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The effect of the “Bull Whip “on Anglo American Platinum Limited (South Africa)

Tariq Suleman Aboobaker

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Business Administration

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ABSTRACT

The purpose of this research report was to quantify if the bullwhip effect (BW) exists in the platinum industry by focusing on the highest cost line item in their books excluding labour, and what the impact of the BW has on its cost structure of the organisation.

The mining industry is encountering two major problems: (1) Escalating labour cost due to the unprotected strikes giving rise to high operating costs, and (2) low demand for platinum. They believe by reducing jobs they will improve their financial status.

Based on the literature review, the autoregressive second order approach was used to quantify the bullwhip effect and the financial implication related to the BW was also calculated. This model summarised the literature on quantifying the bullwhip effect for successful management of supply chains and directly contributing to the company's financials.

Anglo American Platinum was selected as the company to conduct this study on. A quantitative, longitudinal method was employed. The highest cost item (excluding labour) was selected to determine the BW.

The main findings supported the theoretical BW and financial implication operating with the BW. Their supply chain has an excellent service level agreement in place but operating with a BW, this amplifies the net stock amplification variance, thus increasing inventory costs. By halving their lead time, it has reduced the BW by 12.6 percent units. Their total inventory cost associated with the BW is R 4.0 M. It has been concluded that this model could help bring about a successful reduction in the bullwhip effect and even eliminate it completely by aligning their supply chain to their organisation's key indicators. In turn this would require a strategic alignment between supply chain and the key stakeholders.

The model did reflect as relevant as the real business world. It could therefore be used to direct further research in this field.

DECLARATION

I, Tariq Suleman Aboobaker, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Business Administration in the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Tariq Suleman Aboobaker

Signed at ……

On the 27th day of May 2015

DEDICATION

This is dedicated to my late grandfather, Mr Abubaker Ahmed Versia, my wife; Mrs Shakira Aboobaker, my Uncle, Dr. Kassim Albasry, my Aunt, Dr. Yasmin Aboobaker, my two Siblings, Mrs Shaheen Aboobaker, Miss Hebah Aboobaker, last but not least my parents, Mr Farouk Aboobaker and Mrs Mumtaz Aboobaker, without whose love, support and encouragement, this degree would have remained a dream in my mind.

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CHAPTER 1. INTRODUCTION

1.1 Purpose of the study

The purpose of this research is to analyse the inbound supply chain within Anglo American Platinum plc for a simple two stage supply chain that includes one retailer (the plant) and one supplier (the store warehouse) using secondary data, and evaluate the impact of the bullwhip effect (herein after referred as BW), which is also known as “Forrester Effect”, in the platinum industry by using a quantitative approach. The research not only aims to determine if the “BW” (Forrester, 1961) exist in the platinum industry, but also to quantify the effect using an analytical procedure proposed by Luong et al. (2007b), and Disney et al. (2003,2004) i.e., to quantify the increase in variability in the inbound supply chain and finally, examine if this impact can be managed effectively.

1.2 Context of the study

The world’s largest platinum producer, a unit of Anglo American Platinum, and a three tier supplier to the automotive industry, has reported an operating loss of more than ZAR 6 Billion for financial year 2012. It operates in the bushveld complex with more than 10 mining shafts and 15 concentrator’s plants majority of them in Rustenburg.

They mine the ore from the plat, merensky and UG2 reef, approximately 700 metric meters underground. They have only one open cast mine and the remainder of their mines are underground which requires man power and advanced technology to ensure they keep to their promise made to their stakeholders of no harm to their employees and to the environment.

The mined ore from underground is transferred by either conveyer belt or trucks to the nearest concentrator where it is made beneficial. Here the waste is removed by flotation techniques and the platinum group metals (PGM’S) are concentrated. The rich PGM’S are floated, dried and smelted to be concentrated further.

The entrained gange is removed from the dried concentrated ore in the smelting plant using advance smelting techniques and the higher grade matte which consist of high PGM's is transported to the convertor plant. This plant's function is to further remove any entrained impurities by putting it into an oxidized environment. The sulphur dioxide gas which is one of the wastes is treated in the acid plant to produce a 98 percent units (by weight) sulphuric acid.

The high rich matte from the convertor plant is cooled down to effectively form two layers, one the PGM'S and the other an alloy layer. This is rich in base metals which form the magnetic part of the alloy, and the non-magnetic is refined in the precious metal plant to form a final platinum group products.

The sulphur in the rich matte enters the base metal plant and has to be bled out to prevent any build up in their circuit which would cause detrimental impacts downstream, more especially on the plating capacity. The sulphur is bled out with a reagent that forms a sulphur precipitant and leaves the circuit in a solid form. For the purpose of this research and to keep the confidentiality clause intact, the reagent referred to above will hereafter be referred to as the "reagent". This reagent accounts for more than 22 percent units of the total business units cost and is the second highest cost line item for AAPLC one after labour cost.

In recent years there have been numerous strikes and this has put enormous pressure on the mining plant to keep up to the promised figure reported by the company. This meant the plant always has to be ready for days like these and plan forecasting in order to keep to their targets.

If there is a process imbalance or bottleneck in the upstream Anglo process, the downstream will not be able to mitigate it. The downstream internal process will work to the initial plan, by ordering reagent which is controlled by management. The downstream operation uses the SAP system which utilises a base stock policy which will indicate normal levels of reagent and thus no purchase orders will be created. In this case, the upset in the upstream process will cause the

downstream to cut back on reagent consumed; this in turn will offset the supplier's planning.

The impact will be the greatest at the supplier's side of the supply chain as he will have to keep the normal stock level which was forecasted by the customer in his warehouse, and this will come at a price.

Once the upstream operation gets back on its feet, their process equipment will be operating above its design parameters; this will surface down to the down streams operation. Their material requirement planning system (MRP) will place a purchase order automatically generated by a SAP system, which is linked to their supplier's database.

The supplier will readjust his stock levels to accommodate the customer. Due to this the management supply controller will increase his stock levels to ensure he does not run out of orders and if the supplier has a lead time, he will take this into consideration when forecasting his stock level. Once the level is increased, the supplier will see the drastic increase in stock levels this will force him to increase his forecasted number. Once things get back to normal, the impact will be greatest felt at the supplier side rather than the customers side as he will stock more than what he needs. This effect is termed the bull whip effect (herein after referred to as BW).

This has prompted the company to draft a huge cost cutting plan in order to keep their heads above water without triggering conflicts between governments and impatient unions (Mohlahlana, 2013; Reuters, 2013 a).

Contrary to that, it has created anti rivalry amongst unions such as the National Mineworkers union (NUM), and the Association of Mine Workers and Construction Union (AMCU) (Reuters, 2013 b).

The companies cost cutting initial plan was to reduce South African mining jobs by 14 000, which equated to a total reduction of output by 400 000 ounces of platinum. They have amended their cost structure plan in order to minimise the impact on the job market by keeping one of their four marginal shafts in the

Rustenburg section open, which in turn lead to the revised job cut being reduced to 6000.

The impact on the platinum output to the market is a reduction of 250 000 ounces which will be followed by 100 000 ounces over the medium term (Reuters, 2013 a).

The knowledge that 6000 employees stand to lose their jobs has angered a lot of the permanent employees, one employee, Simon Hlongwane, belonging to AMCU, has questioned the company: “Where will this 6000 people go in our economy?” He even threatened the company that they will strike: “We as AMCU will stand ready to fight against the job cuts” (Reuters, 2013 a).

Anglo believes that by reducing the platinum global production and realigning its cost structure, they will be able to influence the platinum price by decreasing supply to the market. The assumption is that the demand remains constant (Reuters, 2013 a). In business there exists a phenomenon of demand variability increasing as one moves up a supply chain which is referred to as the bullwhip effect (BW) (Lee et al., 1997a, b). This in effect means, a slight change in demand ripples both the forward and reverse of the supply chain in a form of magnified oscillations upstream, resembling the “lash of a whip”. Since the supply chain does not match the demand patterns, this result in an accumulation of inventory build-up or relative starvation at the various levels in the supply chain (Lee et al., 1997b).

The question to be asked is whether this problem could have been prevented if they had a better understanding of one of the major causes of inventory variances which has existed for decades, the BW also known as “Forrester effect” and if this understanding has led them to the adoption of appropriate supply chain strategies. Other variables other than the “BW” that influences the reported numbers are the impact that platinum recyclers have and the impact of stockholding at the various levels in the supply chain.

Most of the previous research on the BW has concentrated on signifying its presence, identifying its potential causes and providing techniques for reducing its impact. Particularly, Lee at el. (1997a, b) who established five main causes

of the BW: use of demand forecasting, supply shortages, lead times (rationing and shortage gaming), batch ordering and price variations.

First Proctor and Gamble (Lee et al., 1997 a), followed by HP, IBM and Motorola and many more companies have all experienced this effect. All of these companies operate in a very tightly controlled supply chain environment.

The analysis of the supply chain for the platinum mines is somewhat interesting and it is not the typical “tightly controlled industrial manufacturing environment”.

The platinum miners inbound supply chain structure is as follows:

1. The supplier brings goods to the store ware house, where it is captured on a computation system known as SAP by the stores capturer.
2. The customer to the stores is the production, engineering and laboratory department.
3. The customer places an order on the SAP system and the amount is charged to the end user via the SAP system.
4. Then, the good are despatched at the despatching bay.

The core business for AAPLC is to mine, process and market platinum group metals.

In 2012, 64.7 percent units of the platinum went to the industrial sector which includes the auto catalyst sector, while platinum recyclers supply recovered platinum to the refiner who brings it back into the market. The total amount of platinum recycled was approximately 2 million ounces in 2011, while the total recycle grew by 8.3 percent units from 2005 to 2011. This huge contribution is price sensitive and can change the price of platinum by moving the supply and demand curve (Anglo American Platinum Ltd., 2013 a, pp. 27).

The platinum mining sector, represented by the five largest local primary producers: Anglo American Platinum, Impala, Lonmin, Northam Platinum, and Aquarius are under huge pressure to reduce their operation costs in order to be sustainable, safe and profitable. As reported over the media, there are two problems they are encountering: (1) Escalating labour cost (which resulted in

unprotected strikes) giving rise to high operating costs, and (2) low demand for platinum. These companies have increased their platinum inventories, resulting in a low capital return on their assets and equity and thus a negative investor.

To increase investor confidence, a decision was made by Anglo to close down the marginal shafts and draft a restructuring plan to bring them on positive terms, which would mean a substantial amount of jobs cuts. According to Chris Griffith (CEO for Anglo American Platinum), the bad performance of the mining was due to labour unrest, inflation, difficult economic times and lower metal price. However, this might not be the full truth (Anglo American Platinum Ltd., 2013 b).

The dominant user of platinum being the automotive industry and their demand for new cars has dropped, which meant approximately 2 Million ounces of platinum taken out from the global market in year 2010/2011, which equates to approximately two (2) percent units drop in global demand. Anglo supplies approximately 70 percent units of the world's platinum, which equates to fewer than two (2) percent units reductions for the organisation (Anglo American Platinum Ltd., 2013 a, pp. 24).

In some markets the dealer inventory has risen from 40-55 days to approximately 80-85 days. This clearly shows that there is a decline in global growth and pipe line is getting larger, but not to the extent the platinum miners were anticipating.

These above mentioned facts do not correspond with Anglo's plan of cutting production by almost one-ninth or 250 000 ounces in 2013 (Reuters, 2013 a). The new production target is in the range of 2.2 to 2.3 million ounces; the question to be asked is, is the cut being perceived in a negative way? And the answer is yes, as the share price has dropped by 21 percent units in the past year (Anglo American Platinum Ltd., 2013 b, c).

The difference between the industrial and automotive numbers and the platinum production planning is due to the BW. This must be properly managed or else in the long term they will have the same fate as Proctor and Gambler, HP, etc.

Previous research has led to a number of suggested ways of reducing the impact of the BW. For example, one of the most common approaches is the centralisation of demand information, this entails providing each level of the supply chain with adequate information on customer demand.

The platinum industry needs to investigate how to align their supply chain strategy and the company strategy, so to develop a sustainable, stable and profitable industry. Current results indicate an unstable sector and this will require a change. This change can be managed by the platinum industry, or else the change will be imposed by an external force.

1.3 Problem statement

1.3.1 *Main problem*

Analyse and evaluate the impact of the BW in the platinum industry by focusing on the single biggest cost line item in Anglo's book. The study aims to determine if the "BW" (Forrester, 1961) exists in the platinum industry and also to quantify this effect—that is, to find out whether there is an increase in variability at each stage of the supply chain. Finally, examine if this impact can be managed effectively. From this main question the following sub- questions were developed.

1.3.2 *Sub-problems*

1.3.2.1 Sub – Problem One:

Does the bullwhip effect exist in the platinum industry?

1.3.3.2 Sub – Problem Two:

What impact does it have on the platinum industry (Anglo American Platinum)?

1.3.3.3 Sub – Problem Three:

What tools are out there to reduce the bullwhip effect and can it be practically applied in the platinum industry (Anglo American Platinum)?

1.4 Significance of the study

South African companies, for a number of years have viewed supply chain management as a logistic function with no relationship to the organisational functions (Grobbelaar, 1996). Globalisation and competitiveness has changed this view. This has created an awareness of the advantages of strategic partnerships, and most imperatively, information sharing by integrating supply chain management (Grobbelaar, 1996).

Most research on the "BW" focuses on the entire supply chain, at different levels within the supply chain; initially from tier supplier to tier customer. This research will be limited to the focus company's inbound supply chain (between the store warehouse and the plant) with respect to the platinum mining point of view. Therefore, it is both significant and valuable to expose some flaws during the investigation and to introduce new thinking about how to align the latter half of the supply chain so this can create sustainable shareholder value, resulting in a strategic alignment model of the supply chain management.

This piece of information will provide guidance to the "struggling platinum industry" and it can aid them to better understand the following:

- Their entire supply chain;
- How supply chain integration can assist them to enhance their strategy for the future by enhancing their information sharing (LaLonde, 1998, pp. 8);
- How enhancing their strategy will improve their production forecast, production planning capacity, control inventory and schedule production in real time;
- How to manage the BW; and
- Eventually how to reduce costs without having jobs cut.

1.5 Delimitations of the study

This research will be limited to the largest South African and global platinum producer, Anglo American Platinum (AAPLC) because the information is readily available while the other South African producers will be a challenge to gather data.

Secondly, supply chain management is a combination of the key business processes from customer through to original suppliers but this research focuses only on a simple two stage supply chain that includes one retailer and one supplier, i.e. between the plant and the warehouse (stores). The remaining tier suppliers will be a challenge to gather information from when taking into consideration the time constraints.

Thirdly, the reagent in study accounts for more than 22 percent units of the total cost for one of Anglo's operation and it is the single biggest cost line item for the organisation after labour. This work will be limited to this reagent as it constitutes the largest portion of the organisations total cost, and it will be viable to reduce this number as the value add will be enormous for the group as a whole.

Fourth, this report does not compare the production planning or production performance in conjunction with reagent demand nor does it look at product quality.

Finally, due to limited work performed around quantifying the bullwhip effect using a secondary auto regressive model - AR(2) , estimation has to be made using the first order auto regressive model - AR(1) to calculate the monetary value at stake.

1.6 Definition of terms

These are some of the definitions used in this research:

Echelon: refers to one of a series of levels or grades in an organization or field of activity.

NUMXL: refers to Numerical Microsoft Excel software which is used to simulate the raw data.

Production adaptation cost: refer to cost attached to a company who develops new products by modifying or improving on the product innovations to others to make it more appealing to the target market (Education Portal, 2014).

Production planning: refer to planning of production tasks (utilisation) and availability of equipment (engineering function) to meet planned throughput.

Production performance: this refers to all the performance related to production and increasing throughput.

Product quality: this refers to the quality of product produced to meet the customer's specification.

Stores: it refers to the store warehouse where the entire inventory is received and despatched to the plant.

Utilisation: refers to the time the process was operated for a period with sufficient feed available to safely operate the process.

1.7 Assumptions

First assumption: The assumption made is that the source of information obtained from Enews Channel Africa (ENCA) website is reliable and accurate.

Second assumption: The sample collected represents the entire population.

Third, there is not enough work done on calculating the net stock amplification (NSAmp) variance for an AR(2) model but this study will assume that the NSAmp calculated for an AR(1) will be identical to the AR(2) model.

Fourth assumption: The assumption made is that the source of information obtained from InfoMine.com website is reliable and accurate. Furthermore, the average five (5) year nickel, copper and cobalt market price is a good reflection of the metal price that can be used to calculate the savings when reducing lead time.

Fifth assumption: The assumption made is that the source of information obtained from Stats SA website is reliable and accurate. Furthermore, the average five (5) year inflation rate is a good reflection of the Inflation rate for predicting the reagent price in the future.

Final assumption: The assumption made is that the average mass fraction split of the three metals constituting the total production (Nickel, Copper and Cobalt) over the period obtained from the plant data base is reliable and accurate. Furthermore, this value is a good reflection of the amount of metal produced for this period and this value does not affect the calculation of the basket price for this metal.

CHAPTER 2. LITERATURE REVIEW

2.1 Introduction

To construct the theoretical foundation for the present study, a number of literature streams were reviewed. These are in operation management (OM), supply chain management (SCM). A widespread review of the relevant OM and SCM literature focusing on studies that examined inventory shortage or build up and its impact on inventory performance was conducted.

The type of data used for this study is based on a longitudinal analysis and the level of aggregation at which the analysis is conducted is simplified to one retailer and one wholesaler.

Data sources include secondary data. Rather than a comprehensive list of existing literature, a summary of the most relevant literature and most important founders of this subject is presented.

The literature is broken down into four sections. The first section defines the BW and the following section looks at the existence of the BW within an organisation in order to be better equipped to minimise the impact when faced with one. The third section focuses on quantifying the impact of the BW effect in supply chain. The final section looks at how to prevent something like this from magnifying.

2.2 Definition of Bullwhip effect

A phenomenon exists in supply chain management termed the bullwhip, which transpires when the demand order variability in the supply chain is amplified as one move up in the supply chain from end user (which is your customers) to manufacturers. The basic phenomenon is not new and has been known to management scientists for some time.

Forrester (1961) originated the investigation of the demand variability amplification and concluded that it is a “consequence of industrial dynamics” or

time varying behaviours of industrial organisations. According to Forrester's effect, a 10 percent unit change in the rate of sale at the retail level can result in up to a 40 percent units change in demand for the manufacturer.

There are many examples in literature that illustrate the BW such as Hewlett - Packard, Proctor & Gamble (P&G), the Beer Game and many more, but this research will focus on Proctor & Gamble (P&G) and the Beer Game studies.

Proctor & Gamble (P&G) studied their order patterns for one of their record breaking products, Pampers. They noticed that their retail stores sales were fluctuating but their order variability was not excessive. However, a thorough investigation was conducted and their findings were surprising. When they looked at the orders of materials under a microscope to their suppliers, they were astonished that the swing was even greater. While the customer consumed diapers at a fixed rate, but the demand order variability in the supply chain was amplified as they moved up the supply chain. (Lee et al., 1997a)

John Sterman (1989) defined a classroom game known as the Beer Game where contestants simulate a supply chain. As the game proceeds, a small alteration in customer demand is turned into "wild swings" in both orders and inventory upstream. Sterman endorsed this amplified order variability to player's irrational behaviour or misconception\s about inventory and information that is needed. When participants where making their ordering decisions they completely ignored the pipeline inventory in the supply chain. They failed to take into consideration the time lags between placing and receiving orders, and as a result of that they ended up with making poor decisions.

Richard Metters (1997) conducted a comparative study to define the consequences of the detrimental effect of the amplified demand variability on profitability. Two separate experimental designs are considered:

By incorrectly updating demand and forward buying, seasonality can be prompted month by month on an annual basis.

Seasonality can also be prompted by ordering batching week by week on a monthly basis.

Profitability is studied under three conditions: high, moderate and no demand seasonality. It was found that by removing the BW it can increase product profitability between 10 to 30 percent units, and the “potential” profit increases from diminishing the monthly seasonal changes outweigh those that are related with weekly seasonality.

To determine seasonality, the winter’s exponentially smoothed trend seasonal model using statistical analysis system software (SASS) can be used but according to Luong (2007a) this might lead to a specification error and hence amplify the BW. The sample auto correlation frequency (ACF) is another method used to measure seasonality.

Numerical analysis for excel (NUMXL), Microsoft excel program was used to simulate the data. To detect seasonality, the ACF graph should have sudden peaks indicating seasonality.

Demand distortion results in excess inventory build-up, poor forecasting, excessive or even insufficient production plant capacity, and in accurate production planning across the entire supply chain (Lee et al., 1997b)

Lee et al. (1997a) have proposed four sources of the bull whip effect:

2.2.1 Demand forecast processing,

2.2.2 Ordering batching,

2.2.3 Rationing and shortage game; and

2.2.4 Price variations

In this paper; the focus is on the first two causes. This refers to the variance amplification generated by poor information on product demand. This is fully explained in the next section.

The remainder of sources of the BW will not be covered in this report. These sources are not present in AAPLC because they have processes in place to mitigate market exposure and thus reduce variability in pricing.

2.3 Key elements in establishing demand signal processing in the platinum industry

Does demand signal processing exist in the platinum industry?

2.3.1 *Demand forecast processing*

The purpose of this section is to clearly define the demand forecast processing and the contribution it has to the BW which is the core focus of this research.

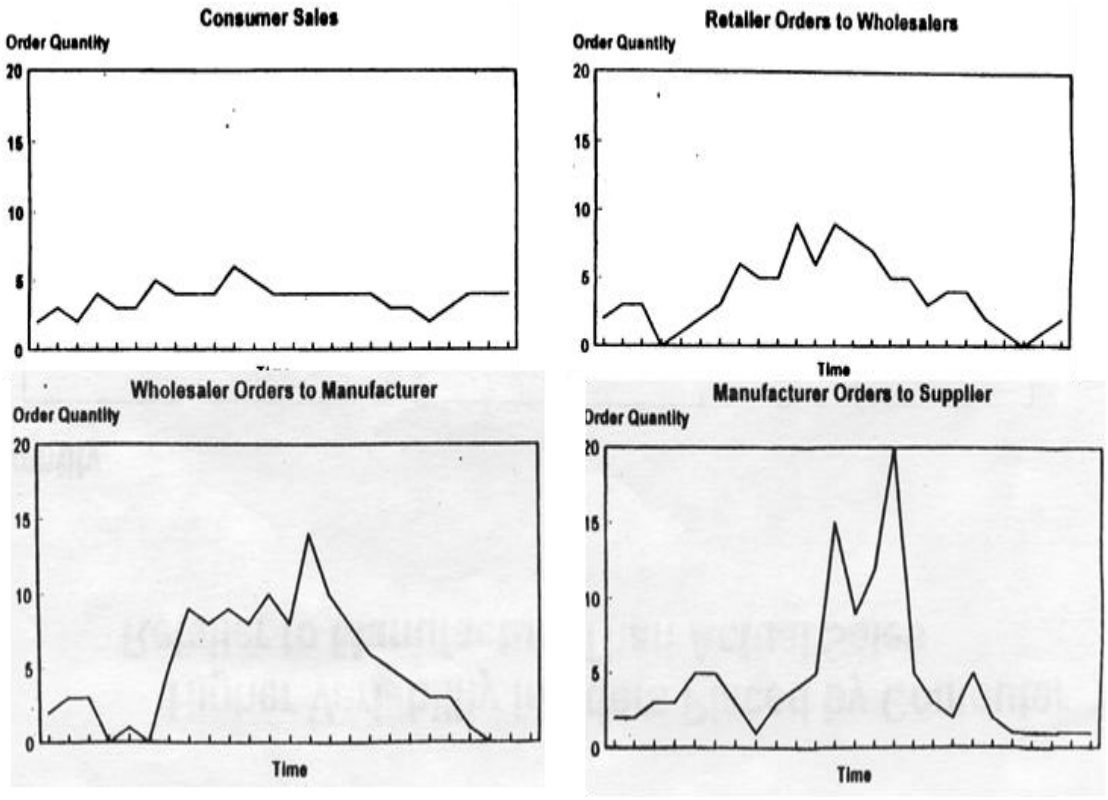
Almost every small to large manufacturing company does product and capacity planning, stock control and material management. Forecasting is often established as a historical figure from the company's customer buying behaviour. The outcomes of the beer game are as a result of many behavioural factors, such as the players' opinion and "mistrust".

An important factor contributing to this is each supply chain echelon estimates the demand based on his or her discretion. When a process plant places a reagent order, the store line manager processes that information as an indicator about future reagent demand. Centred on this indicator, the store manager realigns his demand forecast to accommodate the change and, in turn, the orders placed with the suppliers. Lee et al. (1997b) contend that demand forecast processing is a major contributor to the BW. Only forecast data to predict the final demand of reagent leads to distorted information.

A typical example, a manager who has to decide on the quantity required to be ordered to process his final products, uses a simple method to do demand forecasting, such as exponential smoothing. With this method, future demands are continuously updated as the new daily demand figure becomes available.

The order submitted to the supplier should indicate how much the reagent will be depleted by in order to meet the requirements for future demands and the safety stock. Future demands and safety stock are reconciled using the smoothing technique. With long lead times, there is weeks of safety stocks which result in fluctuations in the order quantities over time and can be greater than those in the demand data.

Figure one below clearly explains how the orders placed by the dealer (retailer) to the manufacturer have much greater variability than that of the consumer perceived needs. Primary reason being the amount of safety stocks that the manufacturer has to carry contribute to the BW.



Sourced: “The BW in supply chain” Lee, H, P. Padmanabhan and S. Wang (1997), Sloan Management Review

Figure 1: “The BW in different levels in the supply chain”

The other contributor that might exist is explained in brief in the next section.

2.3.2 *Order batching also known as Burbidge Effect (Burbidge JL, 1991)*

In supply chain, each manufacturing company place orders with suppliers using some enterprise resource planning system vendor inventory monitoring system, for example AAPLC uses SAP. The vendors add expanded functionality onto their product to make life easy for the supply chain manager. The plant consumes the product, inventory is depleted, but the store manager may not

immediately place an order with its suppliers. He usually waits to reach his minimal stock threshold level then he places an order which is termed batch ordering. There are two ways of batch ordering: Periodic and Push.

Instead of ordering frequently, supply chain managers may order weekly, biweekly, monthly or even per quarter. There are many common challengers with inventory systems based on order cycles. Most often the supplier cannot manage processing regular orders because of the manual administration required and the cost attached to it. Companies who utilise the MRP system, often runs monthly order with suppliers. A slow moving item like mining equipment, a company such as Anglo project division prefer to order on a periodic basis because the equipment has a long life span.

In push ordering, a firm experiences surges in demand of their product from the customer. The firm has orders “pushed” on them from customers periodically because salespeople are measured on a regular basis, sometime monthly, and quarterly or annually, which causes end-of-month, end-of-quarter or end-of year order surges. When companies face periodic ordering by its customers, it results in the BW. If all customers’ order cycles were evenly spread out, the BW would be minimal. For example, if Anglo’s target for platinum per month is 180 000 ounces, in order to achieve the target they will have to push their orders before the time. This periodic surge in demand results in the BW. As a result, the surge in demand is even more pronounced, and the variability from the BW is at its highest.

2.3.3 *Other issues that contribute to the Bullwhip effect*

There are other contributing factors to the BW, which the section below addresses and a brief description will be given. It is a continuation of the already mentioned factors and will emphasise the paradigm.

2.3.3.1 Excessive Inventory build - up

Product proliferation and shorter product cycles can result in demand uncertainty thereby causing excessive inventories (Crandall and Crandall,

2003). Demand planning still remains a challenge for most organisations. Time and again companies sift through their supply side opportunities and discount the demand factor (Gattorna, 1998). According to Gattorna, companies need to think beyond simple efficiency issues and focus more attention towards value creation opportunities. They need to articulate their value proposition to the customer and drive a comprehensive supply and demand chain strategy from that critical insight.

Another focus area is demand volatility. Volatility is frequently increased through an organisation's own policies and procedures and is one of the primary causes of misalignment between the supply chain and customers (Gattorna, 1998). Gattorna claims that customers simply respond to signals sent to them by suppliers. Organisations thus face the challenge of improving their demand management through reducing demand volatility.

There are tools which can aid management to reduce lead time and supply chain cost, tools such as Just in Time (JIT), Quick Response (QR), and Efficient Consumer Response (ECR), Work in Process (WIP), Finished goods (FGI). However, these assume volatility is present. In order to manage demand means smoothing it out by removing the volatility prior to process planning.

According to Lee et al. (1998) promotional discounts distort consumer buying behaviour thus generating high demand volatility. One remedy to the above problem is to introduce free delivery to customers which will shift their ordering pattern. The flip side of the coin, the longer the supply chain, from manufacturer to customer, the larger the distance between supplier and customer, the more staggered their ordering becomes. This result in demand volatility, which is a common flaw found in the system.

Contrary to this, shortening product life cycles pose a threat of variability in the supply chain occurring more often (Davis, 1993).

Moreover, effective supply chain management implies removing complexities out of the business operations (stock outs, obsolescence, labour costs, transportation costs and warehouse costs). Complexity relates to uncertainty (from the supplier's delivery performance, manufacturing process performance

measuring frequency of downtime, reliability of the process, customer demand), increased risk of stock out, increased reliance on accurate and timely information, increased reliance on effective production planning capability, reducing ability to provide accurate information to manufacturing. Increased customer lead times (hence reducing service levels), and increased risk of obsolescence (Davis, 1993)

2.3.3.2 Poor Forecasting

Manufacturers prefer to carry excess inventory to enable them to meet forecast demand because of long lead times (Davis, 1993). According to Crandall and Crandall they achieve this through forecasting methods. The flaw with this system is that some finished, good carrying inventories do not move and become excess or new products replace existing ones, making the latter out-dated.

Forecasting is a critical tool that is available for management (Simchi-Levi et al., 2003). Management also uses the forecast inventory model to decide whether or not to enter a particular market, or to launch a promotion. According to Simchi, there are three basic findings for forecasting, namely:

- Forecasting does not work.
- The longer the forecast period, the worse the forecast.
- Using cumulative forecasts are more accurate.

2.3.3.3. Graphical representation of the BW:

After determining seasonality in the data, a graphical representation of the BW can be visualised prior to conducting the AR model. Plotting the order quantity and demand process over a period of time, it can be seen if the order pattern follows the demand pattern.

If a pattern exists then the BW does not exist and vice versa.

Having covered the graphical part of the bullwhip, the next step is to understand the impact of the BW and be able to measure it. The next section will equip you with these tools.

2.4 Establishing if the bullwhip effect exist

Is there a sign of the bullwhip existing in the Platinum industry?

2.4.1 *Quantifying the Bullwhip Effect*

The previous section provided a detail theoretical background that would suggest that there might be a BW existing in your organisation if those trends are shown.

This section will go into detail quantifying the BW and the following section will equip the user with relevant tools to mitigate the bullwhip.

2.4.2 *Measuring the Bullwhip Effect*

Simple mathematical models are developed by Lee et al. (1997) to prove that the amplified order variability is a result of the rational and optimising behaviour of the supply chain members.

Strategies that can be applied to diminish the distortion are also discussed. Strategies such as “avoid multiple demand forecasts updates”, eradicate gaming in shortage conditions, break order batches and stabilise prices.

Chen et al. (2000) focused on defining the effect of demand forecasting on the BW and measuring the increase in variability at each stage of the supply chain.

The variance of the orders placed by the retailer relative to the variance of the demand faced by the retailer is determined. The first order auto regressive model can be used to quantify these phenomena and highlighted below.

$$\frac{\mathrm{Var}(q^k)}{\mathrm{Var}(D)} \geqslant \prod_{i=1}^{k}\left(1+\frac{2L_i}{p}+\frac{2L_i^2}{p^2}\right). \qquad \textbf{(1)}$$

Source: (adapted from Chen et al., 2000:46)

Where q is the quantity ordered, demand denoted by D, K is the number of echelons composing the supply chain; L is the lead time and ρ is the auto correlation coefficient.

The smoother the demand forecasts the lesser the increases in variability. A longer lead time leads to a larger increase in variability. For **$\rho \geq 0$**: bigger the p value, lesser the increase in variability and vice versa

Chen et al. (2000) also analysed the effect of centralising customer demand information on the BW. He showed that centralising the demand information will definitely reduce the size of the BW, but it will not completely remove the increase in variability.

Dejonckheere et al. (2003) analysed the BW induced by forecasting algorithms in order up to the policies and proposed a new general replenishment rule that can decrease variance amplification significantly.

In order to update the policies the following has to be compared by means of: an exponential smoothing, moving averages and demand signal processing. In order up to the systems the BW is assured when forecasting is essential. It was found that the BW generated by moving average forecasting is much less than that generated by exponential forecasts and demand signal processing.

Regarding the demand process a variety of time-series demand models have appeared in the literature of inventory control and SCM. By far, the first order auto regressive process, AR(1), is the most commonly adopted demand model to study the BW (Lee et al. (1997a,b); Chen et al. (2000 a,b)).

Recent work uses more realistic demand models such as the regressive models: the second order auto regressive model – AR (2) developed by Luong et al. (2007b) and a general AR (p) models; Duc et al. (2008) use an ARMA (p, q) model. In all these models an analytical derivation of the BW measure is presented.

AR (2) case:

The stationary AR (2) demands process satisfies:

$D_t = \delta + \phi_1 D_{t-1} + \phi_2 D_{t-2} + \varepsilon_t$ **(2)**

Where D_t is the customer demand of period t, D_{t-1} is the customer demand for period t-1, D_{t-2} is the customer demand for period t-2, δ is the constant of autoregressive model; ϕ_1 is the first-order auto correlation coefficient; ϕ_2 is the second-order auto correlation coefficient, and ε_t is the forecast error for period t

In the AR (2) case, stationarity implies that the roots of ϕ (z) =0 lie outside the unit circle or equivalently, the parameters ϕ_1 and ϕ_2 must exist in the triangular region bounded by $\phi_1 + \phi_2 < 1$, $\phi_2 - \phi_1 < 1$, $\phi_1^2 + \phi_2^2 < 1$, and $|\phi_2| < 1$.

It can be shown that for a stationary AR (2) demand process the mean (μ) and variance of the demand (σ_d) are

$$\frac{\delta}{1-\phi 1-\phi 2} \quad \textbf{(3),}$$

and $$\frac{\sigma^2}{[1-\phi_1^2-\phi_2^2]} \quad \textbf{(4),}$$ respectively.

If $\check{D}_t$ is the forecast value of D_t with minimum expected mean squares of error, then the minimum expected mean squares of error forecast of lead–time demand can be determined as

$$\check{D}_t^L = \check{D}_t + \check{D}_{t+1} + \ldots + \check{D}_{t+L-1} = \sum_{i=0}^{L-1} \check{D}_{t+i} \quad \textbf{(5)}$$

It is noted that, for the AR (2) process, D_{t-l} can be determined using the following equation:

$$\check{D}_{t+l} = E[D_{t-i}/D_{t-1}, D_{t-2\ldots}] \quad \textbf{(6)}$$

In order to determine $\check{D}_t^L$ in the relationship between D_{t+1} (i = 0, 1, 2…) and D_{t-1}, D_{t-2} will first be investigated.

Lead time demand forecast and standard deviation of lead time demand forecast error can be determined as follows:

$\check{D}_t^L = \delta \sum_{i=0}^{L-1} A_0^{(i)} + D_{t-1} \sum_{i=0}^{L-1} A_1^{(i)} + D_{t-2} \sum_{i=0}^{L-1} A_2^{(i)}$ **(7)**

Where $A_1^{(0)} = \phi_1$, $A_1^{(k)} = \phi_1 A_1^{(k-1)} + A_2^{(k-1)}$; $A_2^{(0)} = \phi_2$, $A_2^{(k)} = \phi_2 A_1^{(k-1)}$; $A_0^{(0)} = 1$, $A_0^{(k)} = A_0^{(k-1)} + A_1^{(k-1)}$ (k = 1,2,….,i) **(8)**

$(\sigma_t^L)^2 = VAR\,(D_t^L - \check{D}_t^L)$

$= VAR\,(D)\,(1-(\phi_1^2+\phi_2^2))\,[1+\sum_{i=0}^{L-2}(1+\sum_{i=0}^{L-i-2} A_1^{(j)})^2]$ **(9)**

Where VAR (D) is the variance of demand

Variance of order quantity:

$$\mathbf{VAR}(q_t) = \mathbf{VAR}(D) * \left[2\left(\frac{1-\phi 1-\phi 2}{1-\phi 2}\right)\{(\sum_{i=0}^{L-1} A_1^{(i)})(\sum_{i=0}^{L-1} A_1^{(i)} + 1) + (\sum_{i=0}^{L-1} A_2^{(i)})^2\} + 2(\phi_1 - \phi_2)\left(\frac{1-\phi 1-\phi 2}{1-\phi 2}\right)(\sum_{i=0}^{L-1} A_2^{(i)}) - 2\left(\frac{1-2\phi 1+\phi_1^2-\phi_2^2}{1-\phi 2}\right)(\sum_{i=0}^{L-1} A_1^{i})(\sum_{i=0}^{L-1} A_2^{i}) + 1\right]$$ **(10)**

Where $\mathrm{VAR}(q_t)$ is the variance of order quantity.

From equation 10, a measure of BW, which is defined as the ratio between variance of order quantity and variance of demand can be developed as follows:

$$BW\,(L, \phi_1, \phi_2) = \frac{VAR\,(q_t)}{VAR\,(D)}$$

$$= \left[2\left(\frac{1-\phi 1-\phi 2}{1-\phi 2}\right)\{(\sum_{i=0}^{L-1} A_1^{(i)})(\sum_{i=0}^{L-1} A_1^{(i)} + 1) + (\sum_{i=0}^{L-1} A_2^{(i)})^2\} + 2(\phi_1 - \phi_2)\left(\frac{1-\phi 1-\phi 2}{1-\phi 2}\right)\right.$$

$$\left.(\sum_{i=0}^{L-1} A_2^{(i)}) - 2\left(\frac{1-2\phi 1+\phi_1^2-\phi_2^2}{1-\phi 2}\right)(\sum_{i=0}^{L-1} A_1^{(i)})(\sum_{i=0}^{L-1} A_2^{(i)}) + 1\right]$$ **(11)**

These equations will be used to show in section 4.2.1.3 that the BW does exist in the platinum industry.

2.5 Financial implication operating with the bullwhip effect

What financial implication does the Bullwhip have on the platinum industry (Anglo American Platinum)?

2.5.1 *Determining the cost implication operating with a BW*

The economic impact operating at either inventory deficit (stock-out) and/ or inventory surplus can be detrimental on the company. Moreover, if that reagent is in deficit which can close either the production pipe line for hours or even days if it has a long lead time. A financial cost implication can also exist which can operate in the boundaries of the BW which is termed switching cost.

If this reagent is only manufactured by one company then the switching cost can soar, in that case it is safer to overstock than under stock which could be the company's strategy, which is the case in Anglo. Companies like those are world class leaders in planning and ensuring they are beating the market and its competitors.

Finally, the cost per period is incurred and some of it was covered above. The inventory costs (C_t^{INV}) shown in equation 12 below, consist of a holding cost per unit (C_h) in inventory (that is when net stock is positive: $NS_t>0$).

$$C_t^{INV} = C_h . NS_t \qquad \text{if } NS_t > 0 \qquad \textbf{(12)}$$

The shortage cost per unit backlogged which is represented in equation 13 below denoted by C_s (that is when net stock is negative).

$$C_s . (- NS_t) \qquad \text{if } NS_t < 0 \qquad \textbf{(13)}$$

The production switching costs shown in equation 14 below denoted by C_t^{SW} are incurred for changing the level of production in a period. Assuming the production level is equal to the quantity ordered denoted by q, the change in production is given by the difference in quantity ordered (denoted by q_t) versus the previous period (denoted by q_{t-1}) (Boute, 2007).

$$C_t^{SW} = C_{SW} . | \; q_t - q_{t-1} | \qquad \textbf{(14)}$$

The focus is not only to measure the BW, but also to quantify the variance of the net stock. Furthermore, this variance has a significance impact on customer

service. This simply means that the higher the variance of net stock, the more safety stock required. Therefore attention needs to be given to measure the amplification of the inventory variance, NSAmp, as:

$$\text{NSAmp} = \frac{\textbf{Variance of net stock}}{\textbf{Variance of demand}} \quad \textbf{(15)}$$

The simulated results of net stock amplification will be compared with the literature.

The thing to note is there is not much information available for an AR (2) model to calculate NSAmp because it gets complicated when you go to a higher order auto regression. However, the only information available in literature on AR is for the first order. To keep it simple and for illustrative purposes, the AR (1) BW effect measures will be used to calculate the NSAmp.

The NSAmp is calculated using Disney et al. (2003) proposed theory, in which the order rate variance amplification ratio is equal to sum of the lead time and the product of square of feedback gain and BW measure which is shown in equation (16).

$$\text{NSAmp} = L + (T_i^2 * BW) \quad \textbf{(16)}$$

Where L is the lead time demand process and Ti is the feedback gain.

Introducing a proportional controller β for the inventory deficit, the β value equals to the following equation:

$$\boldsymbol{\beta = \frac{1}{(2Ti - 1)}} \quad \textbf{(17)}$$

With β is less than and greater than zero units. Forrester (1961) refers to 1/ β as the “adjustment time”. When β is less than one unit (β <1), the inventory shortfall is partially recovered during the next ordering period and the shortfall recovery should be spread out over time. Whereas β is greater than one unit (β >1) infers an overshooting to the inventory shortfall. This adjustment is second order to control engineer. For this reason, the decision rule was generated.

The switching and inventory costs are associated to these variance amplification measures. A high BW measure infers a wide range of order pattern, denoting that the manufacturing level has to alter regularly, consequential in a higher average manufacturing switching cost per period. An increased inventory variance implies a higher holding, backlog costs and thus inflating the average inventory cost per period.

Finally, the customer service level and fill rate can be calculated using Microsoft Excel program. The customer service level signifies the likelihood that customer demand is met from stock, while the fill rate measures the fraction of demand that is immediately fulfilled from the inventory on hand.

For an end user to understand the complete picture, it is important that the BW measures along with the inventory variance amplification are compared to its safety stock. The safety stock is a measure which will explain how much of excess stock the retailer had to carry to achieve the same service level.

The safety stock can be expressed in two measures:

$$SS = z\,\sigma_d\,\sqrt{L} \qquad \textbf{(18)}$$

and,

$$SSLT = z\,\sigma_t^L \qquad \textbf{(19)}$$

Where SS = safety stock, while SSLT stands for safety stock lead time and where z = safety factor, σ_d is the standard deviation for demand process, L– lead time and σ_t^L is the standard deviation of L periods forecast error. The former is a traditionally used in some operational research manuals and it is based on standard deviation on demand over L periods, while the latter is based on standard deviation of L periods forecast error.

The next is to determine the customer service level metric, which is known as the fill rate (Disney et al., 2003). The fill rate is a famous term used in the industry and it will be used to find the link between BW and inventory requirements in order to meet service level agreement.

The service level factor can be calculated using the per unit stock cost, the lead time and per unit carrying cost for the duration of the lead time or it can set by the department to position the company's service proposition or to minimise holding and backlog cost through economic stock out probability.

As proposed by Disney et al. (2003), the fill rate will be predefined with a value of 99.5%. The standard deviation of net stock (σ_{NS}) will be first calculated as follows:

$$\sigma_{NS} = \sigma_d * \sqrt[2]{1 + L + \frac{(Ti-1)^2}{2Ti-1}} \quad \textbf{(20)}$$

$$\text{Fill Rate} = 1 - \frac{expected\ volume\ of\ backorders}{expected\ demand} = 1 - \frac{\sigma_{NS} * E(z)}{\mu_d} \quad \textbf{(21)}$$

E (z) is the expected number of unit's backordered per period for a safety factor, z, of the standard normal distribution.

The time frame considered here is the lead-time. Hence, instead of considering the more typical annual carrying cost H_y, the conventional approach will be used. Where H equals to the product of lead time (denoted by d expressed in days), number of days in a year and H_y ($H = d * 365 * H_y$).

The stock-out cost includes a "minima" of the gross margin, i.e. immediate profit that would have been made if no stock-out had been encountered. However, the loss of gross margin is not the only cost: for example, client dissatisfaction and loss of customer loyalty should also be taken into consideration. As a rule of thumb, it has been observed that many food retailers consider M to be equal to 3 times the gross margin.

The optimal service level is given by Vermorel (2012):

$$P = \Phi \sqrt{2 \ln \frac{1}{\sqrt{2\pi}} \quad \frac{M}{H}} \quad \textbf{(22)}$$

Where Φ is the cumulative distribution function related to the normal distribution. This value can be calculated easily using MS Excel.

E (z) is calculated from (eq. 21). Once E (z) is calculated, z can be determined using the standard z distribution tables. This in turn can be used to calculate the total net stock (herein after referred to as TNS) using equation 23 below, in which making 'a' the subject of the formula, 'a' can be computed.

$$TNS = a*\mu = z*\sigma_{NS} \quad \textbf{(23)}$$

a - number of periods of inventory to meet Service level target of 99.5%

The "a" along with the BW and NSAmp can be compared to find a smooth spot where majority of the savings can be achieved.

An overall replenishment rule accomplished of smoothing ordering patterns even with more demand has to be forecasted is proposed.

The product stream generating the most and least revenue for any organisation needs to be known. This information is so vital for any company to ensure they align their business model to it. It can also use this information and together with the market needs to expand its operations to increase capacity and be able to operate at high throughputs. This tool can also be used to improve the company's image, attract more investor confidence and put them at a competitive edge.

For a company to know how much it generates per hour will require a clear understanding the amount of each product it generates in metric tons per hour. For this research the product it offers are the following: nickel, copper and cobalt.

Multiplying each metal throughput by its average market price and summing it up equates to a basket price for the combination of its metal where the equation is highlighted below.

The Basket price for the three metals can be calculated as follows:

Basket Price (ZAR/ton) = Mass of nickel produced * Market price of nickel + Mass of copper produced * Market price of copper + Mass of cobalt * Market price of cobalt **(24)**

Units for Mass of metal and Market price is metric tons/hour and ZAR/metric ton, respectively.

2.6 Practical solution to address bullwhip effect

What tools are out there to aid an organisation which is suffering from the bullwhip effect and can it be practically applied in the platinum industry (Anglo American Platinum)?

2.6.1 *Solutions to help ease the bullwhip effect*

Can Luong et al. (2007b), Disney et al. (2003) and Lee et al. proposed suggested remedial action be used to reduce the BW in AAP?

2.6.2 *Avoid multiple demand forecast updates:*

Planning and forecasting is part of every supply chain department and that is where the BW is created. When supply chain members process requests input from their immediate downstream member (herein after referred to as process plant) in producing their own forecasts and this data that is requested comes from each member requesting from the member below.

To avoid repetitive processing of consumption data in a supply chain, make demand data of a process plant available to the store warehouse. By implementing a system where raw data is available to both plant and store. This system will significantly offer more information to suppliers who will know what happens after they ship their products.

One way that supply chain partners can share information is they can use electronic data interchange (EDI) which has facilitated information sharing among chain members. This method has been proven useful, but it has its flaws

in that it can still lead to unnecessary fluctuations in the order data placed with the upstream site. Inventory systems can operate better when information from downstream sites is available upstream, and key to optimal inventory control.

Another approach is to try to get demand information about downstream sites by side stepping it. By side stepping the reseller and distribution channels, one can sell directly to the consumer.

Long resupply lead times can aggravate the BW; just in time (JIT), quick response (QR), efficient consumer response (ECR), work in process (WIP), finished goods (FGI) are some of the tools can be used to effectively alleviate the effect.

2.6.3 *Break Order Batches:*

The high cost of placing an order or replenishing stock is one reason why order batches are large and infrequent. By ordering smaller batches or by ordering more frequently is one strategy that companies could use to counteract the BW.

Many companies can reduce the cost by generating an order by using EDI and going paperless using computer assisted ordering (CAO).

Another reason for large order batches is the cost of transportation. The cost to transport goods are increasing and it just makes economic sense to order full truckloads to distributors. The challenge with the current situation is that distributors' orders are infrequent, so time is wasted due to truckload constraints. A suggestion to counter the restraint is to ask distributors to order an assortment of products of which discounts could be offered if ordered from the supplier instead of a full load of the same product.

Using outsourced logistics or third party logistics will also facilitate the process of replenishment of stock. By consolidating stock from different suppliers that are in the same area, suppliers can utilize full truckloads without batches coming from the same supplier.

2.7 Conclusion of Literature Review

The BW Effect is a known subject for many years but companies are getting smarter to strive to survive in this highly competitive market. There are many cases where companies were able to turn their inventory management strategy by focusing their attention on fostering good relationships with their suppliers and customers in the aim to share information

There are different forecasting techniques which use different models to calculate the BW, but the more reliable and accurate one is the one that calculates the forecast error and simulates the data using an auto regression model rather than assumes the error (Luong et al., 2007a).

The tools proposed by Lee et al. (1997a), Disney et al. (2003) and Luong et al. (2007) can be practically applied or even tailor made to suit your business need.

The following are a summary of the research questions:

2.7.1 Is there a sign of the Bullwhip existing in the platinum industry?

2.7.2 What financial implication does the bull whip have on the platinum industry (Anglo American Platinum)?

2.7.3 What tools are out there to aid an organisation which is suffering from the BW and can it be practically applied in the platinum industry (Anglo American Platinum)?

2.8 Regression model philosophy

A simplified schematic representation for the structure of hierarchical regression analyses is illustrated in figure 2 and figure 3, below.

The difference between the AR(1) and AR(2) model is that the former uses one lag while the latter uses two lag terms for demand. They are included in the regression model with a 1 year lag represented by inventory performance (t-1) for the AR(1), 1 and 2 years lags represented by Inventory performance (t-1), and (t-2), for a AR(2). Co current effect (casual links of interest); lagged effect.

Regression model Steps:

AR (1) Model:

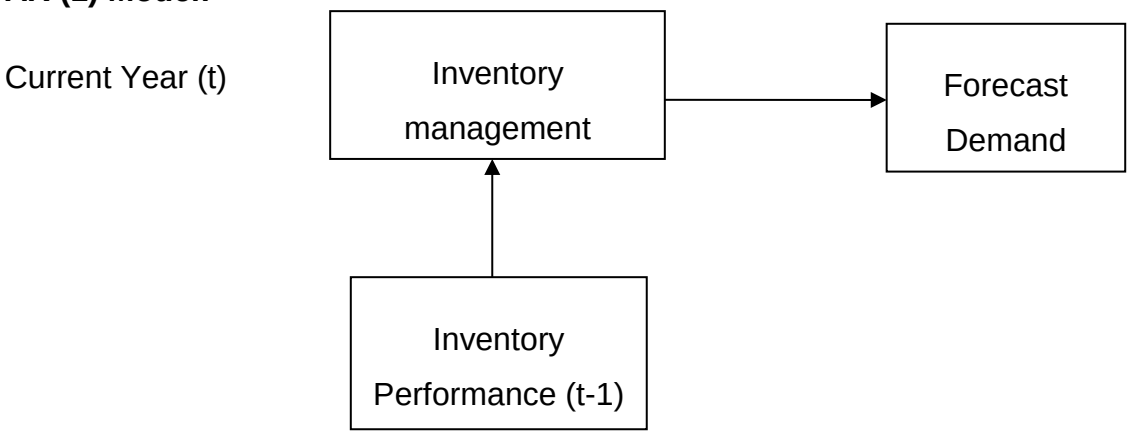


Figure 2: AR (1) model structure

AR (2) Model:

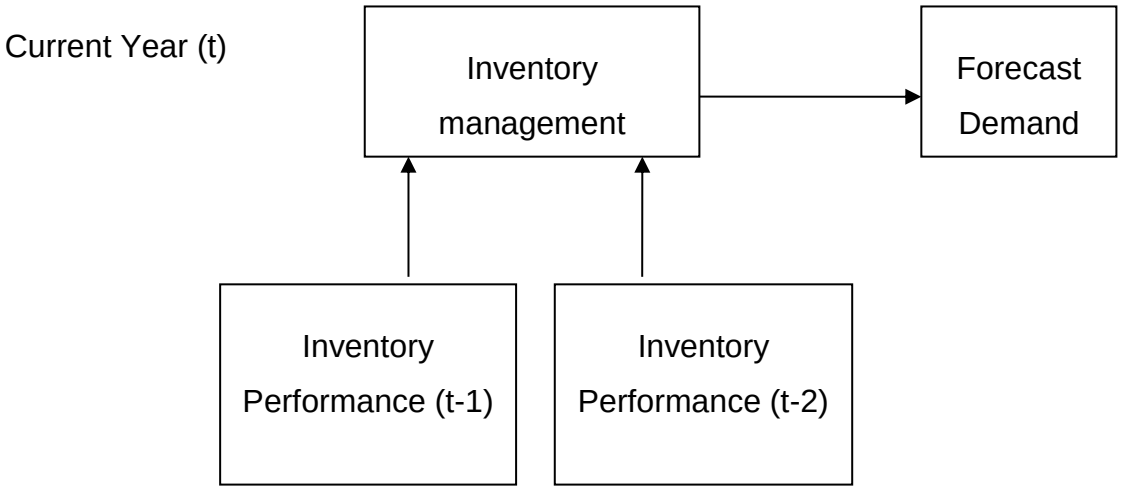


Figure 3: AR (2) Model structure

In order to better estimate the demand value with little error as possible, forecasting technique was used to minimise the expected mean-square forecast error which was considered for the purpose of this research. By using this method instead of a moving average, this will eliminate the specification error which was highlighted in Luong et al. study (2007a).

CHAPTER 3. RESEARCH METHODOLOGY

This chapter starts with a discussion on the research methodology / paradigm that was used in the study. It goes on to explain the research design and its strengths and weaknesses. This is followed by an overview of the criteria that was used to sample, the method of selection and a definition of the population.

A description of the procedure used for gathering data, analysis and interpretation are supplied and the study's limitation is discussed briefly. The chapter is concluded with a brief discussion on validity and reliability

This section describes the methodology that will be followed to address the research questions that are put forward as possible solutions to the sub-problems in the literature review section.

3.1 Research methodology /paradigm

For this research, a quantitative model was used to answer the research questions. For this purpose historical data was collected for a simple supply chain with one retailer and one supplier in which the retailer employs a base stock inventory policy. Various bodies of literature had been studied and analysed in order to identify and present the BW on Anglo Platinum's inbound supply chain model. According to Creswell (2009), the best approach to testing a theory is to use a quantitative approach, and this research is testing the BW, therefore it is valid to use this approach.

The research focused on organisations that are known for their successful or efficient supply chain management systems. Research was also carried out in order to pin point the flaws of operating their supply chain in a distorted manner.

According to Bryman (2012), Quantitative study is a: "research strategy that emphasized quantification in the collection and analysis of data and that entails a deductive approach to the relationship between theory and research, in which the accent is placed on the testing of theories; has incorporated the practices

and norms of the natural scientific model and of positivism in particular; and embodies a view of social reality as an external, objective reality."

More examples showcasing the use of this approach includes Fiala (2005) who used a quantitative approach to address the BW in supply chain and similarly Bottani et al. (2010) who used the same approach when quantifying the impact on radio frequency identification (RFID) technology and electronic product code (EPC) network on the BW in the Italian FMCG supply chain.

3.2 Research Design

The interpretation longitudinal study method was used as a strategy of inquiry in this research. Historical trends for the last twenty one (21) months will be used on a day to day basis to determine if the BW exist in the inbound supply chain within the platinum industry from the production line (Anglo American Platinum) to the first tier supplier to the plant i.e. stores (Anglo inventory management department). The information is readily available and the lead time for this reagent is one day (24 hours).

The advantage of using the longitudinal approach rather than an experimental approach is that it will give a clear picture of the plant performance on a day to day basis; however for this study the internal and external factors such as product inefficiencies, operational performance, labour unrest, etc. are excluded. The experimental design cannot be used for the following reasons: (1) it requires a control group and there is no industry close to the platinum industry; (2) and there is not enough work done on the platinum industry because of the amount of unknowns in this industry; (3) there is nothing close to this industry that can be used as a control group in order to validate the results.

If the experimental approach was followed there will be little or no reliability in the results obtained because of the control group problem addressed above.

The cross sectional approach was not used because the maximum period this method can be used is two (2) years and this will not give the correct conclusion

as this requires more data points, thus reliability and accuracy would be questionable.

3.3 Population and sample

3.3.1 *Population*

Chatfield et al. (2004) has studied on the outcome of lead time, sharing of information and the quality of information on demand variance amplification in a multi-tier supply chain.

The actual instrument used for this study is an analytical model. The data will be collected for the last twenty one (21) months for the lead time, reagent consumption rate, quantity ordered by stores which will be simulated and then examine the effect of lead time, information sharing and the level of information quality on demand variance amplification, and inventory variance amplification. As a result of the simulations, a regression model for variance amplification will be derived from the inbound supply chain.

3.3.2 *Sample and sampling method*

The population for this study is the inbound supply chain of the platinum industry in South Africa. The single supplier will be the main stores situated geographically within the North West province (Rustenburg) on the plant. All attempts were made to contact the local manufacturer of interest to clarify questions that was in mind in order to complete this study.

The sample consisted of a single reagent daily consumption rate at one of Anglo's operations which contributes to approximately 22 percent units of the total cost and the single biggest cost line item after labour on their balance sheet.

One-on-one meetings were scheduled to gather the data required for this study. The data was analysed in line with the theoretical literature review.

3.4 The research instrument

The instrument that will be used for this research is a mathematical model. The mathematical model is made up of two components: 1.) an auto regressive first, and a second order model to simulate the data. Both methods are proposed by Luong et al. (2007a, b) to quantify the BW.

By measuring the BW, the results will be used to calculate the inventory variance amplification to determine the cost implication operating with the BW.

There is a lot of work done around the first order auto regression but majority of the work assumes the demand forecast error which can amplify the BW. Luong (2007a, b) has reduced that impact by measuring this variable.

Luong has found that the higher you go with an AR order the more he realised less focus is been put on the subject, where he measured numerically the second order auto regression. The advantage between the two orders is that, the second order has a second AR parameter which makes the relationship complex between the dependent and the variable which does not agree to certain value of the first order.

3.5 Procedure for data collection

The person responsible to supply AAPLC with their day to day reagent consumption figures from the date it was first captured to current was identified and approached via a telephonic conversation. She was informed about the reason for the research, the importance of her involvement and a meeting was held to answer any issues pertaining the information she is going to supply me. She was insured of confidentiality and that her view would be protected. This allowed her to be open and disclose her view in the interest of the company.

One-on-one interviews took place between her and me in order to clarify the method used to gather data. The data was captured on a MS Excel Document. Once it was collected, this data was compared to two instruments on the plant, one which measures level in the reagent storage tank and the other is the volumetric flow of reagent to the plant (plant consumption rate). This was done

to minimise any human and instrumentation error. This information was shared with her to highlight threads and ideas.

3.6 Data analysis and interpretation

The quantitative data was analysed using three covariates. (1) Time (t) is an index of current year consumption figure in the data set. Time is included to control for the time dependence in the dependent variables. (2) Lagged effects of demand forecast (D_{t-1}), and D_{t-2} are included to examine whether there is variability between quantity ordered and demand. (3) Past performance is an autoregressive term used to control auto correlation effects of the dependent variable that manifest a BW, a statically tool where a reagent stock levels at the beginning of each day for the last 21 months was gathered. This was plotted against each other and a regression and statistically analysis was done in order to quantify and validate the results.

Sampling error was eliminated by ensuring the data is random and since it is a quantitative analysis this ensures the data is a probability sampling. A method proposed by Luong (2007) was used to eliminate specification error.

For periods where the plant was on planned shutdown, the average consumption rate value was used in order to predict more effectively. The data will be quantified using the Luong (2007b) second order auto regressive approach. Once quantified, this was converted into a real monetary value using Disney et al. (2003, 2004) theory.

For consistency purposes, the value will be reported in metric tonnes.

3.7 Limitations of the study

The study focuses on the inbound supply chain within the AAPLC who uses the base stock policy. A special meeting was held between the stores controller and there were challenges at the start to gather data because the person in charge was continuously in meetings. To eliminate bias the same person collected the

data and liaises with the relevant stakeholders as this ensured that typing errors was minimised.

The literature review was performed as comprehensively as possible. There might be some authors and their point of view not discussed in the literature review. The impact of lack of information was minimised by selectively choosing what is important for this study and using the most recent literature and including the originator of the subject matter in question.

To keep this work confidential and minimise time wastage, only those in control of the information were contacted.

To have a good representation, sample size is important, it would be ideal to have data for the last 20 years in order to search for a relationship between the different supply chain tiers. Pre – 2012, all figures were manually recorded and were not backed up on their data base as they did not see the need for this, for this reason the only information that is available is from mid-2012 up to current, on a day to day basis.

This work will only calculate the safety stock for the current data set. The different scenarios with varying standard deviation of demand and lead time in order to determine the two different measures of safety stock will not be covered. This type of work will require more than the conventional Microsoft Excel to simulate the results. An advance computational program such as SCPerf function will implement this method effectively.

3.8 Validity and reliability

Validity can be defined as a “goodness of fit” between the specifics of the research, the validation, and the conclusions deduced from the researchers (Kalof et al., 2008). This study will use both the regression model statistics analysis and Luong et al. (2007b) results to verify the size and accuracy of the analytical model.

The specification error will be removed by using the auto regression model rather than a traditional moving average model (Luong, 2007a), while the

measurement error which includes the instrumentation and/or human error will be reduced by conducting a mass balance around the reagent storage tanks. This error can either inflate or deflate the actual demand forecast value, hence resulting in a size and accuracy problem.

The context issue was eliminated as the data was captured from one database/system and the consumption rate has no impact on whatever the economics condition the plant is operating at.

3.8.1 *External validity*

According to Kalof et al. (2008:157), external validity is “the ability to generalise from a study to larger population.” This means that the ability of the study’s sample to be representative to the larger population, and the results of this study to be relevant to the total population.

For the purpose of this study the population has been identified as the internal supplier chain (inbound) within Anglo.

3.8.2 *Internal validity*

According to Kalof et al., Internal validity refers to a study that draws appropriate conclusions from the data at hand. Furthermore, it is important to note that the correct tool is measured, and the result achieved is the one being measured.

In addition, the researcher should ensure the study measures what is depicted in the literature. On this note, the same procedure and methods proposed by Luong et al. (2007a, b) and Disney et al. (2003) will be used to arrive at the same results. The same person will be used to provide the data to increase validity for this study.

3.8.3 *Reliability*

Bell (2005: 117) defines reliability as “…the extent to which a test or procedure produces similar results under constant conditions on all occasions.” He is of

the opinion that research is considered to be reliable if similar findings are discovered time after time in repeated application of the research.

To ensure reliability exists during this study, all secondary data will be collected by the same person, thus to maintain a consistency in flow a common unit will be used which is metric tonnes. This consistency will thus increase the reliability of the research. Moreover, viewing past and current literature, it serves to confirm that the reliability is accomplished.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

The theory discussed earlier will be used to: validate the data for seasonality, use Luong et al. (2007a) proposed model of auto regression to quantify the BW; and measure the inventory cost associated with the BW.

There will be two scenarios unfolding, 1.) Taking the data as it is and performing a statistical analysis on it, 2.) The other when the planned shut values equal to the sample average. This is conducted to compare the two different cases and proceed to model and evaluate using the one that provides the best size and accuracy value.

4.2 Investigating the bullwhip effect in the platinum industry

4.2.1. Modelling of data

This part covers all the pre and post modelling work completed. The aim of this exercise was to perform final checks on the data before the model could be simulated. This was done in alignment with improving reliability, size of the mean variable, accuracy of the model and visualise if the BW exist. This section is broken into four parts:

- Comparing the results for model 1 (planned shutdown demand value equals to reported value of zero units) and model 2 (planned shutdown value corresponds to average of entire sample size excluding planned shut)
- Seasonality in the data
- Graphical representative of the BW
- Statically results of the BW

4.2.1.1 Comparing model 1 and model 2

Comparison of descriptive analysis between model 1 and model 2 highlighted in table 1 below, where model one is the planned shutdown corresponding to a zero demand value while the latter equals to the average demand process over the entire sample period.

Model 2 has a higher mean value than model 1. However, there is a wider spread over the mean, skewness and kurtosis for model 1.

The results for both models are shown below:

	Model 1	Model 2
Mean	3.51	3.58
Standard Error	0.04	0.03
Standard Deviation	0.92	0.78
Kurtosis	2.12	0.10
Skewness	-1.16	-0.56

Table 1: Descriptive analysis for model one and model two for the same period of study

For the purpose of this exercise model 2 (hereinafter referred as the data), was chosen as the better model from the both, and will be explained further in detail in the discussion section of this report. This data set underwent a seasonality check which will be described in the next sub section.

4.2.1.2 Seasonality in the data

The aim was to determine does seasonality exist in the data. Numerical analysis for excel (NUMXL) program used to simulate the data. From figure 4 below, each line is a representation of a data point and the lines are all following either up or down the x and y axis. The direction changed at a lag value of 137.

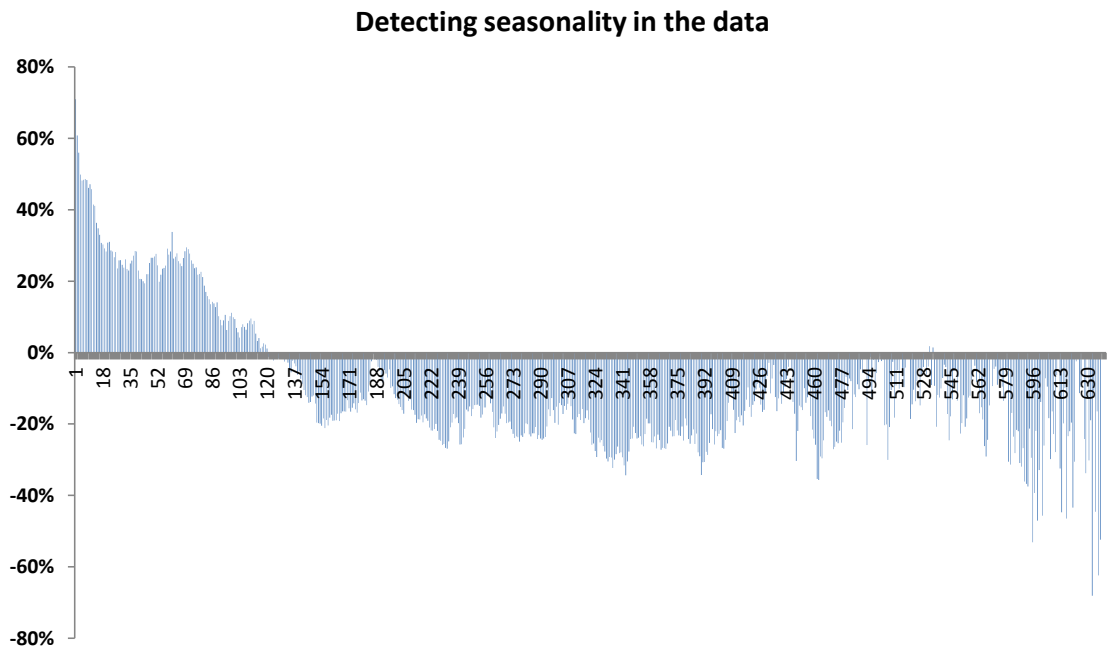


Figure 4: Detecting seasonality in the raw data

After describing the seasonality figure above with respect to the data, the next is to graphically and statically quantify the BW, which is covered in the next two sections.

4.2.1.3. Graphical representation of the BW

Prior to examining the BW in the platinum industry, an investigation was performed to determine whether the inventory levels have decreased over the period of the study.

Conventional computation program can be used to graphically represent the BW by plotting the quantity ordered of reagent by stores against the demand process consumption rate by the process plant.

The analysis indicates that the average inventory levels have trended upwards for both the plant consumption rate and ordering quantity by bulk stores on site as depicted in figure 5 on the next page. Furthermore, there seem to be no correlation between the plant consumption rate and stores quantity ordered.



Figure 5: Stores ordering pattern against the demand pattern change over time

4.2.1.4. Statically analysis of quantifying the bull whip

The AR (1) and AR (2) model was used to simulate the data and the results of both models will be covered. The statically analysis of both AR models is shown in table 2 below. The size or magnitude for both models is shown on the same table, and the accuracy of the model is shown on table 3 and table 4. The next was to measure the BW using both models, which is found in table 5.

Table 2: Comparative magnitude analysis for an AR (1) and AR (2) model

Regression Statistics	First order AR	Second order AR
Multiple R	70.9%	72.6%
R Square	50.3%	52.7%
Adjusted R Square	50.3%	52.5%
Standard Error	0.55	0.54
Observations	640	639

Table 3: Comparative accuracy analysis of an AR (1) model

ANOVA - First Order Auto Regression (AR 1 Model)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	195.35	195.35	646.65	0.000
Residual	638	192.74	0.30		
Total	639	388.096			

Table 4: Comparative accuracy analysis of an AR (2) model

ANOVA - Second order Auto Regression (AR 2 Model)

	df	*SS*	*MS*	*F*	*Significance F*
Regression	2	203.63	101.81	353.97	0.000
Residual	636	182.94	0.29		
Total	638	386.565			

The table below summarise both models:

Table 5: Bullwhip effect for an AR (1) and AR (2) model

Bullwhip effect measurement	
AR(1)	AR(2)
8.32	9.00

The seasonality graph depict there is no evidence of sudden peaks and the graphically graph show that there is a sign of irregular pattern between quantity ordered and demand processing, and this is supported by the BW measure using the AR(1) and AR(2) model.

4.3 The financial implication related to the bull whip effect

Figure 6 illustrates that reducing lead time reduces the bullwhip effect but does not eliminate it.

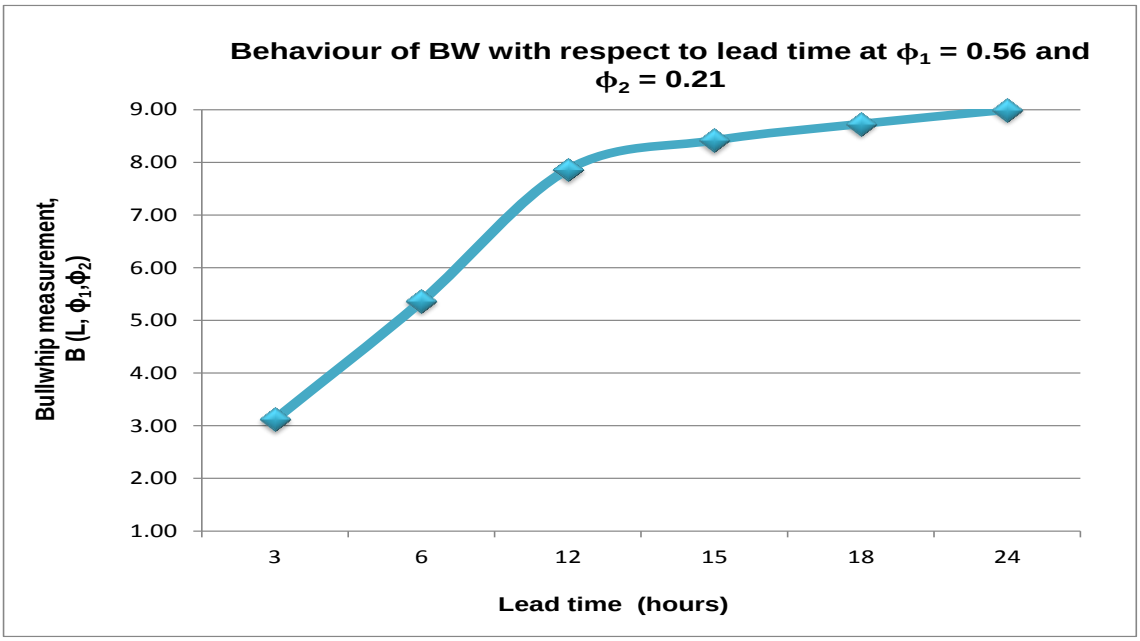


Figure 6: Demonstrating BW with varying lead time using current AR (2) parameters

Table 6 below demonstrate the impact on lead time on the BW for both models. The current lead time for this reagent is 24 hours and with the corresponding BW for each model the corresponding net stock variance (NSAmp), the number of period for inventory and the corresponding total net stock is represented in table 6, below.

Table 6: Comparative total net stock analysis for an AR (1) and AR (2) model

Model	L (hours)	Bullwhip	Ti	NSAmp	Number of periods of inventory to ensure a 99.5% fill rate, a	TNS = a*μ = z* σ_{NS} (tons)
AR(1)	24	8.32	0.56	3.61	4.86	417.7
AR(2)	24	9.00	0.56	3.78	4.99	428.6

4.4 Tools available that management can utilise

The tools that are available for any company for controlling inventory are their demand forecast data which is powerful but it all depends what they use it for. The useful demand data was converted either to one or two variables known as AR parameters all depending on which AR model is used.

The behaviour of the BW with respect to increasing lead time by keeping the AR parameter constant was examined, in order to better understand the dynamics that is taking place with increase lead time.

The impact of the BW can be summarised in the figure 7 below for an AR (1) model:

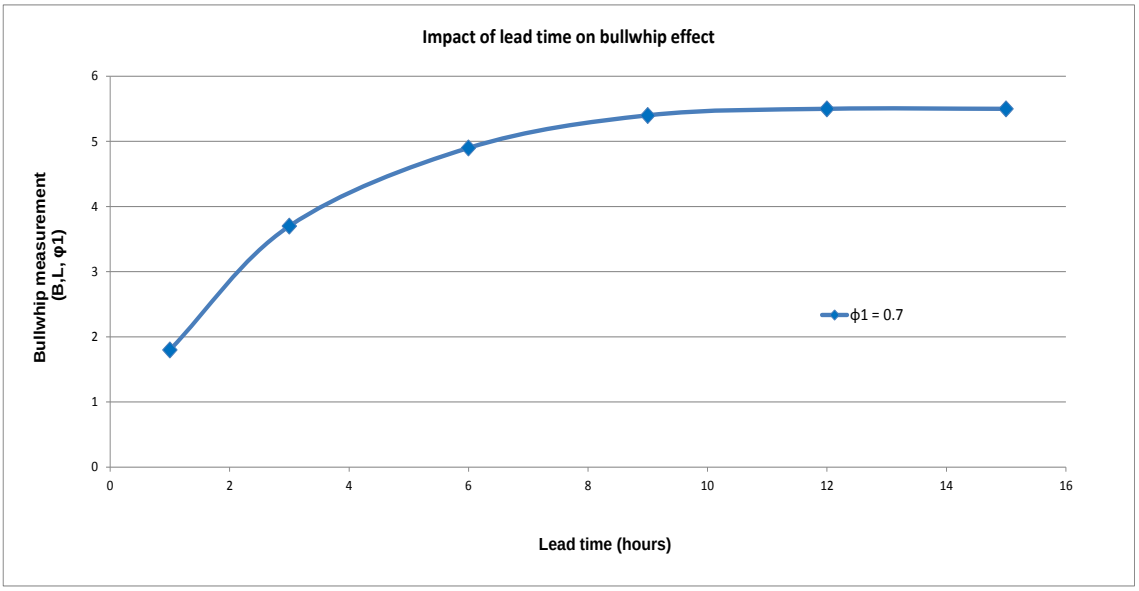


Figure 7: Determining the impact on BW with respect to lead time

The impact of the BW for an AR (2) model with varying one of the two AR parameters and keeping the other constant, can be summarised in the table 7 and table 8.

Table 7: Effect of autoregressive coefficient and lead time on BW (L, ϕ_1, ϕ_2) – the case when $\phi_1 < 0$

$\phi_1 = -0.8$									
ϕ_2	-0.80	-0.60	-0.40	-0.20	0.00	0.20	0.40	0.60	0.80
L =1	****	****	0.09	0.15	0.42	1.00	***	***	****
L=3	****	****	0.21	0.11	0.21	1.00	***	***	****
L=6	****	****	0.13	0.13	0.21	1.00	***	***	***
L=9	****	****	0.12	0.13	0.10	1.00	***	***	***
L-12	****	****	0.12	0.13	0.13	1.00	***	***	***
L=15	****	****	0.12	0.13	0.11	1.00	***	***	***
L=18	****	****	0.12	0.13	0.11	1.00	***	***	***
L=24	****	****	0.12	0.13	0.11	1.00	***	***	***
$\phi_1 = -0.6$									
L =1	****	0.34	0.18	0.14	0.23	0.50	1.00	***	****
L=3	****	0.32	0.29	0.25	0.21	0.32	1.00	***	****
L=6	****	0.16	0.19	0.22	0.26	0.37	1.00	***	****
L=9	****	0.12	0.18	0.22	0.25	0.20	1.00	***	****
L-12	****	0.11	0.17	0.22	0.25	0.25	1.00	***	****
L=15	****	0.11	0.17	0.22	0.25	0.20	1.00	***	****
L=18	****	0.11	0.17	0.22	0.25	0.22	1.00	***	****
L=24	****	0.11	0.17	0.22	0.25	0.22	1.00	***	****
$\phi_1 = -0.4$									
L =1	0.73	0.52	0.38	0.32	0.33	0.42	0.63	1.00	****
L=3	0.45	0.28	0.30	0.37	0.41	0.43	0.52	1.00	****
L=6	0.23	0.14	0.24	0.34	0.43	0.54	0.69	1.00	****
L=9	0.12	0.12	0.23	0.33	0.43	0.49	0.44	1.00	****
L-12	0.09	0.14	0.24	0.33	0.43	0.50	0.53	1.00	****
L=15	0.11	0.15	0.24	0.33	0.43	0.50	0.44	1.00	****
L=18	0.11	0.15	0.24	0.33	0.43	0.50	0.49	1.00	****
L=24	0.08	0.15	0.24	0.33	0.43	0.50	0.48	1.00	****
$\phi_1 = -0.2$									
L =1	0.86	0.75	0.67	0.63	0.62	0.64	0.70	0.81	1.00
L=3	0.43	0.25	0.31	0.47	0.66	0.82	0.92	0.96	1.00
L=6	0.20	0.14	0.29	0.47	0.67	0.91	1.23	1.50	1.00
L=9	0.15	0.18	0.32	0.48	0.67	0.90	1.13	1.21	1.00
L-12	0.20	0.21	0.32	0.48	0.67	0.90	1.18	1.44	1.00
L=15	0.15	0.20	0.32	0.48	0.67	0.90	1.16	1.28	1.00
L=18	0.10	0.19	0.32	0.48	0.67	0.90	1.17	1.38	1.00
L=24	0.09	0.19	0.32	0.48	0.67	0.90	1.17	1.35	1.00

Table 8: Effect of autoregressive coefficient and lead time on BW (L, ϕ_1, ϕ_2) – the case when $\phi_1 > o$

ϕ_1 = 0.2

ϕ2	-0.80	-0.60	-0.40	-0.20	0.00	0.20	0.40	0.60	0.80
L =1	1.14	1.25	1.33	1.37	1.38	1.36	1.30	1.19	1.00
L=3	0.40	0.22	0.41	0.88	1.50	2.11	2.50	2.91	1.00
L=6	0.35	0.39	0.61	0.94	1.50	2.43	3.73	1.64	1.00
L=9	0.35	0.37	0.58	0.93	1.50	2.49	4.26	1.48	1.00
L-12	0.14	0.30	0.57	0.93	1.50	2.50	4.50	2.11	1.00
L=15	0.14	0.32	0.57	0.93	1.50	2.50	4.60	1.83	1.00
L=18	0.20	0.33	0.57	0.93	1.50	2.50	4.64	1.64	1.00
L=24	0.12	0.32	0.57	0.93	1.50	2.50	4.66	1.85	1.00

ϕ_1=0.4

L =1	1.27	1.48	1.62	1.68	1.67	1.58	1.37	1.00
L=3	0.36	0.26	0.64	1.36	2.22	2.87	2.81	1.00
L=6	0.58	0.61	0.84	1.33	2.33	3.92	5.18	1.00
L=9	0.26	0.38	0.76	1.33	2.33	4.30	7.16	1.00
L-12	0.15	0.41	0.77	1.33	2.33	4.43	8.63	1.00
L=15	0.28	0.43	0.77	1.33	2.33	4.48	9.65	1.00
L=18	0.16	0.41	0.77	1.33	2.33	4.49	10.35	1.00
L=24	0.20	0.42	0.77	1.33	2.33	4.50	11.11	1.00

ϕ_1=0.6

L =1	1.66	1.82	1.86	1.77	1.50	1.00
L=3	0.48	1.17	2.17	3.05	3.08	1.00
L=6	0.71	1.06	1.99	3.78	5.50	1.00
L=9	0.47	1.07	2.00	3.95	7.33	1.00
L-12	0.59	1.07	2.00	3.99	8.56	1.00
L=15	0.53	1.07	2.00	4.00	9.33	1.00
L=18	0.56	1.07	2.00	4.00	9.80	1.00
L=24	0.55	1.07	2.00	4.00	10.25	1.00

ϕ_1=0.8

L =1	1.91	1.85	1.58	1.00	
L=3	2.10	3.16	3.30	1.00	
L=6	1.45	3.36	5.66	1.00	
L=9	1.60	3.34	7.18	1.00	
L-12	1.57	3.33	8.04	1.00	
L=15	1.57	3.33	8.50	1.00	
L=18	1.57	3.33	8.74	1.00	
L=24	1.57	3.33	8.93	1.00	

These results will be used to explain the different level of AR parameters value against lead time in the next section in detail.

The total reagent storage volume operated for this study is between 600 and 800 cubic metre (m^3), with an average of 700 cubic metre (m^3) or 519.75 metric tons. Using the current reagent usage of 85.94 tons per day, the inventory can last for 6 days or 145 hours.

The inventory cost per metric ton of reagent is shown in table 9 below, a value of ZAR 6004.90 per metric ton, operating with a storage level of 800 cubic metres (m^3) the excess stock carried per period equates to ZAR 3.05 Million.

Table 9: Reagent actual cost represented in South African Rands (ZAR) per metric ton

Average reagent price in ZAR per metric ton excludes inventory cost	R 5 830.00	ZAR/ton
Inventory cost (estimate)	3.00%	
Actual reagent cost in ZAR per metric ton	R 6 004.90	ZAR/ton

The revenue generated by the individual metals and the basket price for the combination of the metals at RBMR is highlighted in the table 10 below. The basket price for the total base metals is ZAR R 364 880.53 or ZAR 0.36 M per hour of operation and is summarised in the table below. The five (5) year trend for each of the metals can be found under Appendix B and the full calculation of table 10 under Appendix D.

Table 10: Basket price for base metal produced at RBMR represented in South African Rands (ZAR)

Metal	Average BM produced (tons/annum)	Average market price per ton	Revenue generated per annum (ZAR)	Revenue generated per hour (ZAR)
Nickel	13557.64	R 158 000.00	R 2 142 106 732.15	R 277 878.10
Copper	10151.62	R 62 500.00	R 634 476 515.21	R 82 305.48
Cobalt	122.74	R 295 000.00	R 36 207 772.38	R 4 696.94
Total	23832.00		R 2 812 791 019.73	R 364 880.53

These results will be used to explain the benefits and disadvantages of carrying this amount of inventory at any period of time in the next section

From the continuation of the previous section with regard to varying BW and understanding the cost implications with total net stock levels will be discussed in detail in the discussion section.

From the results presented above there is a comparative study conducted on the impact on BW for both models varying lead time and AR parameter/s.

4.5 Summary of the data analysis

This chapter has provided an overview of the quality of data used. It described the details of how the data was processed, screened and analysed. Descriptive statistics of the different models were presented and the outcome of those models where quantified into a single value, known as the bullwhip, and then converted to a cost value.

Some of the tools available to management were described in the previous chapter. The results of data analysis, the reagent cost and the revenue generated by the base metal will be interpreted to determine if the BW exists and what is the cost implication attached to it. Furthermore, to support or go against the theory the relevant questions will be put forward. The answer to the studied sub questions as well as the main research question will then be argued.

CHAPTER 5. DISCUSSION OF THE RESULTS
Quantifying and evaluating the bullwhip effect

5.1 Introduction

This chapter discusses the results derived from the previous data analysis chapter, and reviews the various outcomes. The relevant research questions will be evaluated and verified. It will seek to investigate the BW, looking at the quality of the data (size and accuracy) as discussed in the previous chapter. The overall results show good explanatory ability.

This section aims to answer three important sub questions: 1.) “Does the BW exist in the platinum industry?” 2.) What impact does it have on the platinum industry (Anglo American Platinum)? 3.) What tools are out there to reduce the BW and can it be practically applied in the platinum industry (Anglo American Platinum)?

To answer the first question, the second order auto regression will be used to simulate the data using Microsoft Excel. Some of the statistics are done using the NUMXL program. The findings of the regression model are discussed below.

The BW effect will be converted to a financial cost value determined using the NSAmp equation discussed in the literature survey.

5.2 Analysing the bullwhip effect in the platinum industry

As discussed in the literature, several theories may explain what causes the BW but there are few researchers that quantify the BW and still remain a challenge. However, most past researchers such as Chen et al. (1997 b) focused mainly on the AR (1) model. Proposed by Luong et al. (2007 b) that higher order autoregressive models should be utilised which might improve the forecasting demand process.

It is surprising that this theory did not develop further. Chen et al. (1997b) model was more empirical but he estimated the forecast error term while Luong (2007a, b) calculated it. Djenojaurne (2003) took it a step further, by process controlling the demand which in our example will be too complicated and time consuming.

Perhaps, Luong (2007a, b) came up with a brilliant way of measuring and quantifying the BW which is robust, easily replicated, and determines the forecast error. His method assumes the data is normal distributed, has no seasonality, and no size issues. The previous section addresses and satisfies those assumptions. His method was used to measure the extent of the BW on the platinum industry by starting to measure reagent consumption rate by the plant and comparing it with the quantity ordered.

From the graph of the comparison between stores pattern and consumption rate in figure 5 section 4.2.1.3 , indicate the quantity ordered is all over the show and there seems to be no correlation between the plant rate and the stores. This supports Lee et al. (1997a) theory of the BW that the order of magnitude increases as you go up the chain i.e. from the retailer to the wholesaler, here it is from the plant to the stores.

5.2.1 *Data Validation*

Using the NUMXL program and referring to figure 4 on page 44, it was found that the data does not have any sudden peaks which would suggest seasonality.

After identifying that the data does not have any seasonality, the remaining two parameters that explain the line is the trend and an irregular component.

The graphical representative of the BW indicated that the average inventory levels has trended upwards for both the plant consumption rate and the bulk store orders as depicted in figure 5 section 4.2.1.3.

The quantity ordered has been “all over the show” for the wholesaler as the consumption rate for the retailer increased. This suggests that the quantity

order has a greater variance than the plant consumption rate, hence supporting Lee et al. (1997) theory.

Since there is no seasonality in the data and there seems to be some evidence of the BW existing, the next step is to statically prove it does exist, that is where Luong et al. (2007) AR model will be used to simulate the results.

For the original raw data, the mean has a 95 percent units confidence interval of 3.51 ± 0.92 tons per hour. However, this value does not truly reflect the plant reagent consumption rate when it is operating under normal conditions. Additionally, in order to satisfy the size issue, the planned stoppage values were converted to the sample average, which will be referred to, as the modified data.

The comparisons between the original and modified data demonstrated a size and accuracy problem. In table 11, the skewness, kurtosis and standard deviation are shown. The biggest change was found in the accuracy of the model through the skewness and kurtosis statically analyses. This improvement is demonstrated in the standard deviation of the data value of 15.3 percent units, and this meant the standard error is improved by the same amount.

The standard deviation improvement translates to a confidence limits improvement of the same magnitude. This means that the confidence intervals were narrowed rather than widened by equating the plant shut down figure to the sample average. The modified data will be further tested and used to measure the BW and the cost associated with operating with a BW.

Table 11: Improvement in accuracy and size by averaging the planned shutdown total consumption value

	Improvement (%)
Skewness	51.6%

Kurtosis	95.3%
Standard Deviation	15.3%
Sample Variance	28.1%

5.2.2 *Comparative study between AR (1) and AR (2) Model*

This section will be broken down into three sub sections: model validation; data validation for both the AR models; quantifying the BW.

5.2.3 *Model Validation*

The model was tested on a one explanatory variable that is the demand forecasted on yesterday's demand (D_{t-1}) and the results presented in table 12. There has been a four and half (4.5) percent units improvement in the fit by applying the second order regression fit (shown by the adjusted R-Squared value in table 12).

Furthermore, this improvement has reduced the intercept value from 1.04 metric ton per hour to 0.81 metric ton per hour. This means instead of a 1.04 metric ton per hour of reagent consumption rate without taking into account the independent variable (here it is D_{t-1} and D_{t-2}), only 0.81 metric ton per hour is the best average starting point or constant consumption rate per hour.

In order to forecast demand into the future, the aim is to let the independent variable explain the regression line by minimising the intercept value. Furthermore, the intercept becomes small as possible. This causes the R squared value to increase. Increasing the R squared means that the unexplained in the variance of demand forecast (Error) can be minimised which will improve forecasting.

This change accounts for a 21.4 percent units improvement by moving from a first order to second order AR. The accuracy for both orders which is shown on table 13, measured by ANOVA F Statistics is significant at a level of 0.05 i.e.

this means less than five (5) percent units chance of wrongly rejecting the hypothesis that the estimate is not correct.

The model structure issue was addressed as highlighted above. On this note, the second order auto regressive model (AR 2) will be used to simulate the BW.

Table 12: Comparison of regression fit between first and second order auto regressive (AR) model

Regression Statistics	First order AR	Second Order AR	% Improvement
Multiple R	70.9%	72.6%	2.3%
R Square	50.3%	52.7%	4.6%
Adjusted R Square	50.3%	52.5%	4.5%
Standard Error	0.55	0.54	2.4%
Observations	640	639	-

Table 13: Comparison of regression fit between first and second order auto regressive (AR) model

	ANOVA - First Order Auto Regression (AR 1 Model)	**ANOVA - Second order Auto Regression (AR 2 Model)**
F	646.65	0.000
Significance F	353.97	0.000

To check if the autoregressive model tested was stationary, the sum and difference, including the quotient of the coefficient were calculated and found all to be below one. As highlighted in table 14 and table 15, all the conditions are satisfied for a second order auto regression. This was cross checked with NUMXL, an interesting observation was found that the first order autoregressive model which is represented by the “constant and trend” is also stationary, which concludes the same finding.

Table 14: Stationary test for the demand process with a second order auto regression

Stationary test	
$\phi_1 + \phi_2 < 1.0$	0.77 < 1.0
$\phi_2 + \phi_1 < 1.0$	-0.35 < 1
$\|\phi_2\| < 1.0$	0.21 < 1
$\phi_1^2 + \phi_2^2 < 1.0$	0.36 < 1.0

Table 15: **Stationary test results from NUMXL for the demand forecast process**

Stationary Test

Test	Stat	P-Value	C.V.	Stationary?	5.0%
ADF					
No Const	-0.794	0.372	-1.9474	FALSE	
Const-Only	-5.080	0.100	-2.8808	FALSE	
Trend-Only	-2.251	0.463	-3.4229	FALSE	
Const+Trend	-5.379	0.000	-1.6448	TRUE	
Const+Trend+Trend^2	-7.997	0.000	-1.6448	TRUE	

The percentage of the variance in the forecast demand (D_t) which is accounted for by the regression line is 95.8 percent units for yesterday's demand and 70.2 percent units for previous day's predicator. The former figure explains 95.8 percent units of the demand forecast using a straight line i.e. approximately ninety - six percent units of the variance of demand forecast (D_t) can be explained using the straight line. It is so strongly related with D_t, with a positive correlation with an upward linear pattern.

The pattern on figure 8 indicates a linear association between t-1 and t-2. A positive correlation; but this relationship is not perfectly correlated. The value for D_{t-2} is known then the value for D_{t-1} can be easily calculated from the equation presented in figure 8. The same can be said from the influence of (t-1) on predicting the demand forecast. This information is useful to predict with some certainty the demand for t-1 and so on just by using D_{t-1} and D_{t-2}.

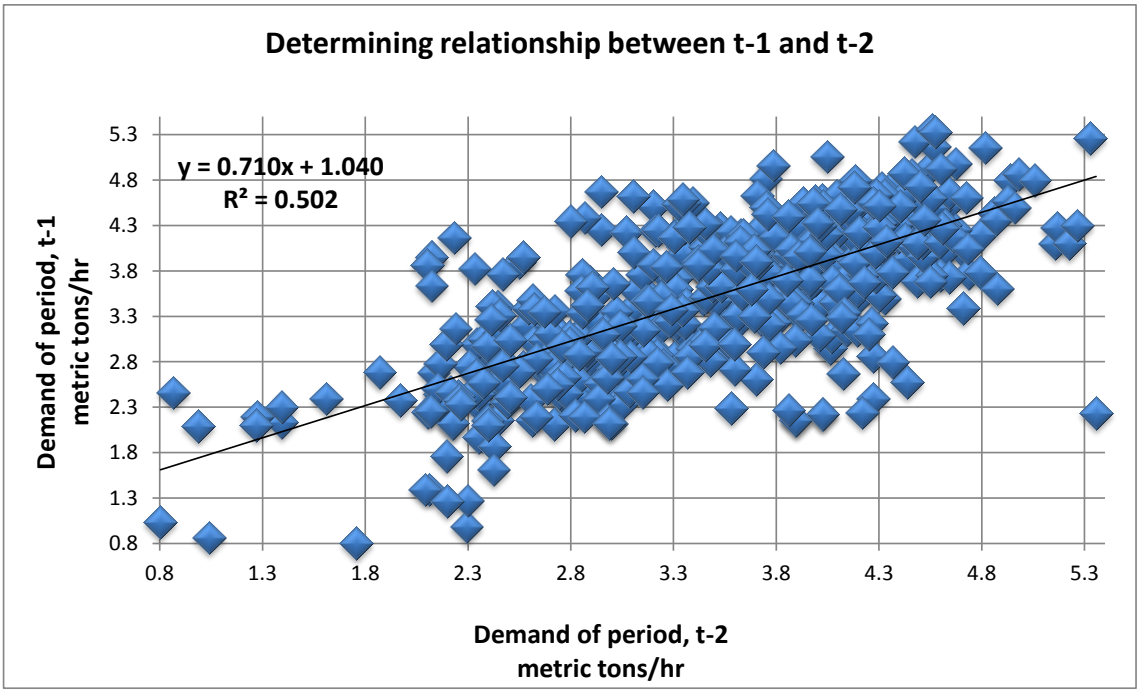


Figure 8: Demonstrating relationship between independent variables by plotting demand of yesterday against previous days

The correlation between the D_{t-1} and D_t, D_t and D_{t-1}, indicate strong linear association between these variables. The average consumption reagent rate of the plant is 85.94 tons and equating it to a production rate input during this period, it is consistent. Therefore it can be said with confidence that this number is correct.

The units of both the slope are in the same units, therefore there is no need to conduct standardised regression slopes, and it is covered further in this chapter. The other thing to note is that the second slope of a value of 0.61 in figure 10 is absolutely steeper than one of 0.71 in figure 9. Since both the slopes are positive and large enough, they do not pose a problem with their predictor variables not linearly related to the dependent variable.

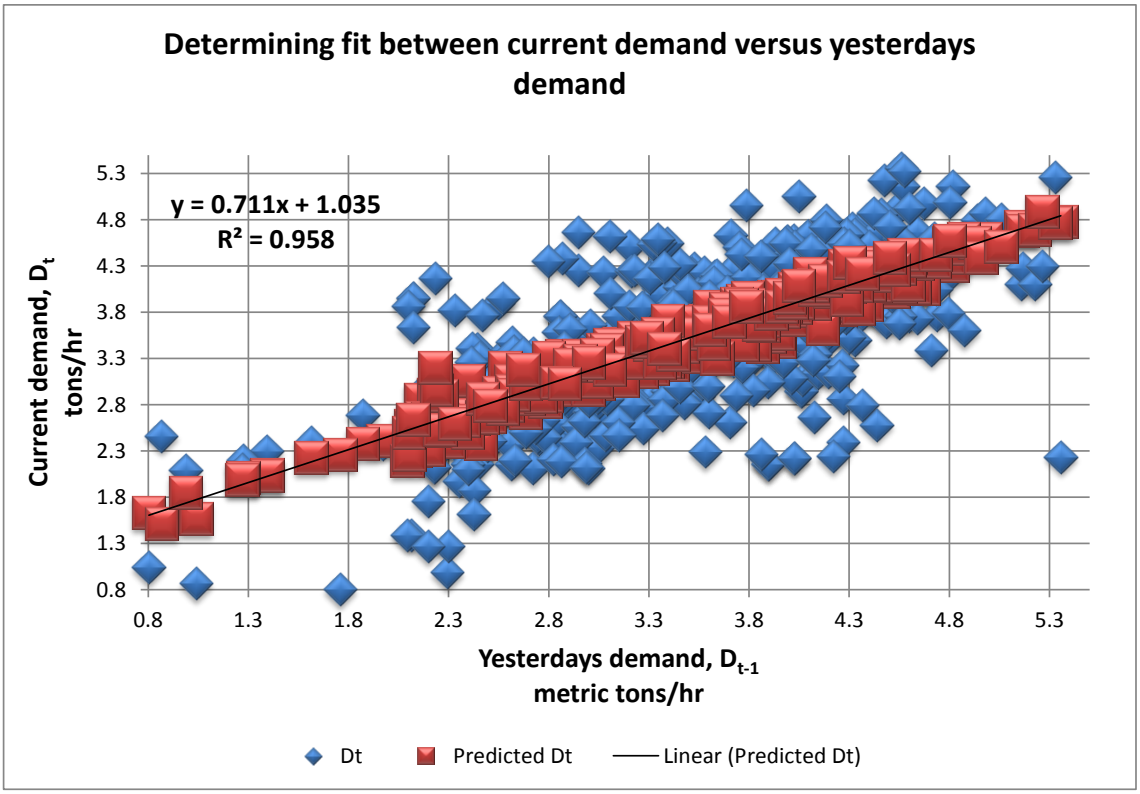


Figure 9: Relationship between current and yesterday's demand

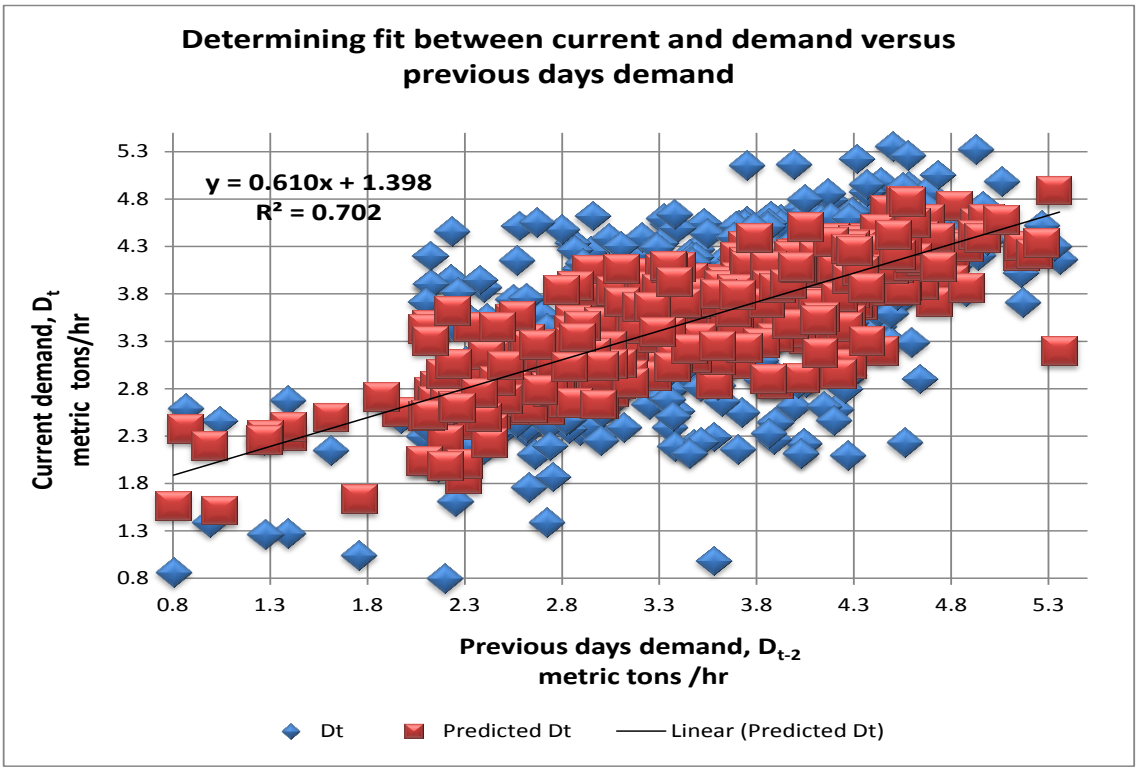


Figure 10: Fitting a straight regression line through the data for a D_{t-2} and D_t

This is a fairly well fitting regression relationship because the data follow a linear shape, not too many observations are far away from the best fitting straight line through the middle.

It can also be said that there is a strongly upward-shaped, slightly steep curve; clearly with a higher previous demand associated on average with a higher recent demand (D_t).

Furthermore, the accuracy of the slope for each independent and dependent variable were measured and indicated a greater than 95 percent units confidence level that the slope is accurate. The confidence limits for each did not include any zeroes to make it non-significant.

The adjusted R-squared for the model is 52.5 percent units. Taking into the consideration the following listed below, this variable is extremely hard to explain with the few defined causes. On this basis, it can be reported that the R Squared calculated is a good fit when taking the complexity into consideration.

Dependent variable (D_t) is highly dependent on a host of variables such as (but not limited to these only):

- Plant or equipment availability;
- Process inefficiencies due to:
    - stop and start of equipment, resulting in more than 70% electrical and instrumentation failure;
    - incompetent employee/s operating the process;
    - current strikes, resulting in shortage of competent and experienced employees operating the process.

The formal test for fit indicates that the p-value is below the accepted value of 0.05, exactly on 4.7×10^{-104}, and based on the estimates of error, this F statistics is significantly at a level of 0.05, giving an extra basis for accepting that the straight line fits our data. Furthermore, the confidence interval does not include zeroes in their intervals, demonstrating it is significant.

It can be concluded that a straight line fits the data sufficiently to continue the analysis step. Since the R squared is reasonable and the ANOVA F is significant for both slopes below the one (1) percent units statistical significance level, backed up with the correlation for all two highlighted above, where the D_{t-1} is strongly positively linear associated with D_t, and D_{t-2} is strongly associated with D_{t-1}. This discounts the low power problem and the sample size represents the population.

The sample size is big enough as it can be seen from the standard error of the mean, with a value of 0.0729.

For this model, there is no evidence of a high power problem with the statistics as the magnitude is big enough and none of the correlation is tiny enough, (i.e. very close to zero) and being statistically significant as its confidence interval lies between 0 and 1.

The next section will follow with the serious regression assumption issues such as: multicollinearity, non-linearity, and outlier effects.

5.2.4 *Testing for less potential issues in model validation*

The testing of multicollinearity was conducted using the correlation between independent variables and variance Inflation factor (VIF's). From the correlation index below, there are no values of approximately 0.9 or above which may pose a problem of multicollinearity.

There are no definitive rules for what "high" should be but the general practice rules suggests that you may have a multicollinearity if one or more VIF's are bigger than 10.

Table 16: Correlation between independent variables

	Dt-1 demand of period t-1	Dt-2 demand of period t-2
Dt-1 demand of period t-1	1	0.71
Dt-2 demand of period t-2	0.71	1

It can be seen that the highest value for VIF from the VIF table below is 6.976 (approximately 7.0) which lies below the maximum limit of 10.0; therefore multicollinearity is probably not an issue. The next was to test for linearity between the independent and dependent variable. From figure 8, of Independent variable D_{t-1} and Independent Variable D_{t-2} against the dependent variable graphically and statistically (by the R Squared value) shows that the relationship is a straight line.

Table 17: VIF as a multicollinearity diagnostic in Excel

Model	*Coefficients*	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*VIF*
Intercept	0.814	0.108	7.547	0.000	0.602	1.026	
Dt-1	0.562	0.039	14.528	0.000	0.486	0.638	6.976
Dt-2	0.211	0.039	5.447	0.000	0.135	0.287	6.976

From the residual plots in figure 11 and 12, for both yesterday's demand and previous days demand establish that the residuals are normal and non-problematic. By forming a fairly even spread, suggesting that no other shape may exist in the data, thus concluding it is unlikely to have any non-linear pattern existing and equality of variances.

The data was examined for potential outliers. From the residual plot highlighted in figure 11 and 12 has few plot greater than ± 2, which most statisticians place their cut-off's deemed an outliers. Some outliers naturally lie outside of $\pm$ 2; nevertheless, the percent units of outliers lying outside the boundaries of ± 2 were determined. From the data set, only 0.16 percent units lie outside the located boundary and allowing for 5 percent units to lie outside the limits and

thus making the data set to be within acceptable limits. In that note, the outlier is not a problem for the regression line or even for the regression model.

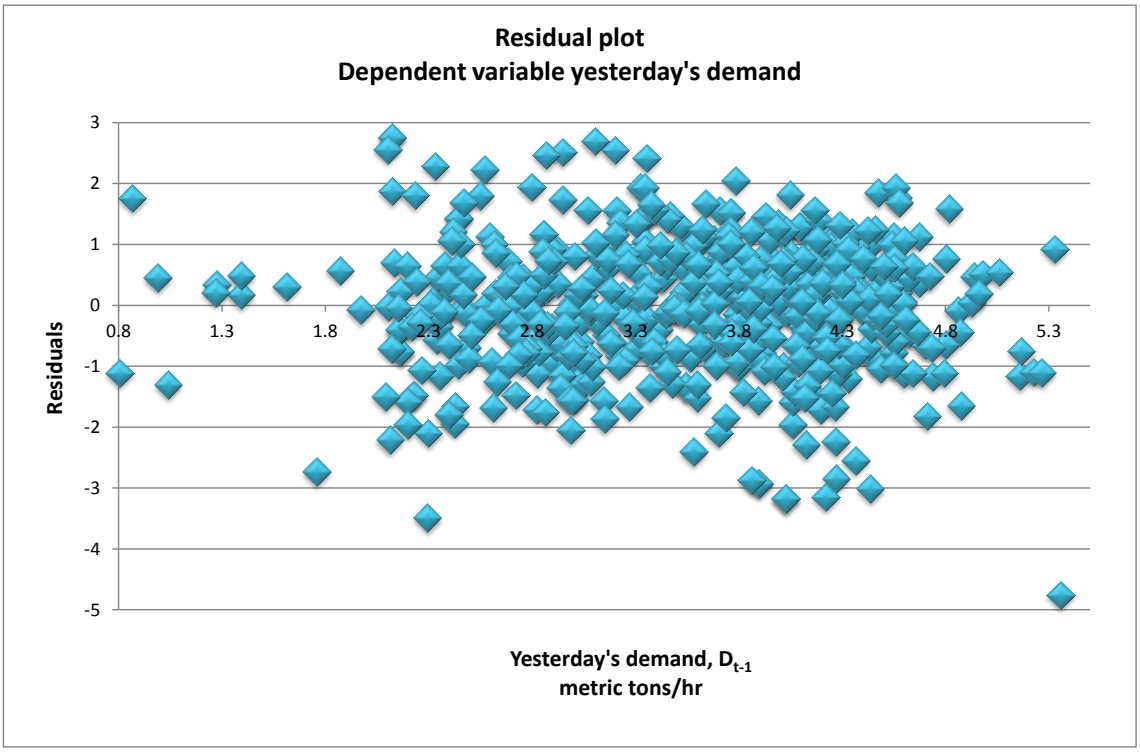


Figure 11: Residual plot of dependent variable yesterday's demand

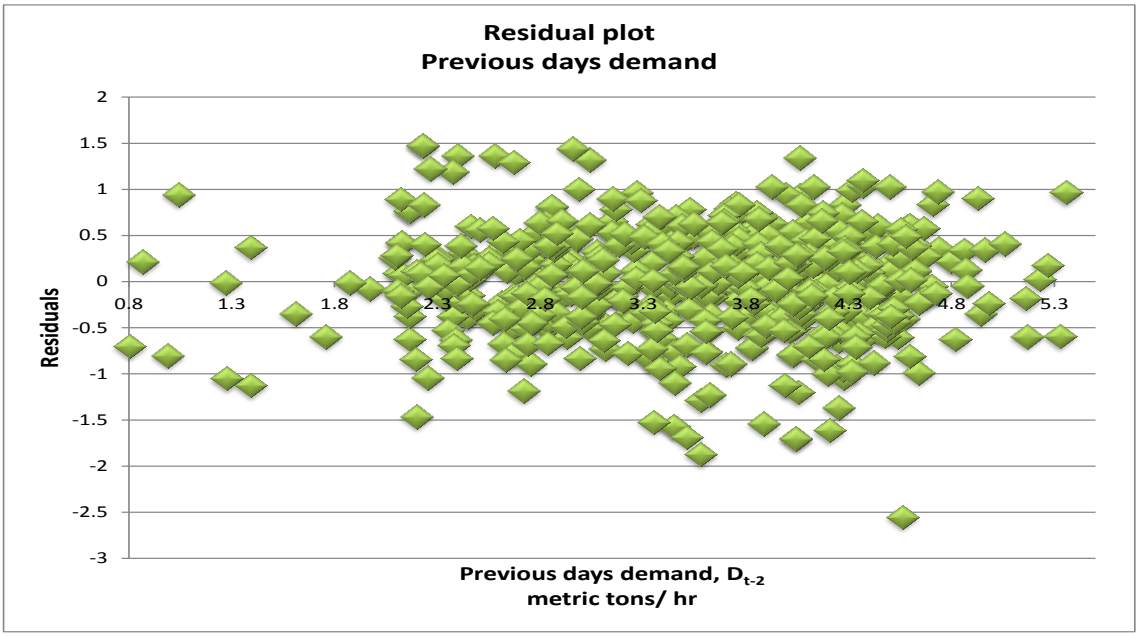


Figure 12: Residual plot of dependent variable previous days demand

Having covered the potential more serious issues with the data, the less serious distributional issues (violation) such as heteroskedasticity, normality of residuals, and autocorrelation will be investigated.

Referring to the figure 9 and figure 10, it is evident that the line does an equally good job of explaining the data all through the range, hence homoscedasticity. Supporting the above, the heteroskedasticity in the residuals graph below most certainly indicate that the residuals are equally distributed along the line, therefore there is no sign of heteroskedasticity.

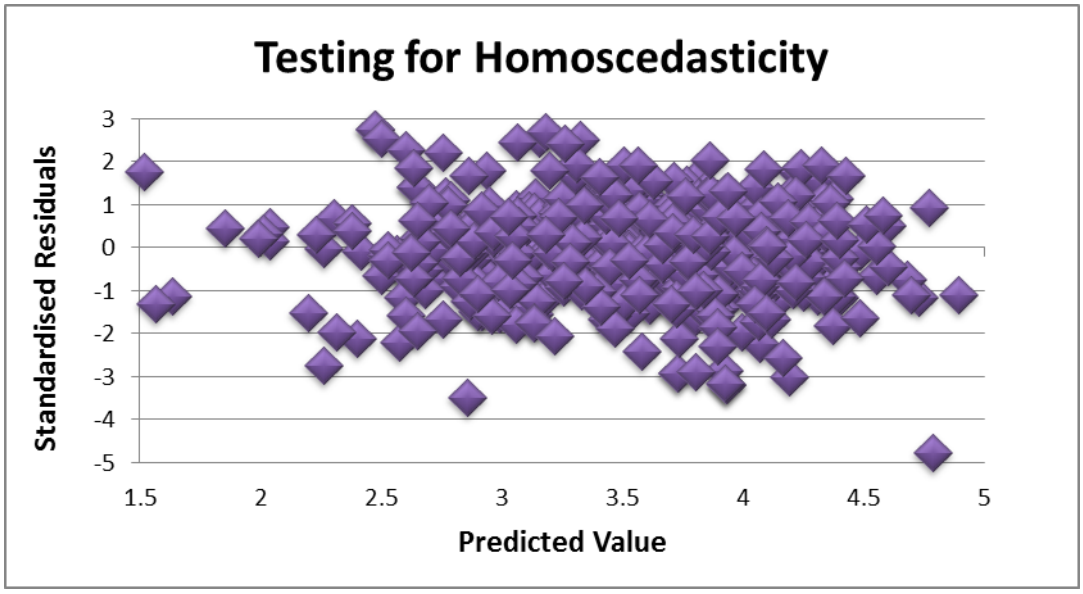


Figure 13: Test if the residuals are equally distributed

The second less serious assumption is normality of residual. It is found from the histogram and the Q-Q plot in figure 14 and figure 15 that there exist a slightly negative skewness and probably making it not normally distributed.

The results indicate that there is a negative skew and a slightly positive kurtosis. A skewed value of - 0.56 and a kurtosis of + 0.1 is sufficiently far away from the zero benchmark to suggest that the data does not fit a normal distribution.

This means that short reagent demand makes for a lengthened left hand tail (figure 14). The long tail on the left; skewness in the data probably means average consumption rate is a bad measurement for the representative number (because left tail drags the average to the left too).

Most statisticians use a rule of thumb that states that a variable is reasonably close to normal if its skewness and kurtosis have a value lying between - 1.0 and + 1.0, and between - 3.0 and + 3.0, respectively.

From this it can be deduced, the results lie between those limits making the data normally distribution.

Both the graphically and statically comparison of demand forecast against the normal distribution seems to indicate the data does fit this type of pattern well

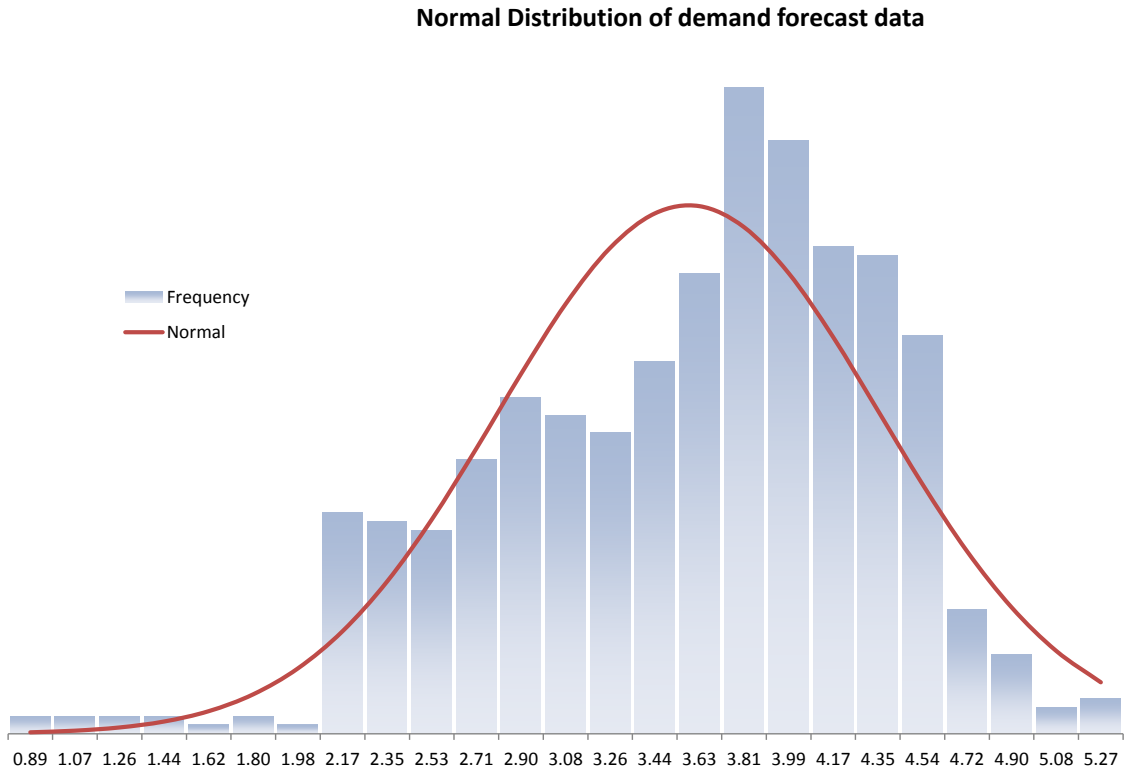


Figure 14: Histogram plot for demand forecast illustrating skewness and kurtosis

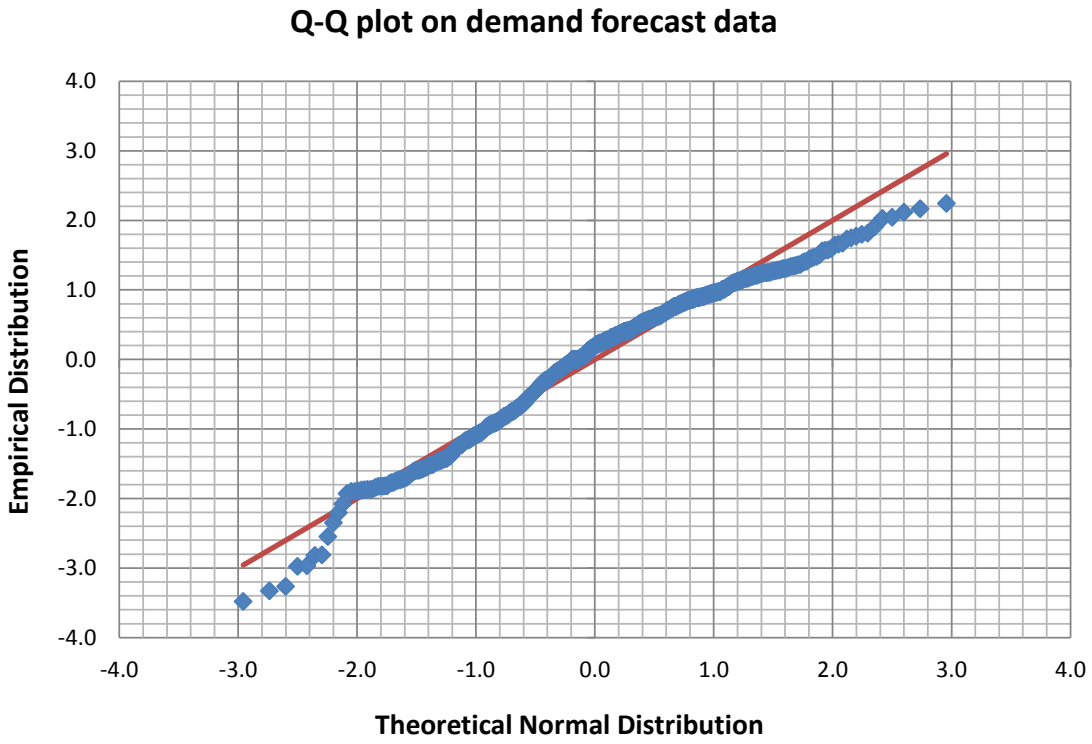


Figure 15: Q-Q plot for demand forecast to illustrate skewness

The last issue is autocorrelation between independent variables. The Durbin Watson method can be used.

Correlation between demand of yesterday's (D_{t-1}) and demand of two days ago (D_{t-2}) shown in table 16 section 5.2.4. , suggests that all major variable are at least moderately related in a positive linear way.

5.2.5 *Bullwhip calculation*

As D_{t-1} and D_{t-2} increases so do the demand forecast. The reason behind this trend is the linear upward relationship exists between the D_{t-1}, D_{t-2} with respect to D_t. The reagent efficiency is measured on the amount of throughput into the plant.

The average consumption of reagent rate is 85.94 metric tons per day and with a standard deviation of 18.68 metric tons per day. A standard deviation value of this means the increase usage is in the range of $\pm$ ZAR R 112 180.65 per ton of base metal produced.

Both the graphical and statistical comparison of demand forecast against the normal distribution seems to indicate that the data does fit this type of pattern well. This means the mathematical model is a good fit and represents the data.

After the model and data analysed, the BW was calculated using Luong et al. (2007a, b) procedure.

There is evidence from the results that the BW does exist in the platinum industry. The measured BW is a value of 9.00 for an AR(2) model and 8.32 for an AR(1) model, which means that the variance in quantity ordered of reagent is nine times the variation in the consumption rate of the reagent by the plant for the former model.

Luong (2007b) method was used to test the different order of autoregressive coefficient and it was found that the first and second order autoregressive coefficient is 0.56, 0.21 respectively. The meaning of these numbers will be covered in the next section in detail

The next section will unpack this number more in detail and will educate the user the cost implication with a BW existing.

The AR (2) model equation is:

$$\mathbf{D_t\,(Y) = 0.814 + 0.562\,D_{t-1} + 0.211\,D_{t-2}} \qquad \mathbf{(25)}$$

5.3 Analysing the financial implication of the bullwhip effect

From the results in Table 7 in section 4.4, it can be noted that when both ϕ_1 and ϕ_2 are negative, the BW does not exist. When $\phi_1 < 0$ and $\phi_2 > 0$, the BW exists only when the absolute value of ϕ_1 is small and ϕ_2 is large enough (for example, when $\phi_1 = -0.2$, $\phi_2 = 0.4$).

It can be noted that there also exist a value of ϕ_2 at which BW (L, ϕ_1, ϕ_2) reaches a maximum value and when $\phi_2 - \phi_1 = 1$, the bullwhip measure BW = 1.00. These trends can be explained in figure 16, for the case when $\phi_1 = -0.2$ and L = 6 hours.

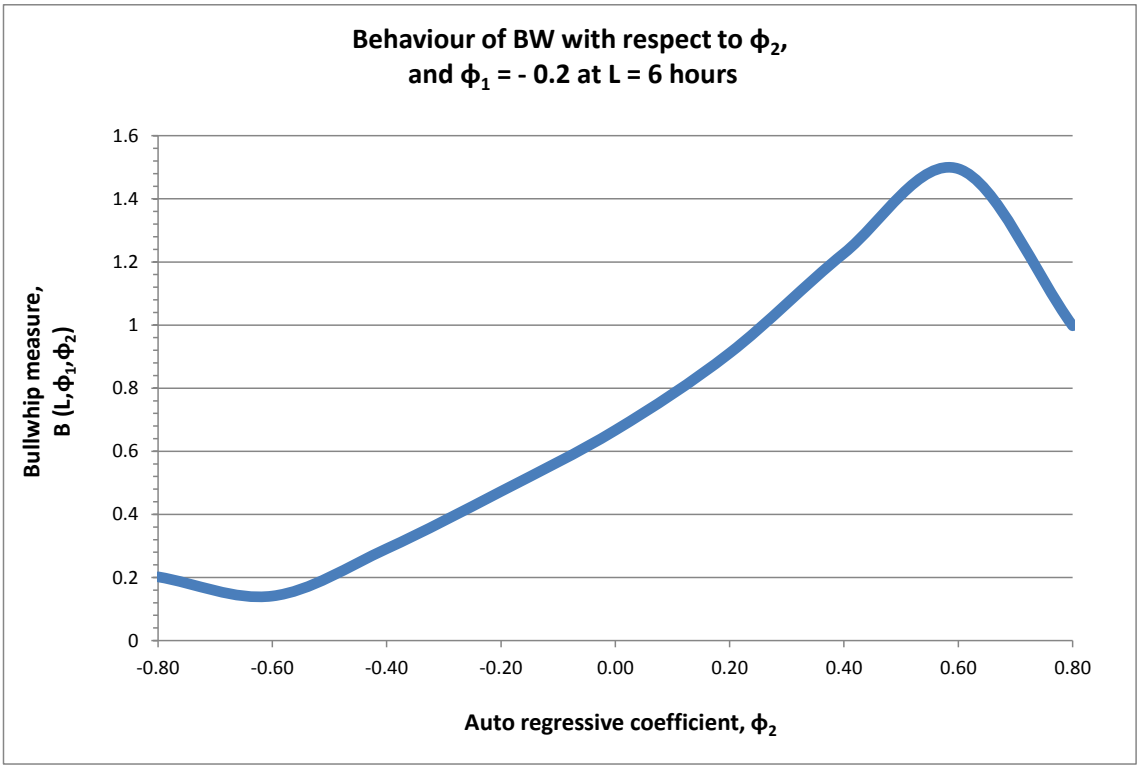


Figure 16: Behaviour of BW for an AR (2) model with keeping ϕ_1 constant and varying ϕ_2

For case $\phi_1>0$, as shown in table 8 in section 4.4, the BW always exists when $\phi_2 \geq 0$ and $\phi_1 + \phi_2 < 1$. When $\phi_2<0$, the BW might exist and independent on the values of ϕ_1, ϕ_2 and L.

The trend represented in table 8 in section 4.4, shows that the BW will exist for large values of ϕ_1 and ϕ_2, and small values of L, which was also found in Luong et al. paper.

An interesting discovery from figure 17 and figure 18, as the lead time increases, it does not always result in an increase in the BW. As illustrated by Luong et al. (2007a) and many researchers that the first order auto regression demand process AR (1) illustrated in figure 19, when the lead time increases, BW will follow suit. This trend was also confirmed in this work when ϕ_2 is equal to zero.

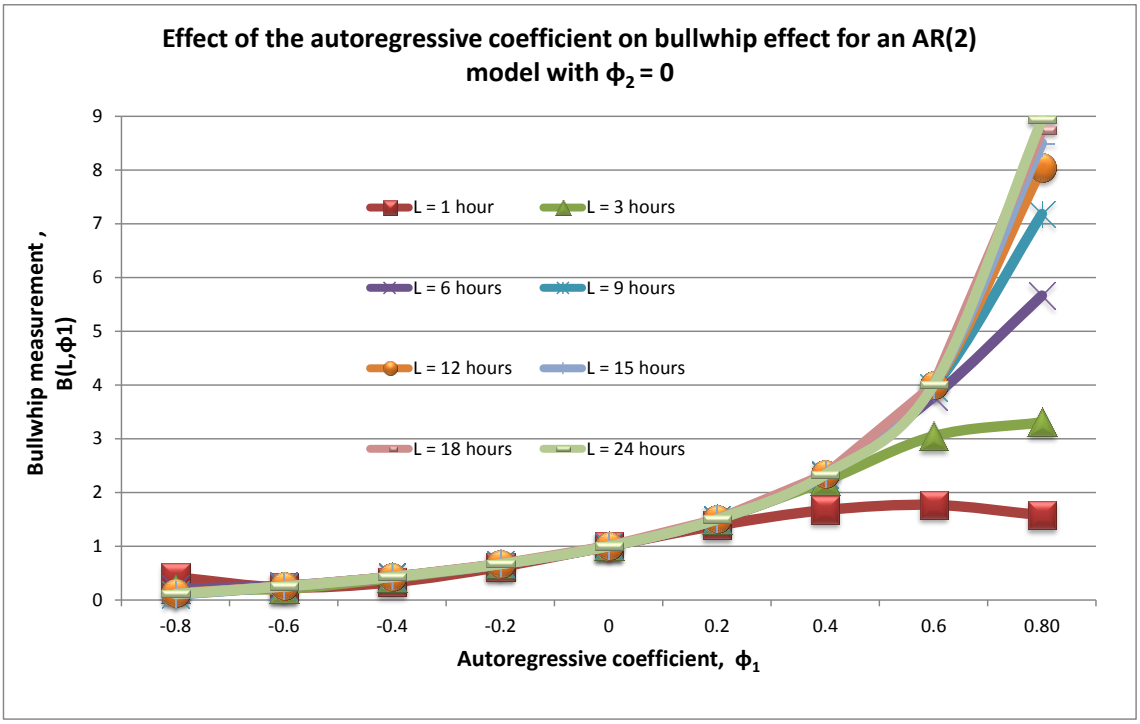


Figure 17: AR (2) model showing the effect of the autoregressive coefficient on the BW with $\phi_2 = 0$

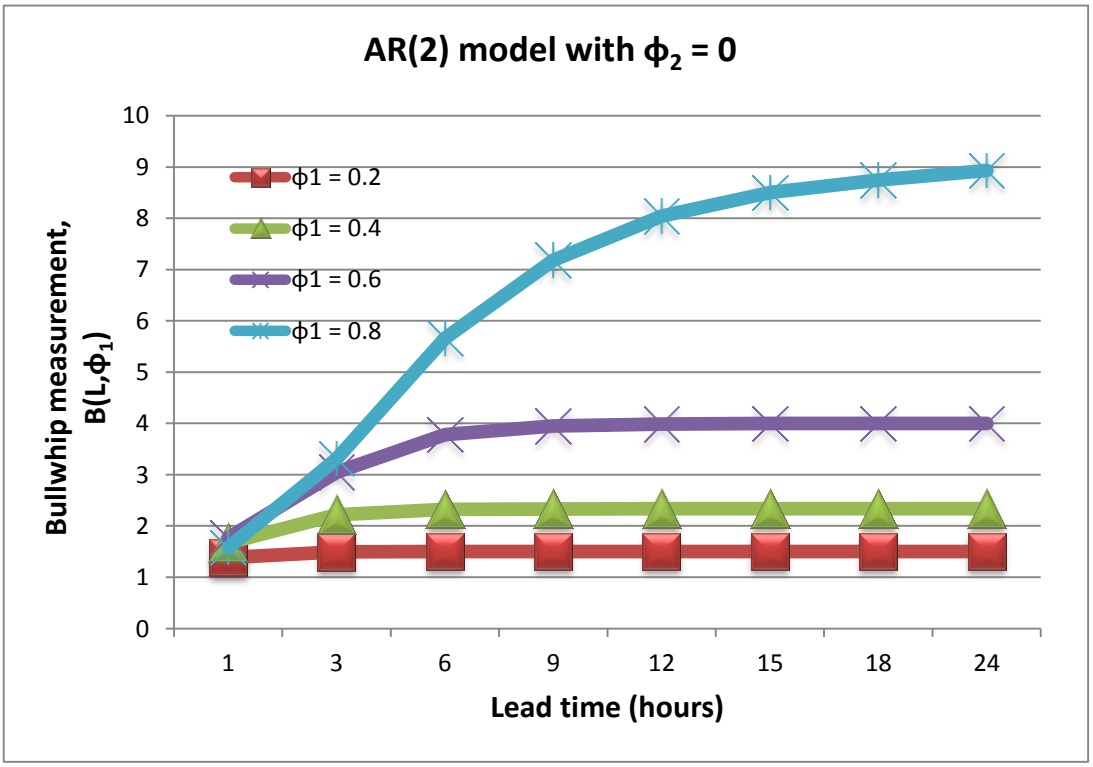


Figure 18: Demonstrating if AR (2) model can agree to an AR (1) model if one of AR parameters equal to zero ($\phi_2 = 0$) by increasing the lead time.

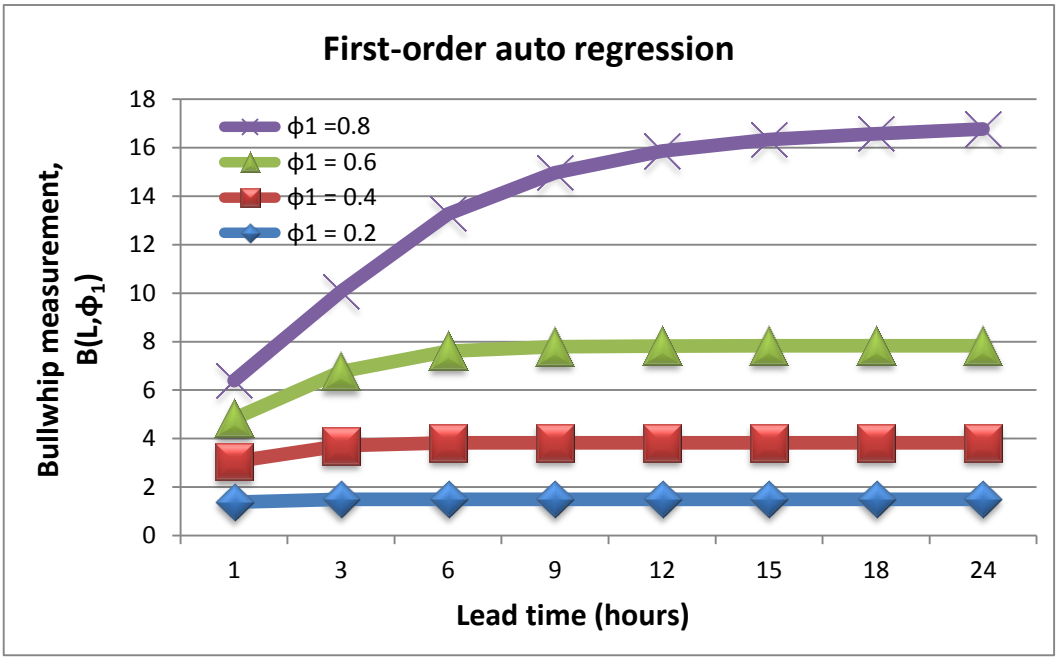


Figure 19: Illustrating BW by varying lead time for an AR (1) model

Additional to the above, when the second-order autoregressive coefficient is greater than zero units, it also holds true that the BW increases when the lead time increases, which is also evident in Luong et al. (2007b) paper. However, for negative values of ϕ_2 (example $\phi_1 = 0.6$ and $\phi_2 = -0.6$) , the above trend does not hold good and it can be noted from above as you increase the lead time from 1 hour to 24 hours (to a large L value) the BW does not exist.

As it can be seen from table 8 in section 4.4, for the case $\phi_1 = 0.6$ and $\phi_2 = -0.2$, when the L increases from 1 to 24, the BW increases first, then decreases, increase again and then stabilises at 2.00 and the minimised BW is found at L = 1. The same observation was noted in Luong et al. study for $\phi_1 = 0.6$ and $\phi_2 = -0.2$ (Luong et al., 2007b).

The explanation for the complex behaviour of the above is due to the fact that the relationship between D_{t-1} and D_t are positively correlated and D_{t-2} and D_t are negatively correlated in the demand pattern. However, due to the complexity nature of the BW measure, it is extremely difficult to identify the range of values for ϕ_1 and ϕ_2 in which the BW will have an inverse relationship with L.

This trend is not similar for other values of ϕ_1 values, in the case for $\phi_1 = 0.4$ and $\phi_2 = -0.2$, the BW decreases when L increases from 1 to 3 and then it decreases further as L increases from 3 to 6 and then stabilises as L increases from 6 to 24.

The higher BW measure implies a wide range in the order pattern, meaning that the production level has to alter more frequently, causing in higher inventory holding costs per period to meet production demand. Higher holding and backlog cost, thus inflating average inventory cost per period.

Figure 20 below, illustrates that using the current regression model, reducing the lead time will decrease the BW but will not completely eliminate it.

Taking into consideration the logistical aspect: ordering, despatching from the supplier and delivered to the plant in time, a reasonable lead time can be reached at 12 hours. There will be no harm during abnormal conditions to order excess provided that they get back to using the regression model.

Furthermore, reducing the lead time to 12 hours will result in an improvement of 12.6% in the BW. This does not equate to a big savings which the company is looking for. But there should be other initiatives that can be collectively adding value. Much more needs to be done to get more value add with an initiative.

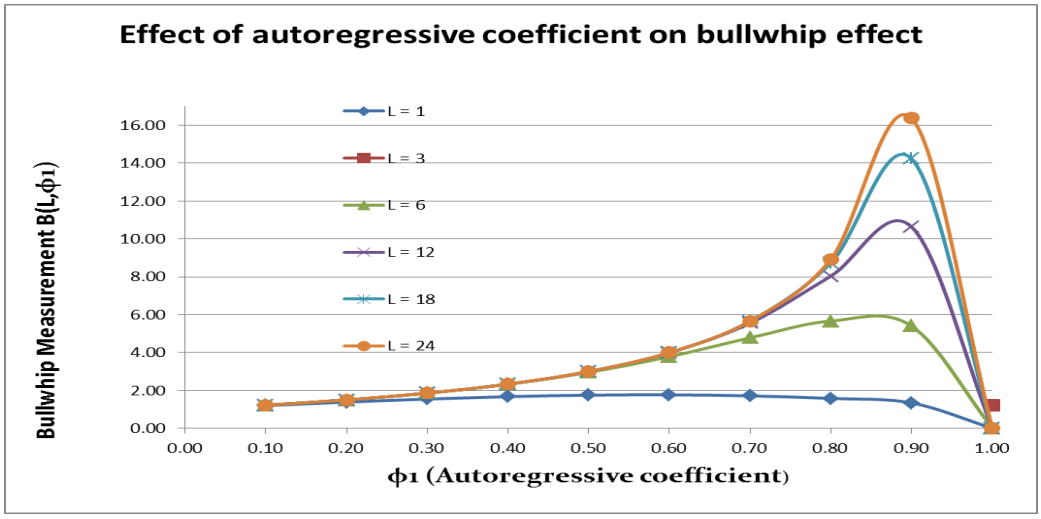


Figure 20: Illustrating the effect of the autoregressive coefficient on the BW when $\phi_2 = 0$

5.4 Evaluating the tools available for management to utilise

These research discoveries have important managerial associations. First, the results suggest that reducing inventories has a significant and direct relationship with financial performance (reducing throughput if not delivered in time). This provides strong validation for managers' continued emphasis on efficient inventory management and supply chain inventory levels.

Perhaps store managers have to seek out appropriate improvement programs applicable to their specific operations. Second, the importance of operational performance cannot be treated in isolation to the above when seeking out for improvement programs.

5.4.1 *Trade-off between bullwhip and inventory variance:*

So far the focus was on the BW putting more emphasis on the quantity order placed and the effect of reducing lead time. However, this addresses one side of the story. In developing a replenishment rule, the focus should also be on the impact on the inventory variance as well; because the variance will have an immediate effect on customer service which will be covered briefly in this report.

From table 18 and table 19, if one of the AR parameters is negatively correlated, the BW will no longer exist. This poses an accuracy and size problem with the model. The lower and upper confidence limits lie between the zero boundaries and the adjusted R squared is well below the actual model where both the AR parameters are positive.

Table 18: Regression statistics for an AR (2) model when one AR parameter is negative

Regression Statistics	
Multiple R	62.4%
R Square	38.9%
Adjusted R Square	38.7%
Standard Error	0.0602
Observations	639

Table 19: Adjusted R-Squared is almost halved when one of the AR parameters is negative, posing a size/ magnitude problem

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*
Intercept	1.606	0.125	12.84	0.000	1.360	1.852
D_{t-1}	0.711	0.039	18.12	0.000	0.634	0.788
D_{t-2}	-0.159	0.039	-4.03	0.000	-0.236	-0.082

To simulate an NSAmp for a second order AR is a challenge as there is insufficient work done on this subject to further investigates the impact with BW and NSAmp. However, there is work done on an AR (1) model which can be used to evaluate the first order AR. Nevertheless, for the purpose of this exercise and to better understand if the practical example agrees to theory, the NSAmp will be calculated for an AR (1) model and compared with a BW of the current first order parameters.

From theory, if the BW can be eliminated, this would reduce the amplification of inventory variance (NSAmp). This means that the inventory and switching costs are minimised because it is related to these variance amplification measures. An inventory variance increase will mark an increase in holding and backlog costs, thus inflating the average inventory cost per period.

Hence, taking into consideration the two following factors: 1.) BW which is correlated to the order variability and the switching costs, and 2.) net stock amplification (NSAmp) which is associated to investment in inventories and the customer service.

Instinctively, in a smooth ordering pattern the result is a high inventory fluctuation. Suppose an Independent (IID) demand, for a Ti (known as feedback gain) which is equal to 1.00 or $\beta = 1.00$, and a lead time of 12 hours, results in an NSAmp value of 13.00. If the lead time was agreed as per contract, L = 24 hours, then the NSAmp is 25.33 which is higher than the above. Hence, decreasing the lead time reduces NSAmp which is also evident in Disney et al (2003) paper. The longer the lead time means a smaller relative Ti value.

Smoothing with $Ti = 1/\beta$, $\beta = 0.50$ or a Ti = 2.00, reduces the BW measure to 0.33, and equivalent decreases the switching cost. Furthermore, this increases

the NSAmp measure to 13.33, together with an increase in inventory costs. In summary, the BW can be smoothened out but this comes at a price that is paying higher inventory fluctuations and more inventory costs.

These observation lead to: designing a trade-off between BW and customer service (as measured by net stock variance amplification). The question needs to be asked: to what extent can production rates be smoothed out in order to minimise production adaptation costs, without adversely increasing inventory costs (Disney and Towill, 2003).

Disney et al. (2004) demonstrates that when demand is IID (independent and identical distributed) and demand is forecasted with the mean, then the sum of the BW and NSAmp is minimised at Ti = 1.618 for all lead time. This can be seen as “the best of both worlds’ solution. This amazing result is termed the “Golden Ratio”. By adding values of the BW and net stock amplification metric, the assumption is that both factors are equally important. It is clear that companies apply weighted averages to their BW related costs and customer’s service related costs.

In this case the total cost curve may be different and be no longer the “Golden” optimal smoothing parameter. According to the cost associated with this study, the BW cost is the most expensive part, while the inventory cost is a much smaller part of the two. It is extremely difficult to estimate the switching cost because there is not much information out there to determine this value.

The total inventory cost for the current operating condition adds up slightly over ZAR 4.87 Million per annum. Approximately fifty nine (59) percent units of the total cost are attributed to stock-outs and the remainder is holding costs. By halving the lead time and extrapolating, this will add to a savings of 12.6 percent units and monetary value of ZAR 614 593.06 or ZAR 0.62 Million per annum. This amount is small compared to the switching cost and therefore more focus needs to be put into reducing the BW. But what can be said with confidence is that there is currently no equivalent proven substitute and equally reliable supplier to the current supplier for this reagent in South Africa, and the imported chemical does not satisfy the quality requirements for the process.

Chen et al. (2000b), pp. 271, demonstrated that SSLT will be greater than SS, i.e., using a time series data analysis; the stores will hold more safety stock to meet the target service level agreement. According to many authors, this behaviour is attributed to SS capturing only the uncertainty due to the random error (ε) and SSLT seizures this uncertainty and the uncertainty D_t^L (mean demand) which is calculated by $\check{D}_t^L$, in this case using the Luong et al. (2007b) forecasting method.

An advanced computational effort such as SCperf function will be required to simulate the different scenarios in order to compare the difference between SS and SSLT. The scenarios are as follows: 1.) vary standard deviation on demand process and lead time in order to determine the BW and the standard deviation of the demand forecast error. This cannot be shown in this research but it would be worthwhile looking at and comparing it to Chen et al. observation.

The safety stock value calculated for this research is the following:

- SS = 17.81 tons
- SSLT = 83.65 tons

This hold true with the findings to Chen et al. (2000b) and the explanation for this is already covered above.

The customer service level and fill rate equation proposed by Disney et al. (2003) will be used. There will be two scenarios investigated, 1.) Current lead time (L = 24 hours) and the other with half the lead time (L = 12 hours) while varying the BW measurement from 9.00 (which was the calculated BW measurement for the current study) to a BW = 0.03 (at Ti = 20.00).

The current customer service level agreement in this company, which is the fill rate, is calculated to be 100 percent units. In an ideal world, this target will be achievable but due to the complexity nature within the mining sector, more especially the external factors which is out of their control, it is exceptional to have achieved a number like that. It can be said that they understood their business risk associated with this chemical. A good number to use is 99.5

percent units, where 0.5 percent units will account for those unforeseen circumstance. The aim of this exercise is to illustrate how much BW removal can be achieved while maintaining a 99.5 percent units service level.

Using the service level agreement (herein after referred to as SLA) of 99.5 percent units and a BW of 9.00, this equates to an ‘a’ and NSAmp value of 4.99 and 3.78, respectively. Reducing the lead time from 24 hours to 12 hours, this equates to a BW of 7.86, using a SLA of 99.5%, the ‘a’ and NSAmp value is 4.37 and 3.00, respectively. This means the stores will carry 4.37 times inventory to meet their SLA agreement. This equates to a 20.6 percent units improvement in NSAmp and reduces their total net stock level from 428.6 to 187.9 tons. This reduction equates to a savings of ZAR 1.45 Million. If 428.6 tons of reagents were carried throughout the year and the required amount was 187.9 tons, an interest rate of six and a half (6.5) percent units per annum then the savings per year would be ZAR 1.54 Million.

From both lead times, it was found in table 20, that the BW can be reduced by 90 percent units (i.e. by setting Ti = 6.00 rather Ti = 1.00). This equates to a 35 percent units (5.35 - 3.47 = 1.88) and 41 percent units (4.98 – 2.94 = 2.04) of a period’s extra inventory by reducing the lead time from 24 hours to 12 hours, whilst maintaining a 99.5 percent units fill rate. This amounts to an increase in inventory by ZAR 0.97 Million (ZAR 969 235.81) and ZAR 0.53 Million (ZAR 527 030.45), respectively.

Table 20: Comparative analysis between two lead times in order to highlight the inventory cost of BW reduction

L (hours)	Bullwhip	Ti	NSAmps	Number of periods of inventory to ensure a 99.5% fill rate, a	TNS = a*μ = z* σNS (tons)
24	9.00	0.56	3.78	4.99	428.6
24	1.00	1.00	2.00	3.47	298.2
24	0.45	1.618	2.17	3.64	312.5
24	0.33	2.00	2.33	3.79	325.8
24	0.20	3.00	2.80	4.21	361.5
24	0.14	4.00	3.29	4.61	395.9
24	0.09	6.00	4.27	5.35	459.6
24	0.05	10.01	6.27	6.64	570.6
24	0.03	20.03	11.27	9.23	793.5
12	9.00	0.56	3.28	4.60	197.7
12	1.00	1.00	1.50	2.94	126.4
12	0.45	1.62	1.67	3.13	134.5
12	0.33	2.00	1.83	3.30	141.9
12	0.20	3.00	2.30	3.76	161.5
12	0.14	4.00	2.79	4.19	180.2
12	0.09	6.00	3.77	4.98	214.1
12	0.05	10.01	5.77	6.34	272.2
12	0.03	20.03	10.77	9.00	386.8

The next step was to evaluate the impact on operating at different service level agreement with respect to inventory coverage using two scenarios: 1.) lead time is 24 hours and 2.) lead time is halved.

Additionally, figure 21 below establishes that there is more benefit operating at a shorter lead time, reduced service level (F) and with a BW measure close to 1.00, which results in carrying less stock to maintain F. This can be illustrated by an example, If BW = 0.44, and comparing both lead times (L = 24 hours and L = 12 hours) F values, F = 85 and 90 percent units, respectively. The former F value corresponds to an “a” value are 1.22 and 0.95, while the latter one correspondence to an “a” value of 1.62 and 1.31, respectively. The former “a” value for the short lead time demonstrates less stock required to be carried in order to meet F = 85 percent units.

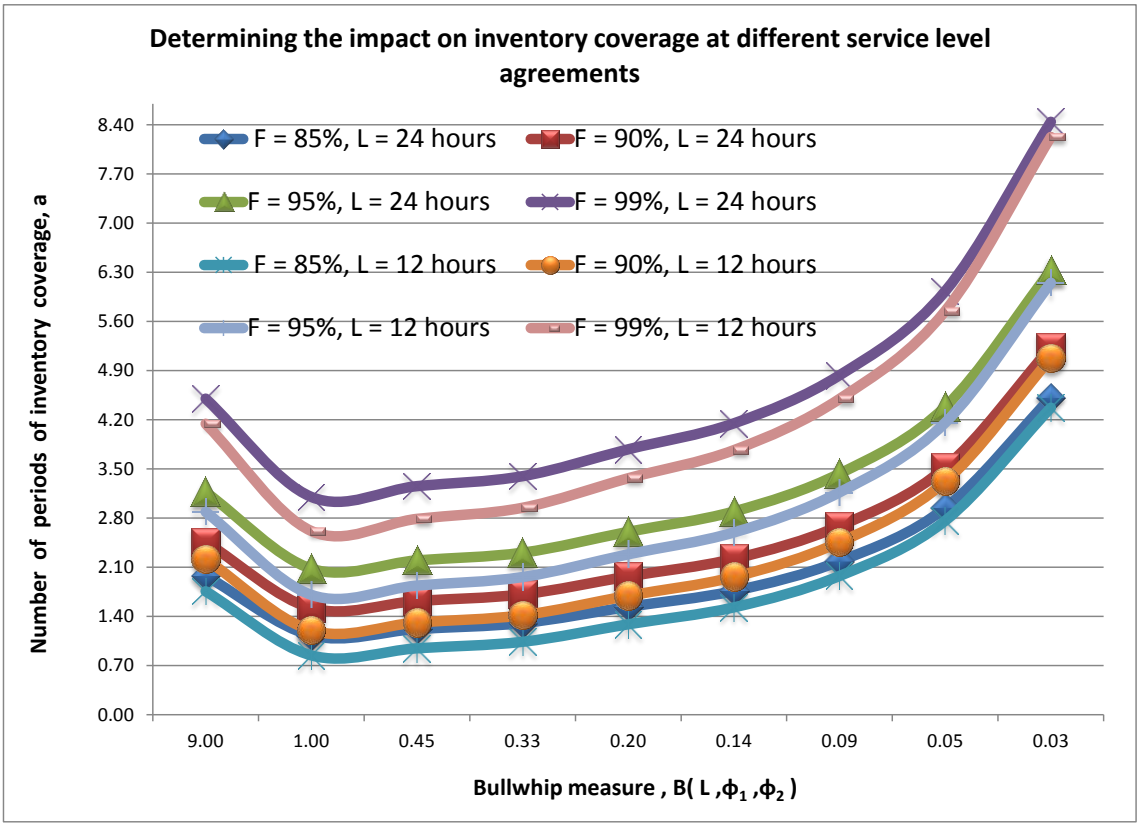


Figure 21: Determining the impact on inventory coverage at different service level agreements

The short lead time and reduced service level is a favourable one because this will reduce the amount of reagent that needs to be carried in order to meet F = 85 percent units. But with a plant as complex as this and most important this reagent can stop the production pipeline, in this case it would not be a feasible to move to a reduced service level agreement.

The inventory costs associated with operating close to a BW of one unit would be a strategic move, because the revenue lost due to stock outs is far more than the savings generated by operating at a lower service level.

The higher difference comes from the former one. This indicates that there is less stock carried for shorter lead time at the lower service level.

When comparing this with a higher service level agreement (F) rather than reducing lead time at operating at the same SL for both. For example, with a BW = 1.00, F equals to 90 and 95 percent unit and lead time of 24 hours, this

equates to a 27 percent units of a period's extra inventory and because the period coverage is higher than the shorter lead time i.e. with a BW measure of 1.00, SLA = 90 percent units, and a lead time of 24 and 12 hours respectively, with almost a quarter of a period's extra inventory (1.52 - 1.2 = 0.32).

The above example accounts for an increase in inventory accounts to a ZAR value of 289 418.71 when leaving the leading time constant and increasing SLA, whilst a reduction if you reduce lead time of ZAR 0.47 Million savings.

It can be illustrated that, most of the benefits can be derived from by merely improving the service level agreement, (i.e. for an F = 90 percent units and F = 95 percent units, with an L = 24 hours, this equates to an "a" value of 1.52 and 2.08, hence a 27 percent units of the extra inventory.

All of the above findings agree to theory proposed by Disney et al. (2003, 2004, and 2006).

5.4.2 *Trade-off between reagent stock outs and base metal production loss*

The total storage capacity of the reagent tanks is 1883 cubic metre (m^3), equivalent to 1400 metric tons. The tanks are level controlled on a level between 600 and 800 cubic metre (m^3) or 445.5 and 594 metric tons, respectively, this equates to a BW measure of 9.00.

From Figure 22, controlling at design capacity with no supply of reagents into the tank, the plant can operate for 390.5 hours or 16.27 days, with current lead time of 24 hours or 1 day, it makes business sense to operate at lower than design capacity. This equates to ZAR 7.88 Million [(16.27 days – 1day) x 85.94tons/hr x ZAR 6004.90/ton] worth of excess stock carried in the storage tank to its current consumption rate.

Operating between 600 and 800 cubic metres (m^3) or 445.5 and 594 metric tons, respectively, with an average of 700 cubic metre (m^3) or 519.8 metric tons, the plant can operate for 145 hours or 6.05 days without reagent. This value is

almost 6 folds higher than the current lead time consumption rate and a monetary value of ZAR 3.05 Million at a storage capacity of 594 metric tons.

Operating at a SLA of 99.5 percent units and halving the current lead time, BW measure is reduced to 7.86. This reduces the total net stock from 428.6 to 187.9 tons, which equates to an improvement of 56.2 percent units. The saving of inventory cost is ZAR 1.45 Million per period or ZAR 1.54 Million per annum.

If the total base metal production loss due to stock outs are brought into account, then the decision making changes. It can be seen from figure 23, the production loss is 8.74 times the throughput rate. It can also be seen the short outs has a greater impact on the financials of the company than the reagent costs. On this note, it is viable to carry extra stock but how much needs to be determined.

If the storage tanks are capped at 187.9 tons, this reagent can last for 2.30 days. Comparing the reagent's storage cost of ZAR 1.18 Million to a BM loss of ZAR 20.14 million if reagent is depleted for the same period, it would be viable to carry the extra stock. Furthermore, the production will pay off the extra stock within 3.23 hours of operation (1.18M/8.76M *24hours).

If the storage level is decreased from 428.6 to 197.7 tons, and an increase of reagent price year and year equivalent to inflation of six (6) percent units, inventory storage cost is three (3) percent units of reagent cost and inventory cost increasing with inflation, this equates to a net present value of ZAR 49.35 Million over 20 years with an interest rate of six and half (6.5) percent units.

Reducing the BW by reducing inventory can be a bad decision if there is an upset with reagent supply which would put the company at a production loss.

The company can suffer from production loss if there is an upset with the reagent supply by reducing the inventory and thus reducing the BW.

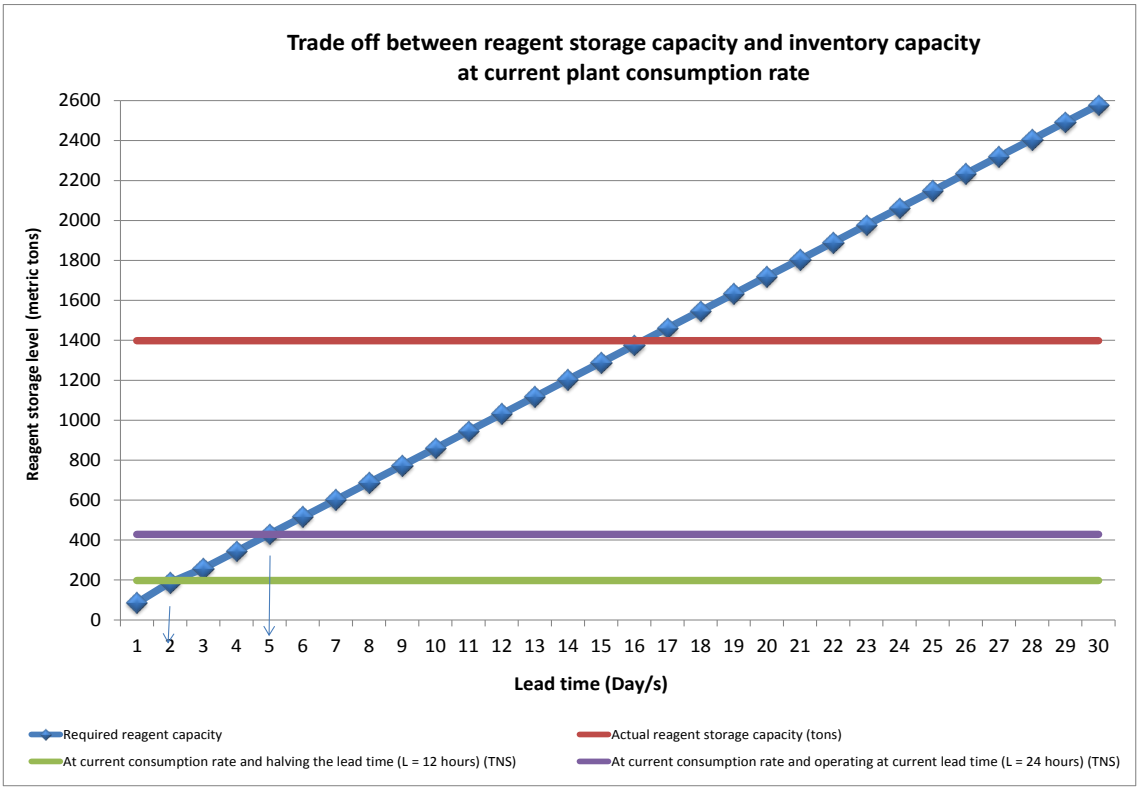


Figure 22: Trade-off between reagent capacity and current inventory capacity to minimise stock outs.

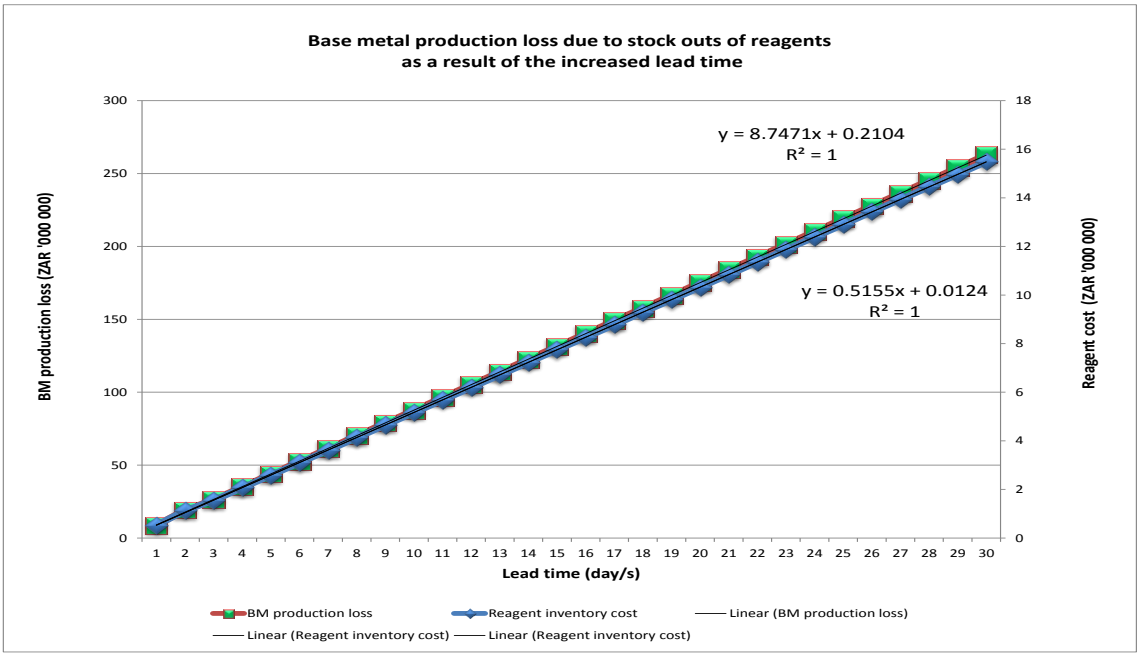


Figure 23: Base metal production loss due to stock out of reagent as a result of delivery delay

5.5 Summary of discussion section

5.5.1 *Summary of analysis of the bullwhip effect in the platinum industry*

Several theories exist around the AR (1) model but very little research has been done on AR (2) models. There seems to be signs of the bullwhip existing by the graphical representation of the BW.

The raw data has no signs of seasonality and the AR (2) model proposed by Luong et al. (2007) was used to quantify the BW.

The model was improved by allocating the planned shutdown value equal to the sample mean and logically it should decrease the normal demand rate when it operates normally. Furthermore, this was a planned task and the value during that period should not be added to your total consumption rate because the equipment was unavailable but the process was. Therefore the period of planned shutdown should be given a value equal to its sample average.

It improved the size and accuracy of the model by the following:

Table 21: Demonstrating improvement in accuracy and size by equating the planned shutdown total consumption amount to a sample average

	Improvement (%)
Skewness	51.6%
Kurtosis	95.3%
Standard Deviation	15.3%
Sample Variance	28.1%

After satisfying the size and accuracy issue of the model, there was a detail comparative analysis conducted between the two methods proposed by Luong et al. (2007a, b), AR (1) and AR (2) and select the one with the best fit and

accurate model to quantify and measure the cost implication related to operating with the BW.

The AR (2) model was found to be having the best fit and contributed to a four and a half (4.5) percent units improvement in the fit. It has the best fit and high level of accuracy which total to an improvement of 21.4 percent units.

It was found that the model satisfied the stationary requirements, enhancing the demand process forecast equation.

From the results, there is a linear positive correlation between yesterday's demand and today's demand. With a 95 percent units confidence it can be said that the average is 85.94 metric tons per day. There is evidence of short reagent demand causing a left skewness. This model adjusted R-squared is 52.5 percent units and is within acceptable limits when taking into consideration the nature of its business.

The value for fit is $4.7 * 10^{-104}$ which is below the value of 0.05, indicating it is significant at a level of 0.05. There is no evidence of high or low power influencing the statistics analysis, because the magnitude is big enough, correlation is neither tiny nor highly correlated between independent variables.

There is no sign of multicollinerity in the data as the VIF's value is lower than the threshold limit of 10.0, and there is no correlation between independent variables that is approximately 0.9 or higher.

The data follows a uniform linear shape and there are no potential outliers in the data. The residual plot of dependent variables suggests that there is no heteroskedasticity with the data. There are no potential distribution issues in the data although the data is slightly negative skewed with a value of - 0.56 and a slight positive kurtosis of + 0.1 but these values are within the limits that deem this data to a fit a normal distribution.

Both the graphical and statistically comparison of demand forecast against the normal distribution seems to indicate that the data does fit this type of pattern well. This means the mathematical model is a good fit and represents the data.

After data and model validation was completed, the BW was calculated using Luong et al (2007) procedure. For a first order AR, the BW was 8.32 while for the second order the value was 9.00.

The AR (2) model equation is:

$$\mathbf{D_t\,(Y) = 0.814 + 0.562\,D_{t-1} + 0.211\,D_{t-2}} \qquad \mathbf{(26)}$$

5.5.2 *Summary of the analysis of the financial implication of the bullwhip effect*

After developing the second order AR equation, the impact of these parameters where investigated in order to understand how it would impact on the BW if any one or both of the AR parameters is positive or negative.

It was found using the AR (2) model and varying AR parameters, the BW effect can and cannot exist at certain conditions, and it becomes complicated to determine the BW. For both negative AR parameters, the BW does not exist.

When one of the AR parameter is absolutely a small value, then the BW exist but it gets complicated when one of the negative values increases.

BW exist when one of AR parameters is positive and the other greater or equal to zero units. The larger the AR parameter and smaller the lead time, the BW exists.

The lead time increases as BW increases for an AR (1) model. The similar behaviour is noticed on an AR (2) model when one of the parameter is equal to zero units.

5.5.3 *Summary of the evaluation of the tools available for management to reduce the bullwhip effect*

When either of the AR parameters is negative, resulting in no BW, however this poses a size and accuracy problem.

When Ti is 1.0 and lead time is 24 hours, the NSAmp is 25.33, halving the lead time, the NSAmp value is reduced to 13.00. When increasing the Ti to 2.0 and using current lead time, this equates to a BW of 0.33 and this reduces the switching cost, however this increases the NSAmp value to 13.33.

Decreasing the lead time reduces NSAmp. The BW can be smoothed out but it results in high inventory fluctuations and more inventory costs. However, the trade-off between NSAmp and BW was found by Disney et al. (2003) at a Ti value of 1.618 for all lead time. This is known as the “Golden Ratio”.

For this research the total inventory cost was calculated to be around R4.87 Million per annum. Halving the lead time, has contributed to savings of 12.6 percent units.

The SSLT and SS for this study agrees to Chen et al. (2000b) and this means the stores carries excess stock to meet target service level agreement. Furthermore, they have an excellent customer service level, calculated to be 100 percent units.

The setting of the feedback gain from six (6) to one (1) unit, has reduced the BW effect and reducing the lead time further decreases the inventory coverage, whilst maintain the agreed service level of 99.5 percent units.

There were more benefits noticed with a short lead time and reduced service level agreement and with a BW measure close to 1.00. However, this is not a viable business model to adapt because this increases the likelihood of stock outs which will have a negative impact on the financials of the company.

Thus, reducing inventory has a significant and direct relationship with financial performance. It cannot be inconclusively said that there is a misalignment between the production department and the supply chain but what can be said from the results is that there is a huge gap between the ordering patterning and the demand rate.

Operating with the current storage capacity, the reagent can last for approximately 16 days, which equates to ZAR 7.88 Million of excess stock

carried. There is a 56.2% savings (ZAR 1.54 Million per annum) in inventory cost by reducing the BW by reducing lead time and operating at a SLA of 99.5 percent unit.

Using the current throughput and storage levels the reagent can last for approximately 6.05 days, equating to an extra inventory of ZAR 3.05 Million per day. The comparison between stock outs due to faulty instruments, no or low supply of reagent is detrimental on the financial of the company.

Proper control and managing the low stock levels can reap a net present value of ZAR 49.35 Million over 20 years.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

The bullwhip exists in AAPLC and this has financial implications attached to it. This section will summarise all the findings and conclude on the findings.

6.2 Conclusions of the study

In this research, a simple supply chain with one retailer and one supplier in which the retailer employs base stock inventory policy was studied. The stores and plant data had no correlation between them.

The BW measure is developed for a second order auto regressive demand process by Luong (2007b) and then the extension for the general autoregressive model was considered on the reagent in study.

All models provided good estimates for the reagent demand forecast. However, forecasting analysis of reagent consumption between 1 May 2012 and 31 January 2014 indicate that an AR (2) model is the best fit and is the recommended model to forecast reagent consumption for the plant. The AR (2) model:

$$\mathbf{D_t\ (Y) = 0.814 + 0.562\ D_{t-1} + 0.211\ D_{t-2}} \qquad \mathbf{(27)}$$

It can now be used to predict daily reagent consumption and use that amount to reduce quantity ordered.

From the numerical calculation of the BW, it can be concluded that this phenomena exist in the platinum industry. This contributed to a net stock amplification value of 3.78, which equates to inventory coverage of 4.99.

The numerical results for the second order autoregressive demand process show that autoregressive coefficients and lead time have a great impact on the

BW. The first auto regressive is large while the second auto regressive is small but both are greater than zero units, thus reducing the impact of BW.

When both first and second order auto regressive coefficient are both positive, the BW exist and it will increase as lead time increases. However, when the first or second autoregressive coefficient is negative, the behaviour of the BW gets complicated and the same increasing trend of BW with increasing lead time is not evident.

The financial cost attached to the current BW indicates that the inventory cost reduction alone will not be a substantial savings if the BW is not reduced further. It is clear that the greatest benefit can be achieved by reducing the switching cost (which means reducing the BW if possible eliminating it completely) and this will reduce the inventory cost substantially.

When the relationship for any of the parameters is negatively correlated, BW does not exist, however the model does not satisfy the size and accuracy criteria.

When reducing the lead time, this results in reducing the BW, hence reducing the NSAmp and this is in agreement with the literature. The smoothening out of the demand pattern can result in substantial savings in cost, not only on switching cost but also inventory cost.

But smoothening out the BW comes at a price, more especially on inventory fluctuation costs. There is trade-off between BW and customer services. The switching cost is enormous for any company.

An interesting finding is that the stores are holding more stock to meet target service levels which also holds for this study. By reducing lead time, you can reduce BW by 90 percent units but it would compromise on the period’s extra inventory, in order to meet the service level target.

However, reducing lead time and the service level agreement will definitely reduce the BW and thus result in carrying fewer inventories on hand. In a business environment, this is not a favourable practice because this can cause

negative repercussions on the profitability of the company as throughput has to compromise, this also holds true for Anglo.

Reducing inventory costs associated close to the BW of 1.00 is a strategic move rather than settling for a lower service level agreement.

Focusing on the inventory and switching cost, there are huge amounts of savings that can be achieved by simply strengthening your ties with your key strategic stakeholders in the aim to reduce cost.

There are huge amounts that can be saved such as ZAR 49.35 Million over 20 years by simply doing the above rather than diverting your attention on the costly job cuts in order to be profitable and sustainable.

6.3 Recommendations for Management

The AR (2) model was the best model that is available in literature and it can be used effectively to Anglo needs. On the other hand, the strict following of a theoretical model is not often feasible and could cause damage in some business environments. This reality requires flexibility. Mechanical use of such a model might even result in business failure.

For example, if the incorrect demand rates were recorded due to human or even instrumentation error, this will result in an inaccurate demand forecast using the equation highlighted in the section above. If the demand forecast value is much less than the actual demand, this can result in huge amounts of revenue loss due to short outs resulting in the production line shutting down.

Therefore this model should be used con-currently with the aid of production personnel, more especially those who are close to the process. Exclusive and robust systems are available in the market that can proper model your demand process for your reagent, however, the traditional MS excel can do almost the same at half the price.

The equation that was developed for Anglo’s demand process can be used for their current throughput but this model does not cover higher base metal

throughput (production), however, with the same methodology and with sufficient data points the demand equation can be recalculated. This information is extremely important in order to reduce inventory and switching cost more especially when this reagent is only produced in abundant by one supplier which they are currently in contract with.

Additional, the supply chain must source other reagent suppliers so that it can put the company at a competitive edge to its competitors. This can take place by putting out tenders to potential suppliers using their vendor system. I request the commodity manager at supply chain to look at this as soonest as possible as the plant is busy ramping up and will need more than what the main supplier can supply them.

They are signs of short demand of reagent and this can cause the BW to develop and the recommendation to this is to align your ordering pattern with the demand pattern by continuously sharing information between supply chain and the production department (production and capacity planner). This will remove the periodic surges in quantity ordered by stores and thus improve the forecast technique for forecasting. This will also aid to remove the negative skewness in the data and prevent the mean to shift more towards the left side of the normal distribution, thus improve your accuracy for the AR (2) model.

The strengthening of relationships with the supplier and the production department and using the demand forecast model concurrently will ensure that there will be no reports on stock outs or carrying excessive quantity of reagent. This strategic alignment of supply chain with production and the supplier will add great value more especially on switching costs.

There are huge savings in inventory costs with reducing lead time. I recommend the company approaches its supplier to amend their contract to reduce lead time by half which is a reasonable request.

The company must continue monitoring their service level agreements as per company’s policy and keep their excellent customer service. If the company continues their good work, they will for sure remove the risk of stock outs which can be detrimental for the company’s financial status.

Once the plant ramps up to design capacity, and into two years on design operating parameters, then this study needs to be relooked at to accommodate the increase in production rate as this is a product efficiency measure.

Therefore my recommendation is to utilise this tool to strengthen their relationship with the key strategic stakeholders in the aim to reduce cost. There are huge amounts that can be saved by simply doing this rather than diverting their attention on the costly job cuts in order to be profitable.

The NSAmp simple calculation is not readily available in literature and it would add more value if the true value is calculated using the correct order of AR. For this exercise, it was assumed the first order NSAmp value is similar to the second order NSAmp. For any business to be the leader in mining, processing and marketing platinum group metals will ensure they understand their cost attached to carrying excessive stock and stock out.

Therefore my recommendation is for management to review their NSAmp true cost when the NSAmp equation for an AR (2) becomes available.

The company needs to understand its risk slightly better by evaluating its switching cost with this reagent if it still wants to be the leader in its industry. This study might be done but circumstance and operating environment changes radically so it is of good practice to review business risks often. Once this amount is calculated, the company needs to mitigate this risk by fostering a good relationship and good collaboration between its current supplier and plant to reduce the switching cost associated with the BW.

There are many tools which can aid management to reduce lead time and supply chain cost, tools such as Just in Time (JIT), Quick Response (QR), and Efficient Consumer Response (ECR), Work in Process (WIP), Finished goods (FGI). However, these assume volatility is present. In order to manage demand means smoothing it out by removing the volatility prior to process planning.

The first tool is not realistic in the mining company as it cannot be phased out to all their suppliers because most of their goods are imported and their OEM’s are based out of the country. However, WIP and ECR, and QR can work effectively

for AAPLC. Therefore I suggest supply chain to look at one of these methods to control or manage the BW effect.

Another recommendation for the operation is to review their reagent stock levels. During this study the total stock levels were between 600 to 800 m^3. With an average BM revenue per hour the plant generates (ZAR 364 880) with ramp up flows of approximately 102.73 tons per day, with an availability of 88% to achieve to 33 kilo tons per annum (Ktpa) of nickel equivalent, equating to a nickel production rate of 4.28 metric tons per hour.

If the last five years inflation rate is about six (6) percent unit and assuming the reagent goes up by that amount year to year. The reagent inventory cost is approximately three (3) percent unit of the total reagent price, and then the reagent average price will be ZAR 6004.90 per metric ton.

Decreasing the inventory from 428.6 to 197.7 tons will not only reduce the BW but it will provide a NPV of ZAR 49.44 million over 20 years. The risk associated with reducing inventory can be enormous in terms of production loss due to stock outs but if the company can tender for more than two vendors this will reduce the businesses risk and thus put them in a competitive edge. I therefore recommend the company seek out tenderer for this reagent and reduce their stock levels.

Trade-off between BM production loss and reagent cost can be effectively resolved by strengthening ties between their entire supply chain. By collaboration between the relevant suppliers and consumer and finding alternative reagent supplier can minimise the company's risk.

An old plant such as the base metal plant has been optimised over the years and more especially the reagent in this study has been here since the plant was started up. The company will have to move away from using this expensive and highly corrosive reagent. It needs to substitute with an alternative one which is not only cheaper but also less harmful to its people and equipment. This will require a change in mind-set moving from an optimise environment which can be done but has limited benefits and not sustainable in the long term to one of innovation.

This innovation has to be filtered from the top managers going down and this can be brought about by awarding employees with the best innovation. It is currently performed at Anglo American but with little or no benefit to the company. In the banking sector, this innovation initiative has saved companies millions in spending on research and development. I recommend that top management should relook into their innovation initiative and try to change it to extract more shareholder value.

There are substitute or reagent in the market which is cheaper and less corrosive, and more process efficient than the current one. This substitute reagent, magnesium hydroxide is unproven technology in the mining process stream, therefore I recommend the company to test this out and conduct a feasibility study on this new reagent.

After testing it and there are benefits, then the research department should design a process that would be able to treat this new reagent without adversely affecting the recovery and quality of the desired metals. If this technology is proven on a pilot scale, I further recommend the company to roll it out to its existing process to extract more shareholder benefit.

6.4 Suggestions for further research

As mentioned in previous chapters, in this research, the trade-off between bullwhip and inventory variance was investigated above, but it would be useful to go further and investigate this impact on customer service, in order to measure if the variance is high. It would provide vital information to the end user and the relationship between excess stocks carried to meet customer service and their required target level. By understanding this parameter, the user will be well equipped with measuring his service level agreement, which is a popular customer service measure (Disney et al., 2006).

Companies who want to gain the competitive edge strive to understand their supply chain from start to end. Those organisations strive to seek knowledge on their inventory cost against the service level agreement related to the existing BW (if it exist) in order to find ways to reduce their cost structure. If it does exist,

they would like to understand where their trade-offs are between inventory cost and bullwhip measure and compare it to their service level agreement target.

For them to measure this, they would require advance computational software such as SCPerf to simulate these scenarios. After extracting this information and evaluating the different scenarios they can choose their “Golden Rule” where they would like to operate in and where they seek the most benefit in cost reduction (by dampening their cost impact). From the service level factor, this demonstrates the probability that customer demand is met from the stock. From that a fill rate can be calculated, which measures a fraction of the demand that is immediately fulfilled from the inventory on hand.

This would be a useful and valuable study to pursue and the future researcher can look into it and provide the value add to the company by choosing the system that is tailored made for them.

The same study can be repeated to determine the switching cost and the NSAmp for an AR (2) model when it becomes available, the true costs can be appreciated more if this exercise is done.

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APPENDIX A

Table of Equations:

$$\frac{\mathrm{Var}(q^k)}{\mathrm{Var}(D)} \geqslant \prod_{i=1}^{k}\left(1+\frac{2L_i}{p}+\frac{2L_i^2}{p^2}\right). \quad (1) \ldots 20$$

$D_t = \delta + \phi_1 D_{t-1} + \phi_2 D_{t-2} + \varepsilon_t$ (2)..... 22

$\boldsymbol{\delta 1 - \phi 1 - \phi 2}$ (3),..... 22

and $\boldsymbol{\sigma 21 - \phi 1\ 2 - \phi 22}$ (4), respectively..... 22

$\check{D}\mathbf{tL} = \check{D}_t + \check{D}_{t+1} + \ldots + \check{D}_{t+L-1} = \mathbf{i = 0L - 1\check{D}t + i}$ (5)..... 22

$\check{D}_{t+l} = E[D_{t-i}/D_{t-1}, D_{t-2\ldots}]$ (6) 22

$\check{D}\mathbf{tL} = \delta\ \boldsymbol{i = 0L - 1A0(i)} + D_{t-1}\ \boldsymbol{i = 0L - 1A1(i)} + D_{t-2}\ \boldsymbol{i = 0L - 1A2(i)}$ (7) . 23

Where $\boldsymbol{A1(0) = \phi_1}$, $\boldsymbol{A1(k) = \phi_1 A1(k-1) + A2(k-1)}$; $\boldsymbol{A2(0) = \phi_2}$, $\boldsymbol{A2(k) = \phi_2 A1(k-1)}$; $\boldsymbol{A0(0) = 1}$, $\mathbf{A0(k) = A0(k-1) + A1(k-1)}$ (k = 1,2,….,i) (8)..... 23

$= VAR\,(D)\,(1-(\phi_1^2+\phi_2^2))\,[1+\mathbf{i = 0L - 2} * (1+\mathbf{i = 0L - i - 2A1(j)})^2]$ (9)..... 23

$\mathbf{VARqt = VARD * 21 - \phi 1 - \phi 21 - \phi 2}\{(\mathbf{i = 0L - 1A1(i)})\,(\mathbf{i = 0L - 1A1(i)} + \mathbf{1}) + (\mathbf{i = 0L - 1A2(i)})^2\} + 2(\phi_1 - \phi_2)\mathbf{1 - \phi 1 - \phi 21 - \phi 2}\ (\mathbf{i = 0L - 1A2i}) - \mathbf{2}\ (\mathbf{1 - 2\phi 1 + \phi 12 - \emptyset 221 - \phi 2})\ \mathbf{i = 0L - 1A1i}(\boldsymbol{i = 0L - 1A2i}) + \mathbf{1}$ (10) 23

$\boldsymbol{i = 0L - 1A2i}) - \mathbf{2}(\mathbf{1 - 2\phi 1 + \phi 12 - \phi 221 - \phi 2}(\ \boldsymbol{i = 0L - 1A1i})\ (\boldsymbol{i = 0L - 1A2i}) + \mathbf{1}]$ (11)..... 23

$C_t^{INV} = C_h . NS_t$ if $NS_t > 0$ (12) 24

$C_s . (- NS_t)$ if $NS_t < 0$ (13) 24

$C_t^{SW} = C_{SW} . |\ q_t - q_{t-1}\ |$ (14) 24

NSAmp = **Variance of net stock Variance of demand** (15) 25

NSAmp = L + (T_i^2 *BW) (16)..... 25

$\boldsymbol{\beta = 1(2Ti - 1)}$ (17) 25

SS = z σ_d L **(18)** 26

SSLT = z σtL **(19)**..... 26

$$\sigma_{NS} = \sigma_d * \sqrt[2]{1 + L + \frac{(Ti-1)^2}{2Ti-1}}$$ **(20)** 27

$$\text{Fill Rate} = 1 - \frac{expected\ volume\ of\ backorders}{expected\ demand} = 1 - \frac{\sigma_{NS} * E(z)}{\mu_d}$$ **(21)** . 27

$$P = \Phi \sqrt{2 \ln \frac{1}{\sqrt{2\pi}} \quad \frac{M}{H}}$$ **(22)** 27

$$TNS = a*\mu = z*\sigma_{NS}$$ **(23)**..... 28

Basket Price (ZAR/ton) = Mass of nickel produced * Market price of nickel + Mass of copper produced * Market price of copper + Mass of cobalt * Market price of cobalt **(24)** 29

D_t (Y) = 0.814 +0.562 D_{t-1} + 0.211 D_{t-2} (25)..... 67

D_t (Y) = 0.814 +0.562 D_{t-1} + 0.211 D_{t-2} (26)..... 84

D_t (Y) = 0.814 +0.562 D_{t-1} + 0.211 D_{t-2} (27) 87

APPENDIX B

Nickel market price for the last five (5) years:



Sourced from: http://www.infomine.com/investment/metal-prices/nickel/5-year/

Average Nickel price for last five years = ZAR 158.00 x 1 000 /ton

Copper market price for the last five (5) years:



Sourced from: http://www.infomine.com/investment/metal-prices/copper/5-year/

Average Copper price for last five years = ZAR 62.5 x1 000 /ton

Cobalt market price for the last five (5) years:



Sourced from: http://www.infomine.com/investment/metal-prices/cobalt/5-year/

Average 5 year cobalt price = ZAR 295 * 1000/ton

APPENDIX C

South African inflation trend for the last five (5) years:

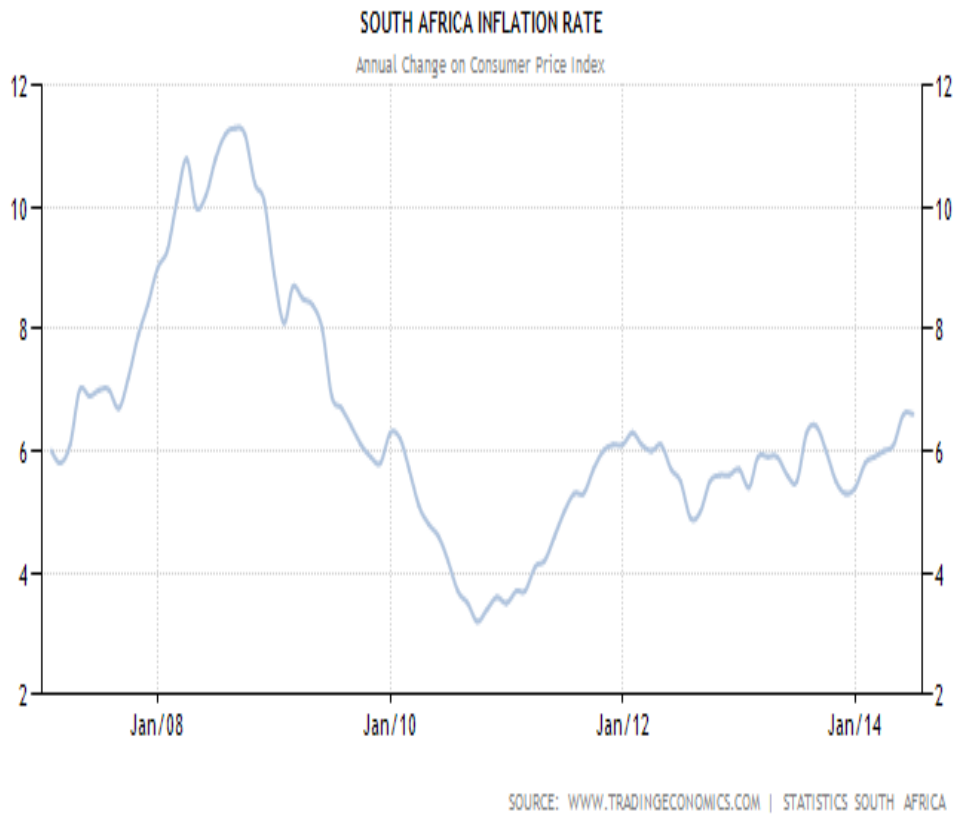

Figure 24: South African inflation rate for the last five (5) year

APPENDIX D

Table 22 Demonstrating the average metals produced per year in tons

Metal	NCM (tons/hr)	PVL (tons/hr)	Total production per annum (tons)	BM split
Nickel	2.97	0.46	26441.46	56.89%
Copper	2.42	0.14	19798.71	42.60%
Cobalt	0.02	0.01	239.38	0.52%
Total	5.42	0.61	46479.55	

Table 23 Calculating basket price for base metal produced at Rustenburg Base Metal Refinery (RBMR):

Metal	**Average BM produced (tons/annum)**	**Average market price per ton**	**Revenue generated per annum (ZAR)**	**Revenue generated per hour (ZAR)**
Nickel	13557.64	R 158 000.00	R 2 142 106 732.15	R 277 878.10
Copper	10151.62	R 62 500.00	R 634 476 515.21	R 82 305.48
Cobalt	122.74	R 295 000.00	R 36 207 772.38	R 4 696.94
Total	23832.00		R 2 812 791 019.73	R 364 880.53