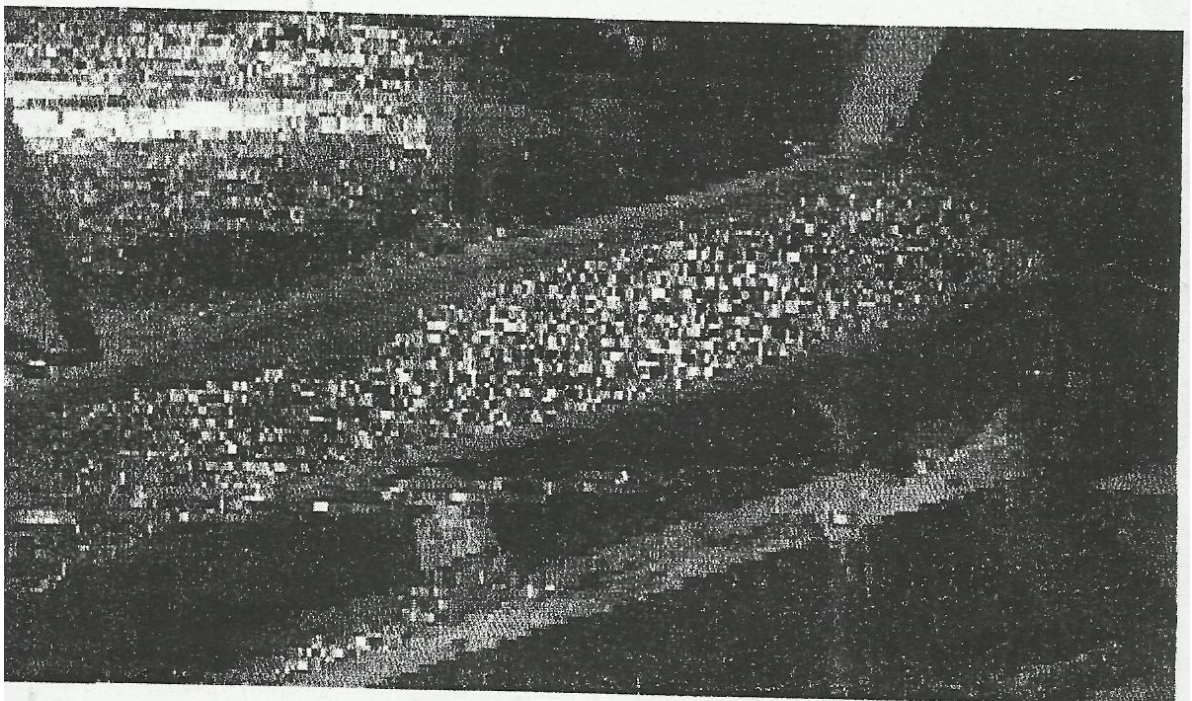
Screen



Temperature gauge



Chain conveyer



Belt conveyer