CHAPTER 3

Empirical Research

3.1 EMPIRICAL RESEARCH

According to Bruns (2010), empirical research is the process of reporting results of a study based on data captured from observation or experimentation. In work done by Robergs (2010) it was mentioned that empirical research indicates the need "Why" the study is important and is generally answered by the hypothesis of the analysis. The acquired data may be quantitative (data typically captured in databases) or qualitative (data that is narrative). For the purpose of this report monthly energy data captured on a historical energy server at the mine situated in the West Wits region of AGAs' operations from January 2002 to December 2012 was used. This provides us with 132 data points for the total energy consumption and per process a total of 924 data reference points. The data is attached in Appendix A (Mine Energy Data) for review. Figure 3.1 shows an illustration of the processes mentioned in Chapter 2 that contribute towards total energy consumption for the respective mine from the Deloitte study (Van Antwerpen, 2011:5).

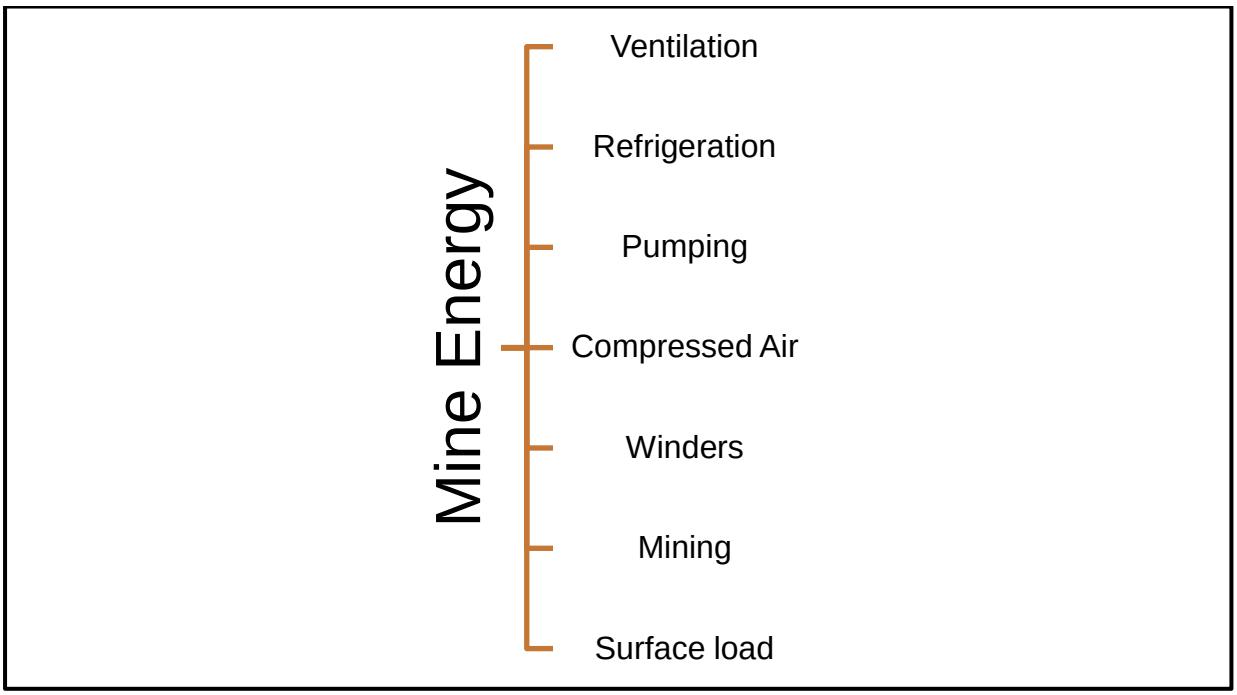

Figure 3.1: Total mine energy and utility processes that contribute towards it

By understanding the utility processes that contribute towards the total mine consumption, a process of variable determination and elimination was applied to build an energy model. This is required for simplicity of the energy forecast model as variables increase complexity and future forecasting error percentages that will be shown later in the chapter. A procedure of

identifying and elimination of variables which affect the utility processes will follow to indicate applicable and non-applicable process variables.

3.1.1 Determination of variables for a mine energy model

In order to understand the variables that affect the utility processes a brief explanation of each utility is provided based on work by Robbins (2013):

- *Ventilation* – In order to sustain liveable underground working conditions, ventilation air is required not only for breathing but also cooling and cleaning purposes. Atmospheric air is sucked with considerable force from surface fans down the shaft infrastructure and with the use of auxiliary inline units ventilated towards the working areas. Its purpose at this stage is twofold, to provide breathable air for the worker and cooling. The exhaled, exhausted and dirty air is then guided via return airways through booster fan configuration to the ventilation shaft where it will be extracted by the main fan units.
- *Refrigeration* – Underground workings and their environmental conditioning are governed by the Mine Health and Safety Act (No. 29 of 1996) (SA, 1996) along with the Minerals Act (No. 50 of 1991) (SA, 1991). The law requires that any working place underground should have atmospheric conditions that are lower than 28 ‘C Wet Bulb. Ventilation in itself for deep level mines cannot handle the heat generated by the Virgin Rock Temperatures (VRT) underground and requires additional cooling assistance. This cooling is typically provided by means of Vapour Compression Cycles (Refrigeration) units situated both on surface and underground that cool a medium (typically water) that is circulated to working places via water networks that cools the air as it enters the working area.
- *Pumping* – As mentioned, a combination of ventilation and refrigeration is used to cool the underground working areas to suitable environmental conditions. The use of these mediums results in both water condensation at the working place and system leakages from infrastructure networks that could span several kilometres. The net effect is water underground from mine workings and fisher water penetrating from surrounding mines or natural fountains that must be pumped to surface. A typical deep level mine will use cascade systems to pump the water back to surface depending on the volumes and static head (height to be pumped) requirements.
- *Compressed Air* – Pneumatic drills are the primary medium for breaking rock underground and have been for the last couple of decades. Atmospheric air is compressed on surface with the use of large radial flow compressors and then piped to the underground working areas. The flow of compressed air is one directional

meaning once it's used at the drill (expanded to atmosphere) it forms part of the ventilation air circuit and returned to surface via the ventilation network.

- *Winders* – The transportation of people, material and explosives is done with the use of winding systems located both on surface and underground. The electrical load requirements for winders is smaller when compared to the previously mentioned processes as the utility is only used when needed and the regeneration effect of a winder that will not be further discussed.
- *Mining* – All the auxiliary equipment used underground and instope for the transfer of broken rock, water, air and lighting of haulages is captured in the mining load. Investigation by AGA South African Region (SAR) energy department indicated that this load is primarily captured under secondary ventilation fans and spindle pumps that transfer water back to station areas. The load itself is one of the biggest consumers of energy for the deep mine as shown by figure 3.2.
- *Surface Area* – General office building, residences and change houses are to name but a few of the energy loads that make up surface area.

Figure 3.2 provides a pie graph of the percentage that each load contributes towards the total energy consumption for the deep level mine. The figure illustrates the total region consumption so metallurgy that encapsulates the mineral processing is also included but not relevant for the purpose of this report, also the missing percentage is Surface load at 2%.

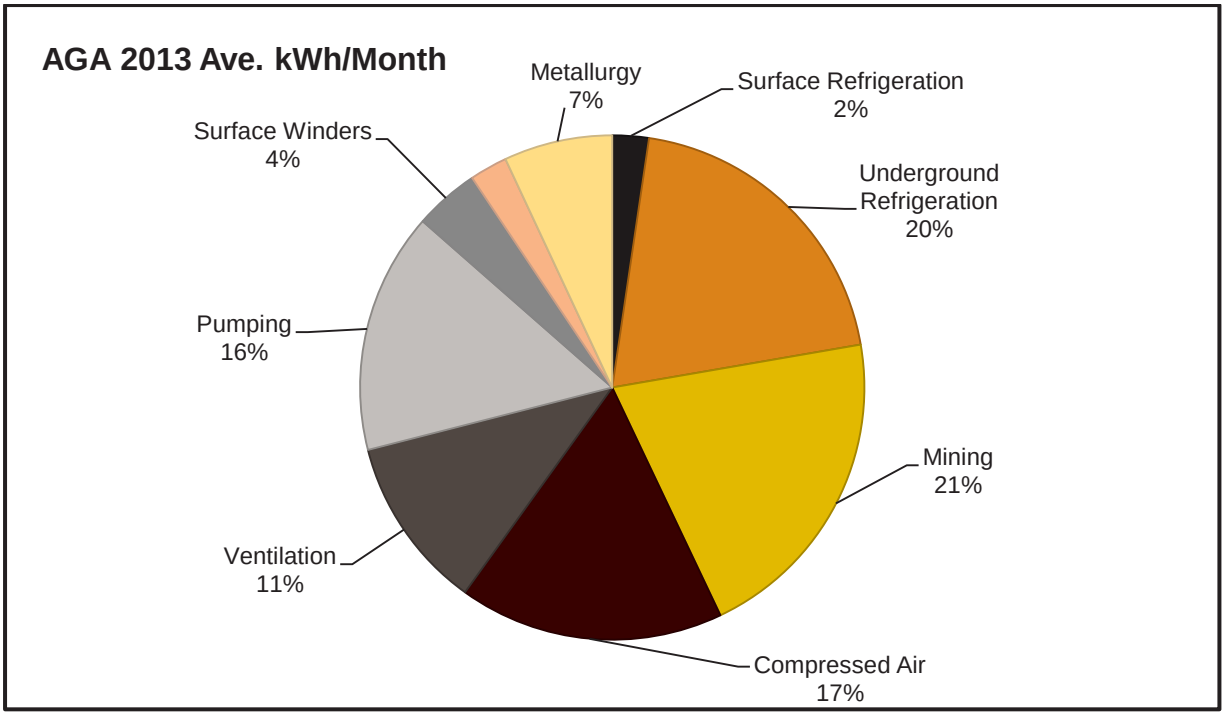

Figure 3.2: Total mine energy and utility processes that contribute towards it.

3.1.2 Input Variable Analysis

Now that we have a better understanding of the utility processes that affects the total energy consumption for a deep mine it is possible to investigate the input variables that might be of statistical importance for consumption levels for use in current and future forecasting models. The 5 variables that were selected in collaboration with the SAR energy department and the Deloittes group are discussed below. The services of the Statistical Consultation Services of the North West University's (NWU) Potchefstroom campus helped to test as a first step the variables correlation with each other and then the utility processes. A typical scatter plot is used as it indicates if there exists a direct correlation or collinearity between variables which can therefore be eliminated. This is known in statistical terms as extraneous variables that according to Psychology World (Hall, 1998) are undesirable variables that will influence the outcomes between variables in the focus research.

- *Ambient Temperature* – As was mentioned, atmospheric air is sucked down the shafts to provide breathable air and cooling for the working places. It was therefore assumed that seasonal changes in ambient temperatures should play a significant role in the energy usage of a deep mine as it contributes in ventilation, mining along with refrigeration to an energy load of 54%. Not considering the pumping requirements from the water distribution that brings the total impact on mine energy usage to 70%.
- *Average Mining Depth* – In a deep mine, mining depth is constantly increasing as development and stoping (physical mining activity of breaking rock) takes place. Therefore given the inefficiencies that are associated with increasing infrastructure *Ex. energy losses that are a result of increased length of piping and differences between ambient and fluid temperatures will result in an increased energy requirement to sustain the same level of underground environmental condition*. The assumption is that this should have a direct effect on the mine energy requirements and therefore on Refrigeration, Ventilation, Pumping, Compressed Air and Mining loads. Cumulatively these equal 87% of the energy requirement and if correlation is found between the variable and the cumulative sum of these utility processes should be an ideal prediction variable.
- *Virgin Rock Temperature* – The majority of underground heating load, also known as the primary source of heat comes from the actual exposed rock face temperature. According to the South African Chamber of Mines (Chamber of Mines, 2013) this exposed rock face temperature is known in the mining industry as the Virgin Rock Temperature (VRT). It acts as the primary heat source that must be cooled by the utilities to sustain a working environment that complies with the mentioned

legislation for the mining industry. According to the article the temperature is very specific for the mining region and has a linear correlation to depth, meaning as depth increases so does the VRT. As mentioned in average mining depth we will need to analyse VRT and its possible correlation to Refrigeration, Ventilation, Pumping, Compressed Air and Mining load.

- *Tonnes Hoisted* – Most mine planning procedures have historically used tonnes hoisted as the primary variable for current and future energy predictions. The rationale behind this comes from the expected gold recovery profile that is calculated based on the ounce/ton statistical history of the mine ore body. Simply multiplying the ounce/ton with the reef tons broken provides the gold produced and therefore revenue generation. Total tons broken is the summated value of the tons broken from reef and waste for development purposes to provide the expected tons hoisted profile. From a statistic point of view it has a high significance factor in that daily production profiles are available throughout the mines history and the most man hours are spent for future mine planning purposes.
- *Years* – It was mentioned that the data provided by the AGA mine is the historical energy consumption of both the total and utility processes. It was therefore considered as a variable due to the future certainty in the Life of Mine (LOM) profile. When the tonnes hoisted profile is generated it is typically done on a yearly total and therefore the years are known from the planning.

Attached in Appendix C (Regression Forecast), Figure C1 show the results of the correlation test between the above-mentioned input variables. Shown in Figure 3.3 is the scatter plot of depth versus. VRT, it is shown that there exists a direct correlation with a coefficient of determination R^2 of 1. The implication of this is collinearity between variables and VRT will not be considered as it is extraneous. Also shown in Figure 3.4 is the scatter plot of tonnes hoisted versus year; it is indicated that there is no correlation between variables with a R^2 of 0.073 and the variable could be considered to have a statistical significance. Table 3.1 provides a summary of the variable analysis as in appendix B the statistical analysis of the variables mentioned.

Table 3.1: Variable Analysis Summary

Variables	**R^2**	**Collinearity**
VRT vs. Depth	1	Yes
Depth vs. Year	0.806	Yes
Year vs. Ambient Temperature	0.0001	No
Ambient Temp vs. Tonnes Hoisted	0.073	No

The result of the variable analysis indicates that there are statistically 3 input variables that could be considered for energy modelling and forecasting they are: **Year, Ambient Temperature and Tonnes Hoisted**. Based on the article by the Chamber of Mines (Chamber of Mines, 2013) the data confirms that there is a linear correlation between depth and VRT. Discussion with Professor Faans Steyn at the Statistical Consultation Services on the above-mentioned results motivated the decision to firstly test year as the primary input variable to compare to the Deloittes work that used tonnes hoisted, but to also consider the variable and base load theory. Deloittes as discussed in Chapter 2 used a Monte Carlo Analysis for the modelling and energy forecasts so it would therefore be possible to compare 2013 actual data against both models. This work will follow later on in Chapter 3, for now it's important to understand the variable and base load portions of each utility process.

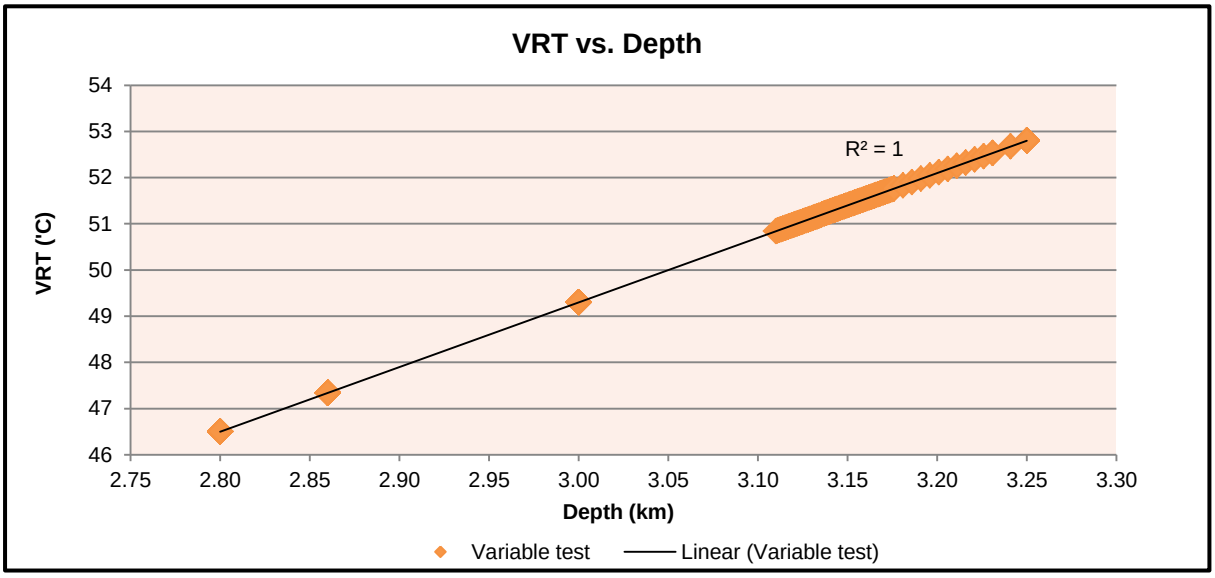

Figure 3.3: Variable Analysis (VRT versus Depth)

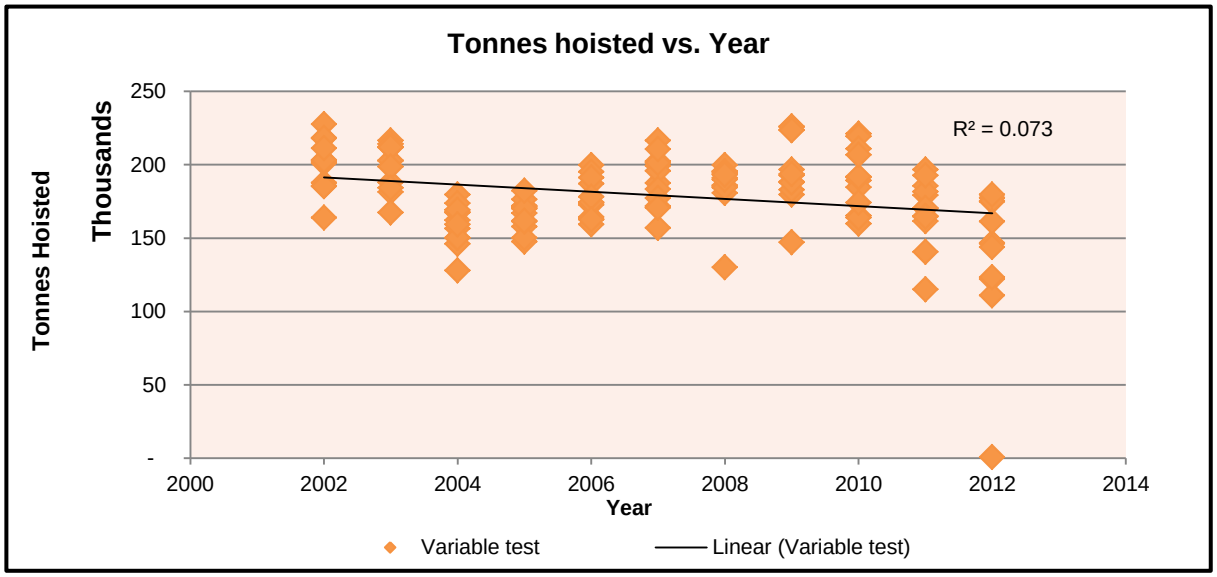

Figure 3.4: Variable Analysis (Tonnes Hoisted versus Year)

3.1.3 Base and variable load calculation

The Deloittes study showed that using base loads per utility process improves the accuracy of the model with the forecasting of energy usage when comparing tonnes hoisted to the remainder of the variable load. According to the Oxford dictionary (2011) a base load is the minimum constant load of power that needs to be supplied. For our consideration in the mining industry the base load is the minimum load that is required by the mine to sustain workable environmental conditions without production. The proof of this concept is found in Figure 3.4 for the month of October 2012. It is shown that during that month there was no tonne hoisted due to the mining industry wide industrial action that was also mentioned in Chapter 2. For the particular month total energy and all the utility processes are compared to the average energy usage. This provides a base load that is considered constant regardless of the input variables. Figure 3.5 shows the utility processes base loads as a percentage of the yearly averaged actual values. The analysis was completed by the SAR energy department as daily totals instead of monthly values based on the history from 2002 were used. The total base load as a percentage of the actual daily load for the mine is calculated at 70.2%. This implies that any selected input variable will only have a 29.8% effect on the energy consumption. Also shown by the graph in Figure 3.5 is that there is also a lot of variance between the actual utility processes and its respective base percentages. Key to the observation is also the fact that Refrigeration, Ventilation, Pumping, Compressed Air and Mining that contribute towards 87% of the energy requirements have the highest base load percentages that also confirm the selection of the input variables.

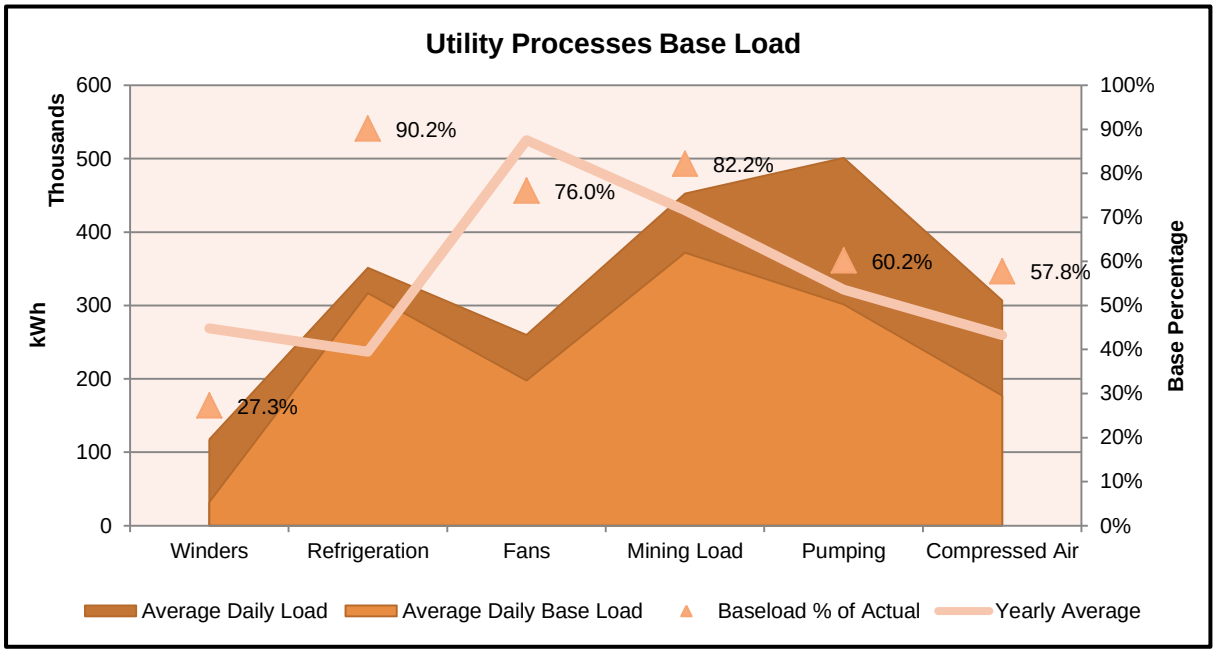

Figure 3.5: Utility Processes Base Load

To prove the accuracy of the base load and variable load concept a regression analysis was needed on the total energy and utility processes. If correct the adjusted R^2 value should increase from the total load to the variable load analysis. The procedure is to test the tonnes hoisted data against total energy and per utility process and then remove the base load as calculated in the graph shown by figure 3.5. The variable loads should also comply with the requirements for model verification based on the residual analysis that are:

- *Linearity* – A plot of the response variable (Y) against the input variable (X) with a visual inspection if there is a linear relationship between the data or not.
- *Independence* – By plotting the residual in equation 4 against the input variables (X, i…n) it establishes if consecutive residuals are independent or not. Should there be a cyclic pattern in the data the residuals are not independent.
- *Normality* – By plotting the residuals in a normal distribution there should be normality between them if evaluated in a frequency distribution i.e they should not depart substantially from the normal distribution.
- *Equal Variance* – An evaluation is done when plotting the residuals against input variables (X) and evaluating the homogeneity (their variability) of the data points, if it has an equal variance to the reference point it is valid for each level of X.

The results of the analysis is also shown in Appendix B (Variable Analysis) and summarized in table 3.2 below. Figure 3.6 to 3.8 are also shown as to illustrate the outcomes of point 1 in table 3.2 for the residual acceptance evaluation.

Table 3.2: Variable Analysis Summary with Tonnes (Tonnes Hoisted – TH, 1 = Yes, 2 = No)

Analysis Criteria (Energy – kWh)	**R^2**	**Linearity**	**Independence**	**Normality**	**Equal Variance**
1. Total vs TH	0.014	1	1	1	1
2. *Variable Total vs TH*	0.019	1	1	1	1
3. Fans vs. TH	0.008	1	1	1	1
4. *Variable Fans vs TH*	0.009	1	1	1	1
5. Total Refrigeration vs. TH	0.018	1	1	1	1
6. *Variable Refrigeration vs TH*	0.003	1	1	1	1
7. Total Pumping vs TH	0.084	1	1	1	1
8. *Variable Pumping vs TH*	0.11	1	1	1	1
9. Total Compressed Air vs TH	0.022	1	1	1	1
10. *Variable Compressed Air vs TH*	0.252	1	1	1	1
11. Total Mining vs TH	0.062	1	1	1	1
12. *Variable Mining vs TH*	0.351	1	1	1	1
13. Total Winders	0.045	1	1	1	1

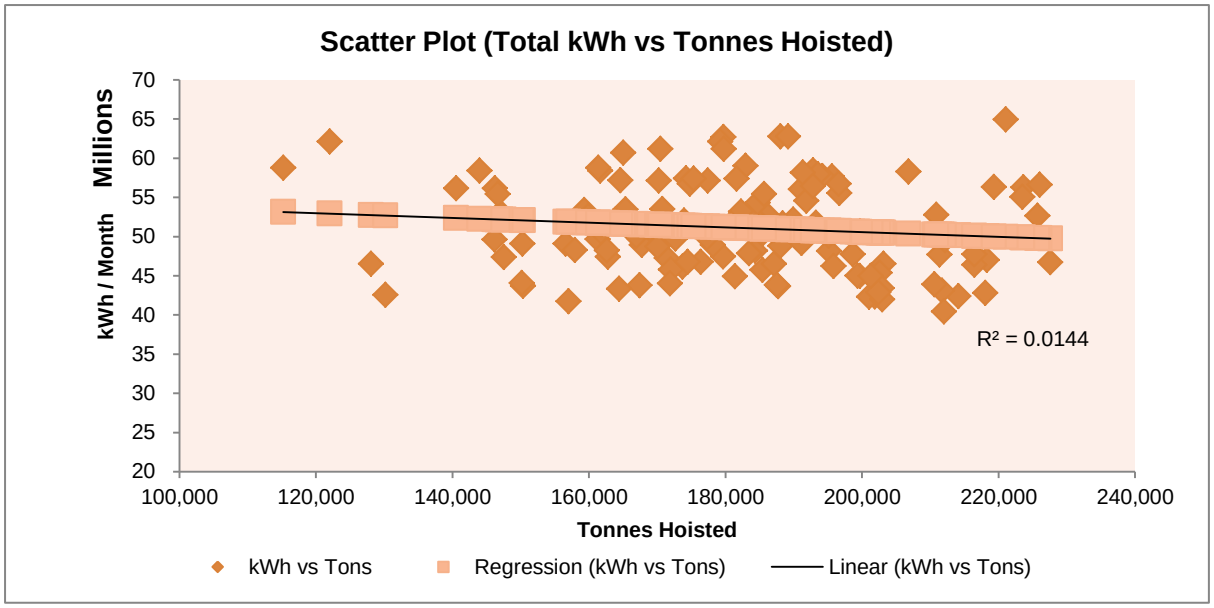

Figure 3.6: Scatter Plot of Total kWh versus Tonnes Hoisted **(Linearity Test)**

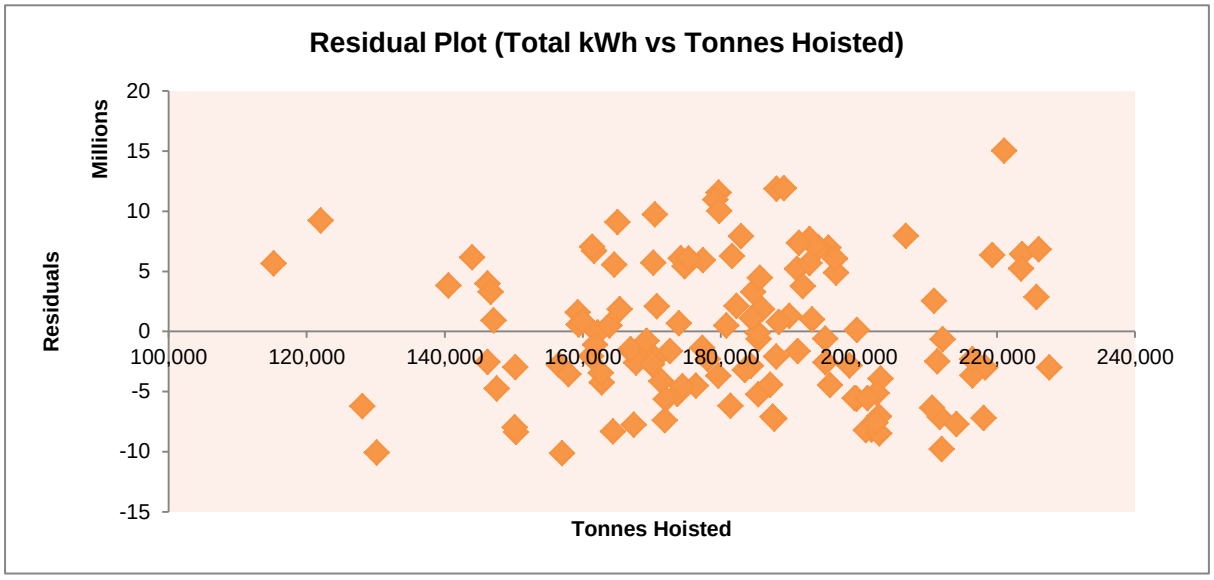

Figure 3.7: Residuals versus Tonnes Hoisted **(Independence and Equal Variance Test)**

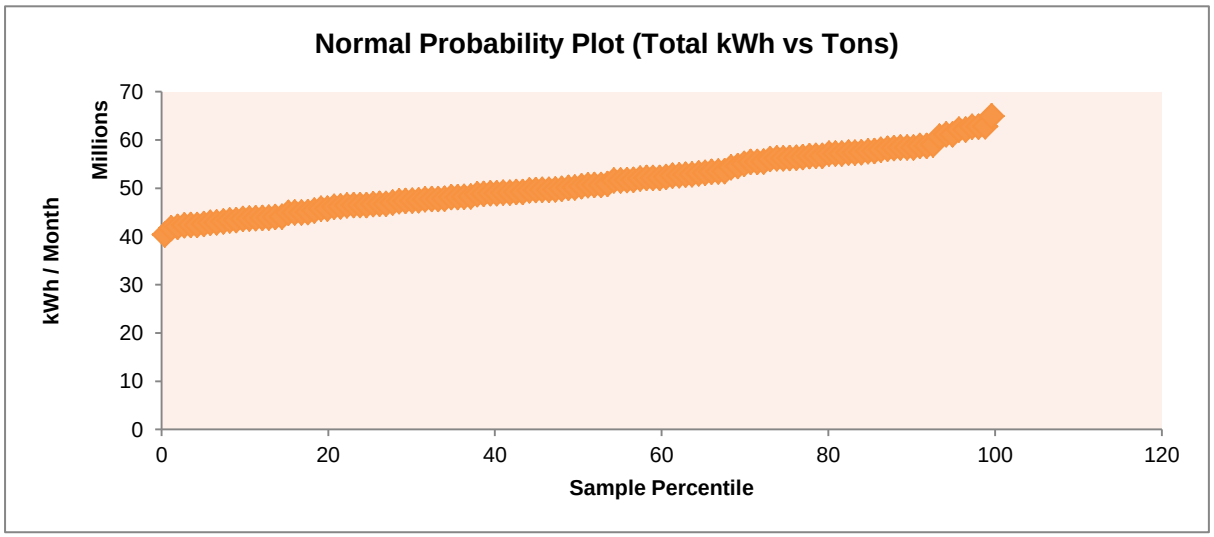

Figure 3.8: Normal Probability Plot **(Normality Test)**

Table 3.2 shows that there is an increase in accuracy from R^2 when removing the variable load from the base load as opposed to using the total energy load so proving the Deloittes evaluation (Van Antwerpen, 2011:5). It is shown that only Refrigeration decreased as a result, and that the entire residual element requirement is satisfied. From the table it is also shown that using a single variable is very risky in that R^2 is very low for all the instances (highest value is 0.351). However when the same analysis is done for depth which ultimately correlates to year from section 3.1.2 as input variable, the results show that the coefficient of determination R^2 increases as shown by table 3.3 to 0.42, and 0.028 for ambient temperature. In consultation with Steyn (2013) ambient temperature was eliminated as input variable to simplify the energy model for forecasting purposes.

Table 3.3: Variable Analysis Summary with Depth and Ambient Temp (Ambient Temperature = AT, 1 = Yes, 2 = No)

Analysis Criteria (Energy – kWh)	R^2	Linearity	Independence	Normality	Equal Variance
14. Total vs Depth	0.420	1	1	1	1
15.*Variable Total vs Depth*	0.170	1	1	1	1
16.Total vs AT	0.028	1	1	1	1
17.*Variable Total vs AT*	0.001	1	1	1	1

3.1.4 Tonnage forecast and the regression year prediction

At this point we have identified that tonnes hoisted and years are the best possible input variables. In the Deloittes study the mine provided a tonnes hoisted profile for the LOM that indicates production will end in 2059 as shown by Figure 3.9. Based on the data history and what Deloittes used from 2002, a future forecast regression model was done up to 2040 along with the Statistical Consultation Services at NWU. Remembering that it was mentioned in Chapter 2 that extrapolation outside the relevant data range (data that is known) increases the error percentage of a regression model and 28 years outside the data range should be sufficient to illustrate this concept based on a 10-year history. The process of establishing the future tonnage hoisted profile comes from collaboration between Mining, Mineral Resource Management (MRM), Financing and the Engineering departments. The outlook provides a Net Present Value (NPV) of the mine with its current infrastructure and Internal Rate of Return (IRR); this is constantly changed depending on the presented value and could be adjusted to increase shareholder value. The process is started during the first quarter of each year for P2V and is finalized during the fourth quarter and submitted (Van Antwerpen, 2011: 27).

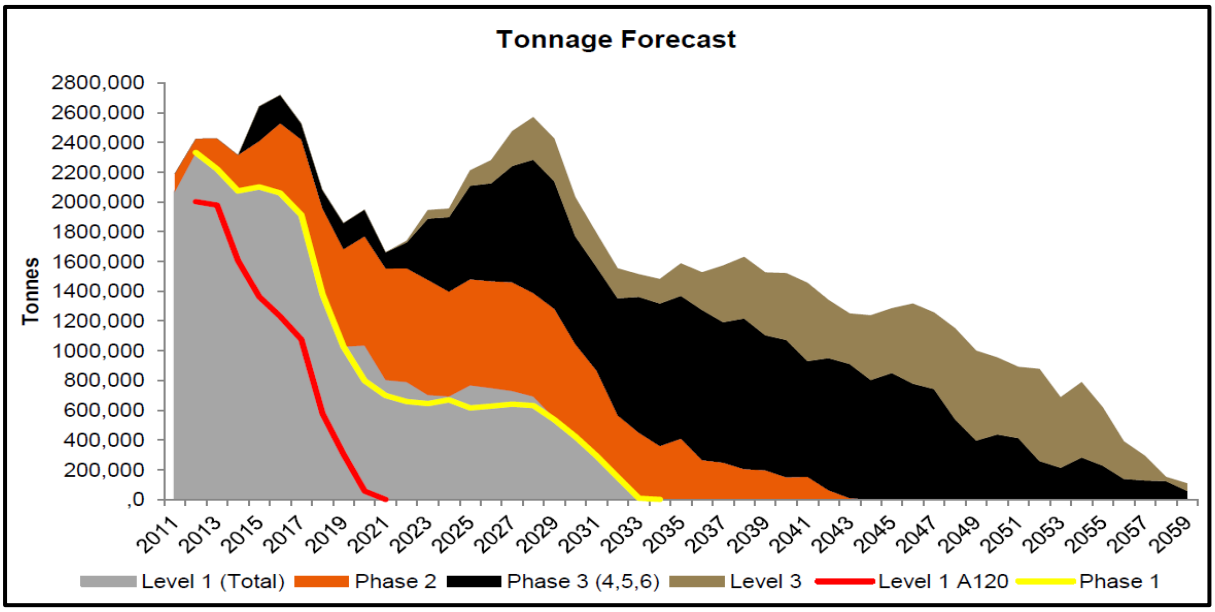

Figure 3.9: LOM tonnage profile based on available BME data

3.1.5 Regression forecast of anticipated energy load from years

The Statistical Consultation Services as mentioned were approached to assist with a regression model to forecast the expected or predicted energy outlook for the deep mine based on the energy history provided and used during the Deloittes study. Data was split according to the utility processes and then extrapolated to 2040 to provide some insight on the predicted load conditions for the resulting year. Figure 3.10 and 3.11 show the results of the analysis when plotting the total energy use for the months of February and August for each of the required years (X-Axis) along with its energy outlook (kWh, Y-Axis). The historical data available as mentioned was at month level and therefore prediction was split per utility process and corresponding month. The results indicated that the total energy increases year on year as mining is continued as was the case from the historical data. Also shown is the 95th percentile (confidence interval – CI) data range added to indicate the bandwidth of the expected values. This is done in statistics to indicate given a certain percentage in this case 5% above and below the expected values what the energy consumption for the total mine should be. The utility processes with corresponding values are added in Appendix C (Regression Forecast – Mine Utility Processes) for reference.

An important observation in both Figure 3.10 and 3.11 is that in the first 10 years of extrapolation the 95th percentile confidence distribution remains fairly constant (distance from predicted to lower and upper CI values) thereafter the distance between reference points starts to increase indicating a larger spectrum of expected values. This is caused due to the uncertainty and extrapolation outside the known data range and increases the error percentage. Looking at the figures the trend seems to be nonlinear so increasing at a larger rate every year after the prior year. Given the tonnage profile as in Figure 3.9 a point is now

reached where a direct comparison between the Deloittes Study (Monte Carlo) on tonnes and Regression analysis on years the identified variable could be compared with actual data for 2013 and available budget expectations for 2014 on the deep mine.

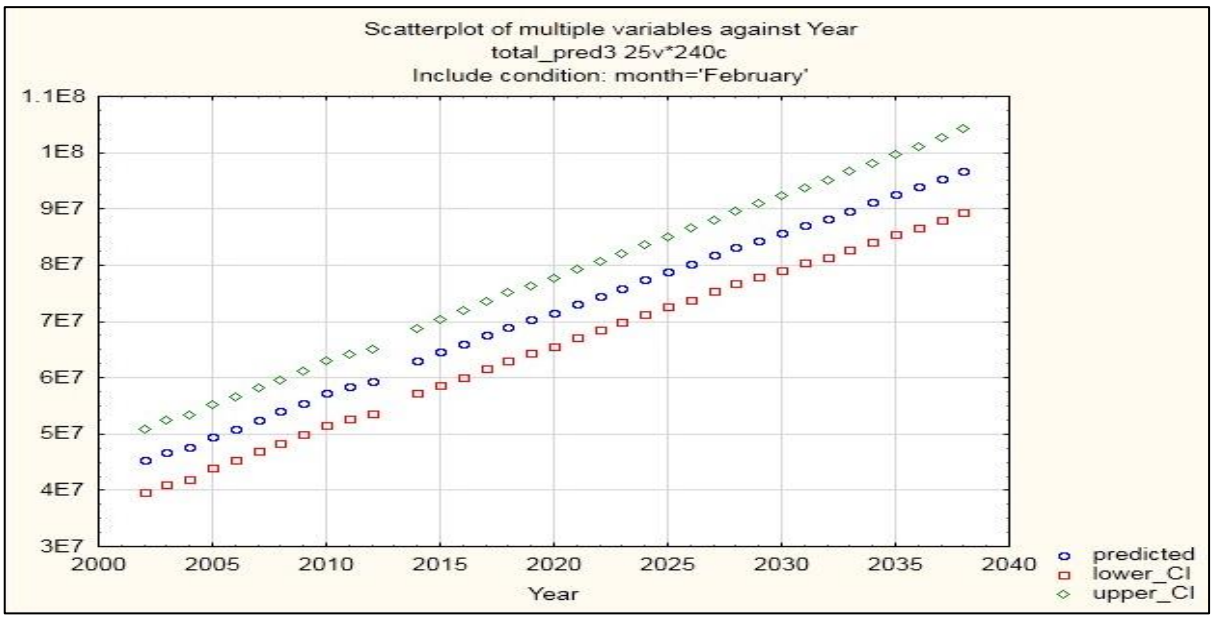

Figure 3.10: Regression prediction for total energy per year in February

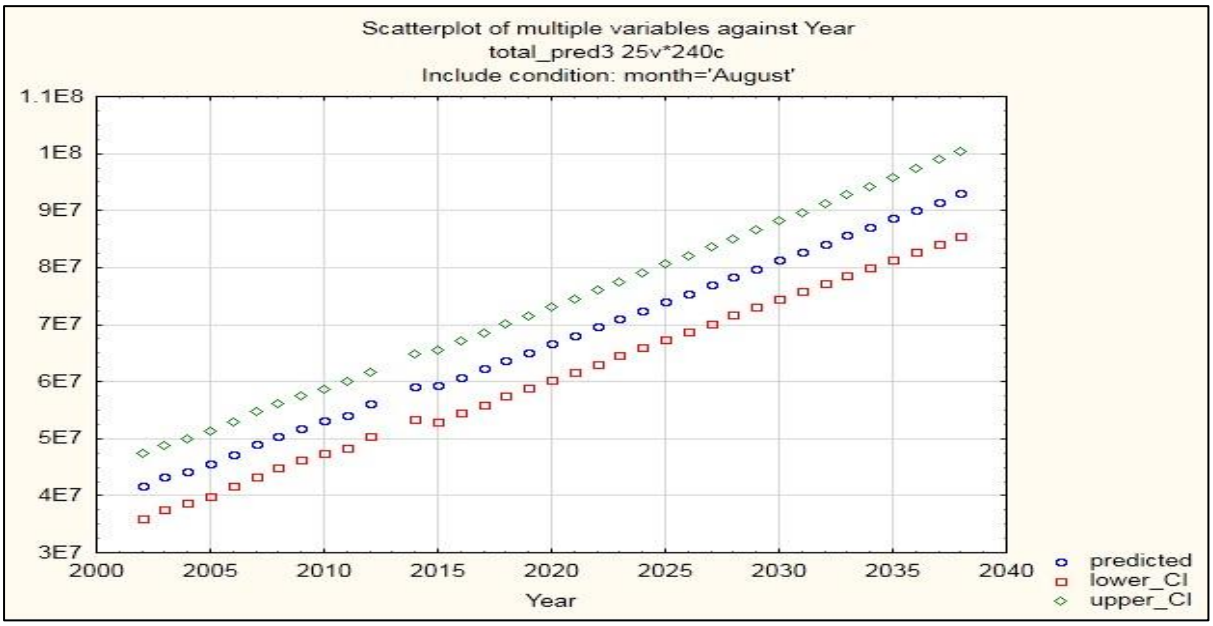

Figure 3.11: Regression prediction for total energy per year in August

3.1.6 Comparison of the Regression Prediction vs Monte Carlo Analysis

Progress to this point identified 2 variables namely: Tonnes Hoisted and Years statistically have the largest influence in the prediction of mine energy for deep mines. A Monte Carlo Analysis in collaboration with Deloittes provided an energy outlook for a deep mine project of AGA. The Statistical Consultation Services (Steyn, 2013) at the NWU decided to use the data provided for the same study based on a variable analysis and with the use of a

Regression model provide an expected energy outlook for comparison. Captured in Figure 3.12 is a graphical illustration of the expected energy outlooks from the models along with the current energy forecast from the mine energy department against the coinciding tonnes hoisted profile. A base case scenario is required to show the percentage deviation along with cost implication for the different models. The existing LOM energy profile for the project based on infrastructure, efficiency and tonnage from the mine was used for this purpose and will be further discussed in chapter 4. Observation of the graph in Figure 3.12 indicates that the Regression model shows a gradual energy increase for the total LOM, the graph indicates total annual energy consumption in 2040 of approximately 130 million kWh. The Monte Carlo is initially higher than the regression analysis due to the increased tonnage profile for the period 2014 to 2017 but then remains fairly constant over the total LOM period with total annual energy consumption in 2040 totalling approximately 60 million kWh.

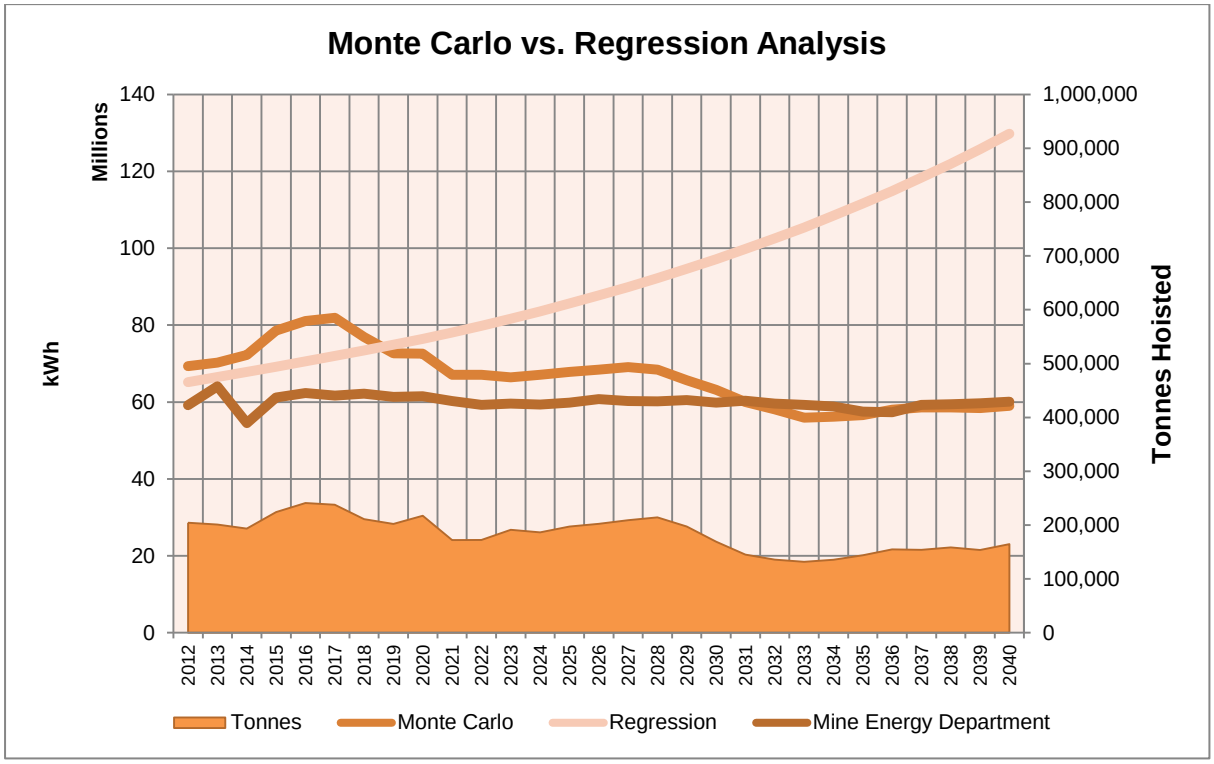

Figure 3.12 Comparison of the LOM energy profile based on the Monte Carlo and Regression model

For management purposes it is important to understand the implication of these energy profiles and the uncertainty regarding them. Looking at the Regression model based on the 10 year energy history, the outlook for 28 years results in an energy profile that increases by 116% when comparing current energy consumption levels to 2040 calculated from equation 5.

$$Percentage\ Increase = \frac{(Annual\ Energy_{2040})}{(Annual\ Energy_{2013})} - 1 \quad (5)$$

The same number when calculated on the Monte Carlo shows a 14.28% decrease and that the expected energy consumption in 2040 will be lower than in 2012 by some 10 million kWh.

A comparison of the total LOM energy profile is shown in Table 3.4 that indicates the cumulative consumption in kWh for the different profiles against the base case. The comparison is required to build a financial model that shows the implication towards operating costs (OPEX) and what effect it has on the NPV and IRR along with Free Cash Flow (FCF) and hopefully the value of statistical models in mine energy forecasting.

Table 3.4: Comparison of Monte Carlo and Regression model vs Base Model

Model	Base Year	Cumulative Total (kWh)	% Increase (5)
1. Base Case (MED)	2012	1 739 091 089	0%
2. Monte Carlo (MC)	2012	1 925 133 319	11%
***3.* Regression (Reg)**	2012	2 645 223 342	52%

The table indicates that according to the mine energy department expected energy consumption for the LOM of the project will cumulatively come to 1.739 billion kWh and 1.925 billion kWh in the case of the Monte Carlo analysis. When calculated from equation 5 11% more energy is required in the outlook as opposed to the base case. The Regression totals 2.645 billion kWh and from a percentage perspective 52% more than the base case.

Unfortunately at this point the actual data available for comparison on both the Monte Carlo and Regression models against actual mine energy is limited up to September 2013 for the past 2 years. For the purpose of illustration the models as mentioned will be plotted against the 2012 and 2013 Year to Date (YTD) monthly actual values as provided by AGA for comparison. The actual values will now be used and termed as the base case and the three models as listed in table 3.4 is then compared for accuracy determination. For the comparison the historical data was used to determine the average monthly energy as a percentage of total annual energy to provide a year profile for the models as mentioned (attached in Appendix D). This process provides additional data points for the evaluation and contributes towards a better understanding of the error percentages that is needed in the evaluation for future cost forecasting. Figure 3.13 shows how the models compared against the actual data for the past 21 months as provided by AGA. All the models have constantly been over estimating the monthly consumption as shown by the lines and read of the primary vertical axis for kWh. The bars indicate the error percentage of each model against

the actual for that specific month and read of the secondary vertical axis for percentage error.

The average of the error percentages for the period (Jan 2012 to Sep 2013) as indicated are:

- ***Monte Carlo Analysis – 20%***
- ***Regression – 13%***
- ***Mine Energy Department (MED) – 6%***

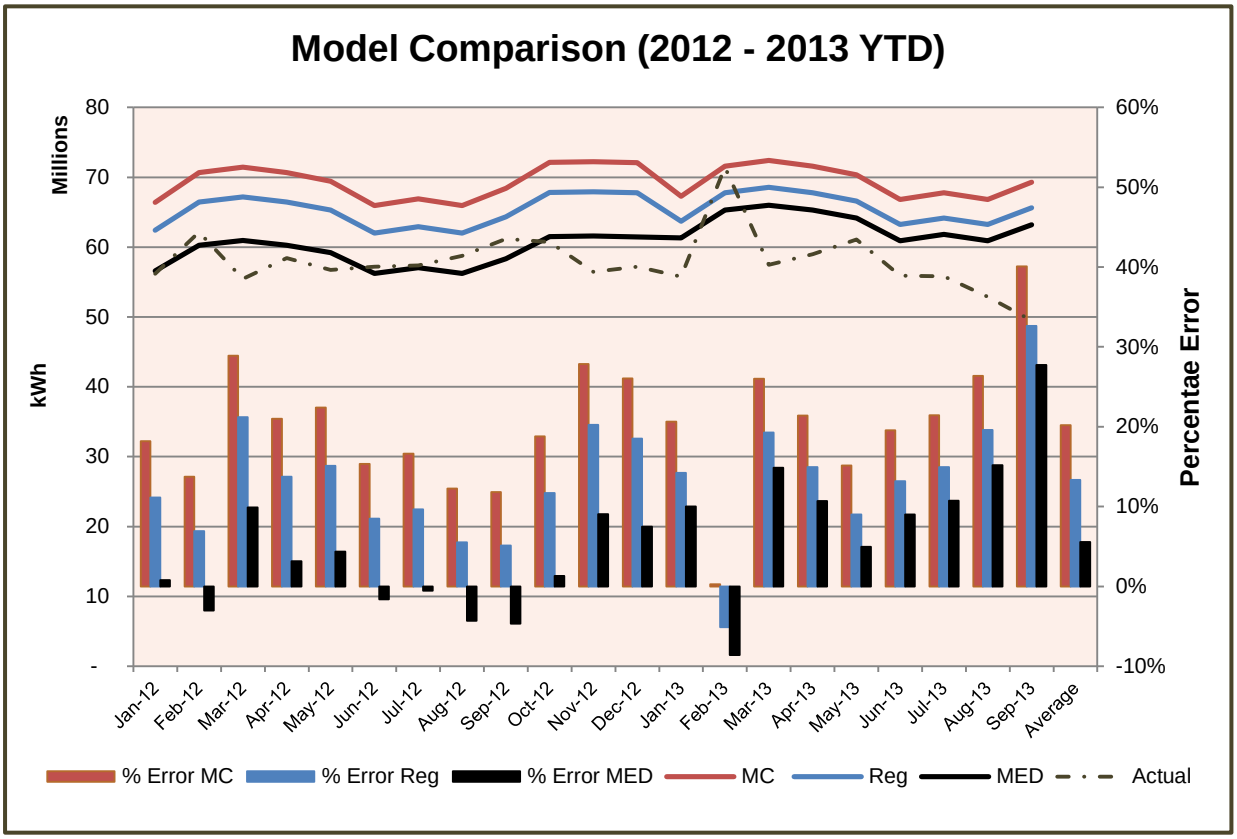

Figure 3.13: Model comparison to actual kWh along with percentage error to actual

In order to provide a perspective on the implication of these findings to management a cost analysis based on historical published financial data for AGA will be used to indicate the impact on OPEX (AGA Financials, 2013). Abbreviated financial statements attached in Appendix D (Abbreviated Financials) were compiled for the period 2002 tot 2011 and used to indicate current market returns of AGA and the expected effect of energy costs on OPEX and the through flow onto the Net Operating Profit after Tax (NOPAT). Understanding that Operating Cash Flow (OCF) is a function of NOPAT and Depreciation for organisations as shown by equation 6, it allows for the calculation of NPV based on the difference in the base case and the associated models.

$$Operating\ Cash\ Flow\ (OCF) = NOPAT + Depreciation \quad (6)$$

3.1.7 Impact on OPEX and Free Cash Flow (FCF) – An overview of AGA financials

- *Balance Sheet overview*

From the abbreviated financials indications are in order to generate sales capital is required to purchase assets. The capital can be either in the form of liabilities or equity from shareholders. From the AGA abbreviated balance sheet, it is indicated that equity is a form of funding for growth in assets within AGA. Shareholder interest has grown from (R 15bn, 2002) to (R 52bn, 2011) illustrating how the shareholders equity and liabilities were applied within AGA. Total assets have grown to (R 84bn, 2011), the majority of which was spent on operating assists up to (R 71bn, 2011). This was mainly due to ore reserve purchases. Net current assets that are used for ore production has increased to (R 15.5bn, 2011). This initially had a negative impact on Free Cash Flow (FCF) that reduced during the acquisition period and has subsequently increased from (R 0.1bn, 2006) to (R 11bn, 2011).

Going further, current liabilities have reduced substantially from (R 33bn, 2009) to (R 8bn, 2011) after the hedge fund removal processes; AGA was able to apply more capital to payments of these high cost items. Long term liabilities have increased to fund the hedge removal process along with retained earnings (equity).

It is summarized that AGA has grown in assets over the past ten years with the predominant use of equity to generate sales. In order to fully utilise market prices the hedge fund was removed. The income statement summary will indicate what effect this allocation of funds made on operating profit or losses.

- *Income Statement overview*

The income statement provides a summary for the changes in equity. As mentioned, AGA has increased assets and the resulting effect of this is an increase in sales as seen in the abbreviated financials. Key income indicators show that total turnover has increased to (R 50bn, 2011) that is an increase of 89% on 2004 during the merger. Total cost of sales remained constant producing a total income of (R 25bn, 2011). Earnings before interest and taxes (EBIT) increased by 149%; the highest it's been for a decade.

Looking at the retained earnings percentage it is still high; this has helped with equity funds. The total return on equity has increased the last 5 years from -18% to 20% that is also shown in the earnings per share for the same period that increased from 99c/share to 380 c/share.

All this taken into consideration share prices has reduced by 33% over the past decade with variance in FCF and Return on Equity (ROE) that averaged at -5% during the same period.

To understand the implications of these fluctuations an analysis is required on the associated risk for AGA in the market space.

- *Understanding historic risk – AGA and the market*

Fluctuations in past sales are a good indicator of risk within AGA. Figure 3.14 shows how AGA performed relative to the market during the past decade. AGA financial year end is 31 December annually.

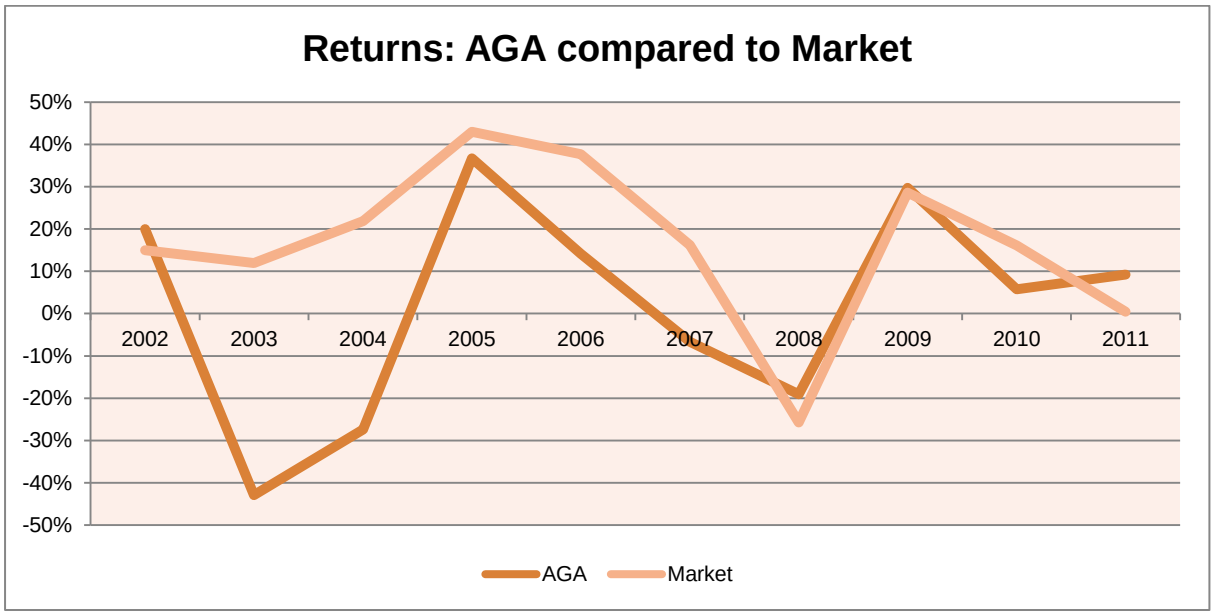

Figure 3.14: AGA returns performance relative to the market

Since the global recession in 2008, AGA has performed relatively in line with the market but for previous years it underperformed substantially as seen in 2003 and 2004. Statistical analysis on this data is shown in table 3.5. It indicates that the average return for AGA during the period was 2% compared to a market return of 17%, in 2003 a low of 43% lowers the average that is 5% without it. The standard deviation shows that AGA is more risky than the market at 26% given the market range of only 19%. The correlation of 0.52 indicates that AGA reacts to the same trend as the market. All indicates that for the past decade AGA stocks have been more volatile than the market with lower returns that is not in line with investor requirements.

Table 3.5: Statistical Analysis on AGA and Market returns

	AGA	**Market**
Variance	657.1360	376.65
Average	2%	17%
Standard Deviation	26%	19%
Correlation	0.52	1.00
Covariance	0.03	0.04
Beta	**0.68**	**1**

Beta, which is an indication of relevant risk from the Capital Asset Pricing Model (CAPM) is calculated and shown graphically in Appendix E. For AGA in the past decade it is 0.68. This shows that on average AGA stock moves less than 1% when the market moves 1%, or rather that AGA will move 68% when the market moves 100%.

In summary when looking at growth within AGA it is found that an average 2% of the total yield was paid out to dividends meaning a high retention rate. This allowed for the growth in equity within AGA that helped finance asset purchases and increase sales. However fixed costs and taxation along with asset purchases up to 2008 resulted in a low ROE and FCF that reduced returns and lower share prices.

3.1.8 Current value of AGA and Security Market Line (SML)

Expected return is what shareholders of AGA stock expects given historical and current return information. The calculated expected return for AGA given this information is 2.12% and 15.41% for the market. The values of the probabilities can be adjusted to accompany different scenarios; for the purpose of this report an average growth in the market is assumed. Yields for the last decade were 2% for AGA and 17% for the market. AGA returns for the last 3 years averaged at 15%, this is more in line with market expectations and was shown by the increase for the same period in share prices. This will be used for future price evaluations later on.

Required Return is the return that AGA needs to produce before prospective shareholders will invest. The Security Market Line (SML) is used to calculate the required return for AGA. Assuming an average market return and based on the historical data a Risk Free Return (Rrf) that equals returns on long-term government bonds of 8% as in equation 7.

$$\mathrm{R_{rr}} = \mathrm{R_{rf}} + \beta(\mathrm{R_m} - \mathrm{R_{rf}}) \quad (7)$$

It's seen that the required rate of return for AGA stock is 11.92%, Figure 3.15 indicates how AGA is placed with regards to the SML. The graph indicates the share is overvalued and that investors will sell the stock until the returns rise or until the SML line gradient is reached. Also shown on the graph are returns for above average growth that surpasses the SML at 15%. Reason for the financial analysis to this point is that not only have we gained insight into the shareholders' view of AGA, but we now have the actual calculated discount rate for AGA based on their financial history over the past decade to use in our NPV analysis on the forecasted energy profile.

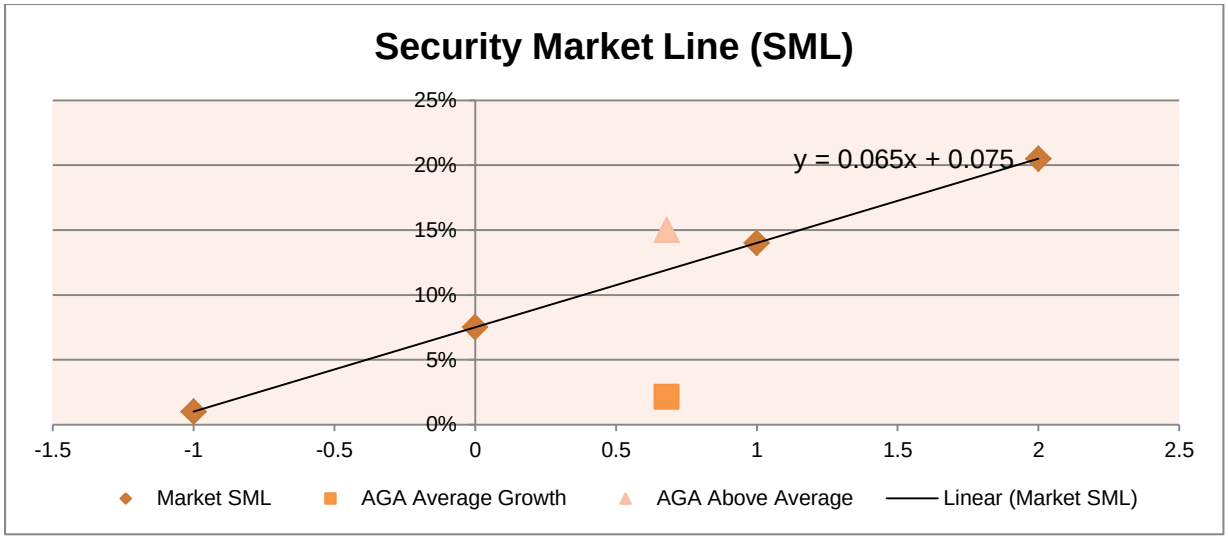

Figure 3.15: Security Market Line with AGA performance indicators

The work in Chapter 2 on the energy price path along with the discussions in Chapter 3 on the model predictions for consumption culminates in the ability to provide an annual energy outlook. Associated cost of energy from the unit price and consumption levels as detailed in the model predictions are then discounted based on the financial analysis to provide a NPV for evaluation with its impact on FCF.

3.1.9 Energy Price Prediction

In Chapter 2 the price cone as was done by the EIUG indicated that, going forward the outlook for energy prices covers a wide spectrum of unit costs (c/kWh). For the purpose of illustration and to show the effect on NPV a high, average and low outlook on the unit cost is selected and their lines plotted in figure 3.16. Given the energy cost associated with each of the profiles an average value of the NPV is calculated based on the cash outflow from the different profiles. The outlook is plotted between 2018 and 2040 to give a total of 22 years' worth of fluctuation in unit cost. Table 3.6 indicates the high, average and low unit cost in 2040. The high outlook point comes too approximately 145 c/kWh and the low point at 95 c/kWh or 103% and 33% respectively. Given the mentioned carbon tax outlook the average impact on OPEX will be based on the high and average outlook as the likelihood of the increase coming in on the low of 33% is not feasible for generation as was shown by the history from 2002.

Table 3.6: Selected outlook on unit cost and associated annual increases

Years	2040 (c/kWh)	Annual Increase (c/kWh)	Increase from 2014
EIUG High 2040	145	0.028	103%
EIUG Average 2040	122	0.018	71%
EIUG Low 2040	95	0.005	33%

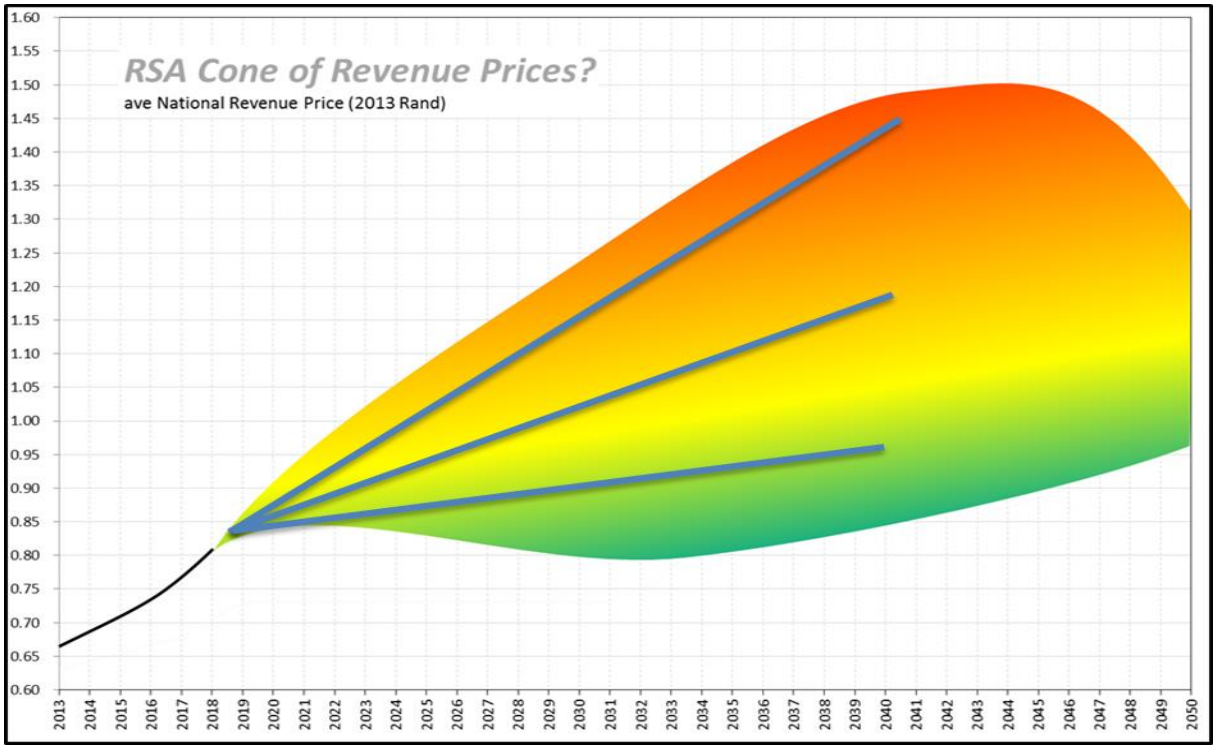

Figure 3.16: High, average and low price unit price path selection

Having the unit price outlook (c/kWh) and the final unit cost in 2040, a linear increase as shown in table 3.6 was calculated that escalates annually for the 22 year period. Based on the energy unit outlook (kWh) from figure 3.12 the energy cost of each model is then calculated. An additional requirement was to establish the percentage that energy would contribute towards OPEX, for this prediction the annual increase in the Consumer Price Index (CPI) had to be estimated for further discussion later on. In collaboration with Lyn Staib (2013) it was decided to use a 6.5% annual growth as from the recent history within AGA that would grow on a compounding rate from 2014 to 2040. The annual cost of energy is calculated from equation 8 and its corresponding NPV from equation 9.

$$Energy\ Cost\ (R) = \ Unit\ Cost\ \left(\frac{c}{kWh}\right) * Energy\ Units\ (kWh) \quad (8)$$

and

$$Net\ Present\ Value\ (NPV) = \sum_{i=0}^{n}\left[\frac{Ri}{(1+I)^{i}}\right] - Initial\ Investment \quad (9)$$

Where:

I = discount rate (11.92%)

Ri = cash outflow from energy cost

N = number of periods (26 years)

For equation 9 no initial cash outflow will be considered as the project capital is not known. What is therefore calculated is the amount by which the FCF should be lowered in order to understand the new NPV for the company. Also stated as the amount by which the current available funds should be reduced as a result of the impending expense from energy. Shown in table 3.7 and figure 3.17 is the effect of the price associated with the different energy models and their reduction towards FCF as illustrated in equation 10 from the NPV analysis.

$$Free\ Cash\ Flow\ (FCF\_new) = Free\ Cash\ Flow\ (FCF_{2011}) - NPV \quad (10)$$

It is shown by table 3.7 that the average reduction from the energy models is in the region of R 5.545 billion. This is the average of the three energy models at an average price outlook and shown graphically in figure 3.17. It is clear that the regression model predicts the highest energy unit consumption and therefore the expected high cost with an average of R 6.271 billion reduction on NPV. Surprisingly when considering the Monte Carlo analysis average of R 5.592 billion versus the mine energy department model average of R 4.773 billion it is expected that the associated cost difference should be lower. In table 3.4 we showed that the unit difference between the models calculated to 11% but the ratio of cost reduction versus unit reduction shows a price difference of 34% when calculated from the percentage difference of equation 5. Investigation into this anomaly is required to provide management with the insight on how applicable the energy models are towards the OPEX outlook.

Table 3.7: NPV calculations of the energy models

NPV	MED	Monte Carlo	Regression	Average
High	R -4 965 383 827	R -5 795 605 253	R -6 584 659 705	R -5 781 882 928
Average	R -4 773 808 058	R -5 592 237 789	R -6 271 109 292	R -5 545 718 380
Low	R -4 548 914 764	R -5 353 502 072	R -5 903 028 372	R -5 268 481 736

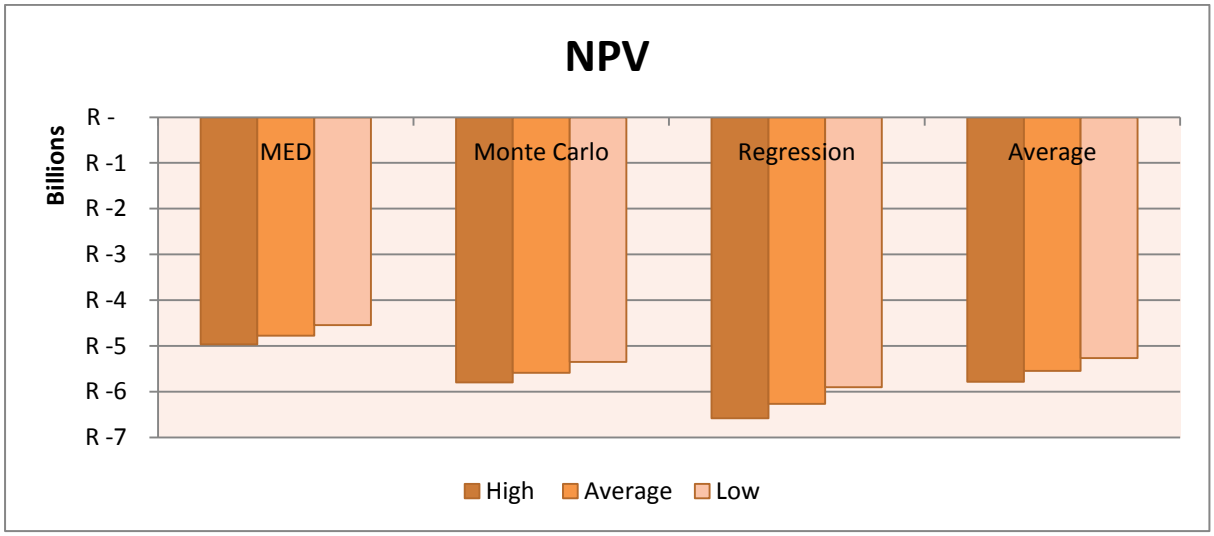

Figure 3.17: NPV calculations of the energy models

As shown in table 3.7 the figures of the pricing models in the Monte Carlo analysis are closely aligned with the average outlook of the different models. The mine energy department has the lowest reduction on the NPV due to the smallest amount of energy units (kWh) from the profile. What is also shown is the fact that even though the difference in the amount of units between the mentioned models is 11%, is that the cost difference from a NPV perspective comes to 34%. Upon investigation it was found that the reason for his comes from the initial difference in cash flow between the Monte Carlo and mine energy model. Equation 9 showed that the NPV calculation is determined by the annual cash flow depreciated at the discount rate of AGA. Figure 3.18 illustrates that for the period 2014 to 2028 the Monte Carlo analysis annual cost is significantly higher than the mine energy model. Even though for the period 2030 to 2037 the prices are lower than the mines model the NPV is highly affected by the high initial cash outflow. The conclusion is made from this that the NPV on the models could therefore be manipulated from the fact that unit consumption could be spread out more evenly or have high initial peaks and lowered towards the end of life to reduce the NPV reduction. This finding is beyond the purpose of the report and will not be investigated further.

Another finding when considering figure 3.18 is the reduced effect that energy has on the percentage it contributes towards OPEX. Mentioned earlier is that the outlook on the CPI index and the decision to have it increase annually by 6.5% on a compounding interest model so to increase by 411% over the total period. When we consider the cash flow from the energy models it is seen that the annual increase in energy cost except for the regression model follows a flattish linear profile and therefore a reduced effect on OPEX.

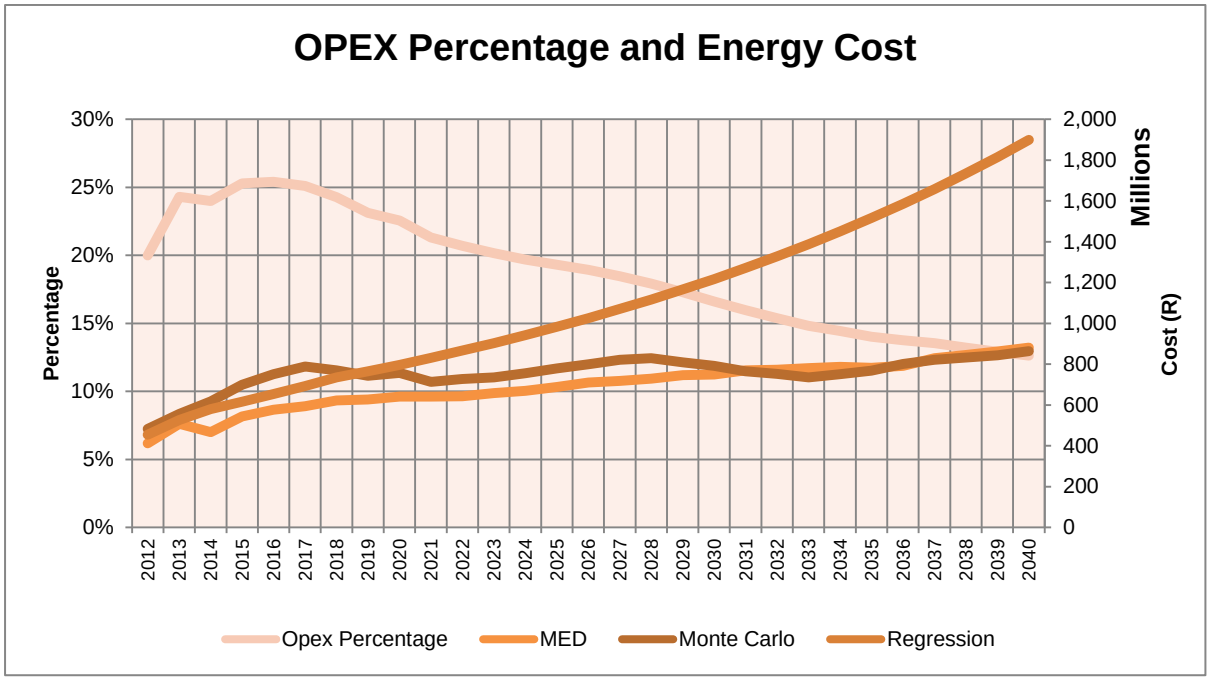

Figure 3.17: NPV calculations of the energy models

3.1.10 Summary

In chapter 3 it was shown that deep level mining consists of several utility processes that contribute towards the total energy consumption profile of the mine. Environmental condition accounts for approximately 83% of this energy requirement as mining regulations call for specific working conditions underground. This also contributed towards most of the variables that were identified that could affect the energy requirement of a mine and their use in predicting energy profiles.

A statistical process of elimination on collinearity tests showed that the best variables for predicting mine energy are tonnes and years. Due to the fact that tonnes was the input variable for the Monte Carlo analysis as done by Deloittes it was decided to use years in a regression model for comparison. The mine energy department also uses a model for prediction and these were compared from 2012 to 2040 on their energy requirements from the different input variables. Surprisingly enough it was shown that when comparing the first 2 years of the 22 year prediction model with actuals provided by the deep level mine that neither the Monte Carlo or regression model were within 13% of the actuals. Only the mine energy model was somewhat aligned with a 6% error on the data provided. The variance in total energy between the energy models based on the consumption was calculated to 52% in table 3.4.

A brief look at the financial history of AngloGold Ashanti over the past decade provided the discount rate to be utilized in the Net Present Value calculation of the energy models. The work done by the mining group in collaboration with the Energy Intensive User Group energy price path was then used to calculate the energy cost associated with the model predictions and their effect on the Net Present Value and OPEX contribution. Table 3.6 showed that for the period 2012 to 2040 there is a variance of 103% on the energy price outlook.

Within all the variation between energy units and energy unit prices it was calculated that the average reduction towards FCF from the models was R 5.545 billion. This could however be manipulated depending on the period when the cash flow from the model was incurred. Also a finding was made that there is an exponential outlook on the CPI index for the country going forward and except for the regression model a linear outlook towards energy costs. This assists with the reduction to OPEX that energy contributes for the outlook provided but considering the error percentages on units and cost is statistically irrelevant.

Final work required at this point is an investigation as to the difference in the mine energy model as it proved to be the most accurate for prediction purposes and then the conclusion for the application of statistical models for deep mine energy forecasting.