

A Design Architecture for SMART Business Processes

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Executive Summary

This project entails the design of a SMART business process architecture to investigate how such a process can make intelligent decisions based on mathematical principles. Together with concepts of adaptive control, this design architecture is then applied to inventory management in a wholesale environment to deliver an ordering policy.

A SMART business process is objectively intelligent as it can adapt itself continuously in a reaction to external changes. Through its application within a decision making process, this design architecture will attempt to reduce most human error, which is a problem when addressing inventory management problems.

A Literature study is compiled to research current applications of SMART business processes, adaptive control principles and inventory management techniques. The study is concluded with the chosen techniques to be applied in this project.

As application, the fulfillment process of a wholesaler is investigated. This process entails placing an order at the depot, delivery to the wholesaler and then order shipment to the client. Data gathered from the wholesaler is used to simulate this process as a SMART self-adaptive model. Together with inventory management techniques, the model will deliver a mathematically validated ordering policy at which customer experience will be enhanced.

Through the application of the chosen techniques, this project aims to prove the proficiency with which one can make mathematically validated decisions regarding ordering policies, safety stock levels, product availability and cash to be kept on hand.

Results from the model are analyzed to understand the output of the model as well as investigate further possible elaborations.

This project attempts to indicate how informed and validated decisions can deliver a proposed solution to an age-old problem of inventory management.

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Chapter 1

Introduction

1.1 SMART business processes

The concept of SMART business processes will be investigated to show how the application of these processes within inventory management can deliver a dynamic ordering policy. Furthermore, the aim is to deliver a design architecture that can not only be applied in an inventory environment, but also in any other business environment. The essence of a SMART process is explained by Kirchner and Marz (2002) as follows: “*These systems can recognize important changes in environmental conditions, simulating their effects and making suggestions for an optimized reorganization.*”

The application of SMART items is proliferating to such an extent that SMART homes have been built with a system that will operate heating, lighting, and household appliances as documented by Chapman and McCartney (2002): “*... how SMART technology might enhance independence, quality of life, security and affordability. They want a home that can respond to emergencies and environmental changes.*”

The importance of SMART business processes in future global innovation is confirmed by Allmendinger and Lombreglia (2005) as follows: “*Soon, it will not be enough for a company to offer services; it will have to provide SMART services. To provide them, you must build intelligence - that is, awareness and connectivity - into the products themselves.*”

Further, Lee (2003) states the following: “*A new thinking paradigm to integrate predictive intelligence for manufacturing systems is becoming a new benchmark strategy for manufacturing companies to compete in the twenty-first century.*”

SMART business processes are thus on the forefront of future technologies and it is imperative that businesses integrate SMART business processes into their current business processes.

As application for SMART business processes, inventory management will be used to demonstrate the proficiency with which the decision making process can be improved by means of a SMART business process. Inventory management, is more often than not, addressed by subjective and non-scientific decision making which irrevocably implies that un-informed decisions are made. This project aims to investigate whether an inventory management problem can be solved by implementing SMART business processes together with

adaptive control principles to deliver a SMART, objective ordering policy, aimed at eliminating human error as far as possible.

1.1.1 Context of SMART business processes

To understand where a SMART business process fits into the business process, or at what stage a business can start to implement the concept, the Business Process Maturity Levels need to be investigated. According to these levels, as shown in the figure below, SMART business processes are allocated to the highest level of maturity, implying that a SMART process is implemented in addition to an optimized process. Thus once a process has been optimized, strategic planning can lead to the implementation of a SMART business process. The integration and implementation of intelligent decision making in addition to optimization, will lead to a new level of maturity in the business process.

As depicted in the figure below, at the fourth level of maturity, a process is managed, which means processes are quantifiable within measurable limits and one can predict trends in quality to a certain extent. Once this level of maturity is reached, one can start optimizing the process. This entails continuous improvement of the process and eventually these improvements become managed as ordinary business activities. Once this level of maturity has been reached, one can start to design a SMART business process.

The creation of a SMART business process within the ordinary business process is described in the next section.



Figure 1.1: Business Process Maturity Levels

1.1.2 Creating a SMART business process

To create a SMART business process within a current business process, one must start with an analysis of the current operations. Thus what do the current operations entail and are these operations meeting the customer's needs. A design architecture for a SMART business process is then integrated into the strategic planning of the company, which will naturally affect the tactical process. In other words, the SMART process is designed to meet customer's unmet needs and this naturally affects long term goals, which again should be evident within short term planning (the tactical process) and evidently affects the operations department.

The sensor network is where the process notices the change in the process. In a chemical application for instance, this could be the noticing of a change in the composition of a fluid. In the context of this project it will be a discrepancy between the instantaneous inventory level and the desired inventory level. The sensed variation will be noted within the data storage section. An analytical process will then adapt the process accordingly and this adaption will affect the tactical process. In the context of the problem, the adaption will affect the amount ordered from the depot, thus increasing or decreasing the instantaneous inventory level to a more desired level.

This process is thus followed once a business process has reached an *Optimized* level of maturity, after which one can start strategic planning for an intelligent, self-adapting process.

This process is depicted in the figure below:

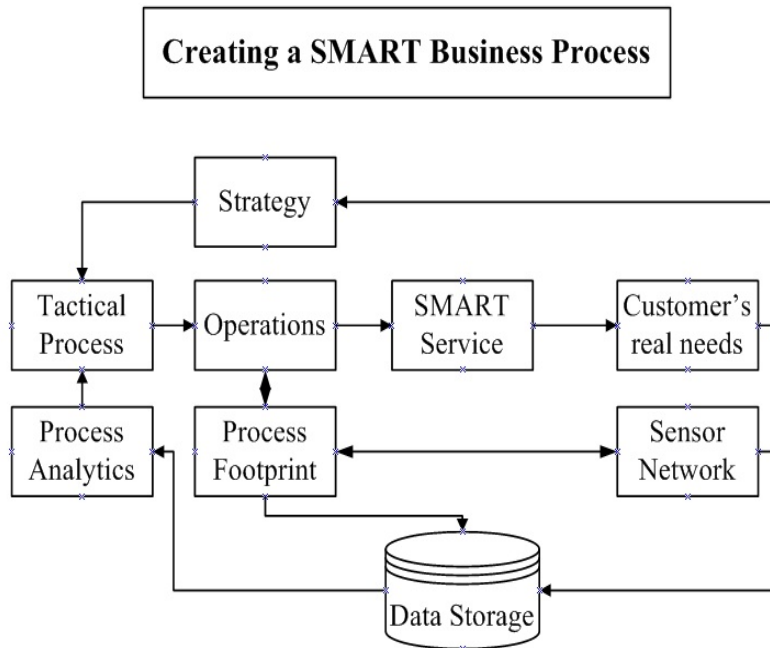


Figure 1.2: Creating a SMART business process

1.2 The Importance of Adaptive Control

An Adaptive Control Process is one that can analyze its parameters based on the necessary intelligence. Then the system can adapt the parameter as a new input to achieve and maintain an optimal process while taking certain target levels into consideration. The importance of self-adaption is described by Forrester (1961) as follows: “*Systems of information feedback control are fundamental to all life and human endeavor, from the slow pace of biological evolution to the launching of the latest satellite. A feedback control system exists whenever the environment causes a decision which in turn affects the original environment. In business, orders and inventory levels lead to manufacturing decisions which fill orders and correct inventories.*”

Adaptive control models will be researched and the appropriate model will be chosen to create the logic of the self-adaptive feedback loops. The model will then be built by using iThink software, creating a simulated environment in which one can repeatedly test and validate alternatives. This simulation allows one to find the optimal ordering policy while taking into account parameters such as cash-on-hand, availability of products and safety stock levels with certain target levels in mind.

An adaptive control process is depicted in the figure below.

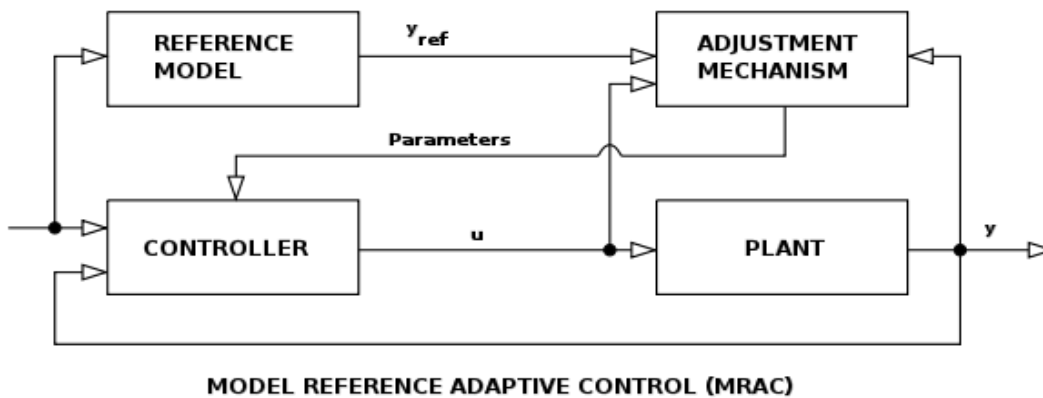


Figure 1.3: An Adaptive Control Process

Chapter 2

Literature Review

The Literature Review conducted is divided into three different research areas which comprise of inventory management, SMART business processes, as well as existing adaptive control models.

2.1 Existing Inventory Management Solutions

Research done concerning inventory management is to be integrated into the model for the calculation of certain parameters and will not be used as a solitary technique in finding the ordering policy. The only two techniques applied are forecasting and Economic Order Quantity (EOQ) models.

2.1.1 Forecasting

By forecasting the future demand, one can establish an idea of how much stock will be needed to satisfy the need of your customers. Forecasting will thus only be an indication of the future demand and will not take into account parameters such as safety stock to be kept on hand, when to order what and in what quantities. In the project model, forecasting will be integrated in addition to adaptive control techniques. The forecasting section will assist in reading the trends of the customers within the model to determine the desired level of inventory to be kept at any point in time.

Described below are a few applications of forecasting techniques as applied within inventory management.

Forecasting models can take into account seasonal and cyclical trends which will be valuable if demand is very unstable and relatively unpredictable. Fildes and Beard (1992) states that two conclusions follow for forecasting series such as these. The first is that there is little point in attempting to establish the "best forecasting model" for a particular series without considerable analysis of its stability over time which means one needs large amounts of data gathered over a long period of time and the analysis of these trends will be time consuming, and in that event such an approach might well prove unprofitable.

Trend forecasts applied to the determination of ordering policies in supply chain management systems often seem to exacerbate periods of shortage and oversupply, sometimes referred to as the bullwhip effect as explained by Padmanabhan et al. (1997). Further, Saeed (2009) comments that it is not surprising that trend forecasting has largely been viewed in the system dynamics community as a source of instability and as a dysfunctional basis for policy.

A smart automated forecasting system as reported by Moss et al. (1994) is a kind of expert system for generating forecasts wholly or partly without human intervention. The interventions normally made by forecasters on the basis of their own judgment and practices are instead made by the application of rules within a computer.

2.1.2 Economic Ordering Quantity

The Economic Order Quantity (EOQ) model and formula were originally presented by Ford Whitman Harris in a paper published in 1913 in *Factory, The Magazine of Management*. Harris's basic EOQ model became the dominant paradigm for order-quantity analysis for the next forty years. Erlenkotter (1990) believes that the EOQ model is so well known that we accept its basic structure as obvious.

An EOQ model is researched to be integrated into the adaptive model, and not to be used as the dominant principle in determining the ordering policy. An EOQ model will thus only be used to calculate the fixed safety stock level to be kept on hand.

Following research into the various available EOQ models, the appropriate EOQ model as described by Simchi-Levi et al. (2005) is a Continuous Review Policy model. This model is applied in inventory systems where the level of inventory is reviewed on a continuous basis thus the instantaneous inventory levels can be determined at any given time. This type of review system typically provides a more responsive inventory management system than a periodic review system where inventory levels are only checked at discrete time intervals such as once a week when stock taking is being done.

To use an EOQ model certain inputs need to be known, then by using these inputs parameters are calculated. These inputs, parameters and the equations used for calculating them are listed in the following three tables.

Table 2.1: EOQ Model Inputs

Input Symbol	Input Description
AVG	Average Demand of the customer
STD	Standard Deviation of daily demand faced by distributor
L	Replenishment lead time from the supplier to the distributor in days
h	Cost of holding one unit of the product for one day at the distributor
α	Service level
K	The cost incurred by distributor when an order is placed

Table 2.2: EOQ Model Parameters and Formulas

Parameter symbol	Parameter Description	Formula
z	Service Factor	Table 2.3
SS	Safety Stock	$SS = z \times STD \times \sqrt{L}$
R	Reorder Level	$R = L \times AVG + z \times STD \times \sqrt{L}$
Q	Order Quantity	$Q = \sqrt{\frac{2K \times AVG}{h}}$

Table 2.3: Service Level and the Service Factor, z

Service Level	90%	91%	92%	93%	94%	95%	96%	97%	98%	99&	99.9%
z	1.29	1.34	1.41	1.48	1.56	1.65	1.75	1.88	2.05	2.33	3.08

Once data has been gathered, the data will be analyzed and the safety stock level will be calculated and entered into the adaptive model. The calculation of the inputs and parameters for the EOQ model are described in further detail in the Data Gathering Chapter.

2.2 Existing SMART Process Applications

SMART business processes are relatively new concepts thus existing applications are few. Some of the existing applications include intelligent maintenance, dominant innovation and service oriented architecture.

Intelligent maintenance offers manufacturing companies the opportunity to extend their customer relationship by offering smart services through e-maintenance and consequently ensuing customer loyalty.

Dominant Innovation offers companies an *approach* to developing new product-service offerings, by capturing “invisible” areas of value and creating sustainable and enduring relationships with individual customers worldwide.

Service Oriented Architecture is concerned with creating a SID (SMART Item Device) used for tracking environmental changes in a product and using these changes to adapt itself automatically. The most prominent example being RFID (Radio Frequency Identification) tags that are able to continuously capture, analyze and adapt information about the product itself.

All these current applications can familiarize one with the concept of SMART processing to comprehend the dynamics behind it. For this project we will use these concepts together with an adaptive control model and apply some of the most fundamental ideas within inventory management.

2.2.1 Intelligent Maintenance System

An existing problem that has been addressed by SMART business processes is to find the optimal action for innovation in the product life cycle. It is imperative that businesses who want to compete in the marketplace in the twenty first century focus on e-intelligence for integrated product design, manufacturing and service delivery as stated by Liu et al. (2005). By implementing the concepts of SMART processes, the focus is on an extended customer solution through the creation of an Intelligent Maintenance System; a product service system that can predict the failure of a product in advance. This feature will allow manufacturing industries to develop proactive instead of reactive maintenance strategies to guarantee product performance and ultimately eliminate unnecessary system breakdowns. This entails the development of SMART and reconfigurable monitoring tools that reduce or eliminate production downtime.

2.2.2 Dominant Innovation

According to Lee (2010) manufacturing companies who are continually seeking new ways to get closer and expand their global reach into the increasingly profitable areas of service delivery and customer support must move into SMART services. This entails developing niche expertise with distinguishable value-added innovation. Lee (2010) describes that one approach is “Dominant Innovation”, a system and a set of tools designed to help create new products and services that can succeed in a changing competitive global market. ”*It helps formulate gaps between a product and customer’s invisible needs, using an innovation*

matrix and application space mapping tools. Ultimately it may help both world-class companies and small to midsize enterprises transform themselves into innovative leaders.” This dominant innovation approach can be used to find the current gaps existing between product requirements and customer needs, and this must be done by implementing a systematic methodology to generate, develop, and implement new concepts.

The Dominant Innovation process will deliver a SMART product by delivering a SMART service. The ease of use and consumer appeal of SMART products is based on a foundation of understanding the user and involving the user in the design process, including both industrial and software design. Such inherent technological capabilities in SMART products are revealing hidden opportunities for business revenue that can be fulfilled through establishing a service framework around a core product. As concluded by Lee (2010): *Smart services require knowledge of product usage, transformation of product usage data into relevant information using enabling technology, and the optimization and synchronization of cost factors.*

AbuAli and Lee (2010) describes how the goal of innovation is to create business value by developing worthwhile customer-centric ideas. This is difficult to achieve due to the lack of a methodology and tools for systematic innovative thinking. This manifests the need for a systematic approach to developing innovative product-services as established in Dominant Innovation.

2.2.3 Service Oriented Architecture (SOA)

Future software systems will operate in a highly dynamic world and will need the ability to continuously adapt themselves in an automated manner to react to those changes. To realize these dynamic, self-adaptive systems, the service concept has emerged as a suitable abstraction mechanism in the creation of software services.

Software services represent the functionality that the software offers and this application constitutes a promising solution to realize dynamically adaptable systems as explored by di Nitto et al. (2008). Self-adapting service-based applications automatically adapt to changes in their execution environment and/or in their requirements. Such changes could include the deployment of new instances of a particular kind of service, the removal of existing ones, and even more global changes in the required application.

Self adaption requires that the service-based applications are capable of automatically discovering new services, automatically choosing among available service providers, selecting from different available contracts and automatically aggregating services into service compositions.

In order to instill self-adaptive behaviour, control loops are established that collect details from the application and its context and act accordingly. In the case of self-adaptive applications, control loops can address different goals. An example of one of these goals is self-optimization; these service-based applications can tune themselves to better meet end-user or business needs. The tuning actions may, for instance, imply choosing new service providers to improve overall utilization.

Further, Bornhovd et al. (2007) is of opinion that the next big step for business process automation and visibility goes beyond Auto-ID (Automatic Identification) and surely lies in sensor networks and collaborative SMART items. As explained by Bornhovd et al. (2007): *We use the term SMART item in the sense of a real world object that is augmented by a device providing some data about its identity and properties. The device that actually makes a SMART item “smart” is called a SMART item device (SID).* Applications of these SMART items include automatic real-time object tracking, through which this SMART item technology can provide its users with accurate data, concerning business operations and therefore streamlining and automating operations. A great challenge in implementing these SMART processes is bridging the gap between the physical and the digital world to integrate automatic data acquisition with existing business processes, as explained by Bornhovd et al. (2007).

Service oriented architecture in a nutshell is concerned with the ability of a process to adapt itself when applied in a different environment. This is applicable to this project in the sense that one should be able to take the architecture of this project and implement it in any environment as a SMART business process.

2.3 Existing Adaptive Control Models

According to Ortega and Lin (2007) control theory is applied to reduce inventory variation, reduce demand amplification and optimize ordering rules, thus proving adaptive control theory an appropriate tool in determining an ordering policy. Research into adaptive control models was conducted to find the most suitable adaptive logic that can be implemented into the model to simulate the self-adapting loops. Many adaptive control models that can be used for this logic exist, a few being described below.

2.3.1 MIT rule

The MIT rule was proposed around 1960 by Osbourne et al. (1961) and is explained briefly by Anderson and Dehghani (2008) as follows: *The model adjusts a scalar parameter in a control law associated with a plant modeled by a known linear system multiplied by an unknown and variable gain.* The model is depicted in Figure 2.1 below.

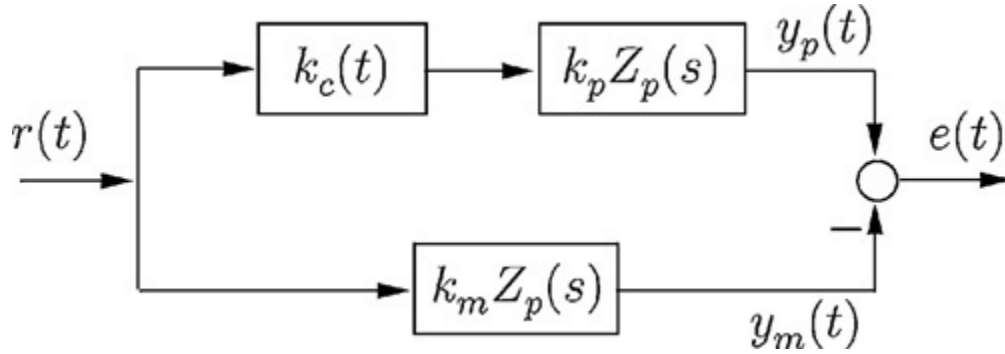


Figure 2.1: MIT rule set-up.

Suppose the plant is $k_p Z_p(s)$ where k_p is unknown apart from its sign, and $Z_p(s)$ is a known and stable transfer function. Set up a model with a transfer function $k_m Z_p(s)$ where k_m is a known gain, with the same sign as k_p , and suppose that the model is driven by a signal r and produces an output $y_m(t)$.

Further assume that prior to the plant is located an adjustable gain $k_c(t)$, and that the cascade of this gain and the plant are also driven by r but produce an output y_p . Clearly, if we were to have $y_m = y_p$ for all time with a rich input r , there would have to hold $k_c k_p = k_m$, and then the value of the unknown gain k_p is effectively known. In the event that $y_m \neq y_p$, a gradient law aimed at minimizing $(y_p - y_m)^2$ as a function of k_c is used to adjust $k_c(t)$, as follows:

$$k_c = -\mu \frac{\partial}{\partial k_c} \left[\left(\frac{1}{2} \right) (y_p - y_m)^2 \right] = -\mu [y_p - y_m] y_m \quad (2.1)$$

Thus by implementing this logic into the model the Inventory Discrepancy will be the signaling element, causing the feedback loop, aimed at minimizing the difference between

revenue from forecasted shipments and revenue from actual shipments. Thus minimizing the error found when forecasting demand.

If this logic were to be applied in the inventory model, the parameters would be defined as follows:

Table 2.4: MIT model parameters

Symbol	Parameter description	Defined as
$r(t)$	Inventory Discrepancy	Desired-Instantaneous Inventory
$k_c(t)$	Availability	Instantaneous/Desired Inventory
k_m	Actual shipments to customers	Data gathered
Z_p	Revenue from shipments	Income/case
k_p	Forecasted shipments to customers	Forecasting technique
$y_p(t)$	Forecasted Revenue	Forecasted Shipments \times Income/case
$y_m(t)$	Actual Revenue from shipments	Actual Shipments \times Income/case

The MIT rule is aimed at minimizing the difference between y_m and y_p in order to determine the unknown gain k_p thus the aim is to ensure that the forecasted shipments are as close as possible to the actual shipments. This is not the aim of the adaptive control model of this project and will not assist in determining an ordering policy as it only addresses the error found when forecasting demand. The MIT rule will thus not be effective if applied in the context of this problem.

2.3.2 Action-Value Method

The action-value method estimates the value of actions and then uses the estimates to make decisions based on the value of the action. As described by Sutton and Barto (2005) the true value of an action is the mean reward received when that action is selected. This method as described briefly by Kim et al. (2005) is suitable to heuristically solve sequential optimization problems in uncertain environments. An applicable domain for the application of this method is a stochastic optimization problem, where the unknown values of each action should be obtained through repetitive applications of the action in either a real or a simulated environment.

Specifically at each decision point of time, a possible action is selected based on a probabilistic function of their value estimates. This concept is incorporated into the following probabilistic action selection rule:

$$P\{\text{newaction} = a\} = \frac{e^{-\text{ValueEstimate}(a)}}{\sum_{a_i \in AS} e^{-\text{ValueEstimate}(a_i)}} \quad (2.2)$$

AS is the set of possible actions. The numerator increases as the value estimate of the action decreases, thus the action with the lowest estimated value would be selected with the highest probability. The denominator is a normalization term to cause the action selection rule to be a probability function. This model will thus always choose the action with the lowest estimated value, making this model appropriate when one needs to choose between various expenditure-related actions, where the objective is to minimize expenditure. The fact that it spends no time at all sampling apparently inferior actions to see if they might be better is exactly what one wants from a self-adaptive model, it implies that all decisions are 100% objective.

The result of the selected action (current value) is then used for learning its objective value. The learning formula employed can be defined as follows:

$$NewValueEstimate = OldValueEstimate + StepSize[CurrentValue - OldValueEstimate] \quad (2.3)$$

Kim et al. (2005) explains that each time a specific action is performed, its new value estimate is updated by adding an error (weighted difference of the current value and the old estimate) to the old estimate. The error indicates a desirable direction to which the value estimate moves.

StepSize is a learning parameter that decides learning speed. According to Kim et al. (2005) it is normally set to a constant which has been experimentally verified. At the next decision point of time, a new action is chosen according to the probabilistic rule with the updated value estimate. This procedure is then repeated until the end of the decision horizon is reached.

In the context of the problem addressed in this project the action corresponds to a control parameter such as lead time or safety stock, both being values that one would like to minimize. The decision point in time implies inventory replenishment time. When a new safety stock is selected, the service level is measured. The result of the safety stock can then be defined as the absolute deviation of the service level from a predefined target service level. The *NewValueEstimate* is calculated by using the equation above and is defined as the weighted average of the absolute deviations of the service levels from the target service level. Thus as the feedback loop progresses, safety stocks with low service level deviations will be given high selection probabilities.

Within the context of the problem, the action value method can be used to find the optimal safety stock level at a predefined target service level. For this project it is not necessary to use adaptive control to determine this safety stock level. The target service level is set at 99%, implying that the probability of the wholesaler experiencing a stock-out to be 1%. The safety stock levels at this target service level was calculated by using the applicable EOQ model as described in section 2.1.2. To find the optimal safety stock levels depending on customer demand is not the focus of this project thus it will be sufficient for the scope of this project to compute a fixed safety stock level using an EOQ model.

2.3.3 PID Control Process

PID Control is concerned with adaptive control that comprises of *Proportional* control, *Integral* control and *Derivative* control, hence the title *PID* control.

The analog PID control process as described by Saeed (2009) can be expressed in the following equation:

$$M(t) = P[e(t)] + I \left[\int e(t)dt \right] + D [d(e(t)/dt)] \quad (2.4)$$

where M is the total correction applied, P (proportional control) is the part of total correction that is proportional to the instantaneous error e , I (integral control) is the part of total correction that is proportional to the integration of the instantaneous error e , and D (derivative control) is the part of total correction that is proportional to the trend or derivative of the instantaneous error e . Instantaneous error e is the discrepancy between the desired level of inventory and the instantaneous level of inventory. Trend manifests in derivative control, which adds a correction in response to the rate of change of error, thus further speeding up correction when error is increasing. Saeed (2009)

The roles of each control term is further explained by Ortega and Lin (2007) as follows; the proportional control improves performance but leaves an offset from the target and the integral term eliminates this offset. The integral term has a destabilizing influence so the derivative term is introduced to restore the necessary stability margin.

As application in the context of the problem, the delivery from the depot will be the total correction applied.

The proportional control comprises the inventory discrepancy, which is the difference between the desired inventory and the instantaneous inventory. Thus an increase in the error caused by a decrease in the instantaneous inventory which in turn will cause an increase in the delivery rate thus the system will be adapting itself continuously to ensure that the desired inventory and the instantaneous inventory levels are nearing one another.

The derivative control term is a function of the trend in shipments to customers as well as an estimated demand of customers. This comprises the forecast in shipments. Thus as the trend in customer demand increases, the orders from the depot to the wholesaler will also increase.

The integral control term comprises the cumulative delivery orders for inventory. Delivery orders for inventory are those orders that are placed to minimize the inventory discrepancy. Thus this term is the cumulation of all these orders.

White et al. (2002) states, concerning ordering policies, that when comparing PID Control to Material Requirements Planning, the latter is not so good when sales rates vary since the master schedule has to be established in advance. The system run by PID control will allow a quicker response, without large capital investment. In the context of the problem such an observation is relevant as this project aims to produce an adaptive and not a stationary ordering policy.

According to Li et al. (2007) PID control provides simplicity, clear functionality, and ease of use and is used in more than 90% of practical control systems. Saeed (2009) states that, PID control as applied to engineering fields, offers a good model for designing stable supply

systems, making it imperative that one should consider replacing demand forecasting with the careful design of proportional, integral and derivative control processes in supply chains.

In conclusion to these existing adaptive control models, the PID control model is proven to be the most suitable model within the context of the problem when taking into account the deliverables of the project. A detailed description of the PID model will be given in Chapter 5.

Chapter 3

Wholesaler as application

To illustrate the concept of SMART business processes in this project, an ordering policy will be generated for a wholesaler. Thus inventory management is used as application to show how SMART business processes can be used to make intelligent decisions within almost any environment.

3.1 South African Breweries

The South African Breweries (SAB) is South Africa's leading producer of alcoholic and non-alcoholic beverages and one of the nation's largest manufacturing firms, thus proving SAB to be a good application for the project.

The company operates seven breweries and 40 depots in South Africa with an annual brewing capacity of 3.1 billion liters. Its portfolio of beer brands meets the needs of a wide range of consumers and includes five of the country's top six most popular beer brands - namely Carling Black Label, Hansa Pilsener, Castle Lager, Castle Lite, and Castle Milk Stout.

SAB is interested in new research topics and their application within the industry thus they were more than willing to assist in the project by issuing data as well as give advice concerning inventory management.

3.2 Wholesale environment

SAB's Waltloo Depot situated in Silverton Pretoria was assigned the role of project sponsor. It was their responsibility to assign a client as application for the project. One of the depot's clients, an independent redistributor who also acts as a wholesaler was chosen.

The wholesaler receives stock on a daily basis from the Waltloo Depot and the deliveries are usually a truck load full, consisting of a product mix of various different brands. They are titled as an Independent Redistributor which means they redistribute stock to other retailers. They also operate as a wholesaler thus they receive large amounts from the depot which is then stored in their warehouse to be purchased by retailers. The end-user can

also buy directly from the wholesaler in this case. Thus the client is a mixture between a wholesaler, a retailer and an independent redistributor.

The client has a capacity for 14000 cases in total, of which 21% is designated for SAB products. The demand is relatively stable and peaks during December as well as during the Easter weekend. Currently the client receives a full truck load every day and the order is placed on intuition of the warehouse manager. The inventory levels can be reviewed continuously by means of computer software that tracks how much inventory more or less is leaving and entering the warehouse. The manager then decides according to this information and from experience, how much to re-order. The manager would like to maintain an inventory level of 110 cases of Hansa Pilsener quarts for example, thus if he sees there are 60 cases remaining, he will order another 50 cases. Currently their ordering policy also rests on the promise that they will never experience stock-outs. Thus they want to ensure that a customer must never arrive at their shop and not be able to purchase the stock they need.

The problem with this ordering policy is that the client is keeping far too much stock on hand. At any given time, they are keeping ten times more stock than the average demand. They are keeping on a daily basis 8000 cases in excess in their warehouse.

Thus there is a great need for an ordering policy that is based on intelligent decisions, by a system that self-adaptively takes into account the current demand trends, cash on hand and product availability.

Chapter 4

Data Gathering

The following chapter explains the data gathering process, the analysis of the data as well as adaption of the data to make it suitable as input to the model.

4.1 Data from Wholesaler

Large amounts of raw data were gathered from the wholesaler. The data covers an eight month period of daily sales data, orders received from the depot and daily instantaneous inventory levels. The data was received in Excel spreadsheets which allowed easy import and export of the data to and from the model. The data was captured for eight of the following SAB products:

Table 4.1: Products captured in data

Product description
Black Label dumpie
Castle Lager dumpie
Castle Lite can
Castle Lite dumpie
Castle Lite quart
Castle Lager quart
Hansa Pilsener dumpie
Hansa Pilsener quart

An example of one of the Excel spreadsheets containing the captured data is shown below. The column with the Debit heading contains orders coming in from the depot, the column with the Credit contains shipments to the customers thus sales data, and the final column shows the instantaneous inventory levels.

Date	TxTp	Doc.No.	Description	Debit	Credit	Balance
1/1/2011	OBAL	0	Opening : 201012	4697	0	4697
3/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	416	4281
4/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	285	3996
5/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	167	3829
6/1/2011	STGRV	19051	GOODS RECEIVED VOUCHER	924	0	4753
6/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	504	4249
7/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	431	3818
8/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	279	3539
12/1/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	537	3002
13/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	333	2669
14/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	488	2181
15/01/2011	STGRV	19117	GOODS RECEIVED VOUCHER	396	0	2577
18/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	1027	1550
19/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	233	1317
20/01/2011	STGRV	19124	GOODS RECEIVED VOUCHER	660	0	1977
21/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	791	1186
22/01/2011	STGRV	19154	GOODS RECEIVED VOUCHER	660	0	1846
22/01/2011	STGRV	19163	GOODS RECEIVED VOUCHER	1056	0	2902
22/01/2011	STKTC	0	STOCK KIT BUILD : CREDIT	0	564	2338
23/01/2011	STSTC	554120	STOCK TAKE ADJUSTMENT	0	1480	858

Figure 4.1: Example of data gathered

4.2 Data analysis

To see the current trends in the amount of stock kept on hand, graphs were created to see the relationship between stock kept on hand and the customer demand. The graph for Castle Lite quarts depicting this relationship is shown below.

This graph indicated the need for an ordering policy. Excessive stock kept on hand is a large expenditure as the stock has a limited shelf life of 90 days. The client is currently renting additional warehouse space to accommodate the large quantities of stock, thus if less stock is kept on hand, the client will possibly no longer need the additional warehouse which will allow less rent expenditure and more cash on hand.

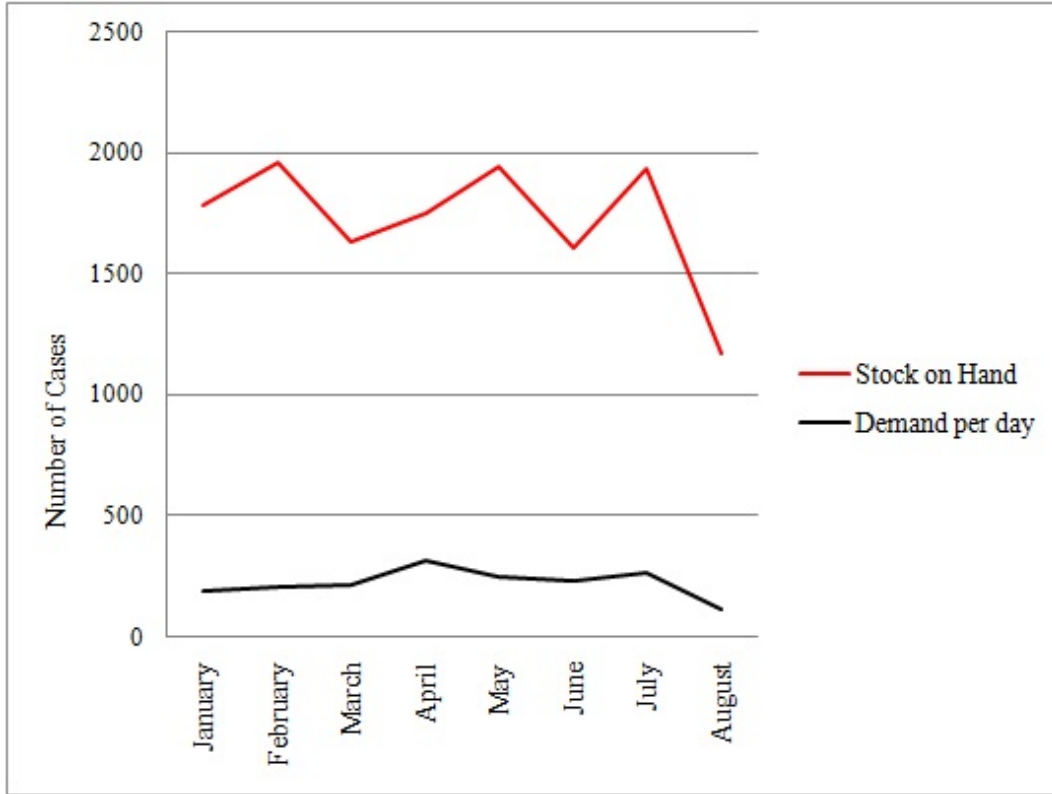


Figure 4.2: Depiction of excess stock kept on hand

4.2.1 EOQ calculations

Further analysis of the data entailed determining the average demand by looking at the sales data and determining safety stock levels by using an EOQ model as described in the Literature review. Results obtained were as follows:

Table 4.2: Data Analysis results using EOQ

Product	Safety Stock	Average Demand
Black Label	10	14
Castle Lager dumpie	10	11
Castle Lite can	11	20
Castle Lite dumpie	58	109
Castle Lite quart	140	223
Castle Lager quart	19	77
Hansa Pilsner dumpie	19	40
Hansa Pilsner quart	119	483

The holding cost was calculated as follows: the total overhead expenditure per month for the wholesaler is R500 000. SAB products only comprise 21% of the warehouse thus reducing the total to R105 000. All values in the model are converted to a daily rate thus per day the overhead rate for SAB products reduces to R4038. In total there are 8 SAB products being sold thus totaling to R505 per SAB product per day. This value is used in the model as an overhead expenditure. If the ordering policy as obtained in this model is implemented, the inventory kept on hand will be reduced to a large extent thus the need for an additional warehouse may no longer be necessary, then this overhead rate will also be reduced as the rent of the additional warehouse space covers a large amount of the overhead expense.

A lead time of one day was used for all calculations as the wholesaler will place an order today and receive the ordered stock tomorrow.

A service level of 99% was assumed. This entails that the probability of a stock-out occurring to be 0.01.

Chapter 5

PID Adaptive Control Model

5.1 Design architecture of model

The adaptive control model was built using iThink software and the model can be divided into three sections, namely; the PID control, the imported sales data and the financial control. These three sections are depicted in the figure on the following page, indicating the breakdown of each section. PID control consists of Proportional, Integral and Derivative control. The Imported sales data is the data as gathered from the depot, that is imported to the model to generate shipment orders to customers. The financial control consists out of all revenue as received from shipments to customers, amounts payable to the depot as well as a fixed overhead expenditure, and cash on hand. All sections as depicted below will be explained in further detail.

5.1.1 PID Control

The adaptive control model used for the project is based upon the PID Control model as described in the Literature review. The model, containing certain logic as created by Saeed (2009), continually adapts itself until certain target levels are achieved and from there onward the process remains stable.

The aim of the model is to minimize the inventory discrepancy, while meeting and tracking the customer demand in order to find an ordering policy. The parameter that is being controlled is the delivery orders from the depot. This is controlled by three different controls as indicated in the following equation:

$$M(t) = P[e(t)] + I \left[\int e(t)dt \right] + D [d(e(t)/dt)] \quad (5.1)$$

Where $M(t)$ is the correction applied, thus the total delivery from the depot. $e(t)$ is the error, which in this case is the inventory discrepancy (the difference between the desired and instantaneous inventory levels). The P indicates derivative control, the I indicates integral control and the D derivative control.

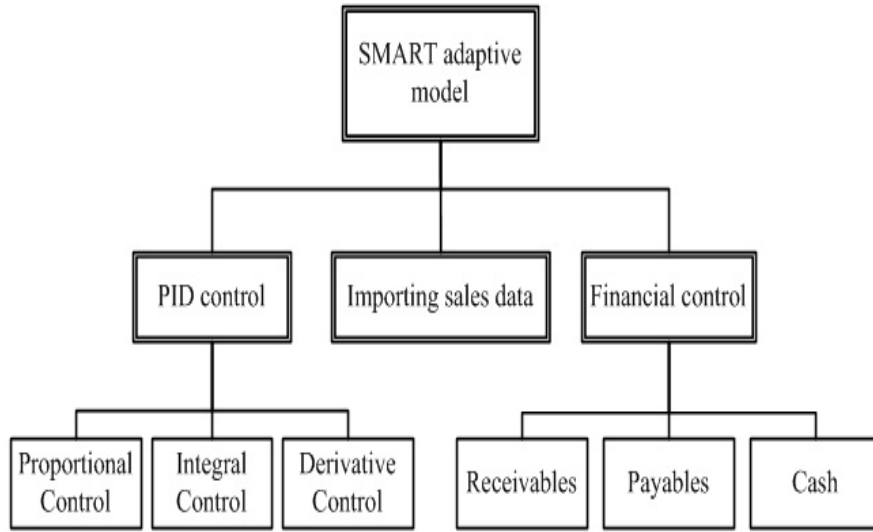


Figure 5.1: The breakdown of model divisions

The three different controls each play a role in determining the orders from the depot, thus the ordering policy. This is broken down into more detail in the following equation:

$$Dr = \frac{1}{Tv}(Ig - Iv) + [Tf \frac{\partial(ED)}{\partial t} + ED] + \sum(Ig - Iv) \quad (5.2)$$

Table 5.1: Description of symbols used in above equation

Symbol	Description
Dr	Delivery from depot
Tv	Inventory correction time
Ig	Desired level of inventory
Iv	Instantaneous level of inventory
Tf	Forecasting time
ED	Estimated demand

Where the first part comprises the proportional control, the second part is the derivative control and the third part is the integral control. A description of each control mechanism will be explained below.

Proportional Control

The proportional control is proportional to the error thus the inventory discrepancy. The inventory discrepancy is the difference between the instantaneous inventory and the desired inventory levels. The desired inventory is calculated by the forecast plus a fixed safety stock level. The forecast is generated through continual tracking of the trend in the demand within the model. A diagram showing the feedback loop of the proportional control is shown below:

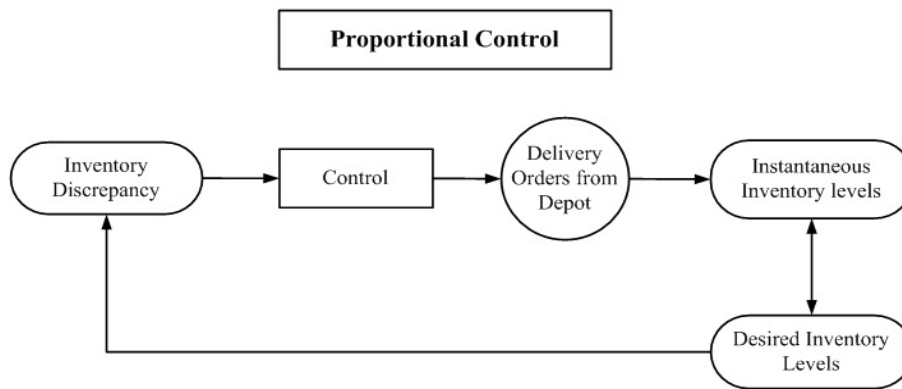


Figure 5.2: Proportional control feedback loop

As shown in the diagram, the inventory discrepancy triggers the control. When the discrepancy increases the delivery orders will also increase thus continuously minimizing the difference between the instantaneous and the desired inventory level.

Derivative Control

The second part is the derivative control and comprises of the estimated demand and the trend in shipments. A diagram showing this feedback loop is depicted below.

This control is started by the imported sales data which indicates the demand of the customers. Availability is the instantaneous inventory divided by the desired inventory. The sales data is multiplied by the availability, this is a constraint on the shipments to customers, for example if the instantaneous inventory is less than the desired, multiplication with availability will reduce the shipments to customers as your inventory levels are lower than what you would like. On the other hand if the instantaneous levels are higher than desired, the shipments to customers will be increased to get rid of the excess stock.

These shipments to customers are then tracked via the trend in shipments and estimated demand. Through these two parameters a forecast of the customer demand is generated, forecast being the trend in shipments plus the estimated demand. This forecast then constitutes the delivery orders to meet the demand, thus affecting the delivery orders from the depot. This again increases the instantaneous inventory levels which again affects the availability thus creating a positive feedback loop.

The forecast plus the calculated fixed safety stock level determines the desired inventory level and this in turn affects the availability, creating another positive feedback loop.

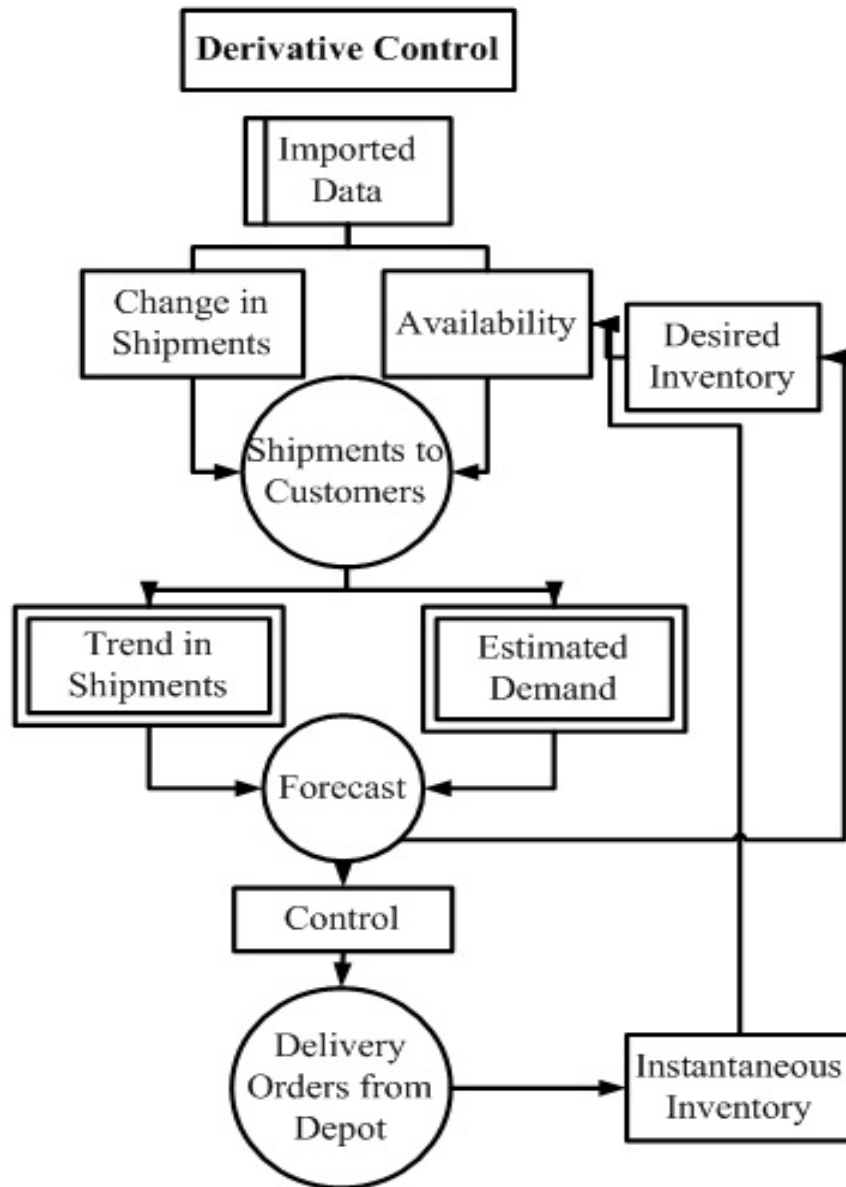


Figure 5.3: the derivative control feedback loop

Integral Control

The third part is the integral control, this is the cumulative orders for inventory. Orders for inventory are the delivery orders from the depot that are made in reaction to the inventory discrepancy. Thus this control is the cumulation of all the inventory discrepancies. This control mechanism is shown in the diagram below:

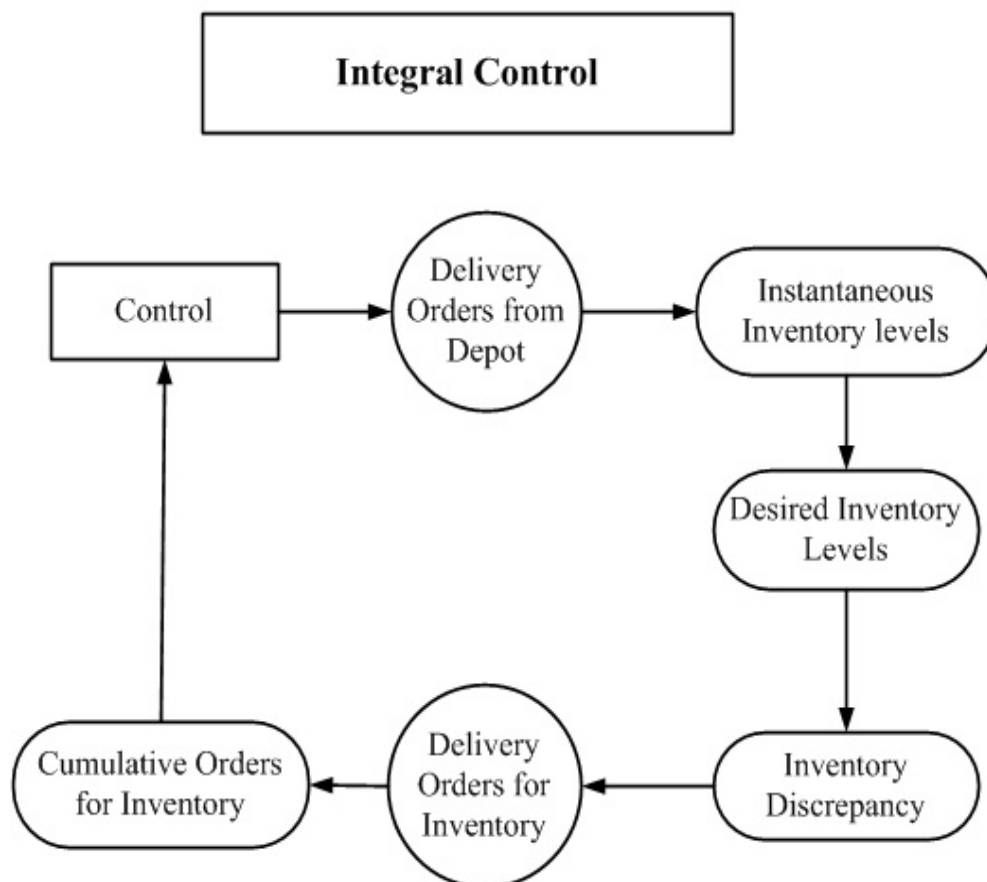


Figure 5.4: The integral control feedback loop

Delivery orders for inventory are those orders that are aimed at controlling the inventory discrepancy. The cumulation of these orders form the integral control.

5.1.2 Imported sales data

The next section is the imported sales data that triggers the shipments to customers. This data, as captured by the wholesaler, was clearly not captured on a regular basis thus the data would show a shipment of Hansa quarts for 2000 cases and then no shipments for five days. Thus the total values are captured but the spread of the data is irregular. To counter this problem, exponential smoothing (a technique applied to time series data to produce smoothed data for presentation) was used to spread out the data points in a more consistent manner. The formula used in the Data Analysis exponential smoothing function, as a built-in Excel function, is as follows:

$$newdatapoint(t) = 0.7 \times actualdatapoint(t - 1) + 0.3 \times newdatapoint(t - 1) \quad (5.3)$$

Below is an example of the imported file:

Actual sales data	Hansa quarts
416	0
285	416
167	324
0	214
504	64
431	372
279	413
537	319
333	472
488	375
0	454
1027	136
233	760
0	391
791	117
0	589
0	177
564	53
1480	411
0	1159
0	348
0	104
557	31

Figure 5.5: Example of imported sales data

5.1.3 Financial Control

The final section is the financial control. This section comprises of all revenue, expenditure and cash-on-hand. The revenue is calculated by using the number of cases sold form the shipments to customers, and multiplying it by the current sales price. 5% of all revenue is written off as bad debt. The remaining 95% is collected as cash. This cash amount constrains the ordering process in the sense that one can only place an order from the depot if one has sufficient cash on hand.

The next part is the expenditure section. Incurred obligations, as shown in the diagram below, is the amount payable to the depot. This amount is calculated by using the number of cases delivered from the depot, and multiplying it by the current purchasing price. This payable amount is cumulated in Meeting Obligations as can be seen in the diagram. A volume incentive is also introduced which states that if the shipments to customers exceeds a certain level, the wholesaler receives a discount on stock purchased in the future from the depot. Thus the volume incentive affects the incurred obligations by minimizing the amount payable to the depot. The overhead cash expense is calculated as described in the Data Gathering chapter. The incurred obligation (amount payable to depot) and the overhead expenditure adds up to be the total expense.

The total expense is then subtracted from the revenue and an accumulated daily profit is calculated. The financial section is shown below:

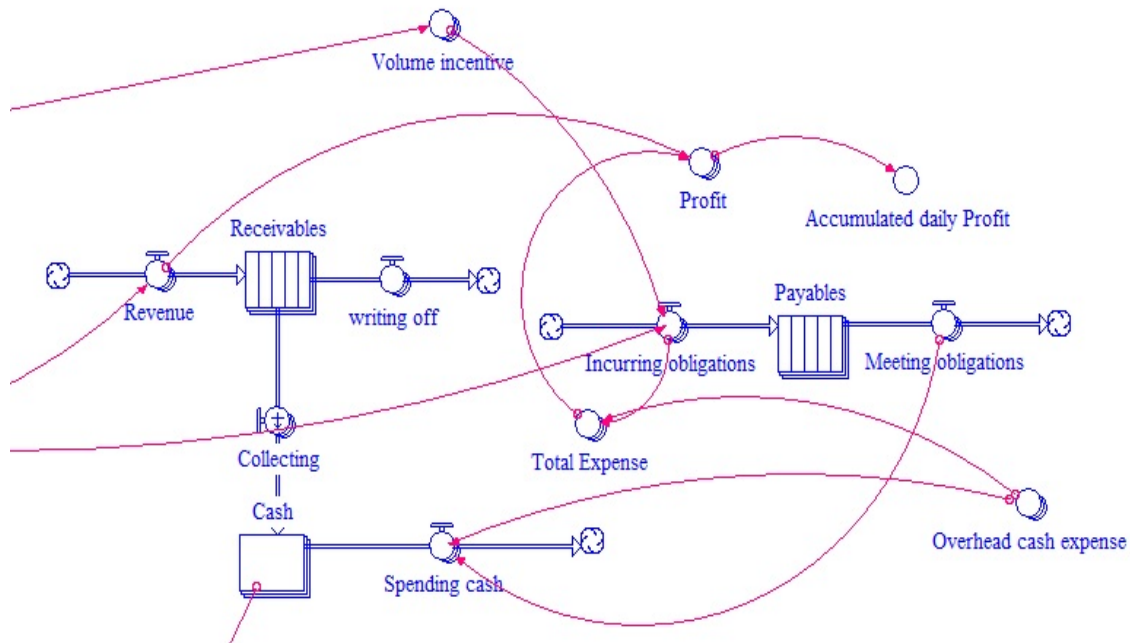


Figure 5.6: Financial sector of model

The complete model containing the three sections as described above is shown on the next page. The formulas for the model are listed in the Appendix.

5.2 Interface

The user interface allows the user to run the model without having to understand or see the model. Other aspects of the interface includes the profit per day, as calculated by the model. There are also three buttons that allows the user to see results of the model as contained in certain excel pages. They include the ordering policy, the resulting excess stock, as well as a graph showing the relationship between the instantaneous inventory level and the shipments to customers. The user interface is shown below:

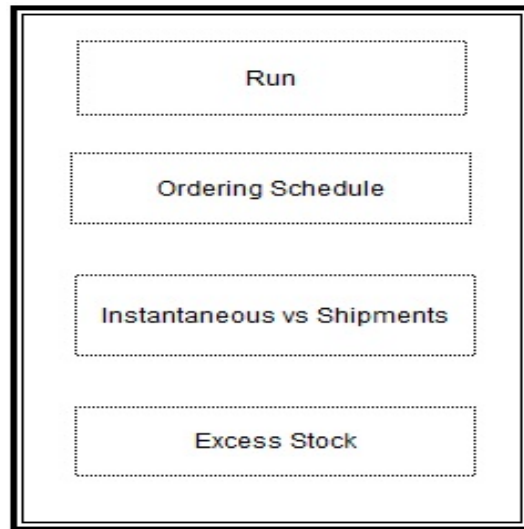


Figure 5.8: User interface

Chapter 6

Results

6.1 Ordering policy

The ordering policy as generated by the model takes into account various control parameters such as the trend in the demand, the cash available on hand, the availability of stock on hand and inventory discrepancies. This ordering policy is truly generated as a result of a SMART self-adaptive process to ensure customer satisfaction within the decisive control parameters. An example of the ordering policy is shown below, and the full ordering policy is in the Appendix.

Day	Black dumpie	Castle dumpie	Castle lite can	Castle lite nrb	Castle lite quart	Castle quart	Hansa dumpie	Hansa quart
1	0	0	0	0	31	0	0	17
2	0	0	0	0	73	0	0	42
3	0	0	0	35	107	0	0	89
4	0	0	0	69	56	0	0	154
5	0	0	0	51	95	7	7	101
6	4	4	6	48	220	18	11	273
7	4	4	8	11	175	30	6	365
8	4	5	6	50	177	44	11	359
9	4	5	10	53	241	59	12	450
10	4	3	7	24	195	75	6	430
11	4	2	6	53	187	92	16	433
12	3	3	7	65	311	66	28	303
13	5	4	2	0	344	95	25	386
14	5	3	6	16	191	113	9	554
15	4	1	13	81	211	74	13	338
16	11	6	8	44	0	124	5	30
17	12	4	6	0	0	117	3	473
18	8	6	19	12	187	25	31	196
19	6	3	11	7	326	0	33	0
20	1	2	5	46	260	0	16	294

Figure 6.1: Example of Ordering policy generated by model

6.2 Excess Stock

As discussed in chapter 4, the current levels of inventory kept on hand in comparison with the demand of the customer is indicative of the need for a validated ordering policy. Thus this relationship is a good indicator of whether the ordering policy as generated by the model will prove sufficient.

This graph shows the accumulated inventory levels for all the products in total, against the accumulated shipments to customers.

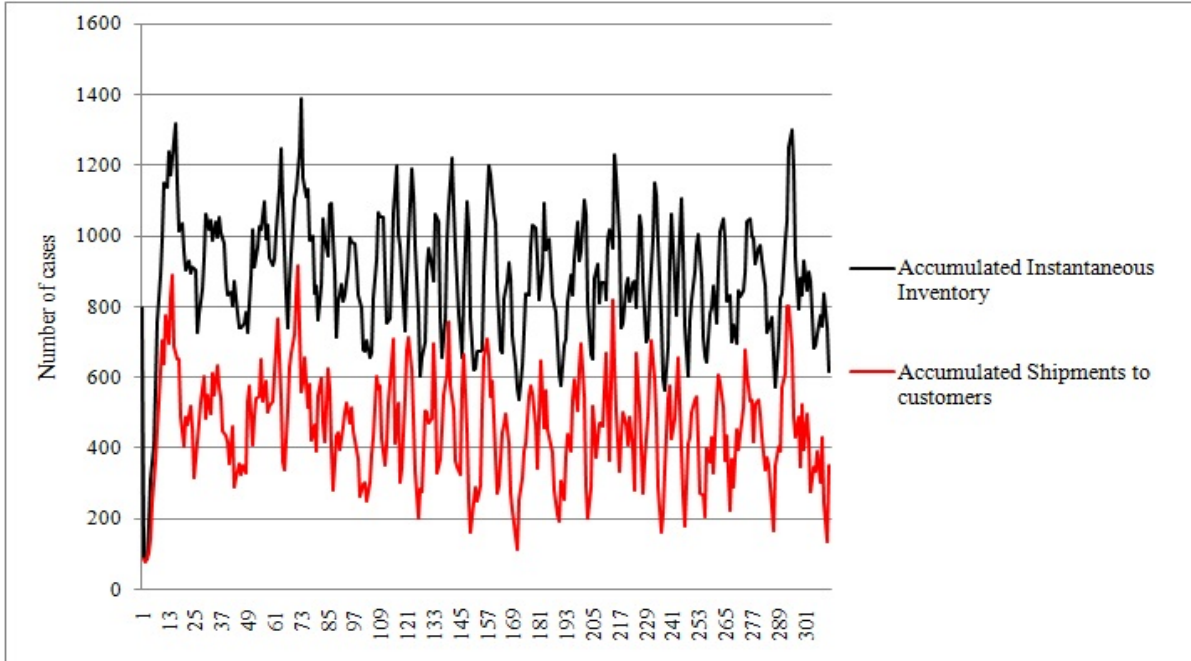


Figure 6.2: Inventory on-hand vs Shipments to customers as recommended in model

The total amount of excess stock kept on hand is also calculated within the model by calculating the difference between the instantaneous inventory level and the shipments to customers. This value is compared with the total amount of excess stock currently being kept on hand by the wholesaler and a cost estimate of the save in excess is shown. This cost estimate is calculated by multiplying the number of cases saved, by the average purchasing price of one case. This value is a monetary value, indicating an amount of money that could be invested if this excess stock is no longer kept on hand. This value is then multiplied by 8%, indicating the interest that could be earned if this money were to be invested.

Analysis of Excess Stock	
Total Current Excess (cases)	8289.68595
Total Optimal Excess (cases)	419.6361983
Nr of cases saved per day (cases)	7870.049752
Interest earned per day	R 76,496.88

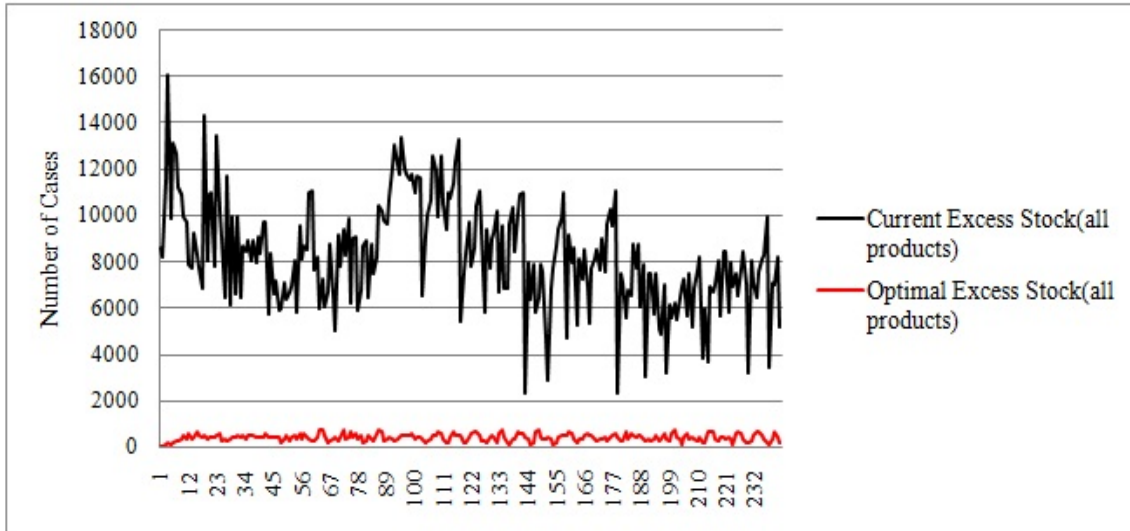


Figure 6.3: Recommended amount of excess stock to be kept on hand

6.3 Validation of model

To prove the validness of the adaptive model, validation of the model was done by setting shipments to customers at a constant value to show how the model reaches a state of equilibrium once the demand is constant. At this state of equilibrium, inventory discrepancy is zero thus one only has stock on hand that will be shipped to the customers plus a level of safety stock. This is only possible at an absolute constant rate of demand as under normal conditions one will impossibly be able to predict exactly how much stock will be purchased every day. At the wholesaler’s normal shipment rate, as simulated in this model, the model converges to this state of equilibrium as far as possible through continual self-adaption.

Equilibrium of the model can be seen in the availability parameter that reaches a value of one and remains at that value for the remainder of the simulation. This indicates that the instantaneous inventory level remains on par with the desired inventory level.

When the instantaneous inventory and the desired inventory levels are the same and the demand is constant, it implies that the only difference between the shipments to customers and the instantaneous inventory levels is the fixed safety stock level. Thus the only excess inventory found will be recommended safety stock thus there is no unwanted inventory on hand. Graphs depicting this validation are shown on the following page.

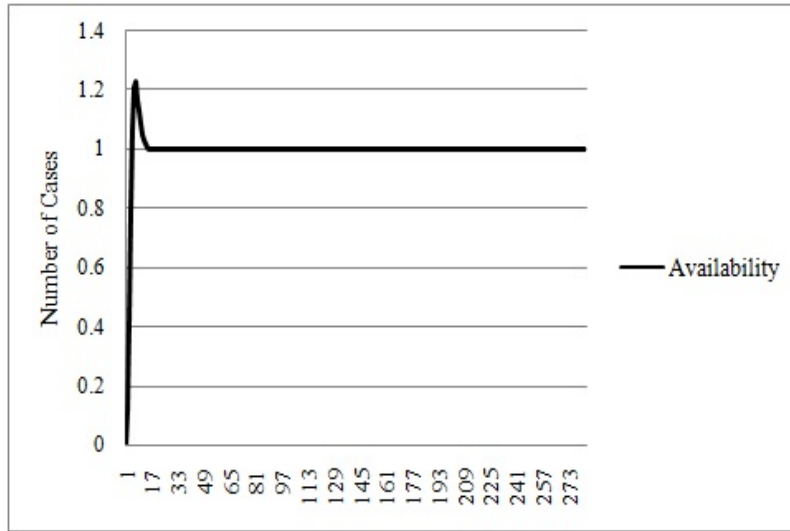


Figure 6.4: Availability of stock reaches a state of equilibrium

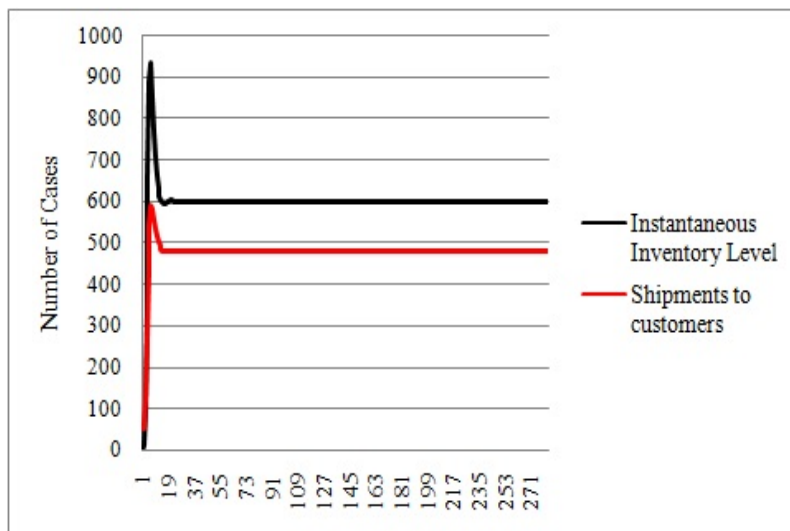


Figure 6.5: Inventory levels at a state of equilibrium

6.4 Conclusion

The aim of this project was to deliver a design architecture for a SMART business process by using adaptive control principles and applying this design in an inventory management environment.

Current applications of SMART business processes and existing adaptive control principles were researched in order to find the best combination of concepts with which to build the model.

Inventory data was gathered from a wholesaler concerning SAB stock being sold and this data together with researched concepts were used to build a SMART self-adaptive model using iThink software.

The aim of the model was to generate an ordering policy that constitutes the principle that as little excess stock as possible is kept on hand while meeting the customer demand at available cash levels with a sufficient profit in mind.

The resulting profit as obtained in the model is R90 000 per month as well as a earning of approximately R76 000 per day as a result of less excess stock being kept on hand.

Future elaborations on this project could include a study on the capacity constraint of a truck load. Thus determining an ordering policy by taking the size of a full truck load into consideration and determining order sizes that will ensure availability of stock, taking into account the size of a truck and the regularity of orders.

The idea is also that this design architecture be applied in any environment through the application of Service Oriented Architecture with the key idea of intelligent, unbiased decision making within any business.

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Appendices