Time Series and Statistical Analysis of Plastic Yield: A Case Study of Finoplastika Industries Ltd, Nigeria

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Abstract– **This work was used to address the problem of time series and statistical analysis of plastic yield on there monthly production in Finoplastika manufacturing industry. Data on production yield were collected from the industry covering a period of three years. Time series technique and statistical tool (method) were applied to precisely determine optimum production yield in the industry. A normality test was used to confirm the adequacy of the models developed. The model was therefore used to suggest optimum monthly production output for different product types investigated. This will prevent the incident of under producing or over producing as identified.**

Keywords– **Forecasting, Time-series, Statistics, Plastic Pipes, 3-D Homogeneity Plot, Normal Probability Plot and Histogram Plot**

I. INTRODUCTION

The case study produced both injection and extrusion plastics. Injection plastics are domestic plastics (e.g. bucket, cup, spoon, etc.), plastic furniture (e.g. chairs, tables, etc) and industrial plastics (e.g. Toilet cover, laptop cover, television cover, etc). Injection machines are used to form these shapes and sizes of the plastics. However injection machines are not used in production of extrusion plastics (i.e. pipes). Extrusion machine are used in production of extrusion plastics. Extrusion machines can produce pipes of different shapes and sizes.

Furthermore, in this research work the following objectives were pursued: Production data were elicited, collected from the company and analyzed to understand the current production pattern and behavior of the production system.

Test for the data model adequacy. Its objective is to test for the fitness of any model developed by the data. To generate histogram chart that develops the frequent accumulation of each products. To develop charts for homogenous test of the product data.

II. INTRODUCTION TO TIME SERIES ANALYSIS

Time series methods are statistical techniques that use historical demand data to predict future demand (Stevenson, 2005). Time series methods take into account possible internal structure in the data Time series data often arise when monitoring industrial processes or tracking corporate business metrics. The essential difference between modeling data via time series methods and using the process monitoring methods discussed earlier in this chapter is the following: Time series analysis accounts for the fact that data points taken over time may have an internal structure (such as autocorrelation, trend or seasonal variation) that should be accounted for. This section will give a brief overview of some of the more widely used techniques in the rich and rapidly growing field of time series modeling and analysis (Stevenson, 2005).

Two Main Goals of Time Series Analysis

There are two main goals of time series analysis: (a) identifying the nature of the phenomenon represented by the sequence of observations, and (b) forecasting (predicting future values of the time series variable). Both of these goals require that the pattern of observed time series data is identified and more or less formally described. Once the pattern is established, we can interpret and integrate it with other data (i.e., use it in our theory of the investigated phenomenon, e.g., seasonal commodity prices). Regardless of the depth of our understanding and the validity of our interpretation (theory) of the phenomenon, we can extrapolate the identified pattern to predict future events.

Two General Aspects of Time Series Patterns

Most time series patterns can be described in terms of two basic classes of components: trend and seasonality. The former represents a general systematic linear or (most often) nonlinear component that changes over time and does not repeat or at least does not repeat within the time range captured by our data (e.g., a plateau followed by a period of exponential growth). The latter may have a formally similar nature (e.g., a plateau followed by a period of exponential growth); however, it repeats itself in systematic intervals over time. Those two general classes of time series components may coexist in real-life data. For example, sales of a company can rapidly grow over years but they still follow consistent seasonal patterns (e.g., as much as 25% of yearly sales each year are made in December, whereas only 4% in August).

Time -Series Analysis and Forecasting

A time series is a sequence of observations obtained through measurements often recorded at equally spaced intervals. Often, time series data have characteristics that facilitate forecasting. These include seasonality, underlying trends, and relationships with past observations or other causal variables. Analysts can improve time series forecasts if they understand the nature of these components and identify the model that will best exploit the data's characteristics.

The purpose of this chapter is to provide a synopsis of time series analysis and forecasting. The first section discusses the characteristics of time series data. It reviews the common components useful in creating effective forecasts such as trend, seasonality, cyclical behavior, and irregular fluctuations. The chapter concludes with an introduction to time series forecasting and an overview of the forecasting model development process (Douglas I. Feiring, 1990).

Characteristics of Time-Series Data

A time series is a "collection of observations made sequentially in time" (Chatfield, 1996). Examples are records of local daily rainfall levels, the quarterly U.S. Gross Domestic Product, and the monthly Marine Corps personnel strength for a particular rank and MOS. Time series analysis provides tools for choosing a representative model and producing forecasts.

There are two kinds of time series data:

• Continuous, where the data contain an observation at every instant of time, e.g., seismic activity recorded on a seismogram.

• Discrete, where the data contain observations taken at intervals, e.g. monthly crime figures.

Unless the data are purely random, observations in a time series are normally correlated and successive observations may be partly determined by past values (Chatfield, 1996). For example, the meteorological factors that affect the temperature on any given day are likely to exert some influence on the following day's weather. Thus, historical temperature observations are beneficial in forecasting future temperatures.

A time series is deterministic if it contains no random or probabilistic characteristics but proceeds in a fixed, predictable fashion (Chatfield, 1996). An example of a deterministic time series would be the data collected while conducting a classical physics experiment such as one demonstrating Newton's law of motion (Gujarati, 2003). More applicable to econometric applications are stochastic time series. Stochastic variables have indeterminate or random aspects. Although the values of individual observations cannot be predicted exactly, measuring the distribution of the observations may follow a predictable pattern. Statistical models can describe these patterns. These models assume that observations vary randomly about an underlying mean value that is a function of time. Time series data can also be characterized by one or more behavioral components; trend, seasonality, cyclical behavior, and random noise.

Trend Component

Trend is the general drift or tendency observed in a set of data over time. It is the underlying direction (an upward or downward tendency) and the degree of change in an observation set when consideration has been made for other components. Graphing a time series can be a useful and simple method of identifying the trend of a particular data set. This indicates an upward trend of the U.S. Gross Domestic Product over a ten year span. Analysts can also discern trends by dividing the data set into a number of ranges, and calculating the mean for each span. A consistent increase or decrease in the mean for the successive ranges indicates trend.

Trends in business or economic series may be due to a growth or contraction process. Trends in service manpower levels may be attributed to external economic factors or shifts in policy due to technical innovation, downsizing, or an increased or decreased operational requirement for certain occupational specialties.

Seasonal Component

In time series data, the seasonal component is the element of variation in a data set that is dependent on the time of year. Seasonality is quite common in econometric time series. It is less common in engineering and scientific data. This component recurs annually, with possible variations in amplitude. Seasonality is attributable to the change of seasons and/or the timing of such events as holidays or the start or completion of the school term. For example, the cost of fresh produce, retail sales levels, average daily rainfall amounts, and unemployment figures all demonstrate seasonal variation.

Incorporating seasonality in a forecast is useful when the time series has a discernible seasonal component. When the data contain a seasonal effect, it is useful to separate the seasonality from the other components in the time series. This enables the analyst to estimate and account for seasonal patterns.

Cyclical Component

Cyclical behavior describes any non-seasonal component that oscillates in a recognizable pattern. The 11-year sunspot cycle has been long recognized as naturally occurring cyclical activity. More ambiguous is the 5 to 7 year business cycle that a number of economists hypothesize influence global economic activity. If the data include a discernible cyclical component, the time series should span enough cycles to accurately model and forecast its effects (Yaffee, 2000). Cyclical behavior in which the oscillations extend over a very long period (such as 20 years) can often be accurately modeled as a trend for short-term forecasts (Chatfield, 1996).

Irregular Component

A significant component of stochastic time series data is irregular fluctuation. This random noise is what remains after the other components of the series (trend, seasonality, and cyclical behavior) are estimated and eliminated. It results from fluctuations in the series that are neither systematic nor predictable. While the irregular component typically has a modest impact on attempts to analyze, model and forecast time series data, it can sometimes have a significant effect. The effect of the 1973 OPEC (Organization of Petroleum Exporting Countries) oil embargo on the U.S. economy is an example of the substantial consequences irregular fluctuations can occasionally inflict on time series data.

Time-Series Forecasting

Univariate time series forecasting models make predictions by extrapolating the past behavior of the values of a particular single variable of interest (Moore & Weatherford, 2001). Successive observations in econometric time series are normally not independent and predictions may be made from previous observations (Chatfield, 1996). While exact forecasts are possible with deterministic time series, forecasts of stochastic time series are limited to "conditional statements about the future based on specific assumptions" (Chatfield, 1996). According to Armstrong (2001), "the basic

Assumption is that the variable will continue in the future as it has behaved in the past." Specifically, time series forecasts are appropriate for stochastic data where the underlying causes of variation – trend, cyclical behavior, seasonality, and irregular fluctuations – do not change significantly in time (Jenson, 2004). Hence, modeling is often more appropriate for short-term than for long-term forecasting.

Forecasts Based On Time Series Data

According to Stevenson, 2005; a time series is a time-ordered sequence of observations taken at regular intervals (e.g., hourly, daily, weekly, monthly, quarterly and annually). The data may be measurement of demand, earnings, profits, shipments, accidents, output, precipitation, productivity, and the customer price index. Forecasting techniques based on time series data are made on the assumption that future values of the series can be estimated from past values. Although no attempt is made to identify variables that influence the series, these methods are widely used, often with quite satisfactory results.

Analysis of time series data requires the analyst to identify the underlying behavior of the series. These can often be accomplished by merely plotting the data and visually examining the plot. One or more patterns might appear: trends, seasonal variations, cycles, or variations around an average. In addition, there will be random and perhaps irregular variations. These behaviors can be described as follows:

- ***Trend*** refers to a long-term upward or downward movement in the data. Population shifts, changing incomes, and cultural changes often account for such movements.
- ***Seasonality*** refers to short-term, fairly regular variations generally related to factors such as the calendar or time of day. Restaurants, supermarkets, and theaters experience weekly and even daily "seasonal" variations.
- ***Cycles*** are wavelike variations of more than one year duration. These are often related to a variety of economic, political, and even agricultural conditions.
- ***Irregular variations*** are due to unusual circumstances such as severe weather conditions, strikes, or a major change in a product or service. They do not reflect typical behavior, and inclusion in the series can distort the overall picture. Whenever possible, these should be identified and removed from the data.
- ***Random variations*** are residual variations that remain after all other behaviors have been accounted for.

III. METHOD USED

The research method used in this work is a quantitative research approach. The data gathered were the daily record of plastic pipes production over the month for three years. The research method followed the steps shown in figure 2.

The method used was time series technique to model for the quantity of pipes (sizes and shapes) to be produced in the industry using predictive tools namely: Excel and Minitab tools for the development of the model and the forecasting of the results.

This model developed was used to predict the actual quantity of the plastic pipe products, the case study industry is supposed to be producing every month. The model developed was used to test the quantity of types/ sizes of plastic pipe, identified produced including: 110mm waste pipe, 20mm pressure pipe, 50mm pressure pipe, 25mm pressure pipe, 160mm waste pipe, 140mm pressure pipe, 40mm pressure pipe and 90mm pressure pipe.

Table 1: Presentation of 2009-2011 Monthly Data plastic yield

Year	*Month*	*PT*	*p1*	*p2*	*p3*	*p4*	*p5*	*p6*	*p7*	*p8*
2009	*Jan*	*50488*	*16526*	*3860*	*9618*	*15571*	*0*	*4493*	*420*	*0*
	Feb	*76031*	*29250*	*40*	*14773*	*10680*	*390*	*18718*	*2180*	*0*
	Mar	*74010*	*26666*	*9960*	*16571*	*11280*	*453*	*6740*	*2340*	*0*
	Apr	*123767*	*52029*	*10315*	*32339*	*11660*	*0*	*12940*	*4484*	*0*
	May	*70704*	*14160*	*17241*	*10788*	*14540*	*0*	*9560*	*4415*	*0*
	Jun	*47610*	*23087*	*2340*	*878*	*6146*	*0*	*8475*	*6684*	*0*
	Jul	*77654*	*29890*	*26785*	*15885*	*1140*	*0*	*3040*	*700*	*214*
	Aug	*61053*	*17981*	*20280*	*9062*	*1540*	*0*	*12140*	*50*	*0*
	Sep	*13538*	*3248*	*0*	*7570*	*2260*	*0*	*0*	*460*	*0*
	Oct	*21476*	*7045*	*7530*	*2611*	*2120*	*0*	*454*	*1716*	*0*
	Nov	*40561*	*16014*	*3768*	*5883*	*2980*	*0*	*6002*	*5914*	*0*
	Dec	*4871*	*3171*	*280*	*0*	*1160*	*0*	*260*	*0*	*0*
2010	*Jan*	*28462*	*7113*	*6311*	*8445*	*4693*	*0*	*1360*	*540*	*0*
	Feb	*16154*	*7284*	*0*	*4595*	*1760*	*0*	*390*	*2125*	*0*
	Mar	*70844*	*22119*	*24975*	*9535*	*7295*	*560*	*6340*	*20*	*0*
	Apr	*64666*	*21134*	*0*	*18843*	*15480*	*0*	*2930*	*6279*	*0*
	May	*46107*	*18848*	*4545*	*4497*	*4180*	*0*	*7760*	*6367*	*0*
	Jun	*49058*	*22172*	*4920*	*14296*	*2589*	*0*	*3733*	*1205*	*143*
	Jul	*33287*	*8767*	*13790*	*2351*	*2278*	*0*	*3040*	*3061*	*0*

	Aug	*37849*	*14790*	*1740*	*10885*	*3900*	*0*	*2080*	*4454*	*0*
	Sep	*29459*	*11975*	*0*	*15023*	*0*	*0*	*1360*	*1101*	*0*
	Oct	*25738*	*5518*	*2245*	*5049*	*1740*	*583*	*3760*	*6843*	*0*
	Nov	*35740*	*17532*	*1830*	*9948*	*3640*	*60*	*2730*	*0*	*0*
	Dec	*60455*	*18452*	*360*	*9489*	*8120*	*0*	*280*	*23754*	*0*
2011	*Jan*	*53480*	*22225*	*160*	*20184*	*3724*	*651*	*2860*	*2860*	*816*
	Feb	*31729*	*14123*	*2140*	*4721*	*5620*	*0*	*2340*	*1408*	*1377*
	Mar	*42625*	*14502*	*2200*	*11137*	*6680*	*262*	*7600*	*0*	*244*
	Apr	*36237*	*16014*	*910*	*1970*	*8880*	*0*	*4560*	*3497*	*406*
	May	*63066*	*24134*	*1062*	*21265*	*7720*	*255*	*8060*	*570*	*0*
	Jun	*60997*	*29097*	*5300*	*20838*	*16160*	*607*	*7750*	*0*	*0*
	Jul	*61892*	*16981*	*17170*	*6210*	*7500*	*605*	*10822*	*2604*	*0*
	Aug	*58988*	*17298*	*7545*	*11877*	*11420*	*733*	*6020*	*4095*	*0*
	Sep	*41820*	*5617*	*20085*	*2421*	*5980*	*277*	*6820*	*620*	*0*
	Oct	*69547*	*20631*	*5960*	*16326*	*6220*	*604*	*14310*	*5496*	*0*
	Nov	*11616*	*4391*	*0*	*1720*	*4173*	*52*	*1280*	*0*	*0*
	Dec	*29053*	*11909*	*1760*	*1706*	*6610*	*558*	*6510*	*0*	*0*

Time series Analysis of plastic yield

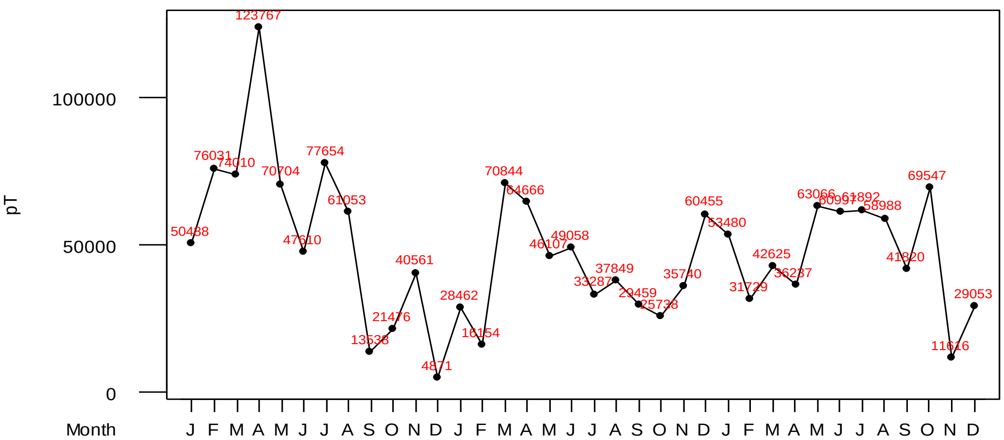


Figure 1: 2009-2011 monthly total Product of finished products (pt) for finoplastika industries ltd, Nigeria

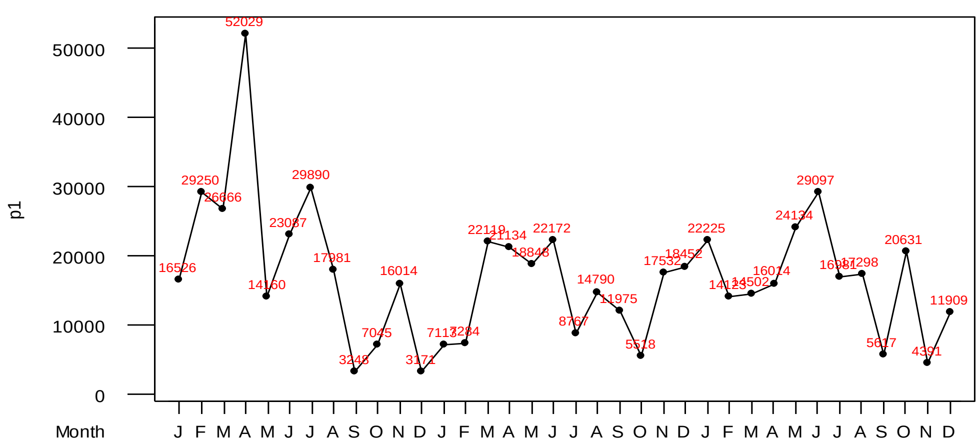


Figure 2: 2009-2011 monthly total Product of finished products (p1) for finoplastika industries ltd, Nigeria

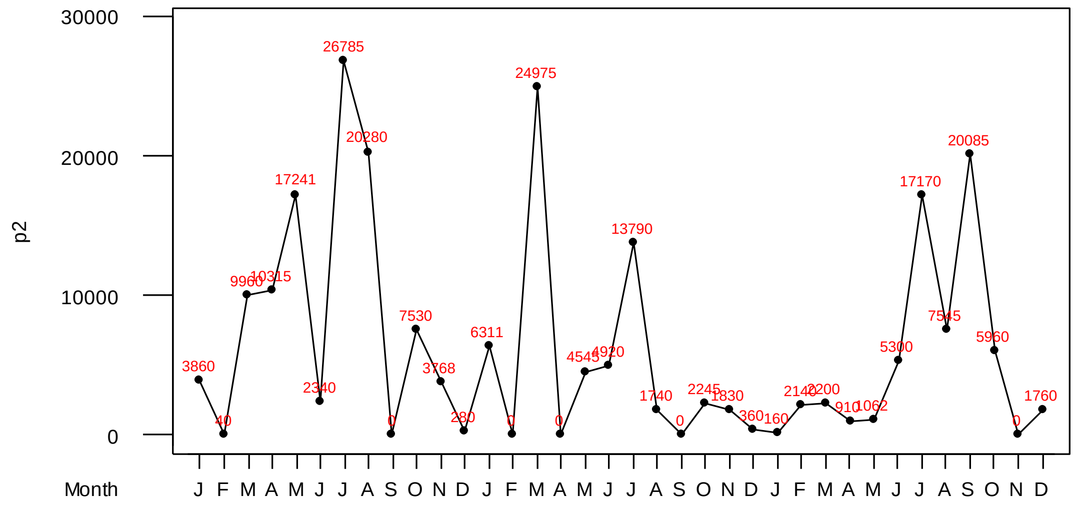


Figure 3: 2009-2011 monthly total Product of finished products (p2) for finoplastika industries ltd, Nigeria

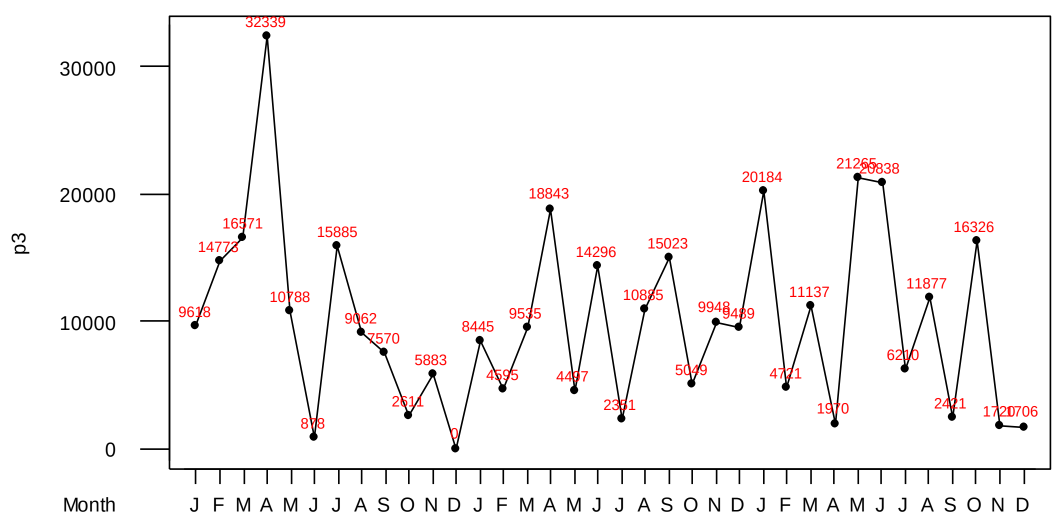


Figure 4: 2009-2011 monthly total Product of finished products (p3) for finoplastika industries ltd, Nigeria

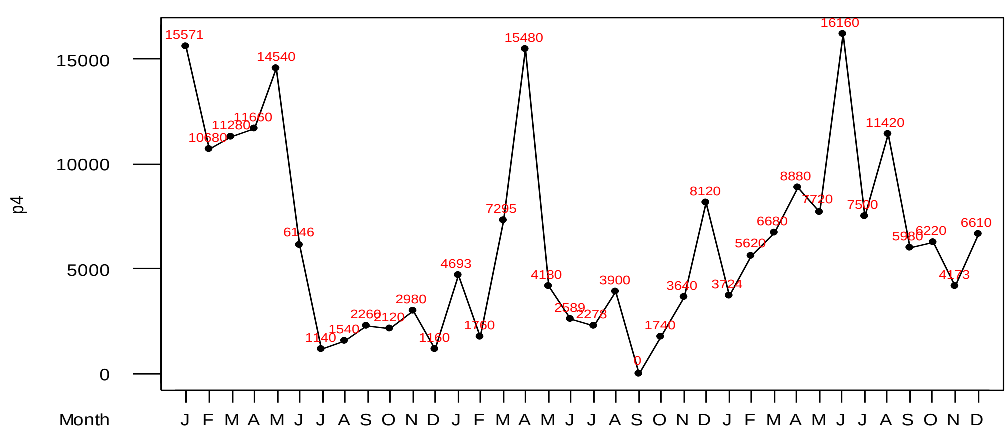


Figure 5: 2009-2011 monthly total Product of finished products (p4) for finoplastika industries ltd, Nigeria

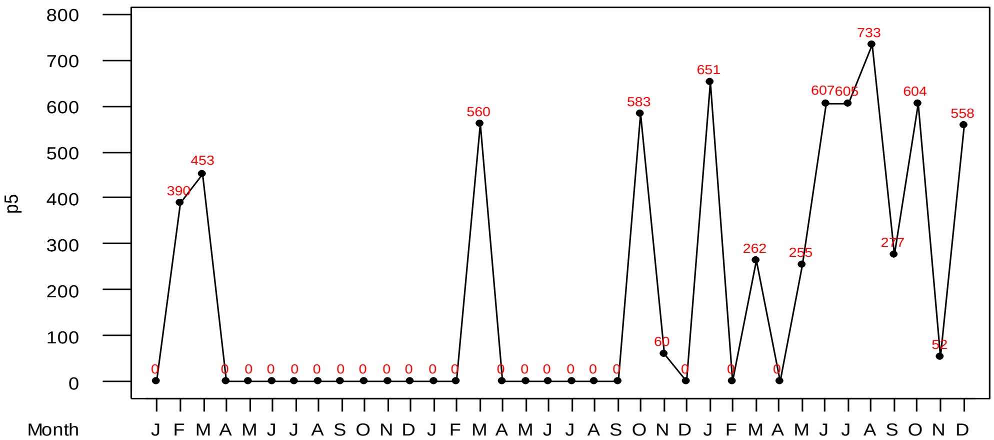


Figure 6: 2009-2011 monthly total Product of finished products (p5) for finoplastika industries ltd, Nigeria

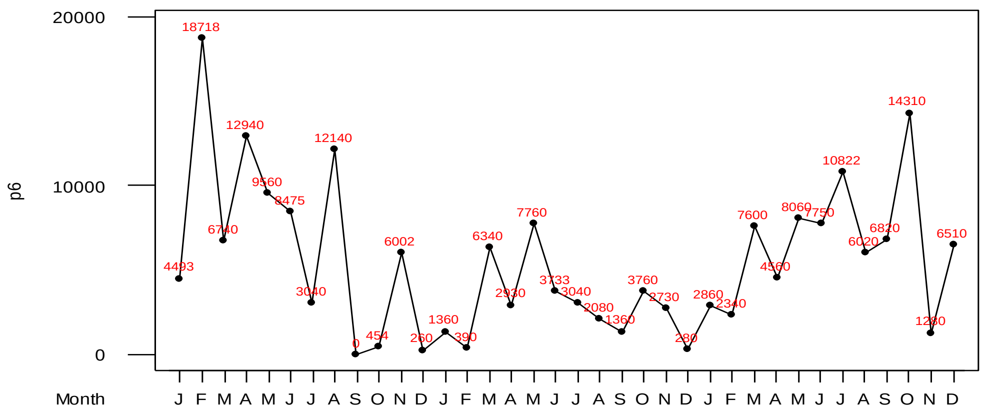


Figure 7: 2009-2011 monthly total Product of finished products (p6) for finoplastika industries ltd, Nigeria

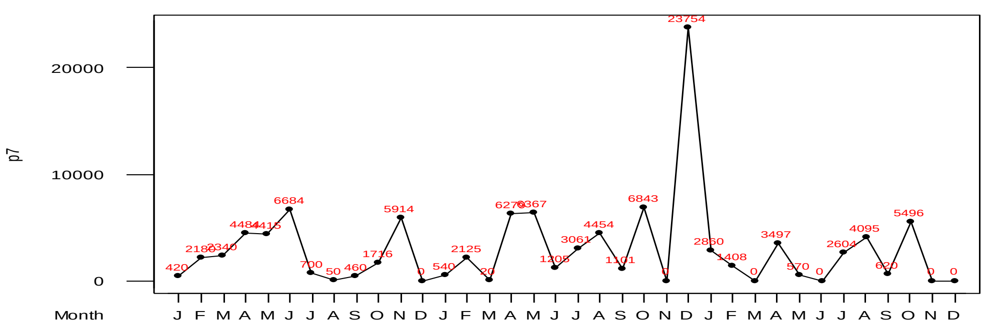


Figure 8: 2009-2011 monthly total Product of finished products (p7) for finoplastika industries ltd, Nigeria

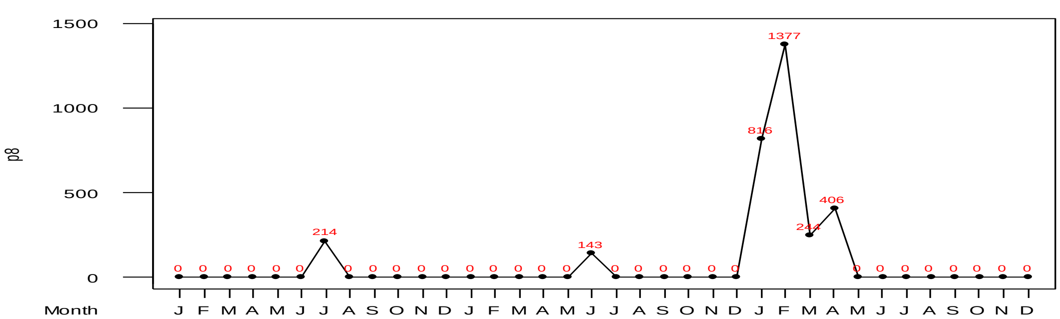
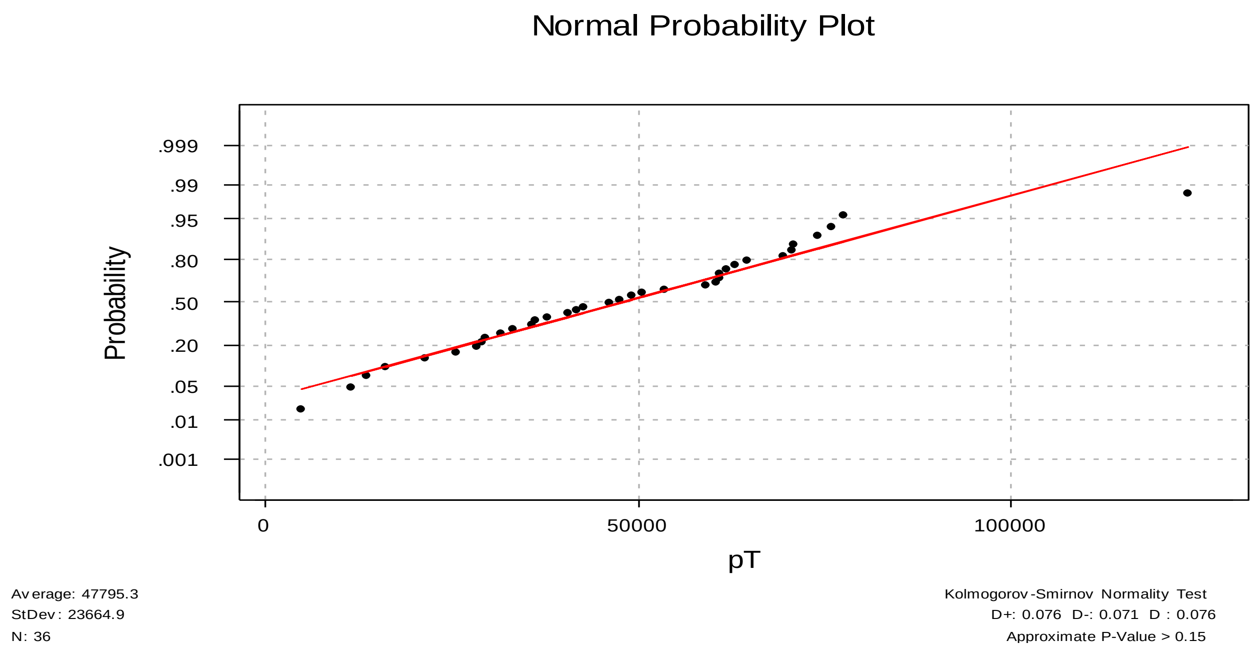


Figure 9: 2009-2011 monthly total Product of finished products (p8) for finoplastika industries ltd, Nigeria

TEST OF NORMALITY OF THE PRODUCTION TOTAL OF PLASTIC



PIPES USING THE SMIMOV KOLMOGOROV TEST

Figure 12: PT Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for PT (i.e. production yield in units) product

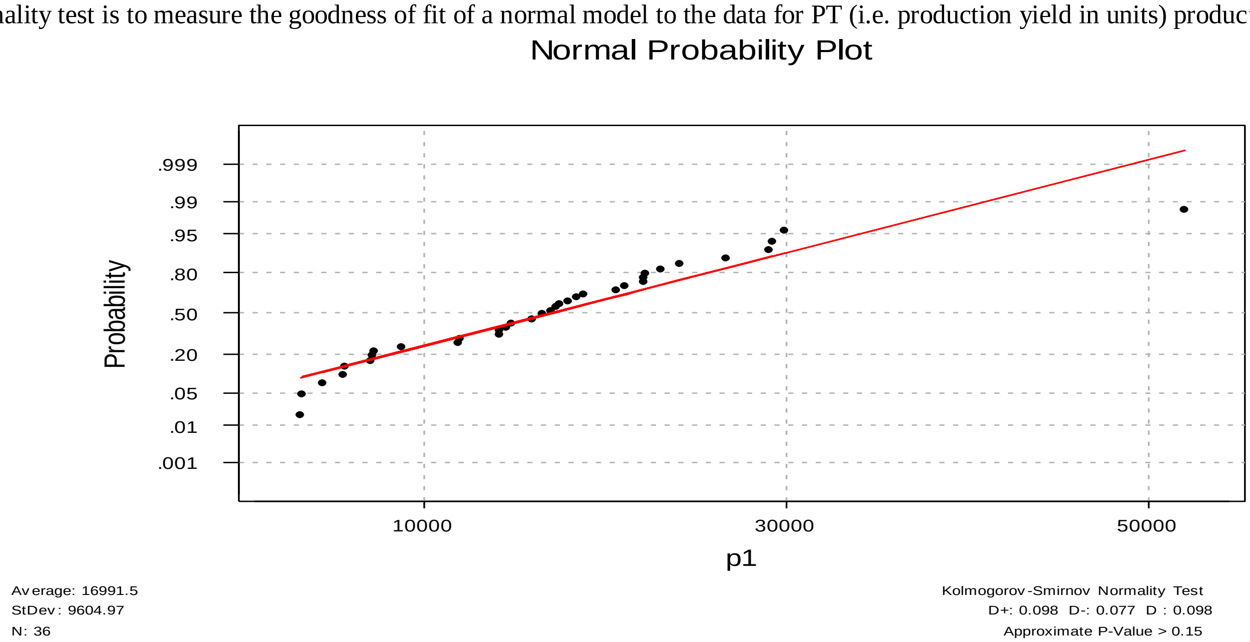


Figure 13: P1 Normal Probability Plot

The result shows that the P1 (i.e. production yield in units) data are normally distributed which means that the data is fit for model.

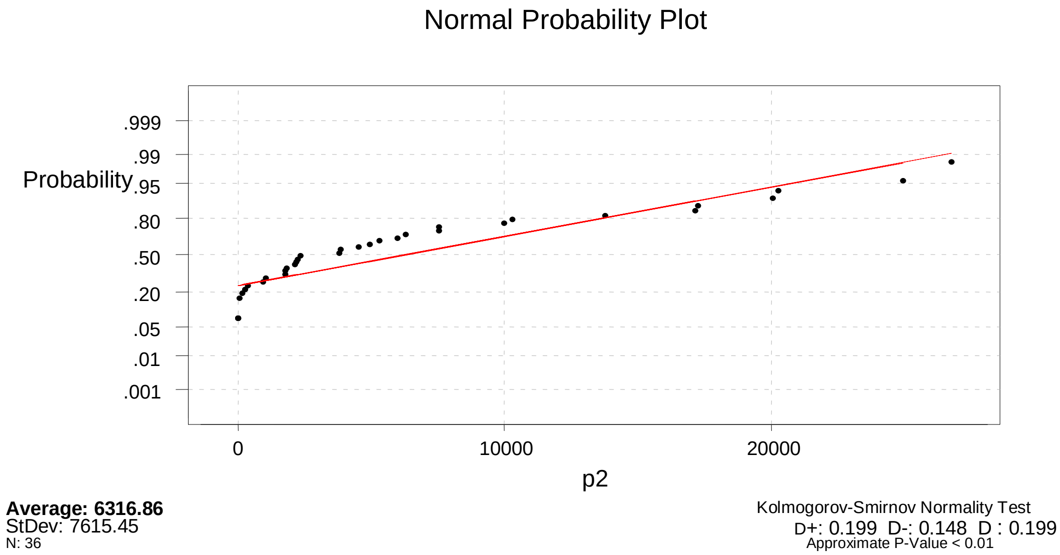


Figure 14: P2 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P2 (i.e. production yield in units) product

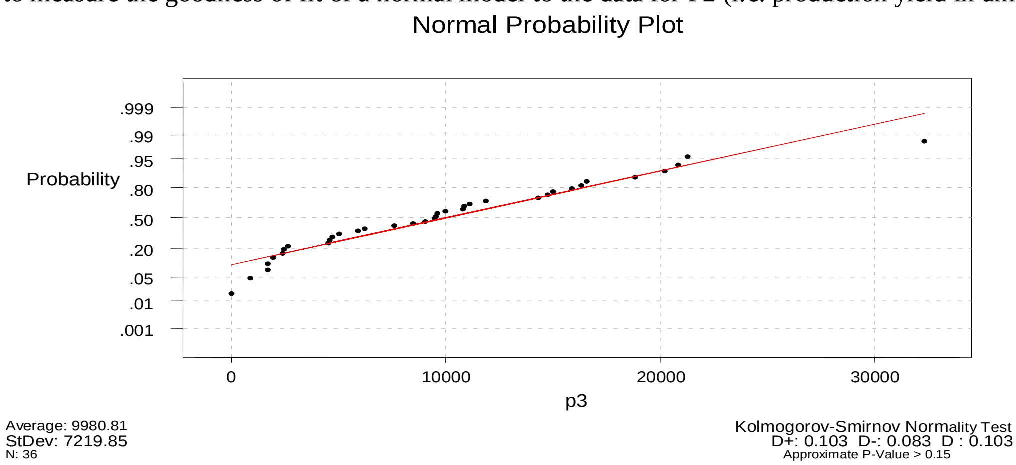


Figure 15: P3 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P3 (i.e. production yield in units) product

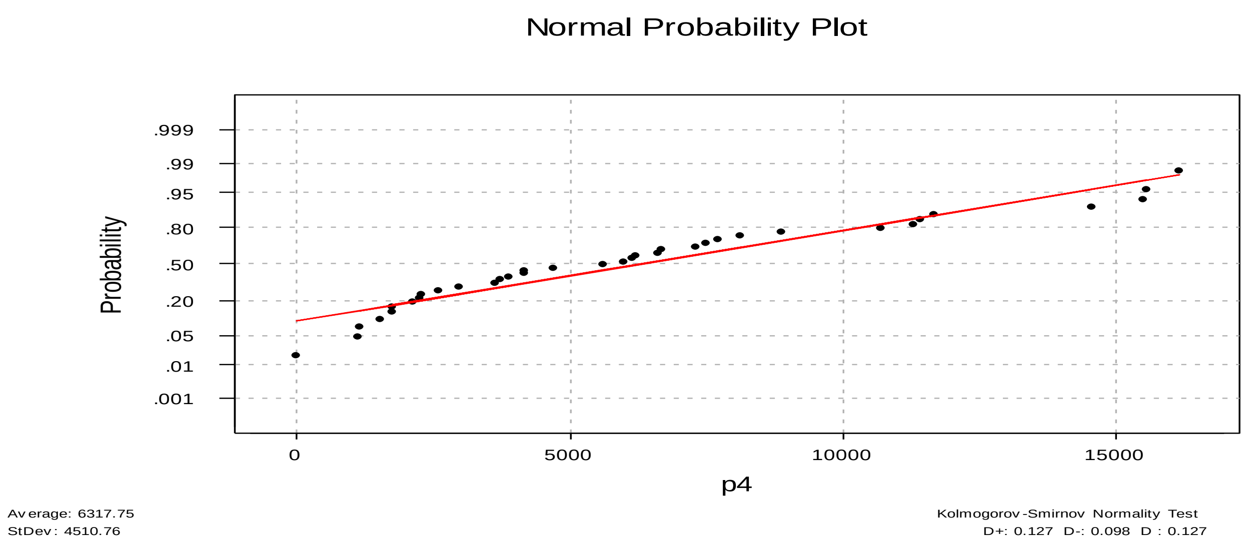


Figure 16: P4 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P4 (i.e. production yield in units) product

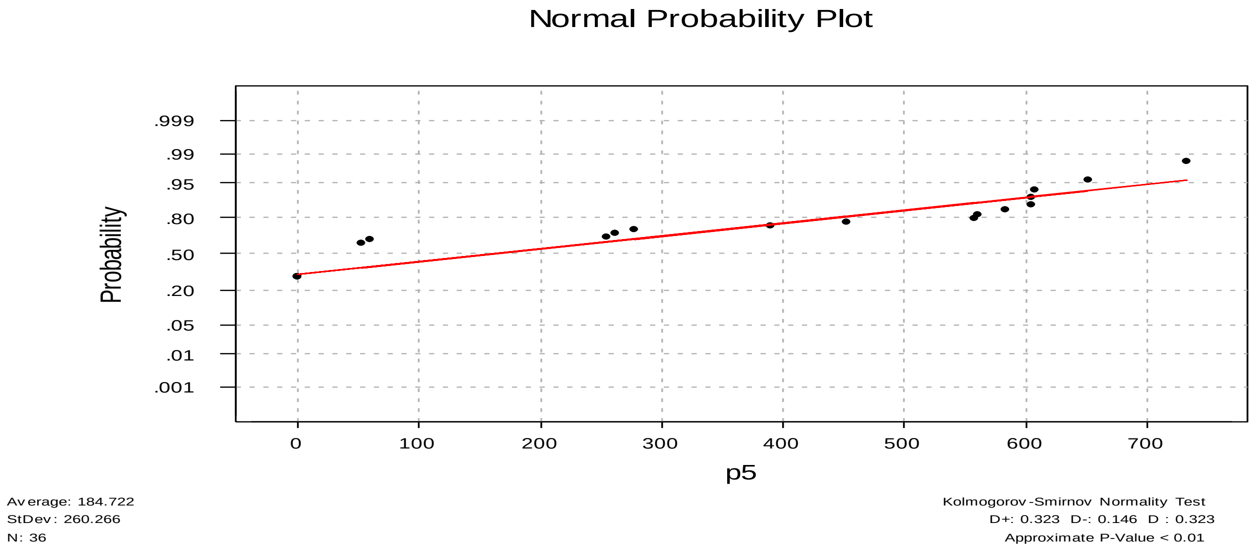


Figure 17: P5 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P5 (i.e. production yield in units) product.

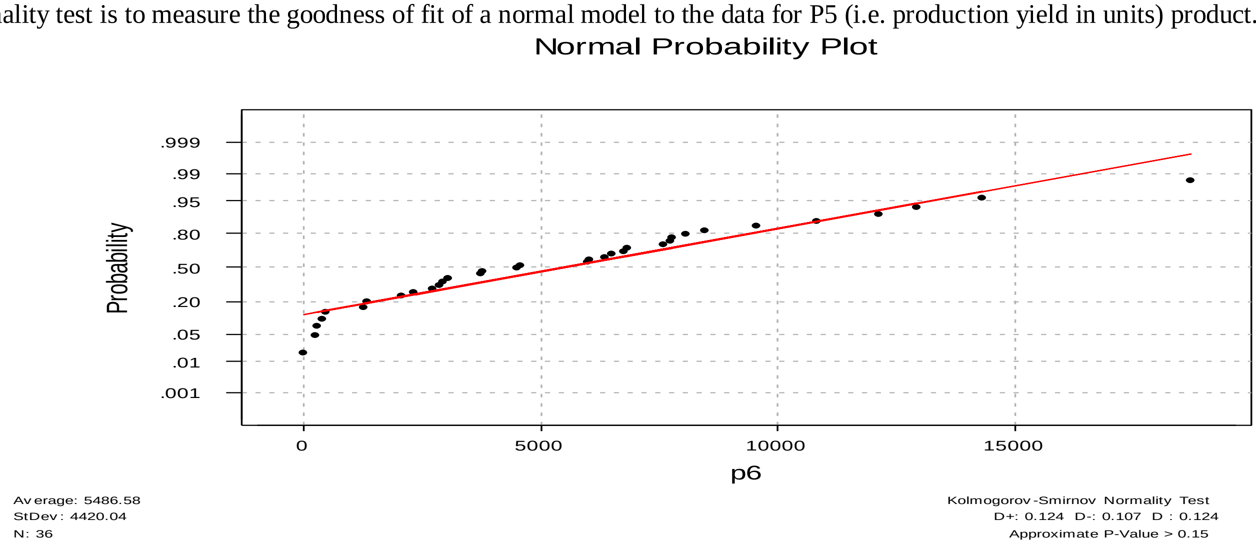


Figure 18: P6 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P6 (i.e. production yield in units) product

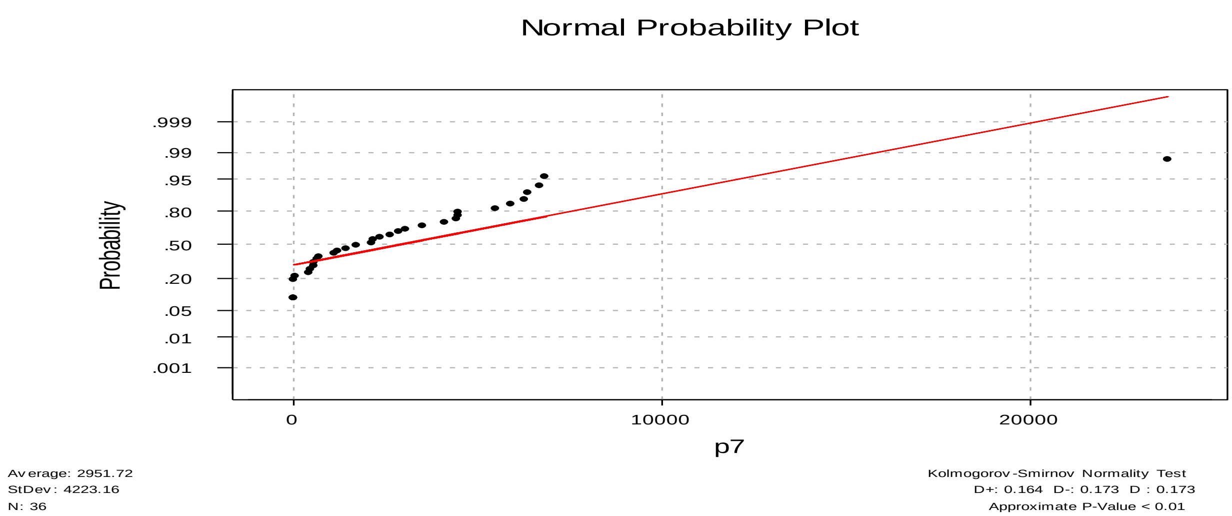


Figure 19: P7 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P7 (i.e. production yield in units) product

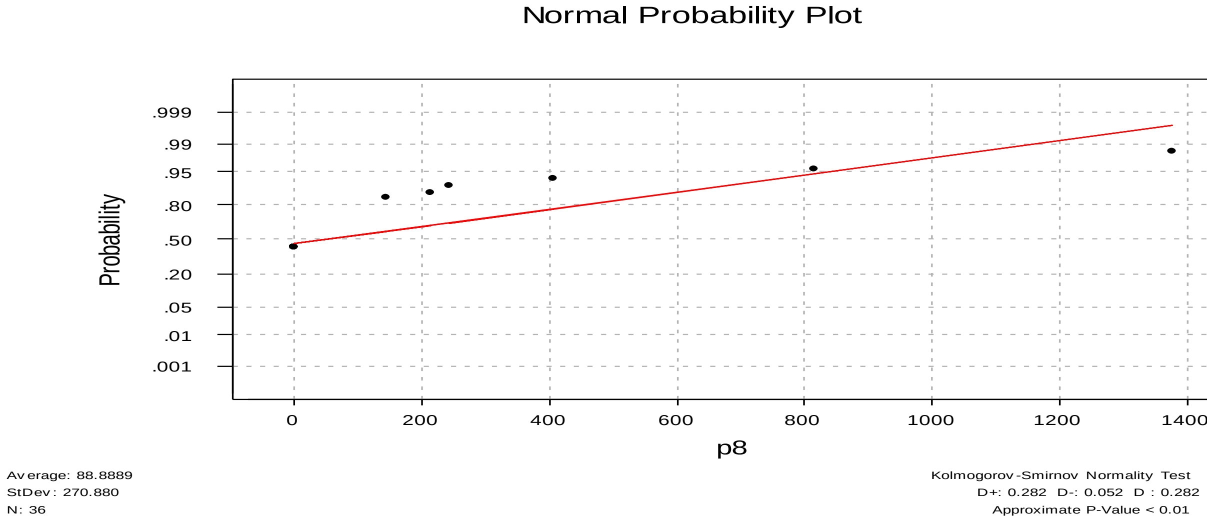


Figure 20: P8 Normal Probability Plot

Normality test is to measure the goodness of fit of a normal model to the data for P8 (i.e. production yield in units) product

TEST OF NORMALITY OF DATA USING THE HISTOGRAM PLOT

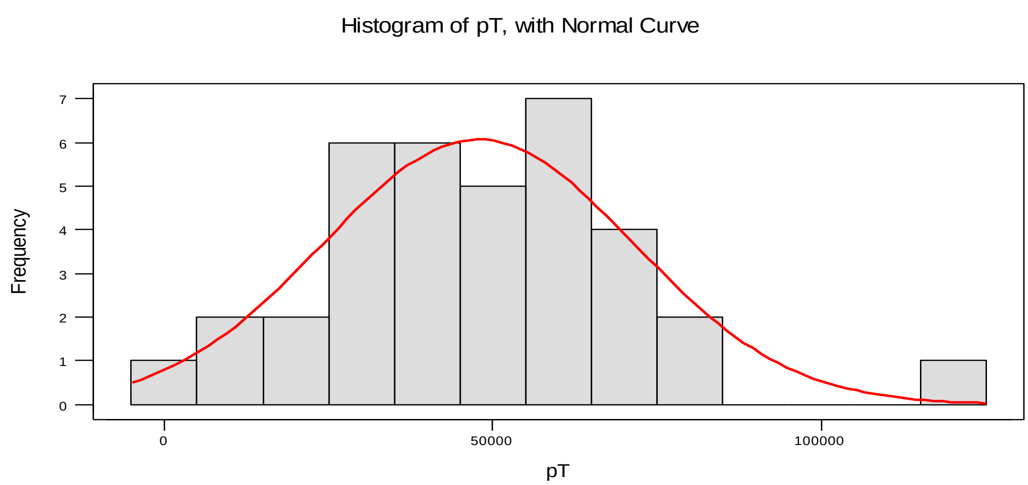


Figure 21: PT Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the PT (i.e. production yield in units) product

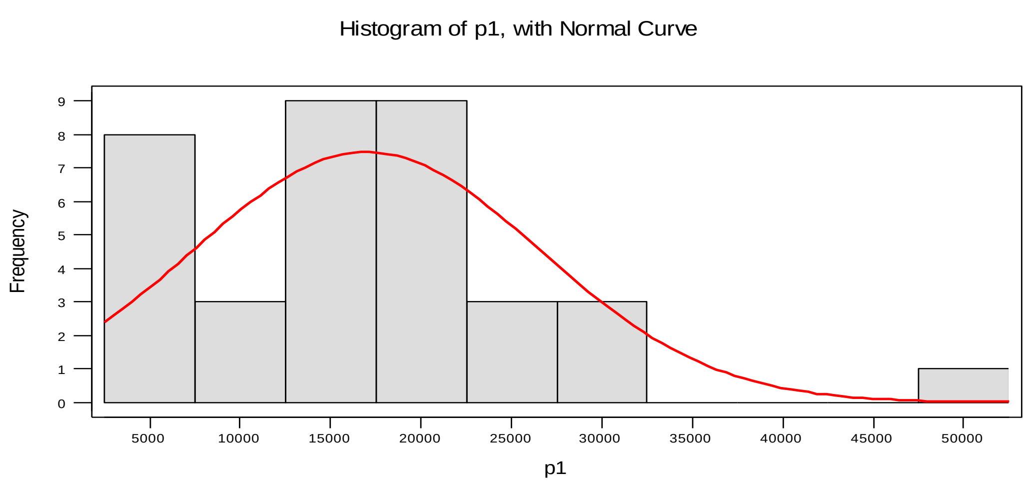


Figure 22: P1 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P1 (i.e. production yield in units) product

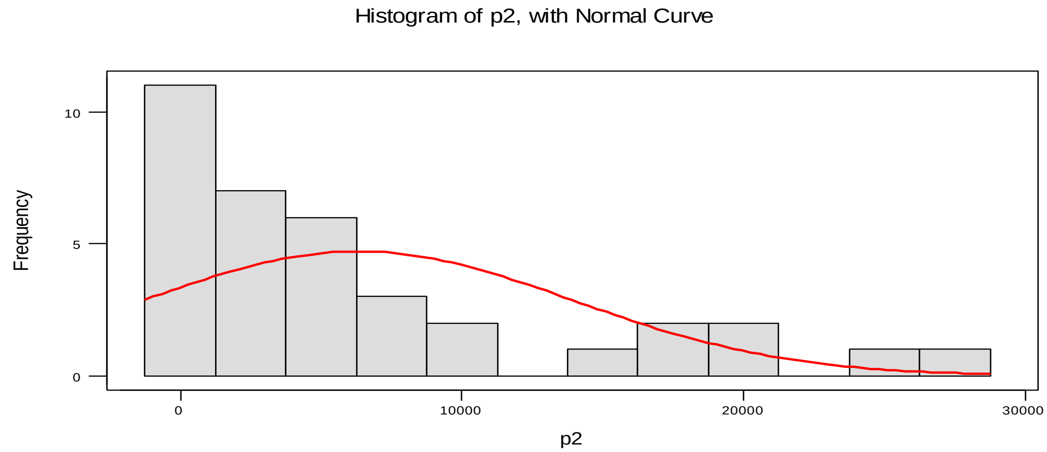


Figure 23: P2 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P2 (i.e. production yield in units) product

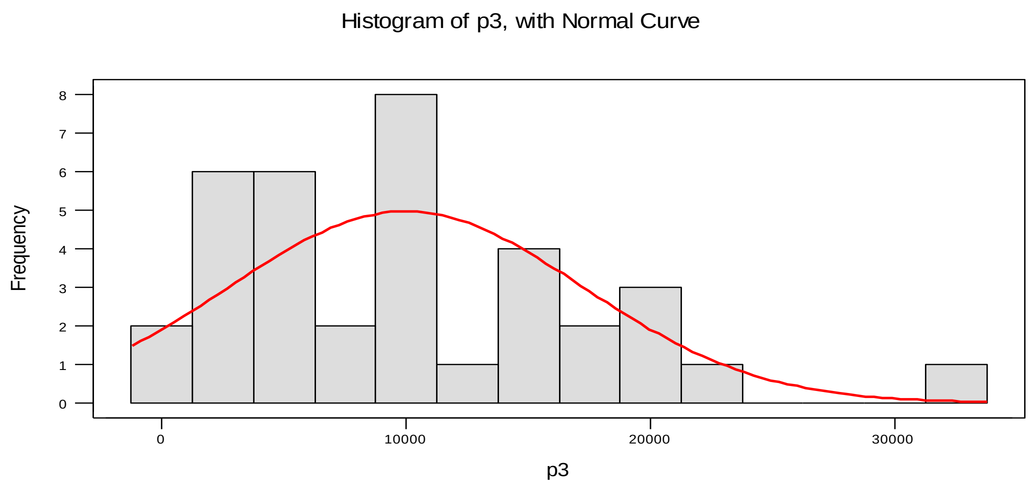


Figure 24: P3 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P3 (i.e. production yield in units) product

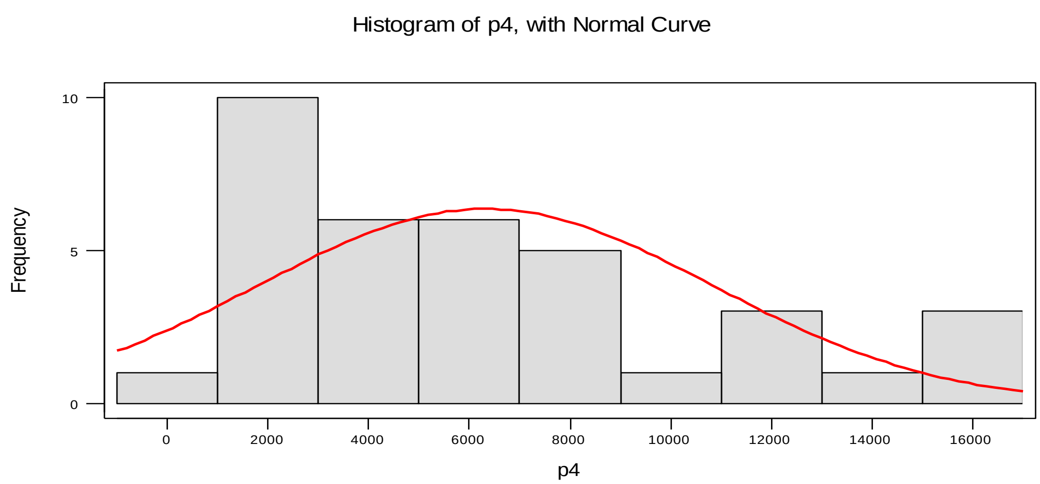


Figure 25: P4 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P4 (i.e. production yield in units) product

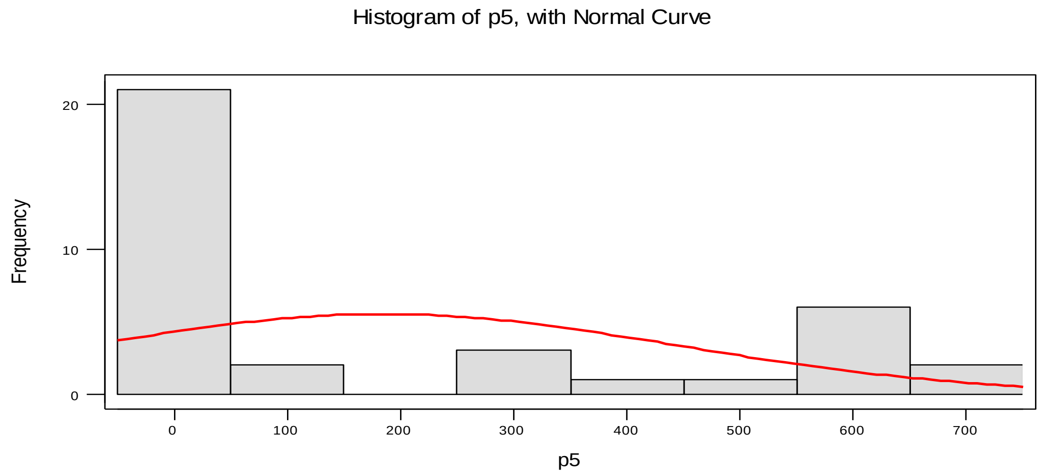


Figure 26: P5 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P5 (i.e. production yield in units) product

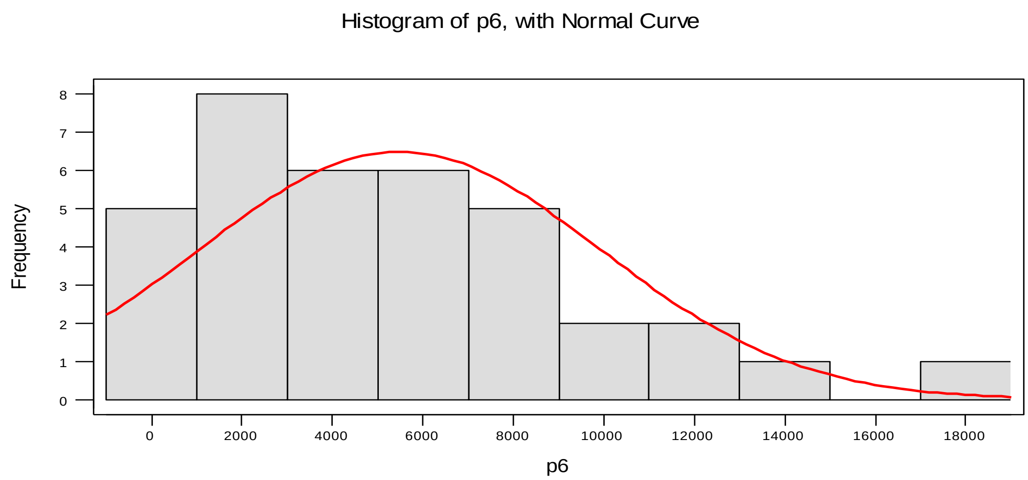


Figure 27: P6 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P6 (i.e. production yield in units) product

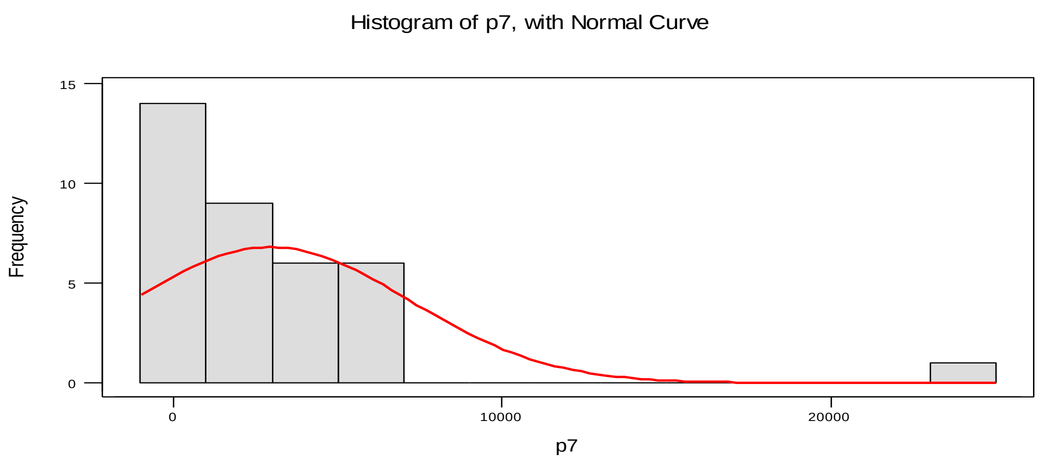


Figure 28: P7 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P7 (i.e. production yield in units) product

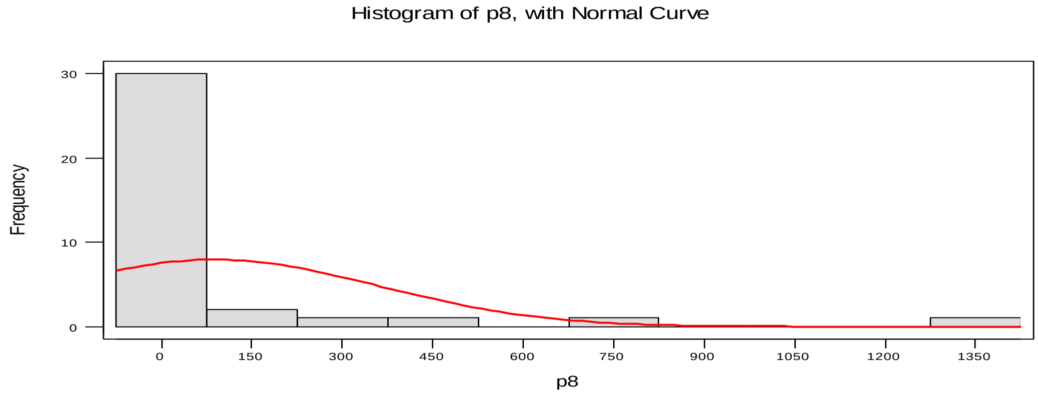


Figure 29: P8 Normality Test Using Histogram Plot

This is a histogram plot of a normality test. It is to show the rate of cumulating frequency of the P8 (i.e. production yield in units) product. 3D Plots Of Different Seizes Of Plastic Pipes On Product Total{PT} and Month; This is to test for the homogeneity of the data. This is to show whether the collected data is real

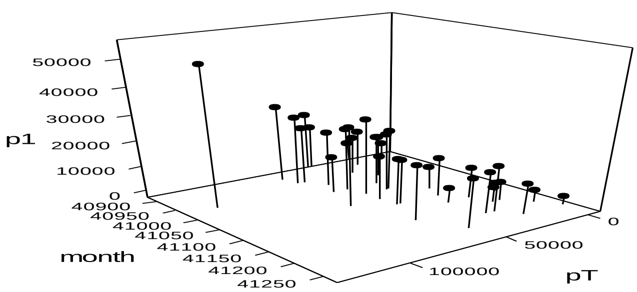


Figure 30: 3-D Homogeneity Plot for P1

Figure 30 is a 3-dimensional view of P1 product, the result shows that they fall within and none exceed the boundary. This means that the data for P1 (i.e. production yield in units) product is real data of the manufacturing Industry

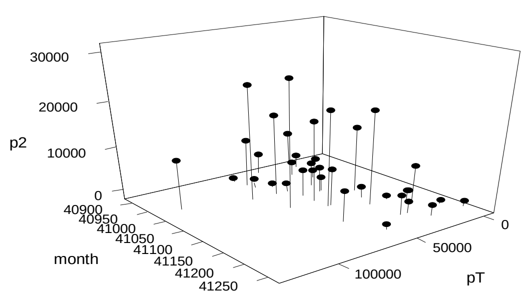


Figure 31: 3-D Homogeneity Plot for P2

Figure 31 is a 3-dimensional view of P2 product, the result shows that they fall within and none exceed the boundary. This means that the data for P2 (i.e. production yield in units) product is real data of the manufacturing Industry

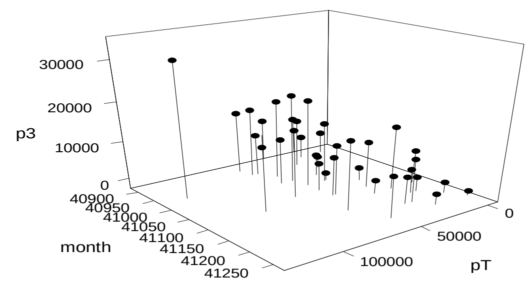


Figure 32: 3-D Homogeneity Plot for P3

Figure 32 is a 3-dimensional view of P3 product, the result shows that they fall within and none exceed the boundary. This means that the data for P3 (i.e. production yield in units) product is real data of the manufacturing Industry

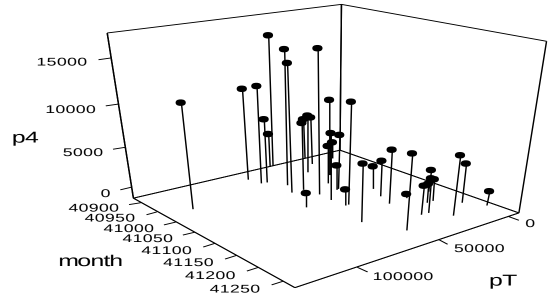


Figure 33: 3-D Homogeneity Plot for P4

Figure 33 is a 3-dimensional view of P4 product, the result shows that they fall within and none exceed the boundary. This means that the data for P4 (i.e. production yield in units) product is real data of the manufacturing Industry

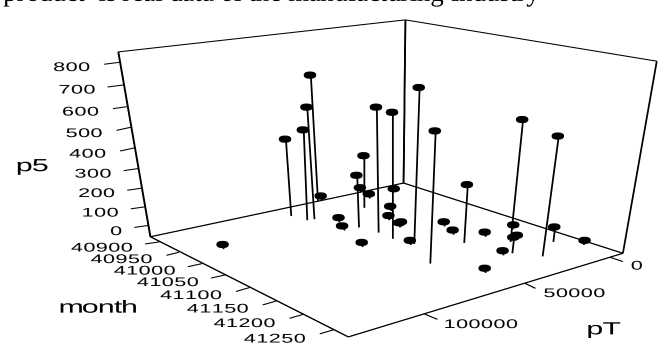


Figure 34: 3-D Homogeneity Plot for P5

Figure 34 is a 3-dimensional view of P5 product, the result shows that they fall within and none exceed the boundary. This means that the data for P5 (i.e. production yield in units) product is real data of the manufacturing Industry

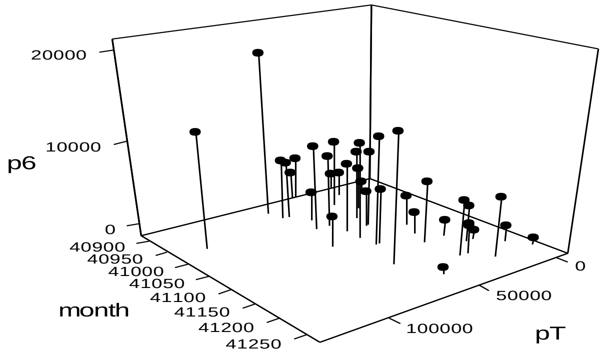


Figure 35: 3-D Homogeneity Plot for P6

Figure 35 is a 3-dimensional view of P6 product, the result shows that they fall within and none exceed the boundary. This means that the data for P6 (i.e. production yield in units) product is real data of the manufacturing Industry

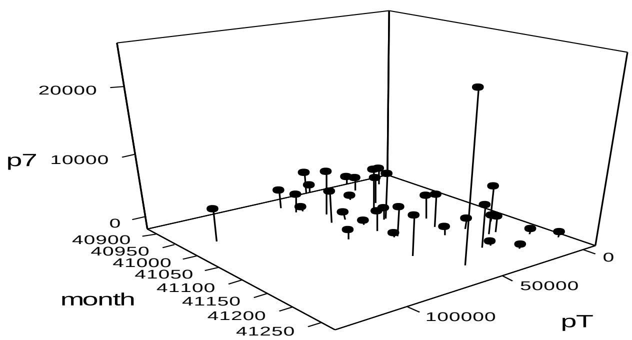


Figure 36: 3-D Homogeneity Plot for P7

Figure 36 is a 3-dimensional view of P7 product, the result shows that they fall within and none exceed the boundary. This means that the data for P7 (i.e. production yield in units) product is real data of the manufacturing Industry

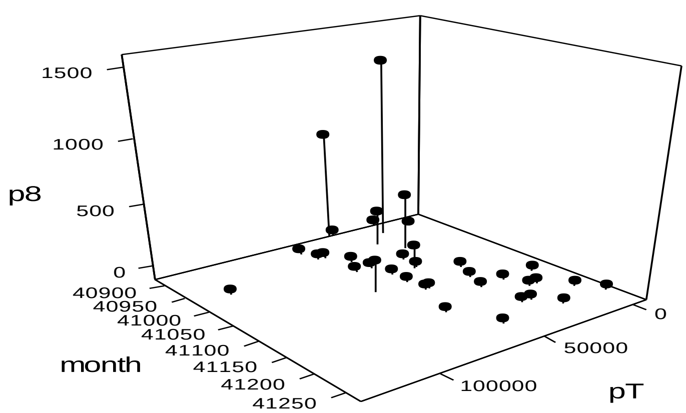


Figure 37: 3-D Homogeneity Plot for P8

Figure 37 is a 3-dimensional view of P8 product, the result shows that they fall within and none exceed the boundary. This means that the data for P8 (i.e. production yield in units) product is real data of the manufacturing Industry

IV. DISCUSSION OF RESULTS

This is based on the results found from the analysis, and also the table and charts developed:

- ✓ Time series analysis were used to analysis and to observe the behavior of the collected data
- ✓ The normal probability plots show that the data are normally distributed which means that the data is adequate or fit for modeling. The results show that they are random around a non zero means therefore, the models are adequate and the data are linear data.
- ✓ The histogram plot of a normality test is to show the rate of cumulating frequency of the products
- ✓ 3D plot for plastic pipe is to test for the homogeneity of the data. This is to show whether the collected data is real. The result shows that when they fall within and none exceed the boundary, this means that the data is a real data of the manufacturing Industry.

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