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MODELING AND CONTROL OF LIQUID BULK SUPPLY CHAIN TO OFFSHORE RIGS WITH COST OPTIMIZATION

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Orientador: Amit Bhaya

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MODELAGEM E CONTROLE DA CADEIA DE SUPRIMENTOS DE LÍQUIDOS PARA PLATAFORMAS OFFSHORE COM OTIMIZAÇÃO DE CUSTOS

Tiago Salviano Calmon

Março/2016

Orientador: Amit Bhaya

Programa: Engenharia Elétrica

Essa dissertação apresenta o modelo de parte de uma cadeia de suprimentos real utilizada por uma grande empresa de óleo e gás. Esse modelo é construido utilizando a metodologia de estoques e fluxos da literatura de sistemas dinâmicos e é baseado em dados reais. A versão de espaço de estados do modelo, que contém atrasos e chaveamento dependente de estado, é submetida a controle retroalimentado, usando diversos controladores da familia do Sistema de Controle de produção baseado em inventário e pedidos. A metodologia de previsão automática de demanda é utilizada para previsão de demanda. Os parâmetros dos controladores são escolhidos por meio de otimização de uma função de custo que reflete o custo operacional total. essa otimização é feita por meio de um algoritmo genético. É feita uma comparação dos controladores utilizando seus parametros ótimos e o resultado que esses controladores atingem na função de custo.

Abstract of Dissertation presented to COPPE/UFRJ as a partial fulfillment of the requirements for the degree of Master of Science (M.Sc.)

MODELING AND CONTROL OF LIQUID BULK SUPPLY CHAIN TO OFFSHORE RIGS WITH COST OPTIMIZATION

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Advisor: Amit Bhaya

Department: Electrical Engineering

This dissertation presents a model of part of a real supply chain used by a large Oil & Gas company. This model is built using the stocks and flows methodology from system dynamics and based on real data. The state-space version of the model, which contains delays and state-dependant switching, is subject to feedback control, using different controllers from the Inventory Order Based Production Control Sysyem family. The automatic demand forecasting methodology is used for demand prediction. Controller parameters are chosen by optimizing a cost function that reflects total operational costs through a genetic algorithm. A comparison of the different controllers is carried out using the optimal controller parameters and the proposed cost function.

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List of Symbols

AIC	Akaike Information Criteria, p. 36
AIC_c	Corrected Akaike Information Criterion, p. 36
BuC	Buying Unit Cost, p. 38
$C(k)$	Total Accumulated Costs up to Day k, p. 38
$CC(k)$	Total Accumulated Contingency Costs up to Day k, p. 38
DuC	Delay Unit Cost, p. 38
EVD	Express Vessel Decider variable, p. 24
$F_r(k)$	Number of filled tanks to transport to rig r at day k, p. 23
G_a	Demand estimator transfer function, p. 26
G_d	Demand Estimation to Work-in-Progress set-point transfer function, p. 26
G_i	Inventory Level Controller Transfer Function, p. 26
G_w	Work-in-Progress Level Controller Transfer Function, p. 26
HuC	Handling Unit Cost, p. 38
I	Inventory level on a general production-to-stock model, p. 26
I_{sp}	Inventory set-point on a general production-to-stock model, p. 26
K	Gain to form set-point via demand estimation on a general production-to-stock model, p. 26
K_d	Derivative gain of a PID Controller, p. 32
K_i	Integral gain of a PID Controller, p. 32

K_p	Proportional Gain of a Controller, p. 28
K_{lt}	Conversion factor from liters to tank, p. 22
K_{pi}	Multiplier associated with the desired range of a given variable, p. 40
L	A function of the Likelihood of the estimatives, p. 35
$L(k)$	Matricial Representation of the function involving the first decision variable, p. 37
$MC(k)$	Total Accumulated Material Costs up to Day k, p. 38
$N(k)$	Matricial Representation of the function involving the second decision variable, p. 37
N_t	Number of tanks, p. 22
O	Ordering on a general production-to-stock model, p. 26
$OC(k)$	Total Accumulated Operational Costs up to Day k, p. 38
$OoSuC$	Out-of-Stock Unit Cost, p. 38
$P(k)$	vector of tanks at port going to all rigs at day k, p. 24
P_{max}	Port Capacity, p. 24
SuC	Storage Unit Cost, p. 38
$TC(k)$	Total Accumulated Transportation Costs up to Day k, p. 38
T_{PSV}	Period of regular scheduled PSV's, p. 24
$W(k)$	Warehouse levels at day k in liters, p. 22
WIP	Work-in-Progress in a general production-to-stock model, p. 26
ϵ_t	Error on variable estimate at time t, p. 35
$\hat{d}$	Demand estimate in a general production-to-stock model, p. 26
τ	denotes delay of τ units of time, p. 12
φ	Function that relates parameters, states, disturbance and delays with control input $u(k)$, p. 39

ζ	Vector of parameters of the Controller, p. 39
b_j	j-th bit on bit string, p. 40
d	Demand in a general production-to-stock model, p. 26
$d_{i,r}(k)$	Demand from rig r for item i on day k, p. 22
e	Summed Error, p. 28
e_d	Demand Error on a general production-to-stock model, p. 29
e_i	Inventory error on a general production-to-stock model, p. 26
e_w	Work-in-Progress error on a general production-to-stock model, p. 26
f	differential/difference function of a dynamic system, p. 12
i	Item index, p. 22
i_{max}	Number of items considered in the simulation, p. 22
k_{horiz}	Last time instant on simulation horizon, p. 39
l	Liters, p. 22
p_i	i-th parameter in parameter vector, p. 40
$q(k)$	truck transportation levels at day k, p. 24
r	Rig index, p. 22
r_{max}	Number of rigs considered in the simulation, p. 22
sC	Cost of Regularly Scheduled Vessel Trip, p. 38
$s_r(k)$	tanks To Supply Vessels at day k, p. 24
$t_r(k)$	tanks ready to transport to rig r on day k, p. 23
$toRig_r(k)$	Tanks in transit to rig r at day k, p. 24
u	control input of a dynamic system, p. 12
w	exogenous input of a dynamic system, p. 12
$w_r(k)$	tanks to truck transport to rig r on day k, p. 23
x	state of a dynamic system, p. 12

x_t	Estimate at time t, p. 35
y_t	Observation at time t, p. 35
y_{wi}	In transit orders at day k (liters), p. 22
y_{wo}	ready to dispatch at day k in liters, p. 22

List of Abbreviations

APIBPCS	Automatic Pipeline Inventory based production control system, p. 4
APIOBPCS	Automatic Pipeline Inventory and Order based production control system, p. 4
APVIOBPCS	Automatic Pipeline Variable Inventory and Order based production control system, p. 4
CS	Conveyor-Stock, p. 17
EMPC	Economic Model Predictive Control, p. 63
ETS	Error, Trend and Seasonality, p. 33
EVA	Economic Value Added, p. 63
IOBPCS	Inventory and Order based production control system, p. 4
MPC	Model Predictive Control, p. 4
SCS	Stock-Conveyor-Stock, p. 16
VIOBPCS	Variable Inventory and Order based production control system, p. 4

Chapter 1

Introduction

Offshore oil production plays a vital role in Brazil's economy, and it is therefore very important to provide robust logistics solutions that can ensure continuous production from offshore installations, under conditions that involve both high values and high risks.

Petrobras is the major state-owned oil company in Brazil, and is responsible for 96% of Brazilian oil and gas production. Recent discoveries of large reserves offshore, estimated to contain about 12 billion recoverable barrels of oil equivalents (b o e) has the potential of transforming Brazil into a world leader in oil production. However,as opposed to the old reserves which are at an average depth of four kilometers below sea level, the new reservoir formations are under an additional kilometer of rock and another two kilometers of salt (in compressed form), in addition ti being about three hundred kilometers from the closest ports on the Brazilian coast. Despite these challenges, Petrobras has set itself the goal of doubling its production in the next five year, and this will necessarily entail a huge investment in its supply chain and a concomitant demand for cost-efficient logistics.

In the current worldwide scenario of falling petroleum prices, Petrobras faces the additional problem of reducing production and logistics costs in order that exploitation of its deep water and pre-salt oilfields remain viable. This is the overall context in which the work reported in this dissertation was carried out with a specific focus on modeling the logistics of petroleum supply chain. The short term objective is to achieve a better understanding of the dynamics of the warehouse-to-offshore part of the petroleum supply-chain and the longer term objective is to develop a tool that could be used to help in dimensioning and economical design.

This dissertation covers the process of modeling the warehouse-to-offshore supply chain using a *Stock and Flow model* [3],[4]. This is followed by the formulation of an economic objective for the supply chain in question and the study of a class of well known control schemes, the parameters of which are chosen in such a manner as to optimize the proposed economic objective.

1.1 Objectives

This report is about modeling and control of a supply chain using a control-theoretic formulation and carrying cost optimization. The specific objectives are:

- To model a real world warehouse-to-offshore rig supply chain, contemplating the main warehouse management issues, problems arising from post management etc., and how these reflect on the total costs of the operation.
- To discuss how this proposed model can be controlled using different strategies such as output feedback, state feedback and compensators that use demand forecasting.
- To formulate an optimal control problem in which controller structure is fixed and parameters must be chose so as to optimize an objective function that represents total cost of the operation.

1.2 Organization of the Report

The text is organized as follows:

Chapter 2 contains a brief bibliographic review of the existing literature on the application of controllers to mathematical models of supply chains.

Chapter 3 briefly reviews *Stock and Flow Models* which are then used to build the final model, step by step. The state-space representation of the final *Stock and Flow model* is also given.

Chapter 4 is devoted to explaining the fixed controller structures that will be used as well as the process of automatically choosing the demand predictor [5]. In addition, an optimal control problem (OCP) is formulated, consisting of the minimization of a function that represents the total costs of the operation, subject to the dynamics of the supply chain to which a controller belonging to the IOBPCS family has been applied. The parameters of the controller are found by solving the OCP using a genetic algorithm.

Chapter 5 shows the results for both controllers and automatic forecaster algorithm and compares controller performances based total cost.

Finally, chapter 6 makes some concluding remarks and suggests some possibilities for future work.

Chapter 2

Bibliographic Review

The problem of controlling supply chains has been studied since the 1950s and has received a lot of attention, with many publications proposing different viewpoints to tackle it. (for a sample see [6] and [7]).

These early papers introduced the simplest mathematical model of a supply chain: a factory supplying a warehouse with a certain lead time or transportation delay, in response to restocking orders from the latter, which, in turn, responds to demand from a client further downstream. In control terminology, the plant consists of an integrator/accumulator, preceded by a delay.

Since these pioneering works there has been a great number of papers on the design of controllers for the simple model of a supply chain described above and Ortega and Lin ([8]) provide a good review of this work.

In terms of modeling and simulation of simple supply chain, there has also been a sustained effort, stemming from the work of Forrester ([9]) and Sterman ([3]).

The proportional integral derivative or PID controller is one of the most widely used types of controllers. A PID controller uses one or more measurements from the system to calculate an error (in the standard case, the difference between a reference or set-point value and the measured value). This error is then subjected to proportional, integral and derivative terms, which are then combined to generate a control signal. Ortega and Lin ([8]) describe the use of PID control ideas in a survey paper.

The basic continuous-time model of a simple inventory process consists of a delay followed by an integrator, This model has been investigated intensively in the literature and Ortega and Lin ([8]) provide a comprehensive survey of the developments and write that "none of the reviewed models implemented a systematic way to calculate all the required model parameters" and furthermore, "some authors presented suggestions to optimize some parameters, but no reference was found that tried to obtain these values from a real system".

Although the Ortega-Lin paper is relatively recent it emphasizes only classical control methodologies. A more recent survey ([10]) complements the Ortega-Lin survey by presenting an extensive review of the application of the so called advanced control methodologies to the production and inventory control problem. Specifically, [10] describes different optimal control methods and, finally, approximate dynamic programming methods. It is noted, however, that much of the literature is devoted to models which are linear (because of the techniques applied) or quite simplified (because of computational complexity of the advanced control methods, specially those involving optimal control or dynamic programming).

In control of production-inventory systems, Inventory level is usually monitored and the IBPCS (Inventory Based production control system) was coined by Towill ([11]) to describe the class of controllers that uses functions of errors defined by deviations from a reference inventory level to generate a control signal.

Numerous studies were made about the tuning and functioning of the IOBPCS (Inventory and Order based production control system) family. For example, [12] uses APIBPCS (Automatic Pipeline Inventory based production control system) control, or order up-to control, to measure bullwhip and investigate system behavior using different values for the tuning parameters.

Bullwhip effect is a disruptive effect that can take place in a logistic system. Since there are delays involved with the production and resupplying, controllers usually use a estimate of the future demand. If that estimate is inaccurate, then inventory level can sharply increase, leading to large variance in this particular state of the system. Bullwhip refers, roughly speaking, to a large variance in inventory level.

The paper [13] relates bullwhip reduction to the minimization of an appropriate functional and proposes a method to optimize APIOBPCS parameters in order to reduce bullwhip. It also proposes a explicit bullwhip formula.

These controllers and others that followed them, such as VIOBPCS and APVIOBPCS are directly linked to classical PID-like control laws and utilize demand forecasting. In fact, all of these controllers produce an input that results from manipulation of state variables and disturbance (i.e. the demand).

These controllers are used on models that consider all product levels aggregate or, alternatively, levels of a single product.

The reader is referred to the paper [14], for a Discrete Event System approach to the production-inventory or supply chain simulation problem. controller.

In this context, this dissertation takes the following approach: The model is built to be as close as possible to the real system, incorporating its non-linearities. The controllers, on the other hand, are taken from the IOBPCS family of PID-like controllers to be described below, with a fixed structure and parameters to be chosen. A realistic cost function is formulated, and the controller parameters are then chosen by optimizing the former with respect to the latter.

Clearly, since the IOBPCS family of PID-like controllers was originally designed for a linear production-inventory plant, when this family of controllers is applied to the plant proposed in this dissertation, which contains non-linearities, the parameters must be chosen with an approach valid in the non-linear case. This is done using a genetic algorithm to find the controller parameters, for each chosen and fixed controller structure from the IOBPCS family, that optimizes a proposed (and realistic) cost function.

In order to use controllers of the IOBPCS family one must tackle the problem of forecasting demand in almost all variants, the only exception being the IBPCS Controller itself, which only requires one feedback loop. The IBPCS controller block diagram is depicted in figure 4.2 and it is explained briefly in section 4.1.1.

There has also been much research on the demand forecasting problem and its relevance to the supply chain problem. Some researchers claim that demand forecasting can lead to impaired stability, or even that PID control performs the same role as forecasting but more efficiently, since PID Controllers are aware of the feedback loops they create, unlike demand forecasting [15].

Specifically, the claim made in [15] is that, while forecasting and derivative control have similar reasoning behind them, the former often leads to more uncertainty and the latter, less. Although both derivative control and forecasting predict trends, they do so in different ways.

The paper [2] provides overview of all commonly used methods for forecasting an unknown or stochastic variable.

The book [5] provides a comprehensive framework for demand predictor selection that will be explained in more detail in section 4.2. It uses training data in multiple tests of several models of exponential smoothed demand forecasting and calculates a functional that computes the **likelihood** of the prediction provided by each model, subsequently choosing the model that maximizes the likelihood.

The papers [16] and [17] use a simple production-to-stock model coupled with a controller from classic control theory. While [16] has an interesting approach to both the control and the forecasting problem by using respectively a PID control attached to the APIOBPCS control scheme and Kalman Filters to forecast demand, [17] is a generally simpler approach to the same problem and its goals are to provide an educational resource and control tuning recommendations.

The paper [18] uses the same system structure in a different context, a chemical process. Since the model to be controlled is the same, controllers proposed to control supply chain models could also be applied in this case or other analogous contexts. Similarly, the control scheme proposed by this work could also be used to control supply chains.

Chapter Summary: This chapter provided a brief summary of the literature on control approaches to the production-inventory dynamical system model and contextualized the approach taken in this dissertation to the specific problem of modeling and control of a real supply chain.

Chapter 3

Modeling Liquid Supply-Chain Bulk Process

This chapter provides a general overview of part of the process that will be modeled, commonly referred to as the upstream supply chain for offshore oil and gas production. In order to arrive at a prototype model, the systems dynamics (SD) approach, based on stocks and flows, was used initially and this modeling process is described in detail. The chapter closes with a description of the cost function as well as the state space model, which was used to write MATLAB code for the final model, including the controller and cost function.

3.1 The upstream supply chain for offshore oil and gas production

Figure 3.1 shows a schematic view of the upstream and downstream supply chains to offshore installations

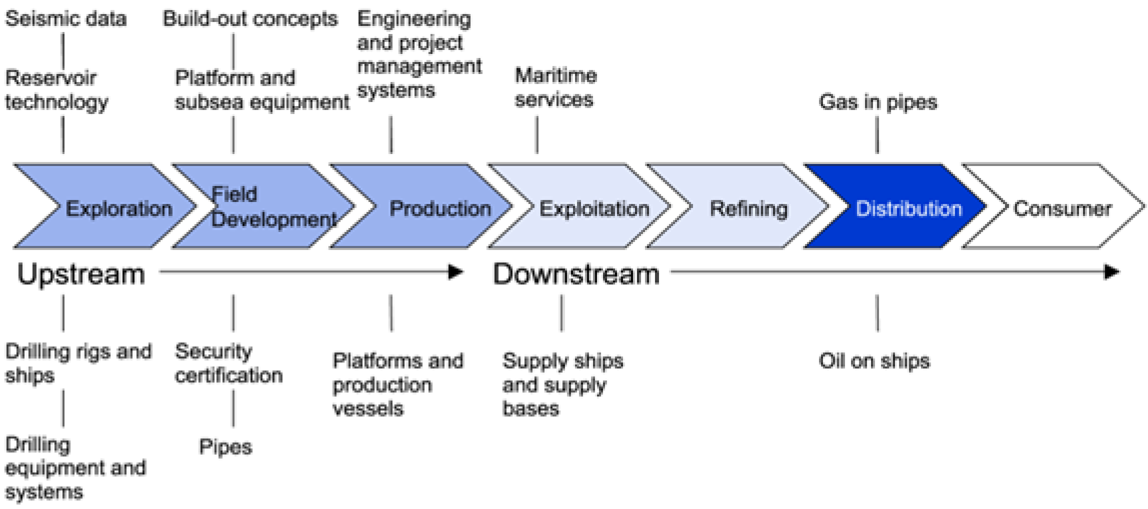


Figure 3.1: Schematic of upstream and downstream supply chains. Source:[1]

The present dissertation limits its study to the upstream part of the supply chain to offshore oilfields owned and operated by Petrobras, in the southeast of Brazil, an area known as the Campos Basin. Within the upstream supply chain, for reasons that will be given below, the study is further restricted to liquid bulk items.

Offshore installations need to be kept supplied with a large variety of items (the complete list is available at Petronect, 2015). The term offshore installations used in the title and body of this dissertation includes traditional production platforms, floating production storage and offloading units (FPSOs), as well as drilling rigs. These installations place requests to an onshore warehouse for supplies to be delivered. Offshore installation sizes vary from small, in the case of unmanned units, to large, manned by several hundred workers. Platform supply vessels (PSVs) ply on scheduled routes and serve these supply requests or demands, transporting cargo from the port to the set of installations on their routes and also bring material (waste, empty containers, etc.) from the installations back to the port (this reverse transport, also referred to as backload, will not be considered in this dissertation). The most crucial aspect of this supply chain is to fulfill all the demands in a timely manner, so as to guarantee uninterrupted production of petroleum.

Petrobras, like most oil companies, charters PSVs from third parties. The cost of chartering and operating PSVs is around USD 100,000 per day and is one of the largest upstream logistics costs, so that immediate and important objectives are to use as few PSVs as possible and, at the same time, maximize the use of each one [19].

The overall goal of this dissertation and the project is to create a modeling and simulation platform that is sufficiently general to encompass logistics and supply chains that commonly occur in upstream supply chains for oil, but also providing tools that allow inclusion of process detail in the specific case considered.

3.2 Modeling and simulation approaches for supply chains

In order to justify our choice of modeling only the liquid bulk supply chain in this dissertation, we first present a brief overview of the existing literature using all methods, followed by one of related work using systems dynamics methods ([4], [3]).

There is a reasonable amount of literature in journals on operations research, warehouse and supply chain management, as well as more specialized journals on marine economics and logistics on the general topic of optimization different stages of the process and some of the relevant papers will be cited below, although we will mostly restrict ourselves to citing the literature using SD methodology. Supply chain management issues are discussed by [20], where several strategies are examined to improve supply chains in the oil and gas industries. An extensive review of general supply chain modeling strategies is presented in [21], where the key challenges and efforts to solve this problem are presented.

Computer simulation based analysis of logistics processes is also an important field of research, computer simulations may provide important insights about the whole process, allowing effective planning and optimization. Object-oriented simulation is used by [22], while stochastic programming modeling and solution techniques are used in [23] to solve the problem of planning logistics operations of oil companies. Other approaches using discrete event simulation and stochastic methods to address the problem of logistics and supply chain operations can be seen, for instance, in [24], [25].

3.2.1 Models of upstream supply chain

As far as models of the upstream supply chain are concerned, most published studies deal with the last stage, namely optimization of PSV routing and scheduling and up to date bibliographies can be found in [1], as well as [26], to which we refer the reader.

Systems dynamics models of the upstream supply chain have focused mainly on problems related to maritime transport (see review [27]) and optimization of tanker freight modeling ([28]) or tanker sizes ([29]) and container sizes ([30]). There are a few papers devoted to more complete models (not specifically for upstream SCs), such as [31] (modeling and simulation of the rail-port cycle).

Since there appear to be no published warehouse-to-offshore installation integrated models, this dissertation is devoted to proposing such a model. Furthermore, even the existing models are devoted to dry bulk transport and, as far as we know, no models exist for liquid bulk transport. This fact, combined with the practical observation from Petrobras data that the largest demand from offshore installations is, in fact, liquid bulk, led to the decision to focus on the latter.

3.3 Brief overview of the upstream supply chain

Figure 3.2: Stages of the offshore oil & gas upstream supply chain

Figure 3.2 shows the successive stages in the upstream supply chain, from demand handling to delivery, including the picking process in the warehouse; the containerization of picked items to be transported to each offshore installation; truck transportation from the warehouse to the port; the loading operation at the port; and the shipping, using the scheduled routes of PSVs serving the offshore installations.

Figure 3.3 contains an overview of the process timeline used for planning the logistics process. All orders are processed by an Integrated Planner (IP), which distributes demands in accordance with PSV schedules and criticality of the demand. When all demands have been handled and ordered appropriately, the IP starts planning how to meet the demands, segmented by operational area. A representative of the operational area performs a demand versus capacity analysis and returns his conclusions to the IP. The IP then negotiates new due dates with the offshore installations for the non-critical orders that are over capacity. Finally, it plans daily activities for warehouse and transport operations, in order to ensure that the planned schedule can actually be met in practice, when a limited amount of uncertainties and unforeseen delays are present.

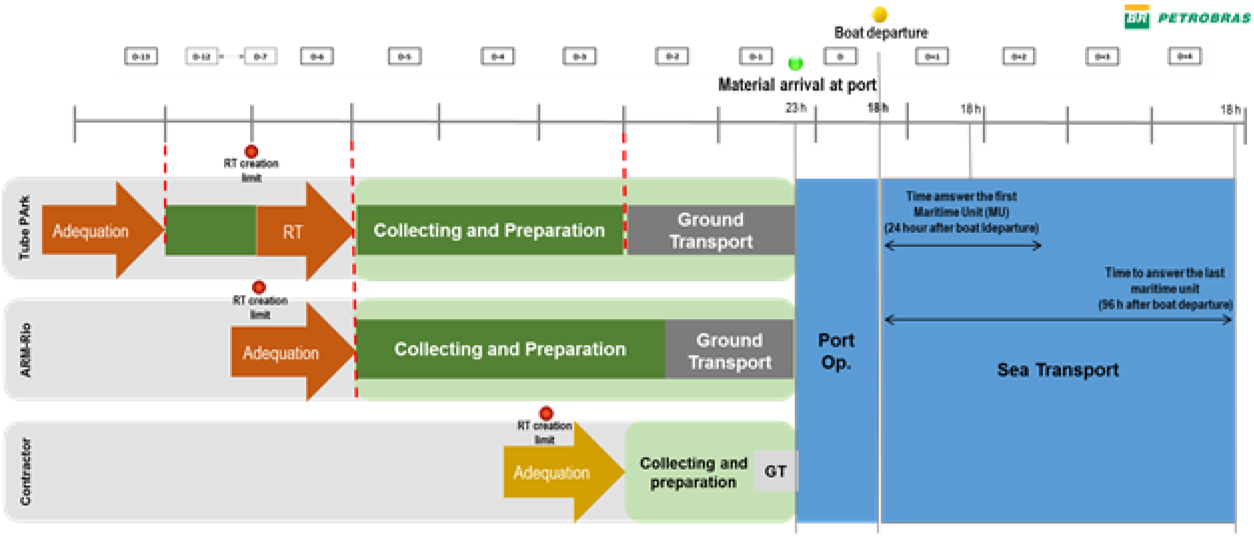


Figure 3.3: Timeline for Offshore Oil & Gas Logistics planning used by US-LOG, Petrobras

After the planning phase, the job of the logistics team is to execute the plan. As shown in Figure 3.3, different types of materials shown in the three separate horizontal flows, have different time-frames. Tubes (top flow) must start to be prepared 14 days before scheduled PSV departure, materials in the warehouse (middle flow) must have a transport requisition ready 7 days before and contracted materials (bottom flow) must be planned in a 4-day ahead window.

The process is similar for the 3 branches shown in Fig. 3.3, although the time-frames are different. The warehouse process is composed of picking the requested items and making them available for packaging and, subsequently, containerization. Containers are packed and loaded into a truck to be transported to the port. Truck transportation has its own timeframe. When the containers reach the port, they are loaded on to the scheduled PSV and transported to their respective destinations. Each ship departure has a route, which usually consists of four to five destinations. The ship unloads containers at each destination and then receives the backloads (anything that needs to return to land). Routes are revisited periodically

3.4 Model building and assumptions for liquid bulk supply chain

3.4.1 Model building methodology

The model presented in this dissertation was built as part of a collaborative project involving Petrobras as client, the company EMC^2® as consultant to Petrobras for logistics and big data analytics and a university team (from COPPE/UFRJ) as consultant specialists in modeling. Engineers from Petrobras/CENPES (the research center), researchers from EMC^2®, and professors and students from the university met regularly, in addition to visits to one of Petrobras' warehouses. In addition, engineers and operational staff from Petrobras' logistics planning center (GIOP, US-LOG) were interviewed and provided logged data of the logistics operation over one year, information, as well as flow charts pertaining to the upstream supply chain. These were the elements used to build the mathematical model described in this dissertation.

3.5 Stock and Flow Diagrams

Stock and Flows diagrams are a convenient way to build and visualize complex dynamic systems as well as to understand macroscopic behavior by analysing Feedback Loop Diagrams ([3],[4]) or the *Stock and Flows diagram* of the dynamical system.

Stocks are a representation of integrators or accumulators and the stock level is usually referred to as the state of the system. The iconic representation of a stock and a flow is shown in 3.4.

The stock, with its associated flow, corresponds to the discrete-time state space recurrence on dynamical system:

$$x(k+1) = x(k) + f(x, u, \tau, w) \tag{3.1}$$

where x is the state, u represents the control input, k represents discrete time, τ represents a vector of integer constants that can be used to access previous states of the system ,w represents disturbances, stochastic or deterministic and h is the sampling period. The iconic representation is shown in Fig 3.5.

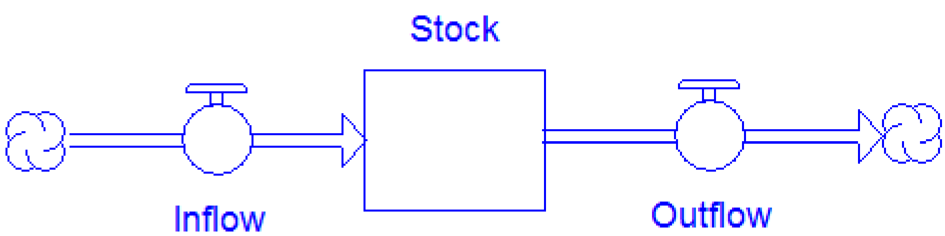


Figure 3.4: Icon that represents a Stock and two flows

Flows are a way to represent rates of flow to and from stocks. The representation of a Flow is an arrow, emanating from a source or stock and passing through a valve, to terminate in a sink or another stock. Sources and sinks are depicted by cloud icons. Flows determine the rate of changes of states over time, thus represent $x(k+1) - x(k)$.

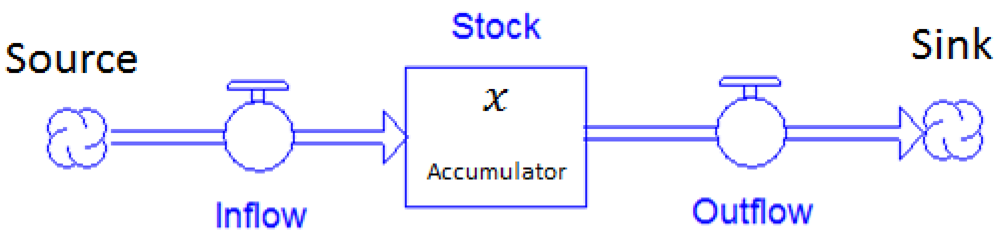


Figure 3.5: Icon that represents a the interconnection of a stock and a flow and correspondence to equation 3.1. $f(x, u, \tau, w)$ is the difference $Inflow - Outflow$.

3.5.1 Conveyors

Conveyors are a special kind of stock-flow connection (in that order) used to represent delay. Conveyors are idealized versions of assembly lines: once an item enters a conveyor, it stays in it for a specified amount of time (which can be deterministic or random) and leaves it as soon as the residence time limit (also referred to as a delay τ) is reached. Figure 3.6 shows the iconic representation of this structure in a stock and flow model.

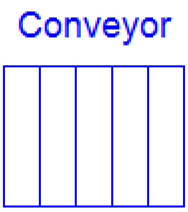


Figure 3.6: Icon that represents a Conveyor in a Stock and Flow Diagram

3.5.2 Converters

Converters are used to define inputs to flows (allowing the introduction of formulas) or to represent data coming from an external source, such as demand. Converters are represented by a circle, as shown in Fig. 3.7.

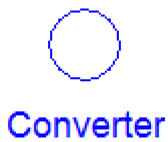


Figure 3.7: Icon that represents a Converter in a Stock and Flow Diagram

3.5.3 Interconnections

Stock, flows and converters are interconnected to build models. Figure 3.8 shows an interconnected model containing all of the aforementioned structures. This simple model, widely studied in literature, is called the manufacture to stock model.

The only element present in 3.8 that was not explained earlier is the single arrow (the one emanating from the stock to the converter), which represents information flow. In figure 3.8, Converter 1 carries out some calculations based on (possibly historical) information about Stock 1 levels, while Flow 1 is a function of what was calculated in Converter 1. Integrators such as Stocks or Conveyors can only supply information, while Converters and Flows can either supply or receive information from other structures.

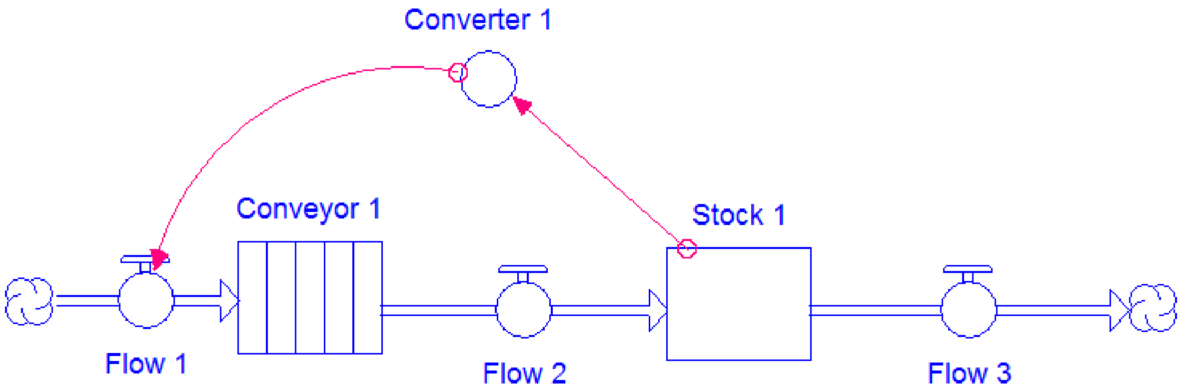


Figure 3.8: The manufacture-to-stock model, shown in the figure, is a simple instance of the use of the elementary building of stocks, flows, converters, conveyors and information flow between them. This model is also referred to as conveyor-stock or CS model. The conveyor represents the delay between placing an order (arrow from converter 1 to flow valve 1), based on stock level at stock 1(arrow from stock 1 to converter 1) and its arrival at stock 1, through Flow 2.

3.5.4 Model building assumptions and hypothesis

In the early stages of the modeling process, it was decided to build two models, an aggregate model that would serve as a flight simulator and was intended to help in making strategic decisions, as well as a more detailed microscopic model, that would bookkeep movements of essentially every item in the whole process and is intended to be used together with big data analytics to make predictive models, as accurate as possible of specific process variables, such as lead time. This dissertation reports on the former model, which was built using SD methodology, while the latter is reported on elsewhere ([32]).

Given that the warehouse has the usual structure, it was a natural decision to use the standard stock-and-flow model of SD. For illustrative purposes, in this dissertation, we decided to use just two offshore installations (one a production platform and the other a drilling platform). The criterion for the choice of these two was that the logged data showed that they had the highest volume of demand for a one year period. As far as the demanded items are concerned, we chose, for the purposes of the study reported here, the two items which had the highest demand, and turned out to be the same two liquid bulk items, here referred as product A and product B. This information led us to model the warehouse as a vector stock of the two liquid bulk items. The demand from the two offshore installations (abbreviated as rigs in this section, for brevity) is modeled as an array (rig X items) and, in the experiments shown below, real data for a two month period was used. The warehouse receives the processed rig demands and, since these are liquid bulk items, we assume that they are grouped into separate tanks of a fixed capacity. Each tank carries the label of the rig that demanded it. Tanks are transported by truck to the port and grouped by PSV that contains their destination (i.e., demanding) rigs on their route, using an FCFS queue for the tanks. Liquid bulk cargo, such as the products mentioned above, are stored in separate storage compartments below deck and thus do not compete for deck space with the dry bulk containers. In addition, delivery of dry bulk containers and liquid bulk can occur simultaneously, since the latter is pumped into tanks on the rig, while dry bulk containers are offloaded, from PSV to rig, by cranes (Aas et al. 2009).

Since purchase data was not available, we used a simple model for restocking based on a desired minimum stock level trigger. For the baseline case, all transport delays (to warehouse, truck transport and maritime transport) were chosen as fixed and compatible with the available real data.

The modeling process is now detailed step by step.

3.5.5 Summary of model assumptions and hypothesis

- The model represents the two liquid bulk items that had highest demand in the analysed real data.
- The warehouse is modelled as a vector of the two liquid bulk items mentioned in the first assumption.
- The demand is represented as an array: rig $\times$ items.
- Items are grouped into separate tanks for each rig.
- One rig has fixed priority over the other one.
- Tanks are transported by truck from warehouse to port
- Port dispatches tanks to rigs on Platform Supply Vessels (PSVs);
- Tanks are grouped by supply vessel that contains their rigs on its route [First-Come First-Served queue for tanks].
- Supply vessels are fed from FCFS queue according to their deck capacity.

3.6 Modeling Process

We are now ready to explain the modeling process.

We start by discussing the CS module in 3.8. This model represents a workstation, i.e., one module of the overall process. A generic item called a "job" enters the conveyor, which represents the process module with its corresponding delay. When the process finishes, the item is put in the stock and is ready to be "delivered". If the process module has limited capacity of handling a job (or for instance the job inflow rate exceeds the process module capacity), it becomes necessary to place a stock in front of the conveyor, as shown in 3.9.

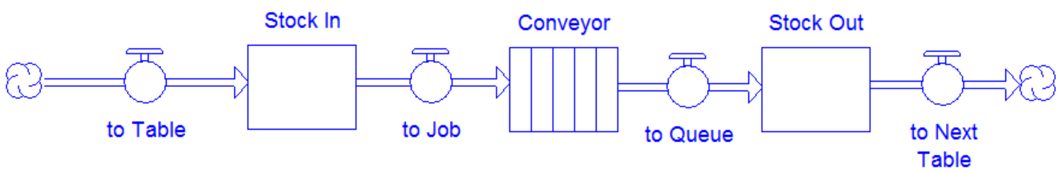


Figure 3.9: The SCS Module. A Stock is added to the CS model in 3.8 to accumulate Jobs that cannot be processed because of process capacity limitation

This new structure incorporates process module capacity limitation by adding a stock of "jobs" wating to be processed. Such modules are widely used (e.g. in the chemical industry [18]) and in the description of business processes, in which there could be delays in both the entrance of the processing unit, as well as in the processing itself.

The first step in modeling the process studied in this report was to represent each task in the liquid bulk supply chain by a CS module. Subsequently, the CS modules were connected in series in accordance with a process flow diagram provided by logistics specialists of the oil & gas company. This resulted in a fairly complicated model, and one that was difficult to be checked consistency using provided data.

Subsequently, after several meetings, interviews with the logistics specialists of the company and data access, it became possible to arrive at a model that could capture all the relevant process and give insightful information, yet simple enough to be data verifiable. This final model is subdivided in three smaller submodels, namely the Warehouse submodel of the model, the Loading Consolidation submodel and, finally, the maritime transportation submodel that represents transportation of liquid bulk from the port to the rigs.

In the warehouse portion 3.10 the model is similar to a stock-to-sales model. Demand from rigs must be fulfilled in this portion, which accounts for the outflow from Warehouse levels. The CS module is also used to describe the warehouse replenishment process. The control input is the quantity of liters bought from suppliers, and it is the most important control in the model. Good control of this quantity means being able to fulfill the demand without letting the warehouse levels become too high.

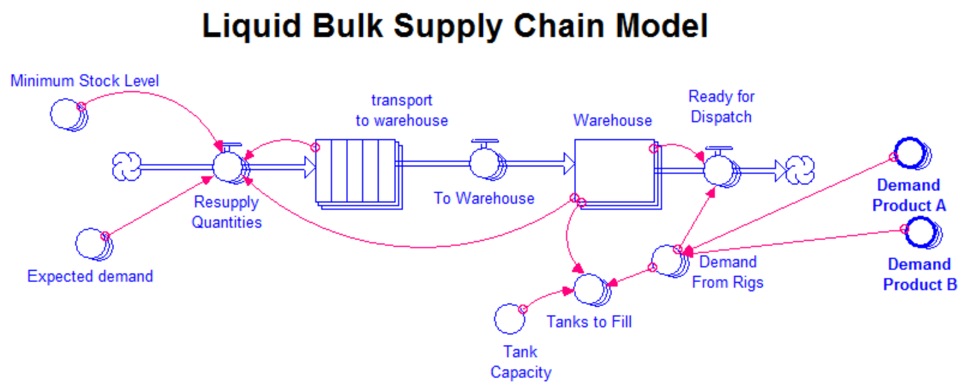


Figure 3.10: Warehouse submodel of the Liquid Bulk Supply Chain Model

The warehouse submodel feeds into the load consolidation submodel. The first block of the load consolidation submodel is a conveyor to represent the process of storing the liquid supply in tanks. This is followed by stock representing queue of tanks ready to transport. The tanks are moved to the next conveyor using the following rule: If the stock levels in port area plus transport to port stock levels are below a specified maximum allowed quantity, tanks are sent to the port until there are no more tanks to send or the port capacity is reached. The port area for tanks, represented by the stock port, is emptied on a periodic basis by loading tanks on to a "regularly scheduled vessel". The operator of the system also has the opportunity to send these tanks on an express vessel, in case of an emergency (meaning that a regularly scheduled vessel is not available). Express vessels cost more than regularly scheduled ones. In the Cost analysis that follows it will become clear that there is a trade-off involved in avoiding the use of express vessels because longer queues also mean increasing costs.

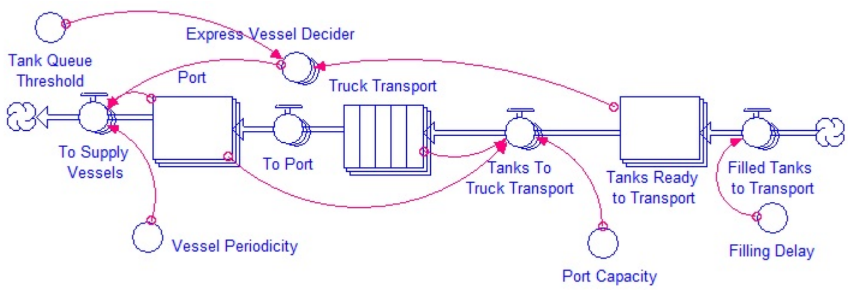


Figure 3.11: Ground Transportation portion of the Liquid Bulk Supply Chain Model

Finally, there are two flowcharts representing maritime transportation, one for regularly scheduled vessels and another one for express vessels. These two flowcharts are just conveyors since the levels of storage on the rigs are not relevant for this particular model.

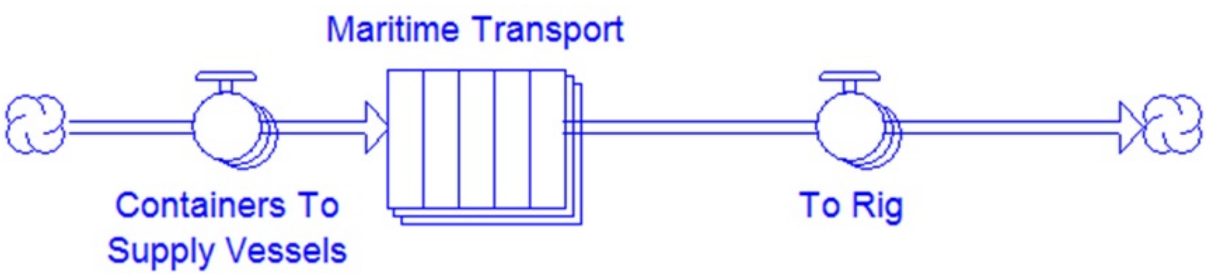


Figure 3.12: Maritime Transportation portion of the Liquid Bulk Supply Chain Model

Figure 3.13 shows the complete model. There are some converters to perform the appropriate unit conversions, a matter that will be discussed more thoroughly in section 3.7

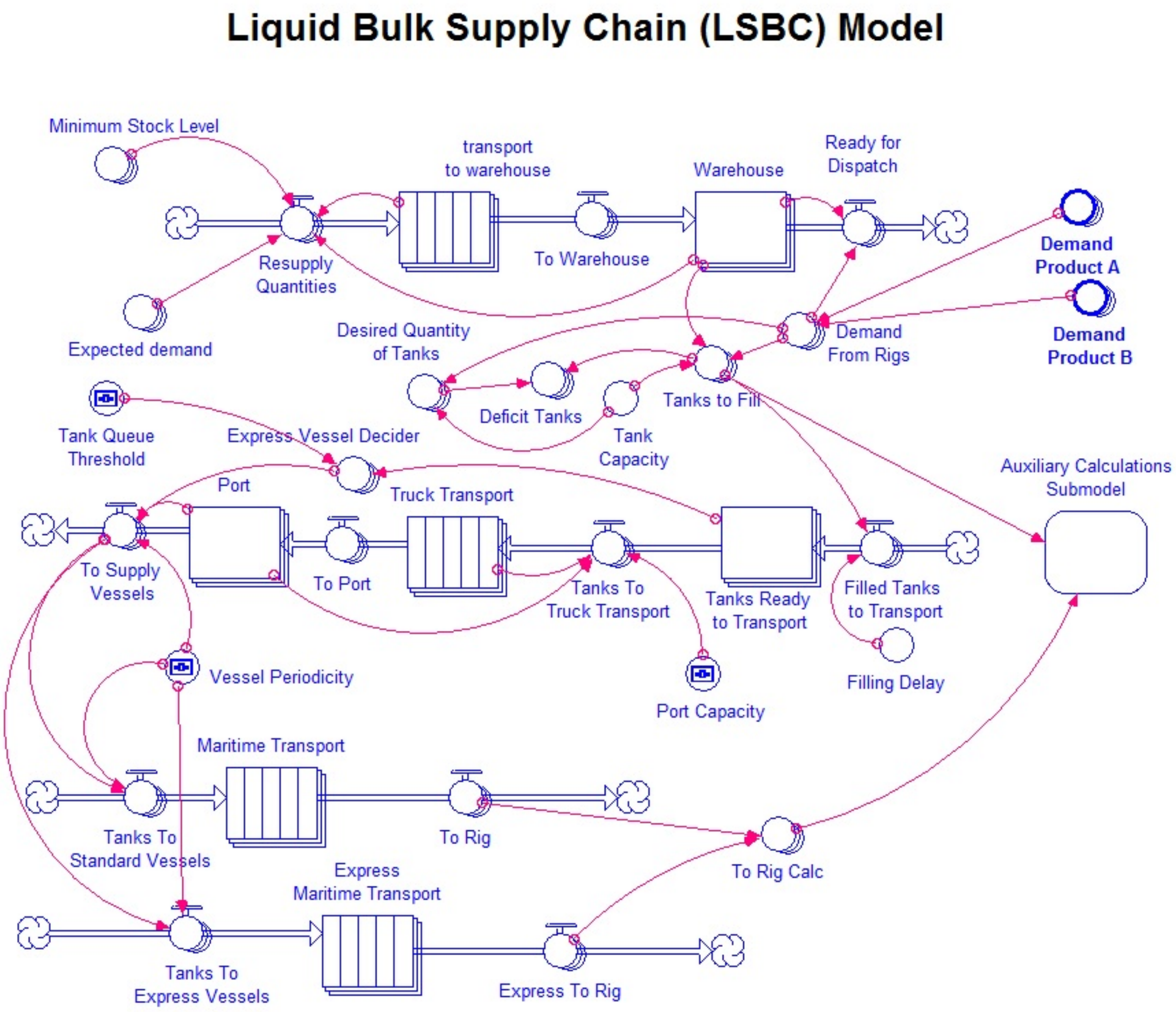


Figure 3.13: Complete Liquid Bulk Supply Chain Model

Our interest is to calculate how this model fares in terms of cost of the whole operation. To do so, we must use some values from variables in 3.13 to calculate these costs. We also need a model that tells us how these costs are calculated. This model is shown in figure 3.15

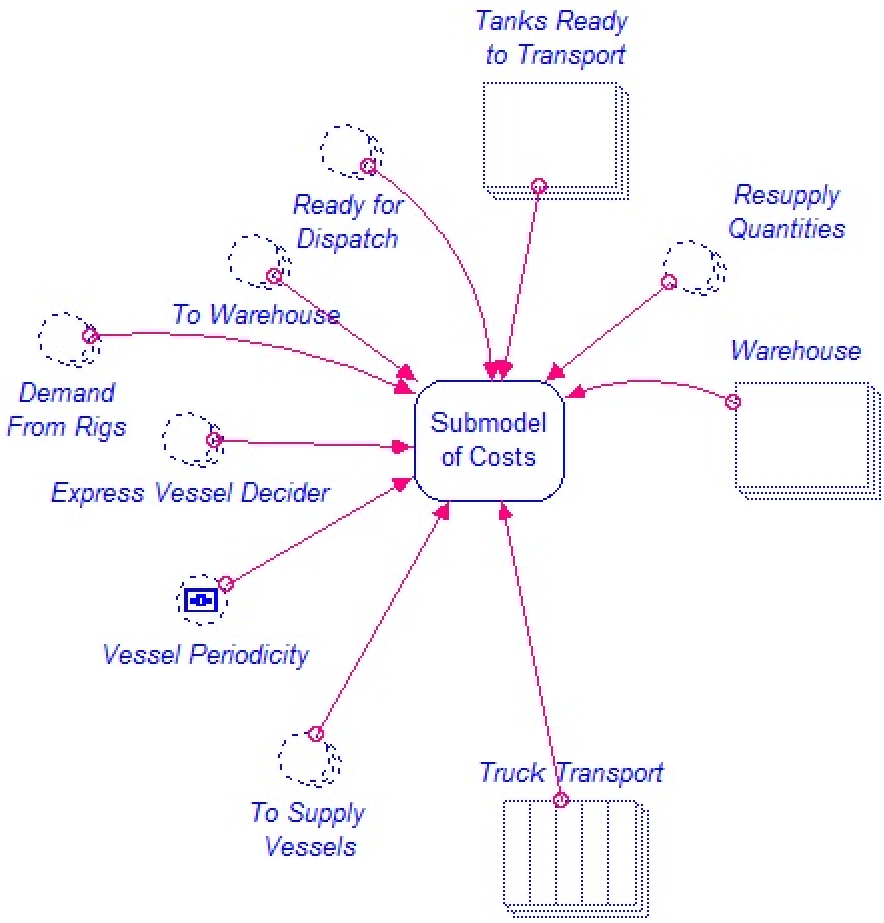


Figure 3.14: Variables from the main model used in the sub-model of costs

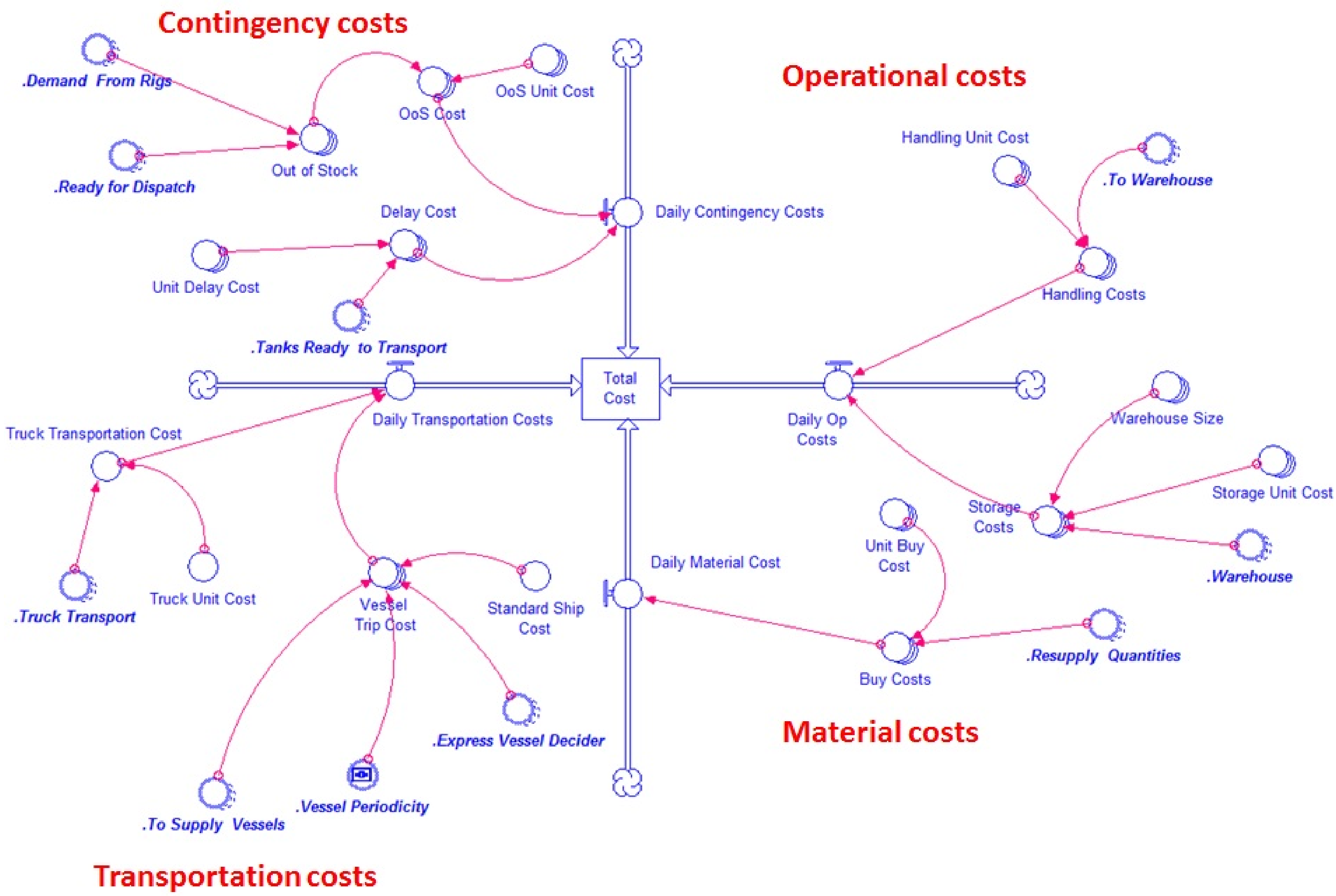


Figure 3.15: Sub-model of Costs

The sub-model of Costs is divided in four main areas. The first cost associated with this operation management is the Operational Cost, which comprises handling costs associated with resupplying and maintaining the Warehouse. Another important cost that is directly linked to the Warehouse are the Material Costs, or the prices paid in the act of buying goods to resupply the Warehouse. Contingency Costs are penalties incurred due to delays in operations or the inability to fulfill a particular demand. If one of these problems occurs, the Rig will need to stop producing at some point, and there is an important cost (loss) associated with such an event. Finally, transportation costs measure how much is spent in the act of transporting the goods from the warehouse to the rig. These costs can increase dramatically if the company needs to use Express Vessels often and, thus, good port management is fundamental to keep these costs low.

3.7 Mathematical Representation of Full Model

In this section the stock and flow model described in section 3.6 will be written as a difference equation model. This difference equation or state-space model will be used to formulate the optimal control problem of interest in this report, which is discussed in section 4.3.

The Warehouse sub-model state vector consists of the Warehouse levels $W(k)$ and the state equations can be written as follows.

$$\begin{aligned} W(k) &= W(k-1) + O(k-\tau) - y_{\mathrm{wo}}(k) \\ y_{\mathrm{wi}}(k) &= y_{\mathrm{wi}} + O(k) - O(k-\tau_1) \\ W(0) &= [W_{1_0} \cdots W_{i_{max0}}]' \\ y_{\mathrm{wi}}(0) &= [0 \ \cdots \ 0]' \end{aligned} \tag{3.2}$$

where $W(k)$ are the warehouse levels of liquids in liters at day k, i_{max} is the number of different items, $tW(k)$ means *to warehouse* and measures the amount of liters in transit, $O(k)$ is the order placed by the Warehouse on day k, τ is the resupply delay in days and $y_{\mathrm{wo}}(k)$ means *ready to dispatch* and is a vector of sent items that can be represented by equations 3.3

$$y_{\mathrm{wo_i}}(k) = min\left(\sum_{r=1}^{r_{max}} d_{i,r}(k), W_i(k)\right) \tag{3.3}$$

where i represents the item dimension and $d_{i,r}(k)$ represents the demand of rig r and item i in day k, r_{max} represent the total number of rigs considered and $d_{i,*}$ is a column vector and represents the demand from all rigs for the item i.

After being processed in the warehouse, the liquid bulk goes through load consolidation, i.e. is pumped into tanks. The units used for liquid bulk change from liters to tanks. The relationship between these two units is given by (3.4)

$$N_t = ceil\left(\frac{1}{K_{lt}}.l\right) \tag{3.4}$$

where N_t is the number of tanks, K_{lt} is the conversion rate (number of liters that can be stored in a tank) between liters and tanks and l represents the quantity in liters, and *ceil* operation is a function $f : \mathbb{R} \mapsto \mathbb{Z}$ and returns the first integer greater than or equal to the quantity evaluated. This report uses a fixed value in simulations, since real data indicate that this is the case. It is, of course, possible to simulate with different tank sizes whenever it is the case of interest.

After the liquid bulk is placed in tanks, the number of tanks (partially or fully filled) needs to be accounted for in the bookkeeping process. Also, after this consolidation into tanks, it is only necessary to consider where these tanks need to be delivered. Thus , after load consolidation, the number of tanks and the destination rig become the variable to be accounted for.

Based on warehouse practice determined from interviews, the following assumptions are made in order to convert liters of dispatched liquid to number of tanks filled:

- Each destination rig has a known priority.
- Rigs with higher priority are supplied, to the fullest extent possible, ahead of those with lower priority. Thus, for example, in the case of two rigs, with one having higher priority over the other, the full demand from the higher priority rig is met first, whenever possible, followed by the demand of the lower priority rig.

Equation 3.5 embodies these assumptions in a single mathematical formula.

$$F_r(k) = ceil\left(\frac{\sum_{i=1}^{i_{max}}(\max(\min(d_{i,1}(k), W_i(k) - \sum_{j=1}^{r-1} F_j(k)), 0)}{K_{lt}}\right) \tag{3.5}$$

where $F(k)$ means *filled tanks to transport* and measures how many tanks are going to each rig, from the priority rig $r = 1$ to the lowest priority rig $r = r_{max}$.

A delay is used to represent the time required to fill the tanks, as follows:

$$\begin{aligned} t_r(k) &= t_r(k-1) + F_r(k-\tau_2) - w_r(k) \\ t_r(0) &= 0 \end{aligned} \tag{3.6}$$

$t_r(k)$ denotes *tanks ready to transport* to rig r on day k, and τ_2 is the delay associated with the process of filling tanks. The next step in the process is once again represented by a coupled CS module, involving $q_r(k)$ or *truck transportation* on day k and $P(k)$ or Port levels (in number of tanks) on day k. This system is represented by the state equation below:

$$\begin{aligned} P(k) &= P(k-1) + w(k-\tau_3) - s(k) \\ q(k) &= q(k-1) + w(k) - w(k-\tau_3) \\ P(0) &= [0 \ \cdots \ 0]' \\ q(0) &= [0 \ \cdots \ 0]' \end{aligned} \tag{3.7}$$

where $P \in \mathbb{Z}^{r_{max}}$ is a vector representing tanks at the port going to all destination rigs, $q \in \mathbb{Z}^{r_{max}}$ is a vector that represents tanks in transit by *truck transportation* from warehouse to port, τ_3 represents truck transport delay, w represents *tanks to truck transport* and is given by (3.8), and s stands for *to Supply Vessels* and is given by (3.9).

The formula for tanks-to-truck transport, indexed by rig r is given by:

$$w_r(k) = min(t_r(k-1), P_{r,max} - (P_r(k) + q_r(k))) \tag{3.8}$$

where $P_{r,max}$ stands for port maximum capacity for each rig. Equation 3.8 is interpreted as follows: If there is space at the port, send all tanks ready to transport. If not, send as much as possible to fill all the available space at the port. For simplicity, we will assume $P_{max} = P_{r,max}$ for all rigs. This means that it is being assumed that the port has an equal area set aside for each Rig.

The total tank load to supply vessels, denoted s is calculated as follows:

$$s_r(k) = \begin{cases} min((P_{max}), P_r) & \text{if } k \bmod T_{PSV} = 0 \\ min((P_{max}/2), P_r) & \text{if } k \bmod T_{PSV} \neq 0 \text{ and } EVD(k) = 1 \\ 0 & \text{otherwise} \end{cases} \tag{3.9}$$

where T_{PSV} is the period of regular scheduled PSV's, EVD stands for *Express Vessel Decider* and is a decision variable and $a \bmod b$ is the operation defined by the function $mod : \mathbb{N} \times \mathbb{N}^* \mapsto \mathbb{N}$ which returns the remainder of the division a/b.

Finally, the travel time of the PSV to the Rig is represented by a simple conveyor, as follows:

$$toRig_r(k) = toRig_r(k-1) + s_r(k) - s_r(k-\tau_4) \tag{3.10}$$

Since this process is assumed to occur with the same delay for regular and express vessels, it is not relevant for the cost analysis.

Chapter Summary: This chapter described the general and specific contexts underlying the liquid bulk supply chain (LSBC) model proposed in this dissertation. The main assumptions that were made to build a stock-and-flow model of the LSBC are then described, followed by the modeling process itself. A cost model and the discrete-time state equations and formulas which characterize the proposed model finalize the chapter.

Chapter 4

Control of the proposed LSBC model

This chapter focueses on control of the LSBC model introduced in chapter 3. The control strategy, in general terms, is to use the well knpown family of IOBPCS controllers, also described in chapter 3, originally designed for the simplest plus integrator linear model of a production-inventory system, for the (nonlinear) LSBC model. Since several controllers of the IOBPCS family use demand prediction, the automatic demand forecasting methodology, due Hyndman et al. [2] is also briefly described. Finally, in order to choose controller parameters, a genetic algorithm is used to optimize the cost function (described in chapter 3) with respect to the parameters. Controller performance is evaluated based on the use of these optimal parameters.

4.1 The Inventory and Order Based Production Control System (IOBPCS) family of Controllers

This section reviews control of warehouse level $W(k)$, which is the conventional approach to supply chain control, focusing specifically on the family of IOBPCS (Inventory and order based production control system) controllers.

In this report, controllers from the IOBPCS family for the warehouse submodel will be compared. These controllers are usually used to control linear plants with a single delay and a single integrator. Figure 4.1 shows the general structure of the IOBPCS family of controllers.

These controllers rely on three kinds of policies for error handling, the Inventory Policy, which processes the error of Inventory levels, the Demand Policy, which adds demand prediction to the decision variable and the Work-in-Progress(WIP) Policy, which creates an error between the quantity that actually is being processed and the desired quantity being processed at a given time instant.

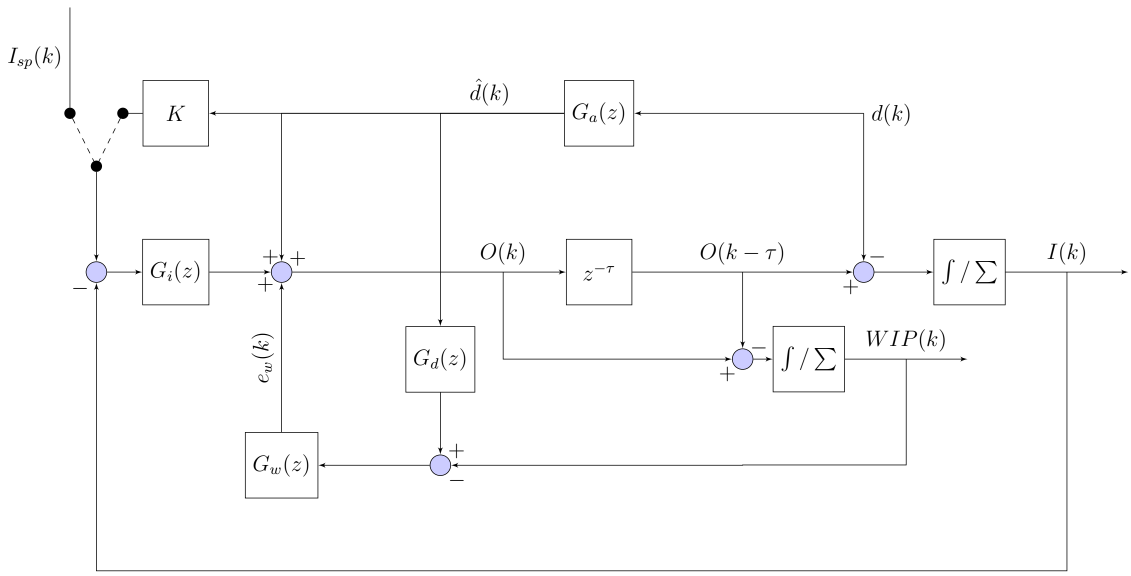


Figure 4.1: The IOBPCS family of Controllers

Table 4.1 gives a detailed description of these blocks in each controller from the IOBPCS family, for a linear plant consisting of a delay followed by an integrator (accumulator)

Controller	Inventory Ref	Inventory Policy	Demand Policy	WIP Policy
IBPCS	Constant	$G_i(z) = K_p$	$G_a(z) = 0$	$G_d(z) = 0$ $G_w(z) = 0$
IOBPCS	Constant	$G_i(z) = K_p$	$G_a(z) = \frac{1}{1-(1-a)z^{-1}}$	$G_d(z) = 0$ $G_w(z) = 0$
VIOBPCS	Multiple of Demand Prediction	$G_i(z) = K_p$	$G_a(z) = \frac{1}{1-(1-a)z^{-1}}$	$G_d(z) = 0$ $G_w(z) = 0$
APIOBPCS	Constant	$G_i(z) = K_p$	$G_a(z) = \frac{1}{1-(1-a)z^{-1}}$	$G_d(z) = \tau$ $G_w(z) = K_w$
APVIOBPCS	Multiple of Demand Prediction	$G_i(z) = K_p$	$G_a(z) = \frac{1}{1-(1-a)z^{-1}}$	$G_d(z) = \tau$ $G_w(z) = K_w$

Table 4.1: Transfer functions defining the IOBPCS family

In most MRPs (Material Resource Planning Systems), the controller that manages orders is a simple relay-type control. It is assumed that the resupply delay is known, if deterministic, or, if stochastic, that the mean, variance and probability distribution function are given.

The controllers keeps track of inventory levels. When these levels are below the mean demand times resupply delay, the system orders a (usually fixed-size) bulk of materials from the suppliers.

In this work we use a control similar to the ones present in MRP but more sophisticated because the control used here does not always orders a fixed bulk, the orders are instead a function of the demand prediction.

4.1.1 IBPCS: One Input, One Output

The simpler controller of the IBPCS family is the P-IBPCS (Proportional IBPCS), which is simply achieved by making Inventory the only controlled variable and using the error directly as the control input. More sophisticated IBPCS carry out some calculation to obtain control input from error. This is the case of the PID-IBPCS, which computes the control input after passing the raw error through a PID-Compensator. Other structures could be used to sophisticate the IBPCS controller even further, but the main focus of this work are the P-IBPCS and PID-IBPCS controllers

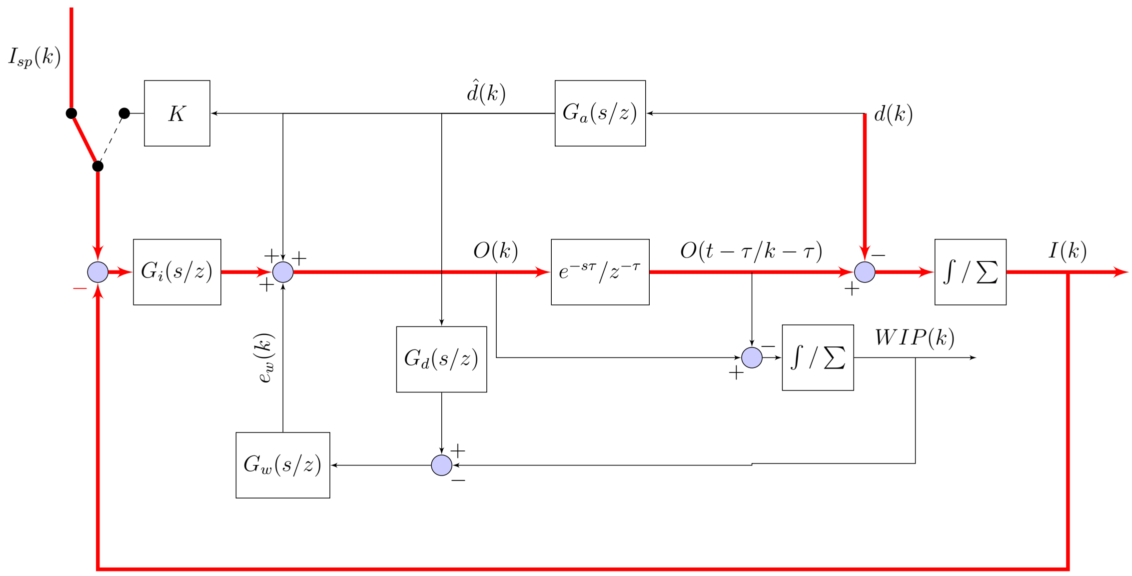


Figure 4.2: The IBPCS Controller. The thicker lines indicates the parts of the full block diagram which are used by this controller.

Equation 4.1 gives the equations corresponding to an IBPCS controller. $I_{sp}(k)$ is usually a constant I_{sp} (*Inventory Set-Point*). This controller has two adjustable parameters, K_p and I_{sp} which are chosen using conventional tools from a linear plant ([33],¡CITE ORTEGA¿), but will be chosen using optimization of a cost function for the proposed nonlinear LSBC model.

$$
\begin{aligned}
e_i(k) &= I_{sp}(k) - I(k) \\
e(k) &= e_i(k) \\
u(k) &= K_p e(k)
\end{aligned} \tag{4.1}
$$

4.1.2 IOBPCS: Two Inputs, One Output

IOBPCS Controller is a more elaborate version of the IBPCS controller. It has everything IBPCS Controllers have and a new branch that adds demand prediction to the error previously found on the IBPCS controller. This way, if a big fluctuation in demand occurs, the IOBPCS controller should, in principle, respond better, since the information from the disturbance (demand) is present in this controller. Figure 4.3 shows the structure used by an IOBPCS Controller.

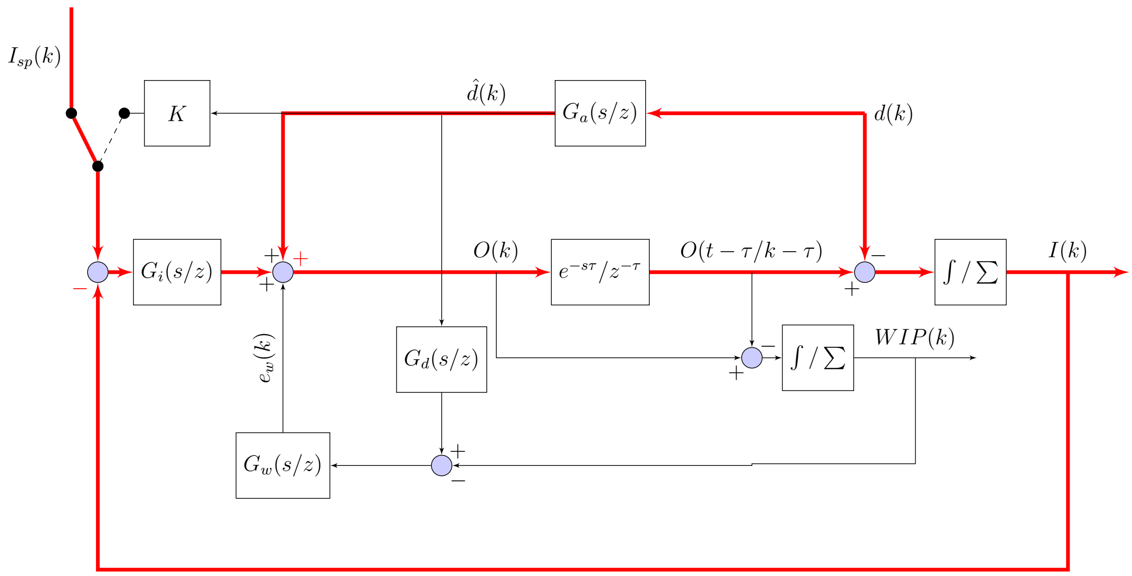


Figure 4.3: The IOBPCS Controller.The thicker lines indicates the parts of the full block diagram which are used by this controller.

The discrete time equations for an IOBPCS controller are given in 4.2 shows how works in a discrete system. Once again, $I_{sp}(k)$ is usually a constant I_{sp} (*Inventory Set-Point*). This controller has the same adjustable parameters as its predecessor, but since it also relies on demand prediction, more parameters need to be set. If, however, automatic demand forecasting, described latter, is used, then only K_p and I_{sp} need to be chosen.

$$
\begin{aligned}
e_i(k) &= I_{sp}(k) - I(k) \\
e_d(k) &= \hat{d}(k) \\
u(k) &= K_p e_i(k) + e_d(k)
\end{aligned} \tag{4.2}
$$

4.1.3 VIOBPCS: Two Inputs, One Output

The complexity added by the VIOBPCS Controller when compared with the IOBPCS Controller is that, in the VIOBPCS structure, the set point for inventory levels is no longer a fixed parameter, instead, it is now a function of the demand prediction. Again, several structures can be used to increase the complexity and sophistication of this controller, such as PID controllers. The basic P-VIOBPCS produces the output by comparing one state variable (I) with a function of the demand.

While this feature may appear to be an improvement, the fact that we use the demand information twice, in both producing the set-point for inventory and adding it directly to the error variable, turns out to make this controller (and all the other ones with variable inventory set-point from this family) quite sensitive for the nonlinear plant, as shall be seen subsequently in simulation results.

Figure 4.4 shows the structures used by this controller.

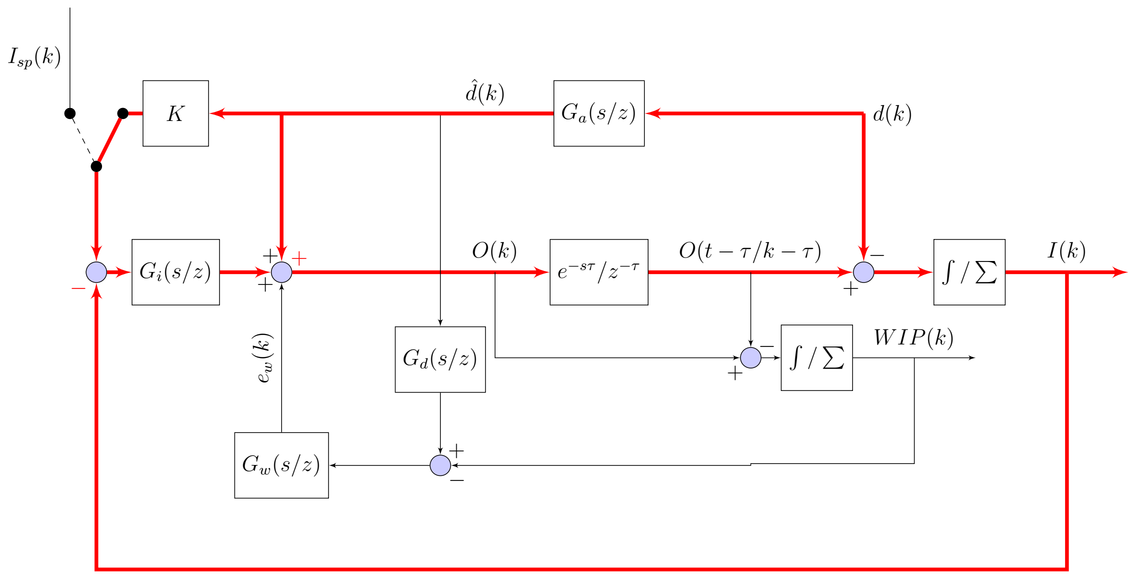


Figure 4.4: The VIOBPCS Controller. The thicker lines indicates the parts of the full block diagram which are used by this controller.

The discrete time equations for VIOBPCS are given in 4.3. As stated previously, this controller relies on a variable reference for inventory level derived from demand prediction. This controller has two adjustable parameters, which in this case are K_p and K, the gain to transform demand prediction into inventory set-point.

$$\begin{aligned} e_i(k) &= K\hat{d}(k) - I(k) \\ e_d(k) &= \hat{d}(k) \\ u(k) &= K_p e_i(k) + e_d(k) \end{aligned} \tag{4.3}$$

4.1.4 APIOBPCS: Three Inputs, One Output

The AP prefix stands for Automatic Pipeline, which means that this family of controllers uses information from both states now, rather than just from Inventory Levels. This extra structure permits it to calculate errors using the *Work-in-progress* or WIP variable. Since there are two error variables, two PIDs could be used to handle each error or one PID that acts on the aggregate error.

The main advantage of this control scheme is that it considers past control decisions that have not yet influenced the Inventory State. Thus, if the system decided to buy a large amount of goods at one time instant, this information will influence its next decisions from the very next instant. This is an improvement from previous controllers, in which the delay in receiving an order did not influence subsequent decisions, which could lead to ordering a large bulk quantity repeatedly in a short period of time, leading to undesirable Inventory Peaks.

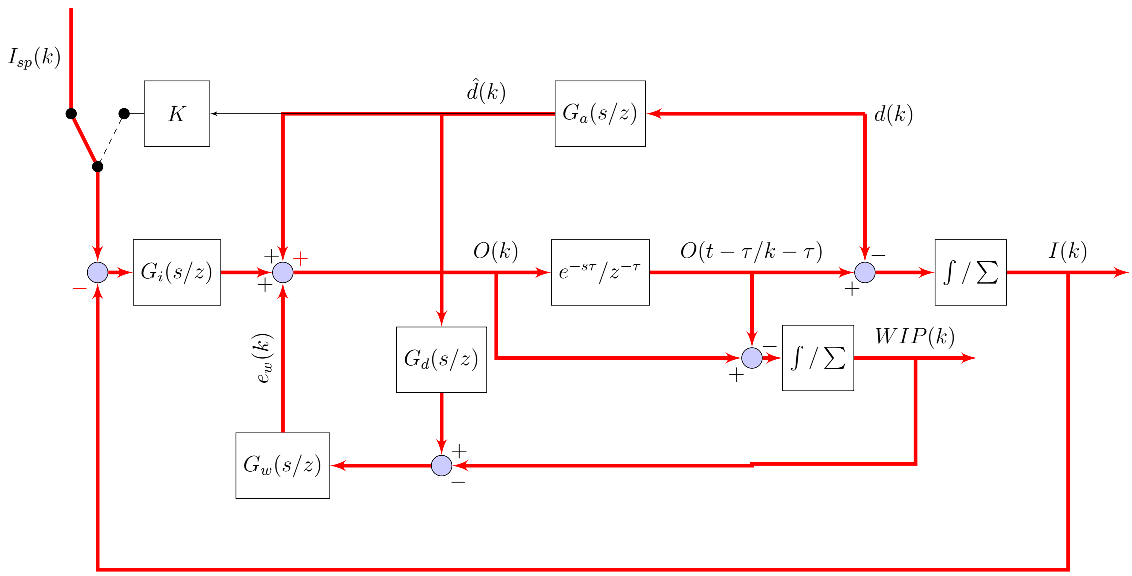


Figure 4.5: The APIOBPCS Controller. The thicker lines indicates the parts of the full block diagram which are used by this controller.

The APIOBPCS equation for discrete systems (4.4) has the same terms in 4.2 plus a new component in error, the WIP (*Work-In-Progress*) error. This component aids specially when there are larger delays, since it perceives the amount of goods in transit and inhibits repeated requests for supplies, which are, in fact, in the pipeline, that would lead to undesirable bullwhip effect.

$$\begin{aligned} e_i(k) &= I_{sp}(k) - I(k) \\ e_d(k) &= \hat{d}(k) \\ e_w(k) &= \tau.\hat{d}(k) - WIP(K) \\ u(k) &= K_p e_i(k) + e_d(k) + e_w(k) \end{aligned} \tag{4.4}$$

4.1.5 APVIOBPCS: Three Inputs, One Output

APVIOBPCS, as the name suggests, is a combination of all the controllers already described. It works similarly to the APIOBPCS controller, but uses a variable set-point for Inventory, in the same way that the VIOBPCS does.

Again, this apparent improvement may not produce better results if compared to its fixed set-point version. The reasons for this are explained on the next paragraph.

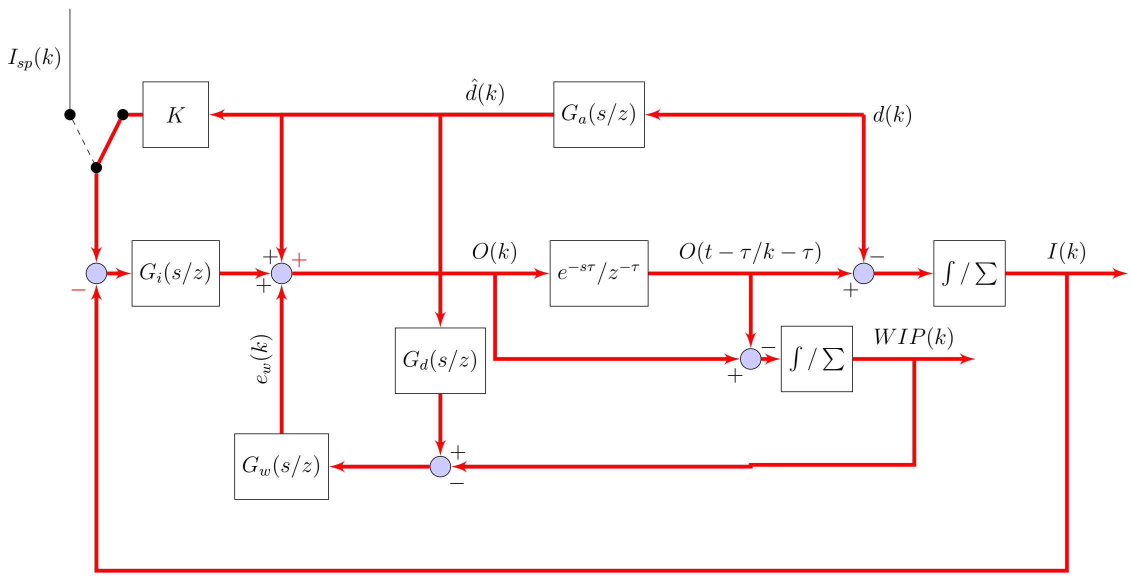


Figure 4.6: The APVIOBPCS Controller. The thicker lines indicates the parts of the full block diagram which are used by this controller.

While this controller seems to be the most advanced when compared to others from the IOBPCS family, the fact that it relies on demand prediction to calculate all three errors makes it heavily dependent on accurate demand prediction. If demand is not reasonably precise, this controller might not perform as well as, for instance, the APIOBPCS Controller.

$$\begin{aligned} e_i(k) &= K\hat{d}(k) - I(k) \\ e_d(k) &= \hat{d}(k) \\ e_w(k) &= \tau.\hat{d}(k) - WIP(K) \\ u(k) &= K_p e_i(k) + e_d(k) + e_w(k) \end{aligned} \tag{4.5}$$

4.1.6 Coupling PID Control with the IOBPCS family

The most widely used Controller from Classic Control Theory is the Proportional Integrative Derivative Controller, or PID in short. The PID generates Control Input using error as its input as described in equation 4.6

$$u(t) = K_p.e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt} \tag{4.6}$$

Since this work studies a discrete system, the discrete version of 4.6 is more relevant. The discretization can be performed in several ways, one of which is the backward Euler approximation. To do so, we differentiate the control law in order to calculate $\dot{u}$, which is shown in 4.7

$$\dot{u}(t) = K_p\dot{e}(t) + K_i e(t) + K_d\ddot{e} \tag{4.7}$$

Now applying the backward Euler transformation to (4.7) yields

$$\frac{u(t_k) - u(t_{k-1})}{h} = K_p \frac{e(t_k) - e(t_{k-1})}{h} + K_i e(t_k) + K_d \frac{e(t_k) - 2e(t_{k-1}) + e(t_{k-2})}{h} \tag{4.8}$$

where h is the sampling period. For a discrete model it is usual to use h as 1, since the sampling period is chosen to be equal to the time constant, this:

$$u(k) = u(k-1) + K_p[e(k) - e(k-1)] + K_i e(k) + K_d[e(k) - 2e(k-1) + e(k-2)] \tag{4.9}$$

Finally, it is enough to use the error, calculated from any of the controllers previously described, in the formula given by (4.9) to have a controller of the IOBPCS family and a PID controller working in synchrony.

4.2 Automatic Demand Forecasting

This section is based on [5] and briefly reviews the idea of so-called automatic demand forecasting. The basic idea is to provide an automatic mechanism to choose between the large variety of demand forecasting methods. Hyndman et al [5] introduce a unified state-space description of the major forecasting methods and propose a figure of merit that, when optimized, leads to the optimal method with respect to this figure of merit.

Exponential Smoothing methods are a popular way to forecast a given stochastic variable, and rely on 3 complementary kinds of forecasting: Error, Trend and Seasonality. These models are known by the acronym ETS, meaning error, trend and seasonality, respectively.

There are two different kinds errors, additive and multiplicative. Seasonal components can be additive, multiplicative, or simply not exist. Likewise, Trend can be additive, multiplicative, additive damped and multiplicative damped. Combining the two kinds of error, three kinds of seasonality and five kinds of trends, 30 different exponential smoothing methods are possible.

All of these 30 exponential smoothing methods can be written as an innovation state space model, and they work as depicted by figures 4.7 and 4.8.

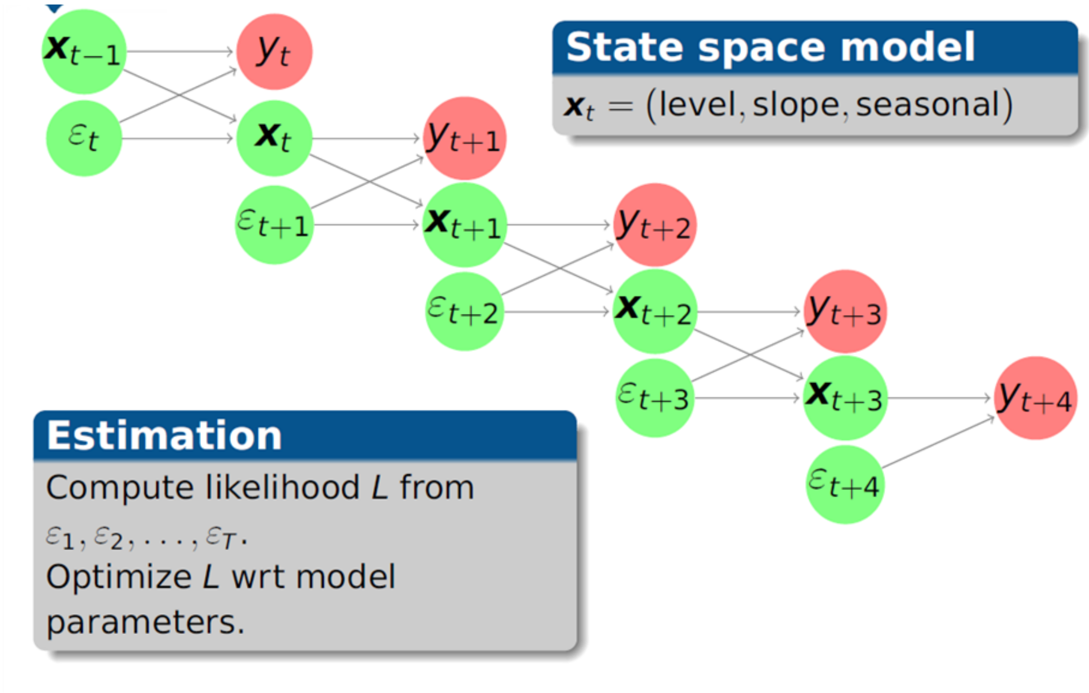


Figure 4.7: Process of obtaining estimate for a given variable. From estimate x and error ϵ,, observation y is made for a given time instant. The process goes on until variable t reaches its prespecified limit.Figure reproduced from [2]

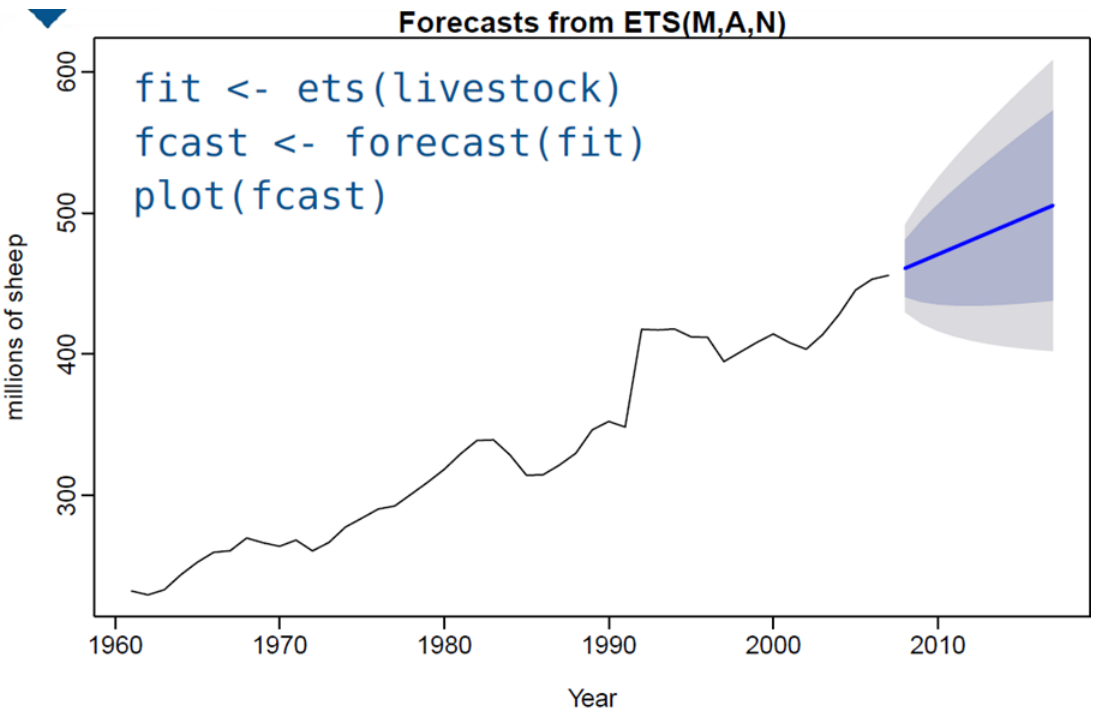


Figure 4.8: An example of Automatic Forecasting Selection working. From all exponential smoothing models, ETS forecasting with M, A, N) for Error, Trend and Seasonality, which means (Multiplicative, Additive, None), is selected. Time Series is plotted as well as forecasting error (the part with greyed area around).Figure reproduced from [2]

The goal of the automatic forecaster is to minimize the likelihood L computed from ϵ_i, $i = 1, 2, ..., n$.

Writing the coupled system-observer as state equations, we get equation (4.10).

$$\begin{aligned} y_t &= h(x_{t-1}) + k(x_{t-1})\epsilon_t \\ x_t &= f(x_{t-1}) + g(x_{t-1})\epsilon_t \end{aligned} \tag{4.10}$$

Then, for additive errors, $y_t = \mu_t + \epsilon_t$ so that $k(x_{t-1}) = 1$. If error is multiplicative, then $y_t = \mu_t(1 + \epsilon_t)$ and $k(x_{t-1}) = \mu_t$.

The objective function being minimized is a function of the likelihood, and is given by equation 4.11

$$L(\theta^*, x_0) = n \log \left(\sum_{t=1}^{n} \epsilon_t^2 / k^2(x_{t-1}) \right) + 2 \log |k(x_{t-1})| = 2 \log(likelihood) + constant \tag{4.11}$$

The goal then is to minimize L with respect to $\theta = (\alpha, \beta, \gamma, \phi)$, which are parameters of the estimator, and x_0. One version of this function is known as AIC, or Akaike Information Criteria, and it is a penalized version of the Likelihood, as written in (4.12).

$$AIC = -2log(L) + 2k \tag{4.12}$$

where AIC is the Akaike Information Criterion, L is the Likelihood and k is the number of parameters being estimated.

If L is Gaussian, $AIC \simeq c + T\log(MSE) + 2k$ where c is a constant, T is the length of the time series, and MSE is calculated from one-step forecasts on training sets.

For small T, AIC tends to over-fit. To correct this biased behaviour, corrected AIC, denoted AIC_c adds another term to AIC, as shown in equation 4.13.

$$AIC_c = AIC + \frac{2(k+1)(k+2)}{T-k} \tag{4.13}$$

Since in the practical case studied in this dissertation, the data provided by the company contained only relatively small time series to analyse (up to 60 days), the best estimator will be selected using the AIC_c criteria.

4.3 Formulation of the Optimal Control Problem

4.3.1 State Space Form of LSBC model

The system model presented in section 3.7 can be represented in state space form (with the state $toRig(\cdot)$ being omitted since it does not affect the costs in this model) by choosing the state vector as follows:

$$x(k) = \begin{bmatrix} W(k) \\ y_{\text{wi}}(k) \\ t(k) \\ P(k) \\ q(k) \end{bmatrix} \tag{4.14}$$

where

$$W(k) = W(k-1) + O(k-\tau_1) - y_{\mathrm{wo}}(k) \tag{4.15}$$

$$y_{\mathrm{wi}}(k) = y_{\mathrm{wi}}(k-1) + O(k) - O(k-\tau_1) \tag{4.16}$$

$$t(k) = t(k-1) + F(k-\tau_2) - w(k) \tag{4.17}$$

$$P(k) = P(k-1) + w(k-\tau_3) - s(k) \tag{4.18}$$

$$q(k) = q(k-1) + w(k) - w(k-\tau_3) \tag{4.19}$$

Choosing the pair $u(k) = [O(k)\ EVD(k)]'$ as controls, interpreting demand as an exogenous input, we can introduce the notation introduced below permits the expression of the model dynamics in state space form

Let

$$u(k) := \begin{bmatrix} O(k) \\ EVD(k) \end{bmatrix} \tag{4.20}$$

$$L(k) := y_{\mathrm{wo}}(k) = f(D(k)) \tag{4.21}$$

$$N(k) := g(EVD(k), k) \tag{4.22}$$

$$x(k) = x(k-1) + \begin{bmatrix} O(k-\tau_1) \\ O(k) - O(k-\tau_1) \\ 0 \\ g(EVD(k), k) \\ 0 \end{bmatrix} + \begin{bmatrix} -f(d(k)) \\ 0 \\ f(d(k-\tau_2)) \\ 0 \\ 0 \end{bmatrix} \tag{4.23}$$

$$x(k) = x(k-1) + \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} u_1(k) + \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0 \\ 0 \end{bmatrix} u_1(k-\tau_1) + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} N(k, u_2(k)) + \begin{bmatrix} -1 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} L(k) + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} L(k-\tau_2) \tag{4.24}$$

4.3.2 Formulation of the cost function in terms of the state variables

The function that it is desired to optimize is a *Total Cost*, and it is represented by the sum of four main costs, namely the *Operational Costs*, which accounts for inventory maintenance and storage process costs; the material costs, or the ones associated actively with buying liquid bulk from (possibly multiple) suppliers; the transportation costs, which are the costs associated with transporting the tanks from the ports to the rigs; and, finally, the contingency costs, costs associated with out of stocks or tanks waiting without being able to move because the port capacity is being used at its maximum.

This function is expressed mathematically by equation 4.25

$$C(k) = OC(k) + MC(k) + TC(k) + CC(k) \tag{4.25}$$

Each of these four cost components are represented by equations that relate the State Variables from the main model with these costs. These are seen in 4.26, 4.27, 4.28 and 4.29.

$$OC(k) = OC(k-1) + \sum_{i=1}^{i_{max}} (tW_i(k).HuC + W(k)_i.SuC) \tag{4.26}$$

$$MC(k) = MC(k-1) + \sum_{i=1}^{i_{max}} O_i(k).BuC \tag{4.27}$$

$$TC(k) = TC(k-1) + \sum_{r=1}^{r_{max}} ((EVD_r(k) + 1).s_r(k).sC) \tag{4.28}$$

$$\begin{aligned} CC(k) = CC(k-1) &+ \sum_{i=1}^{i_{max}} \left(\sum_{r=1}^{r_{max}} D_{i,r}(k) - y_{\mathrm{wo_i}}(k) \right) .OoSuC \\ &+ \sum_{r=1}^{r_{max}} t(k).DuC \end{aligned} \tag{4.29}$$

$$\tag{4.30}$$

where HuC and SuC are the Handling Unit Cost and Storage Unit Cost, respectively; BuC is the Buying Unit Cost per liter, sC is the Shipment Cost for Regular Scheduled Vessels, and since $EVD(\cdot)$ can only be 0, when Express Vessels **are not** used and 1 when Express Vessels **are** used, using this variable directly in the Transportation Cost formula has the effect of doubling it when Express Vessels are used. $OoSuC$ is the (theoretical) cost associated with Out of Stocks that prevent Demand from being fully fulfilled. DuC is the Delay Unit Cost and measures how the delay of Tanks not able to proceed for the port impact the operation.

4.3.3 Formulation of the Optimal Control Problem

Finally, the optimal control problem is to minimize $C(k_{horiz})$, in which the variable k_{horiz} denotes the last day of the simulation horizon. Let $u(k)$ be defined with a state feedback function $\varphi : \mathbb{R}^{\zeta} \times \mathbb{R}^{2i_{max}+3r_{max}} \times \mathbb{R}^{i_{max}r_{max}} \times \mathbb{R} \times \mathbb{R} \mapsto \mathbb{R}^{i_{max}+r_{max}}$ with ζ denoting the parameters to be optimized, i.e.:

$$u(k) = \varphi(\zeta, x(k), \hat{d}(k), \tau_1, \tau_3). \tag{4.31}$$

where ζ is a vector containing IOBPCS parameters and the Queue Thresholds EVD_{thresh}.

The Optimal Control problem can now be defined mathematically as

$$\begin{aligned} &\min_{\zeta} C(k_{horiz}) \\ \text{s.t. } &x(k) = G(x(k-1), \varphi(\zeta, x(k), \hat{d}(k)), \tau_1, \tau_3) + L(k) + L(k - \tau_2) \end{aligned} \tag{4.32}$$

For $EVD(\cdot)$ control, $t(\cdot)$ levels are observed and it will be activated when a certain threshold is met, the *Waiting Line Threshold* or *Queue Threshold*. This constant is different for each destination r and will be selected by the Genetic Algorithm, along with the parameters needed by the IOBPCS family of controllers.

4.4 Genetic Algorithm for the optimal control problem

Genetic Algorithms provide a way to deal with difficult optimization problems, specially the ones without analytical solution, such as the one described in section 4.3, in which the underlying dynamical system possesses non-linearities and delays.

This section explains the use of a genetic algorithm to find an optimal set of parameters in the optimal control problem presented in section 4.3.

Genetic Algorithms are one of the many stochastic search optimization algorithms from the class of meta-heuristic algorithms. Such algorithms, instead of finding the global optimum analytically using derivatives of the objective function and its constraints (e.g. KKT conditions), focus on incremental improvement of the value of the objective function, relying on evolution and mutation (the names vary from one algorithm to another) to get as close as possible to the global optimum without getting stuck in local optima.

In this section we describe the basics of a genetic algorithm, the choice of algorithm parameters and describe the mutation and crossover functions. For further knowledge of evolutionary algorithms, [34] is a comprehensive source.

4.4.1 Parametrization

The concept of individual is central to GAs. An individual, is an n-tuple made up of all n parameters that are going to be optimized. As an example, for the IBPCS Controller from section 4.1.1, the parameters K_c, I_{sp} would define an individual, or more specifically, the individual's *phenotype*.

The *genotype*, on the other hand, is represented by the bits that code this individual. The phenotype and genotype are then, respectively, the individual itself and a representation or codification of this individual. There is a function that relates the phenotype with the genotype and it varies from one implementation of the Genetic Algorithm to another.

In this work, the genotype is represented as a binary bit string and the phenotype is represented as a n-tuple of Real Numbers. The relationship between these two representations is as follows:

$$\begin{cases} p_1 = (b_1 + 2^1 b_{n+1} + 2^2 b_{2n+1} + \cdots + 2^m b_{(m-1)n+1}) K_{p1} \\ p_2 = (b_2 + 2^1 b_{n+2} + 2^2 b_{2n+2} + \cdots + 2^m b_{(m-1)n+2}) K_{p2} \\ \vdots \\ p_n = \underbrace{(b_n + 2^1 b_{2n} + 2^2 b_{3n} + \cdots + 2^m b_{mn})}_{\text{m bits}} K_{pn} \end{cases} \tag{4.33}$$

where p_i is the i-th parameter of the n-uple, b_j is the j-th bit from the string, n is the number of parameters, m is the number of bits used to represent one parameter, mn is the size of the bit string and K_{pi} is a multiplier associated with the desired range of the parameters.

As this representation shows, the phenotype of each parameter is scrambled in the bit string with the others. This allows the algorithm to change all parameters at once using a more simple crossover function, which will be discussed in next sub-section.

4.4.2 Selection, Mutation and Evolution of the Algorithm

The Genetic Algorithm works as follows: Several genotypes are generated randomly and the corresponding individuals (parameters) are used to simulate the dynamic system which is being studied and thereby evaluate the cost function. The individuals are compared in terms of the total cost they result in at the end of the simulation horizon. The individuals that achieved the minimum costs are more likely to reproduce (i.e. copied into the next generation of individual with higher probability). The best one is copied without changes into the next generation: this is referred to as elitism and functions as a kind of algorithm memory.

Reproduction is the process through which individuals combine and produce a new one. This combination is performed through an operation called gene crossover, now described briefly. The crossover mechanism used by this dissertation is single point crossover, and it splits the bit strings in two at a randomly chosen position. The new individual will inherit the first segment from one parent and the other segment from the other. More complex crossover mechanisms exist, and they range from two point crossover, which is analogous to the first case but with two splitting points and multi-point crossover, in which an entire bit string with the size of an individual is randomized.

Mutation is performed next. After a new generation is formed, a number from a uniform probability distribution (0,1) is generated for each gene. If this number is lower then or equal to the mutation probability, then the gene value is flipped. This mechanism reduces the probability that the algorithm gets stuck at local minima, but a high mutation probability can lead to excessive variation in individuals, causing the algorithm not to converge.

After reproduction and mutation, a new generation is formed and re-evaluated. This continues until a termination condition is met. In this work, the only termination condition used is a maximum number of generations, but other conditions such as tolerance values, relative change from one iteration to other, amongst others, can be used

Figure 4.9 shows a flowchart of the GA used in this dissertation.

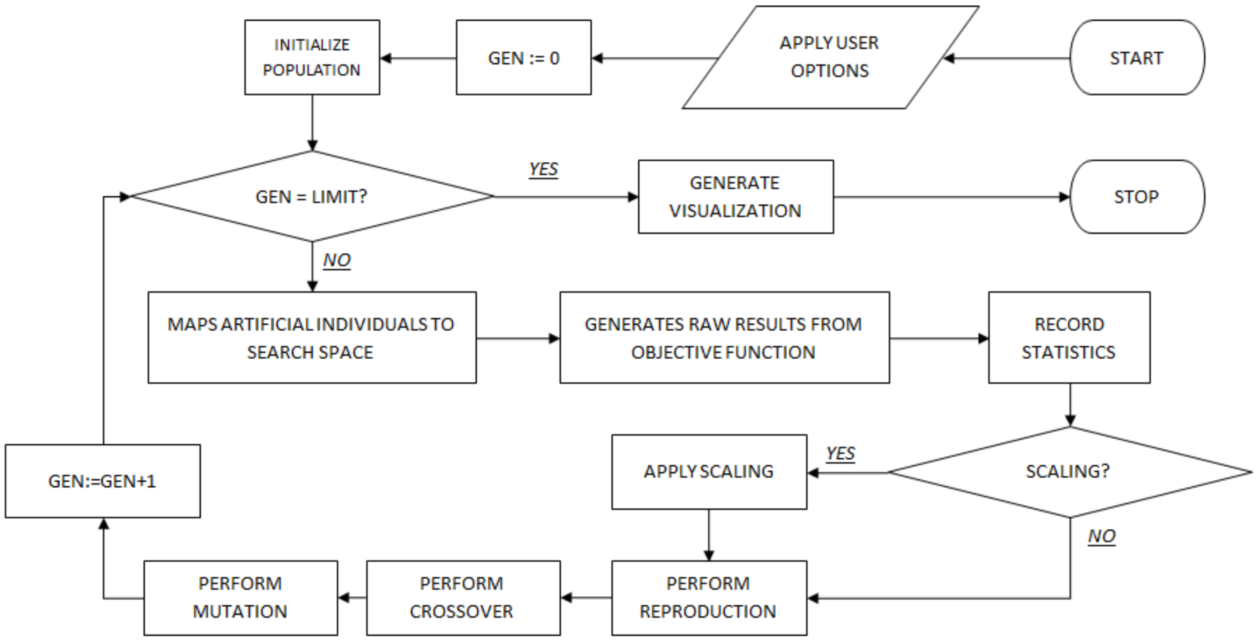


Figure 4.9: Genetic Algorithm flowchart

Chapter summary: This chapter details the proposed control strategy for the LSBC model presented in chapter 3, presenting its main ingredients. These are (i) a fixed controller from the IOBPCS family, (ii) a demand prediction from the family of exponential smoothing methods chosen by the so called Automatic Demand Forecasting methodology, and (iii) a genetic algorithm to find optimal controller parameters by solving an appropriately formulated optimal control problem.

Chapter 5

Comparison of proposed controllers for the liquid supply chain model

This chapter compares the performance of the controllers discussed in Chapter 4 through simulation in which different parameters are varied.

This chapter is divided into three sections. Section 5.1 presents the methodology used and details the use of the Genetic Algorithm together with the model.

Section 5.2 presents simulation results followed by a brief explanation for those results.

Section 5.3 is dedicated to a discussion of the results and an evaluatio of the controllers in the context of the chosen application.

5.1 Test Methodology

In order to compare the family of controllers proposed in chapter 4 for the LBSC, a test methodology, applied to all controllers, as well as some parameter choices common to all the tests, is given first. This is followed by a flowchart describing how the various components (controllers, plant, predictor and GA) interact in order to find optimal parameters for each controller and evaluate the corresponding controller performance.

Each of the controllers are tested multiple times in order to achieve the best possible performance for each one of them. One way to do that, and the way we will use, is to subject the couple System-Controller to a series of runs in a Genetic Algorithm.

The simulation works as depicted in figure 5.1. First, all parameters are started by the Genetic Algorithm Toolbox in MATLAB. This makes one individual. The toolbox then generates several other randomized individuals to compare. For each individual, a full simulation of the system is triggered and, at the end of it, total cost is computed.

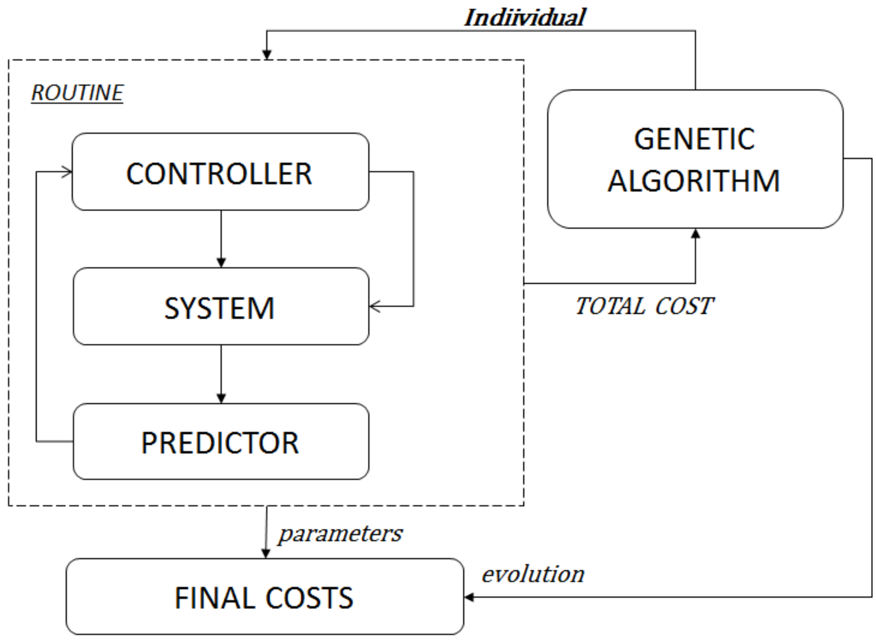


Figure 5.1: Connections between model, Genetic Algorithm and Results

The total cost is the variable that will be used to compare parameters, or the goal variable. It is an obvious choice based on the Optimal Control problem we are trying to solve, written in equation 4.32.

The best individual of a single run is then stored, and afterwards compared to the best individuals of other runs. To achieve meaningful results, we will use 100 simulations of the Genetic Algorithm for each controller.

Results are shown both with respect to best individual run of 100 simulations, with tables and graphics showing control and states evolution and regarding all 100 simulation, with tables showing mean costs and standard deviation regarding each best individual.

Lastly, we will present a brief analysis on the demand predictor performance.

For all control strategies being tested we will present the resulting gains and references, when applicable, found with the genetic algorithm.

All simulations are subjected to the same demand pattern, shown in figure 5.2, and the same parameters, shown in table 5.1

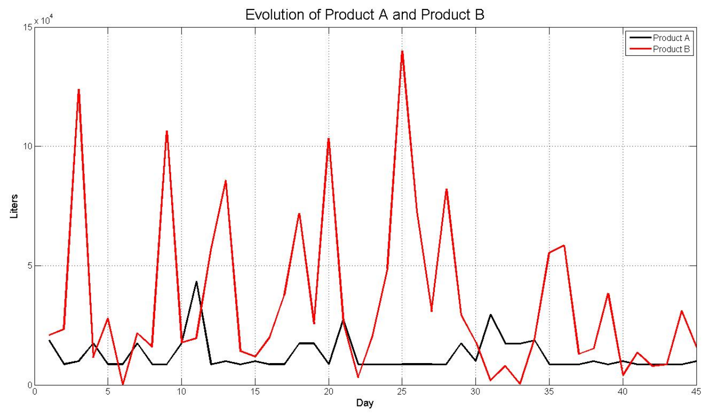


Figure 5.2: Demand of Product A and Product B over time in Liters

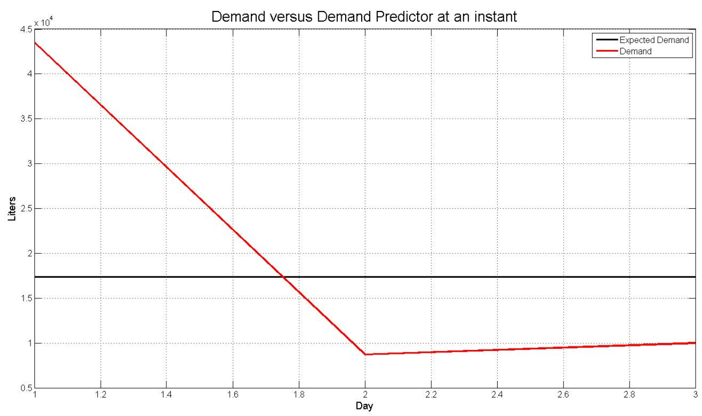


Figure 5.3: Demand Predictor and Demand at a given instant for Product A

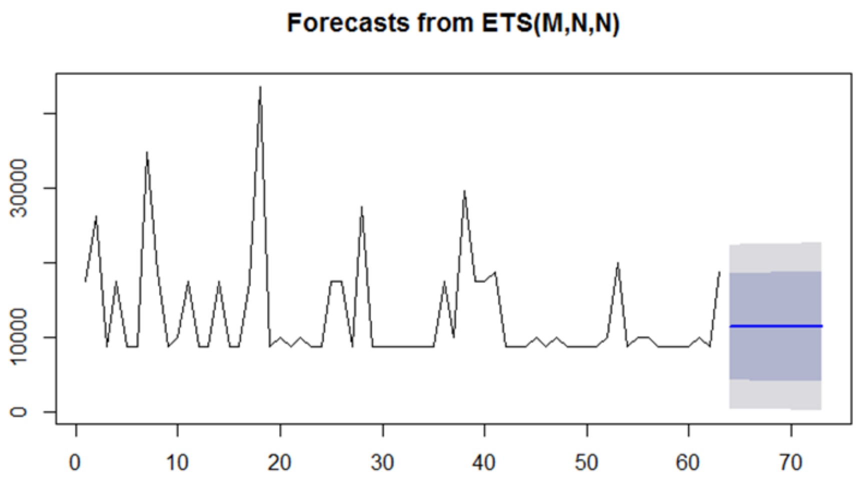


Figure 5.4: Automatic Forecasting Choosing Algorithm applied to the demand of Product A by one Rig

Table 5.1: Values of simulation Parameters

Parameter	Value
horizon	45 days
τ_1	3 days
τ_2	2 days
τ_3	3 days
τ_4	2 days
T_{PSV}	7 days
i_{max}	2
r_{max}	2
W_{10}	200.000 l
W_{20}	400.000 l
K_{lt}	5.000 l
P_{max}	100 tanks

The data presented in table 5.1 reflects how the real process works and were obtained through interviews, documents and meetings.

For each controller it will also be presented the overall performance of the genetic algorithm. Better controllers should have not only the lowest cost in best run, but also a low mean and standard deviation of total cost along all runs.

Finally, we will show a comparative table containing information about each controller scores. This is shown in table 5.16 and it is an easier way to compare scores.

5.2 Results

5.2.1 IBPCS Controller

IBPCS Controller is the most simple compensator of the level controllers. We need to optimize three parameters in this first case, the controller gain K_p and two fixed Inventory references, one for Product A and another one for Product B. They will be represented I_{sp1} and I_{sp2} respectively

Overall Performance

Table 5.2: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	84288
Mean Cost	89437
Standard Deviation	431.14

Best Run Performance

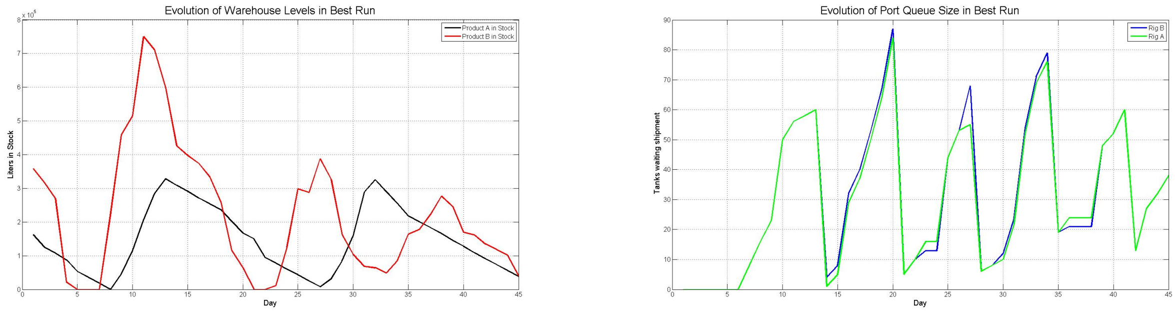


Figure 5.5: Evolution of Warehouse levels (Liters) and Port Queue (Number of Tanks) using IPBCS Controller

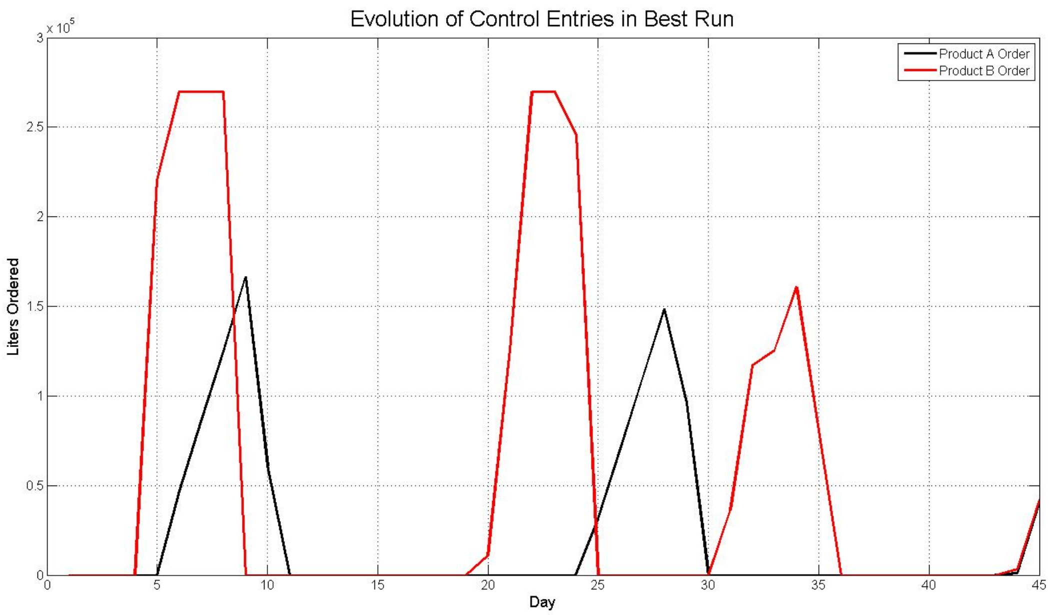


Figure 5.6: Evolution of Controlled variable level for the IBPCS Controller

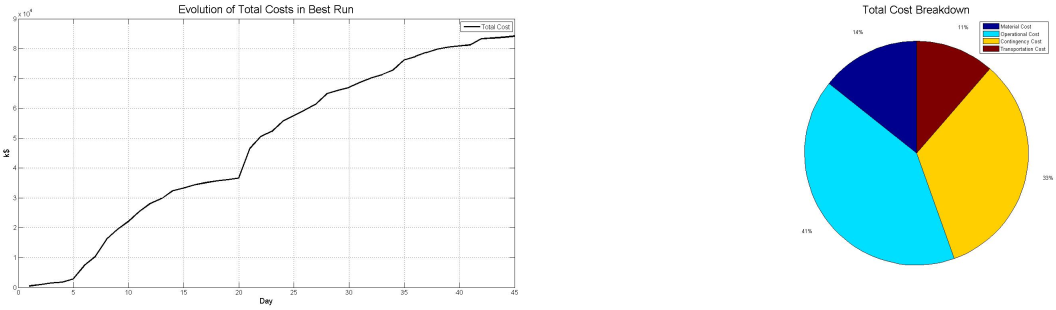


Figure 5.7: Total Cost Evolution and Final Day Total Cost Breakdown for the IBPCS Controller

Table 5.3: Final Day Cost Breakdown for the IBPCS Controller

Type of Cost	Value	Color
Material Cost	12039	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	34706	Cyan
Contingency Cost	27884	Yellow
Total Cost	84228	-

5.2.2 IOBPCS Controller

The IOBPCS Controller is more complex compared to the IBPCS Controller. The only difference here is that Demand Prediction is utilized to calculate the control variable, as shown in fig. (4.3). Again, three parameters need to be optimized, the controller gain K_p and two Inventory references, one for Product A and another one for Product B. They are denoted as I_{sp1} and I_{sp2}, respectively.

Overall Performance

Table 5.4: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	78196
Mean Cost	81756
Standard Deviation	438.91

Best Run Performance

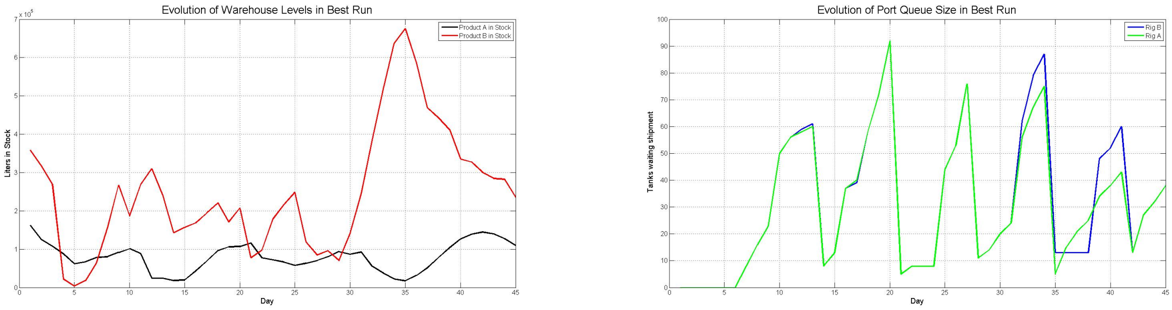


Figure 5.8: Evolution of Warehouse levels (in Liters) and Port Queue Size (number of Tanks) using IOPBCS Controller

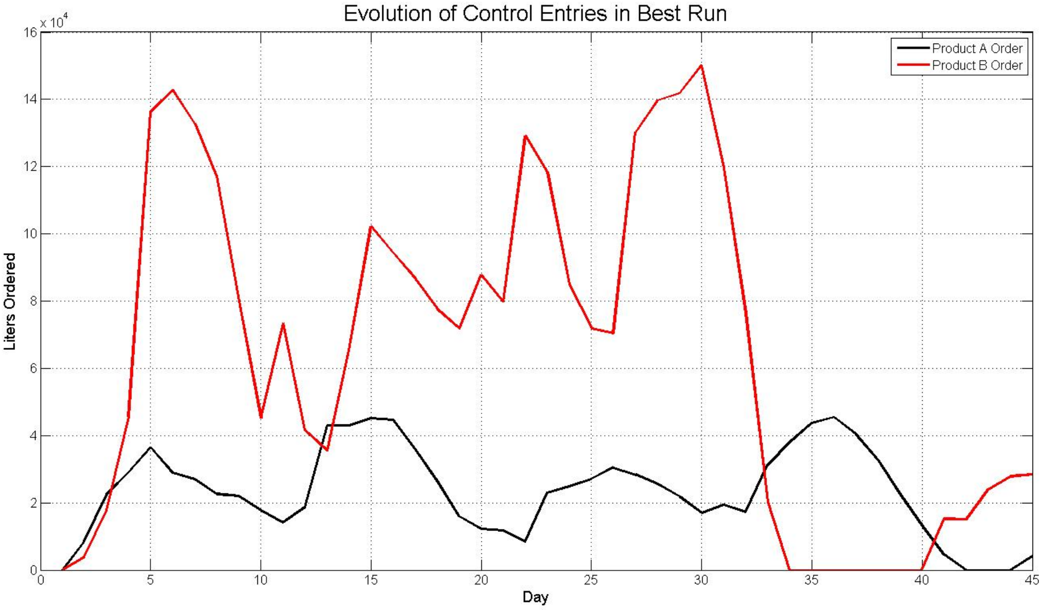


Figure 5.9: Evolution of Controlled variable level for the IOBPCS Controller

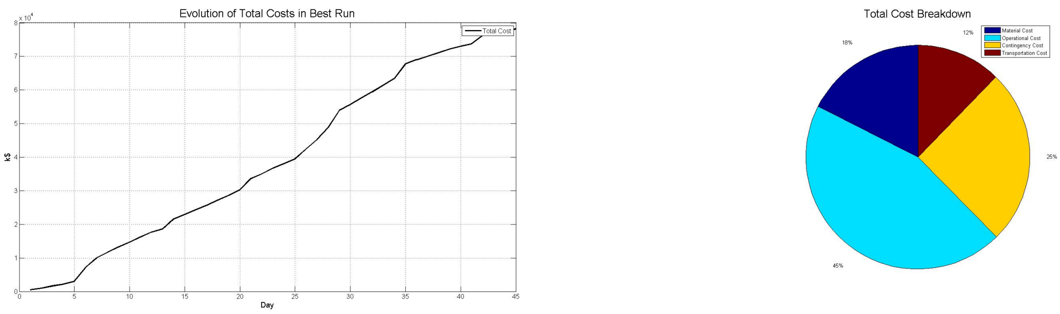


Figure 5.10: Total Cost Evolution and Final Day Total Cost Breakdown for the IOBPCS Controller

Table 5.5: Final Day Cost Breakdown for the IOBPCS Controller

Type of Cost	Value	Color
Material Cost	13694	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	35083	Cyan
Contingency Cost	19819	Yellow
Total Cost	78196	-

5.2.3 VIOBPCS Controller

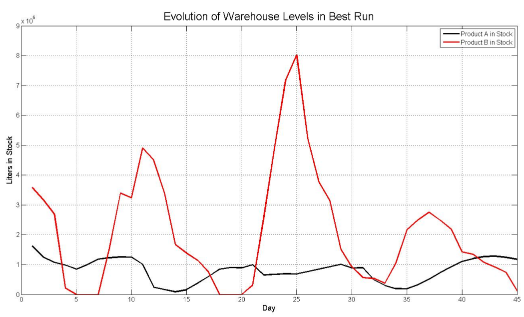
The VIOBPCS Controller is different from the two previous controllers. While the two first feedback controllers rely on fixed set-points, the VIOBPCS controller chooses the set-point as a multiple of the current demand prediction, as shown in fig. (4.4). Again, three parameters need to be optimized, the controller gain K_p and two gains to find references, one for Product A and another one for Product B. They are denoted as K_a and K_b, respectively.

Overall Performance

Table 5.6: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	88613
Mean Cost	91726
Standard Deviation	223.74

Best Run Performance



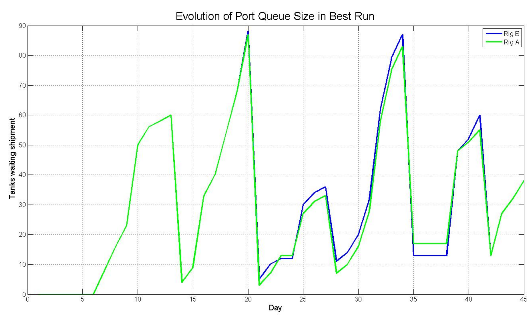


Figure 5.11: Evolution of Warehouse levels (in Liters) and Port Queue Size (number of Tanks) using VIOPBCS Controller

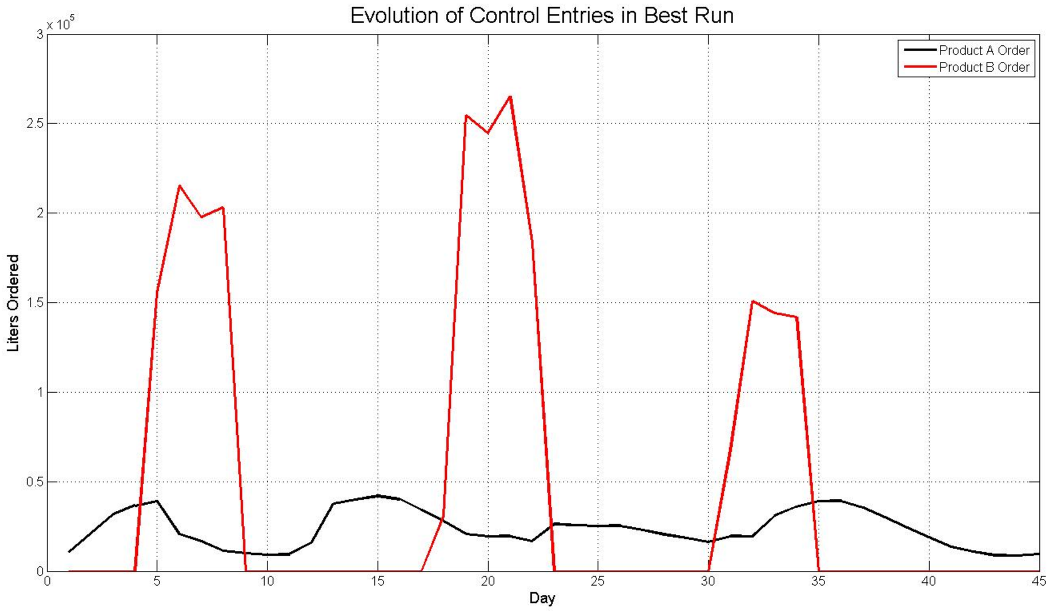


Figure 5.12: Evolution of controlled variable level for the VIOBPCS Controller

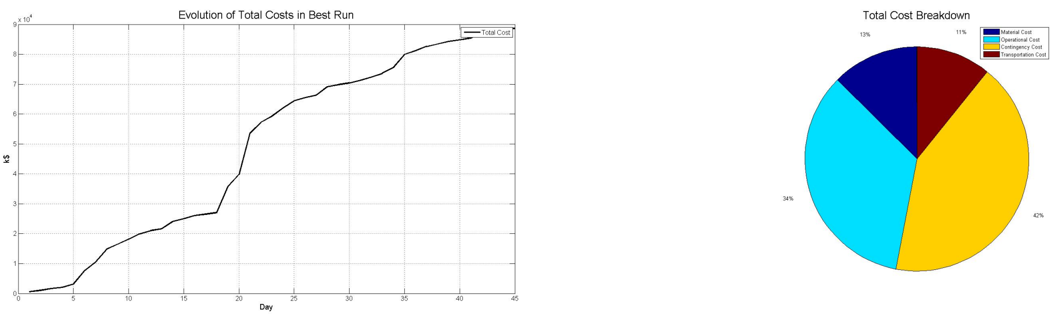


Figure 5.13: Total Cost Evolution and Final Day Total Cost Breakdown for the VIOBPCS Controller

Table 5.7: Final Day Cost Breakdown for the VIOBPCS Controller

Type of Cost	Value	Color
Material Cost	11122	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	30520	Cyan
Contingency Cost	37370	Yellow
Total Cost	88613	-

5.2.4 APIOBPCS Controller

APIOBPCS Controller is the first controller from the IBPCS family to incorporate WIP feedback and, thus, it is an evolution from all prior controllers with exception of the VIOBPCS. The figure describing APIOBPCS is given in (4.5). Again, three parameters need to be optimized, the controller gain K_p and two Inventory Set-Points, one for Product A and another one for Product B. They are denoted as I_{sp1} and I_{sp2}, respectively.

Overall Performance

Table 5.8: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	77212
Mean Cost	81940
Standard Deviation	245.72

Best Run

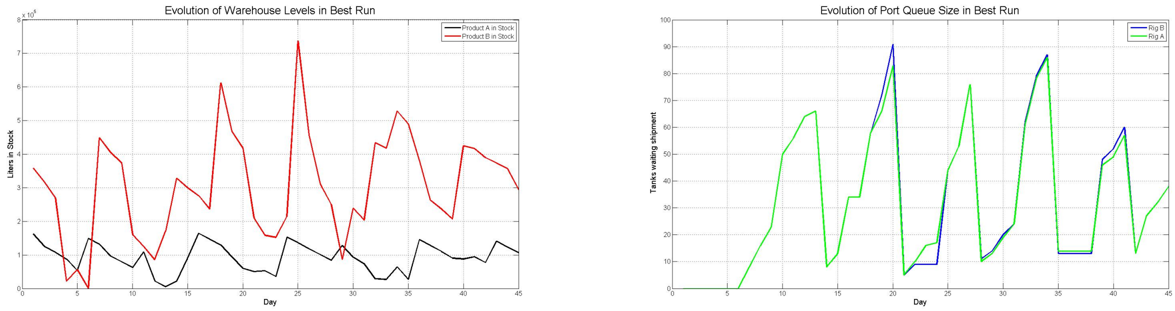


Figure 5.14: Evolution of Warehouse levels and Port Waiting Line using APIOPBCS Controller

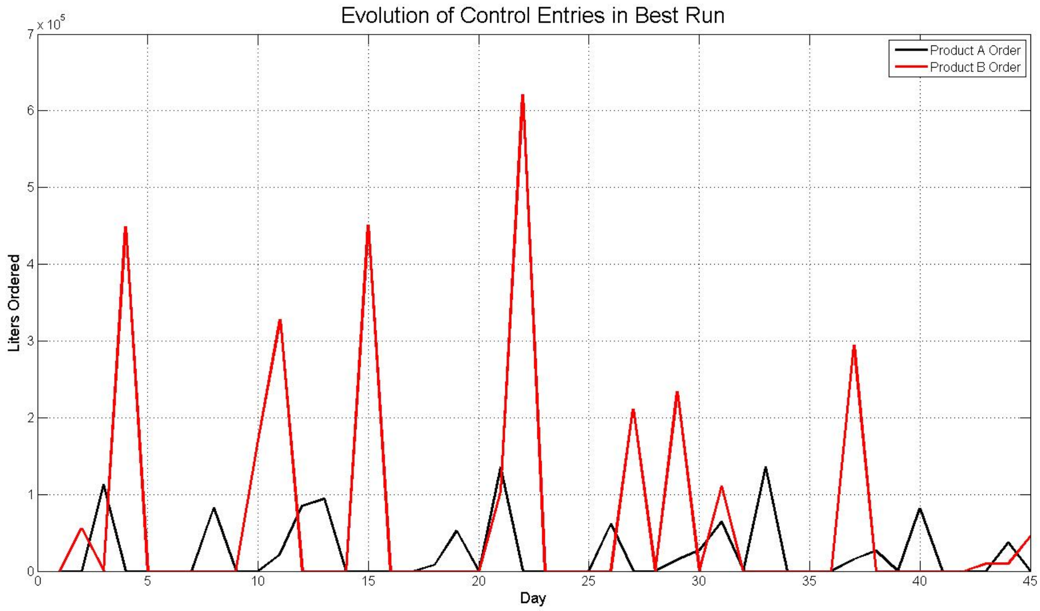


Figure 5.15: Evolution of Controlled variable level for the APIOBPCS Controller

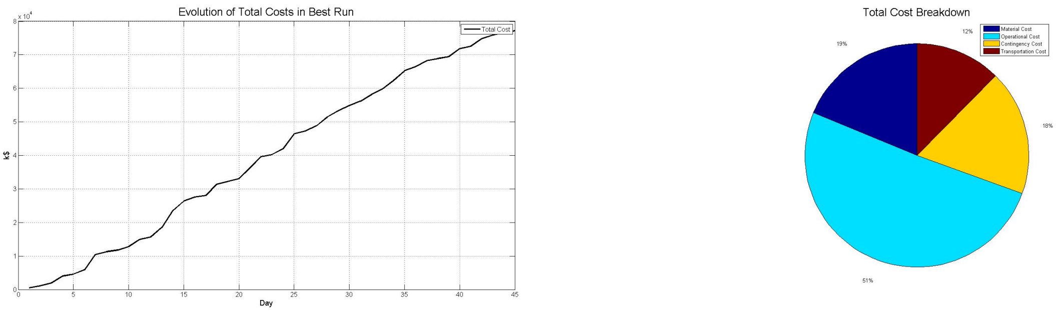


Figure 5.16: Total Cost Evolution and Final Day Total Cost Breakdown for the APIOBPCS Controller

Table 5.9: Final Day Cost Breakdown for the APIOBPCS Controller

Type of Cost	Value	Color
Material Cost	14495	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	39143	Cyan
Contingency Cost	13974	Yellow
Total Cost	77212	-

5.2.5 PID-APIOBPCS Controller

PID-APIOBPCS Controller is a controller derived directly from the APIOBPCS Controller. Instead of only using a proportional controller on the feedback loop, a PID controller is used. Thus, it is necessary to optimize five parameters, the controller proportional, integral and derivative gains (K_p,K_i and K_d respectively) and two Inventory Set-Points, one for Product A and another one for Product B. They are denoted as I_{sp1} and I_{sp2} respectively.

Overall Performance

Table 5.10: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	76629
Mean Cost	83593
Standard Deviation	343.99

Best Run

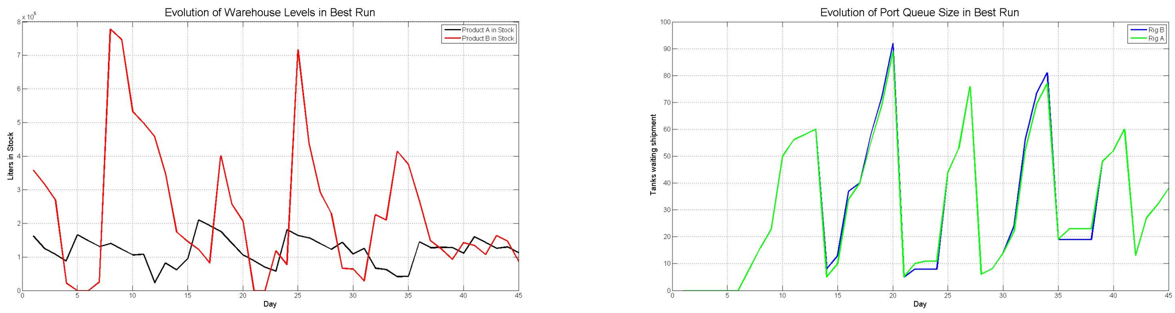


Figure 5.17: Evolution of Warehouse levels and Port Waiting Line using PID-APIOPBCS Controller

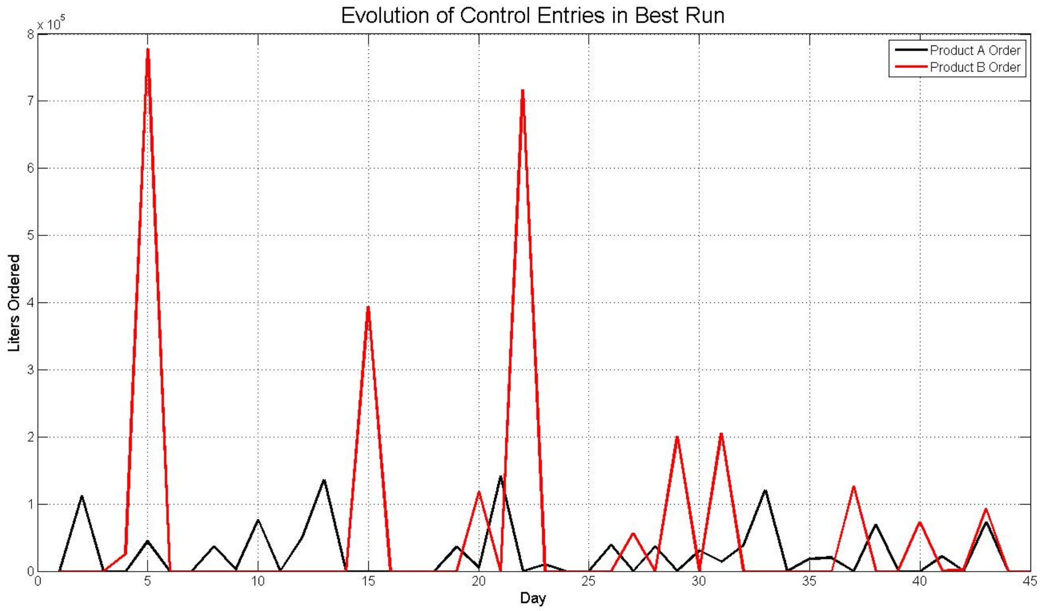


Figure 5.18: Evolution of Controlled variable level for the PID-APIOBPCS Controller

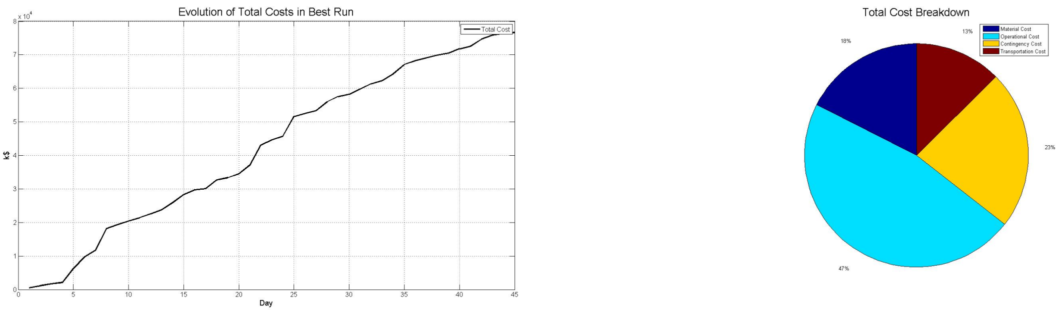


Figure 5.19: Total Cost Evolution and Final Day Total Cost Breakdown for the PID-APIOBPCS Controller

Table 5.11: Final Day Cost Breakdown for the PID-APIOBPCS Controller

Type of Cost	Value	Color
Material Cost	13427	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	35984	Cyan
Contingency Cost	17653	Yellow
Total Cost	76629	-

5.2.6 APVIOBPCS Controller

The APVIOBPCS Controller is a controller that has features from all previous controllers, except PID-APIOBPCS, since this controller does not incorporate a PID in its structure. It contain a feedback loop to calculate errors in Inventory and WIP and has a variable set-point. The APVIOBPCS is described in fig. (4.6). Again, three parameters need to be optimized, the controller gain K_p and two gains to find references, one for Product A and another one for Product B. They are denoted as K_a and K_b respectively.

Overall Performance

Table 5.12: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	80039
Mean Cost	87738
Standard Deviation	303.92

Best Run

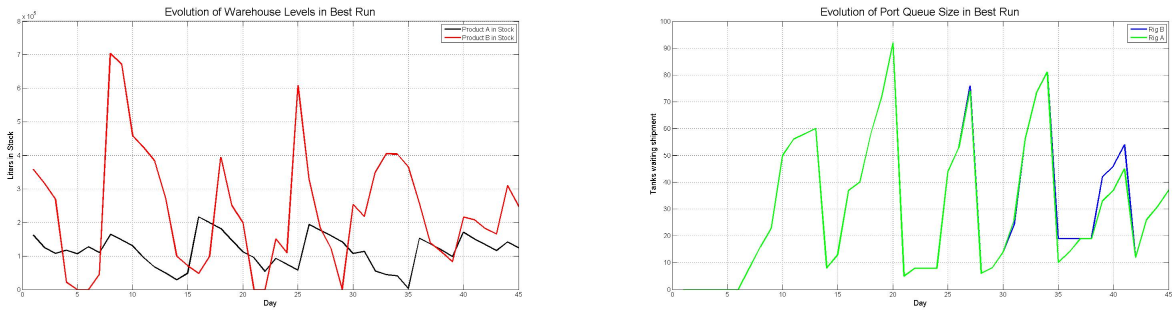


Figure 5.20: Evolution of Warehouse levels (in Liters) and Port Queue Size (number of Tanks) using APVIOPBCS Controller

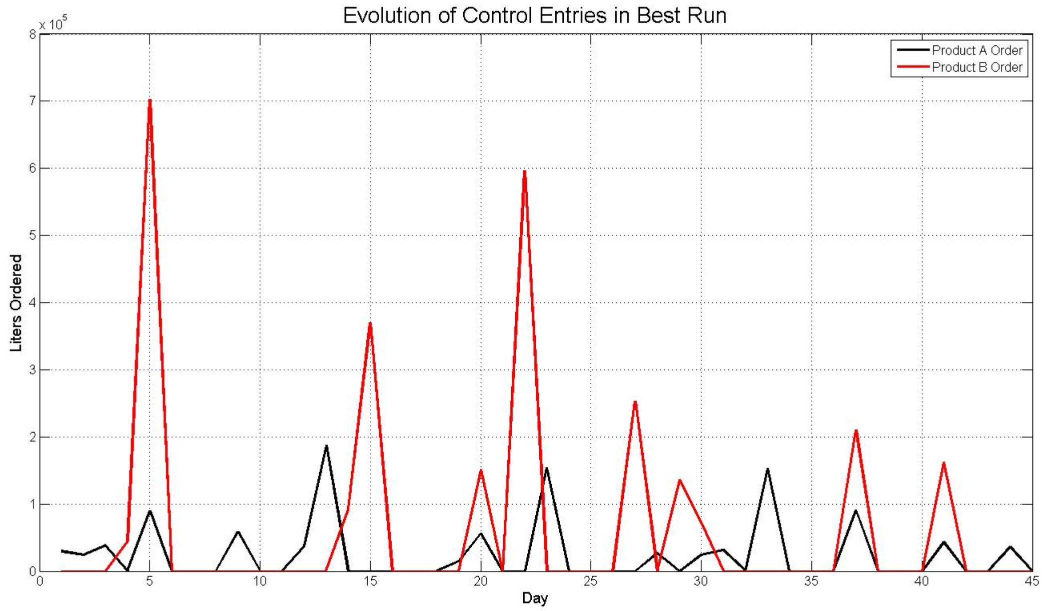


Figure 5.21: Evolution of Controlled variable level for the APVIOBPCS Controller

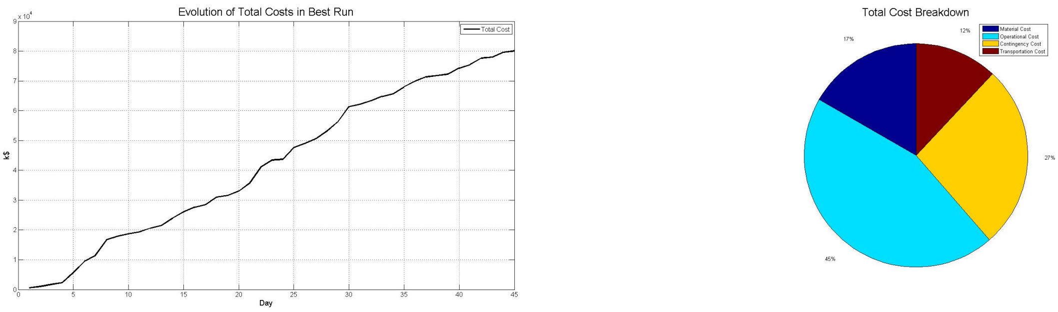


Figure 5.22: Total Cost Evolution and Final Day Total Cost Breakdown for the APIOBPCS Controller

Table 5.13: Final Day Cost Breakdown for the APVIOBPCS Controller

Type of Cost	Value	Color
Material Cost	13346	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	35817	Cyan
Contingency Cost	21275	Yellow
Total Cost	80039	-

5.2.7 PID-APVIOBPCS Controller

The PID-APVIOBPCS Controller is the most complex controller tested in this work. A PID controller is used on the feedback loop, with all other features of the APVIOBPCS family being present. Thus, it is necessary to optimize five parameters, the controller proportional, integral and derivative gains (K_p,K_i and K_d respectively) two gains to find references, one for Product A and another one for Product B. They are denoted as K_a and K_b, respectively.

Overall Performance

Table 5.14: Best Run, Mean and Standard Deviation in 100 GA run

Statistic	Value
Best Cost	77524
Mean Cost	89147
Standard Deviation	868.57

Best Run

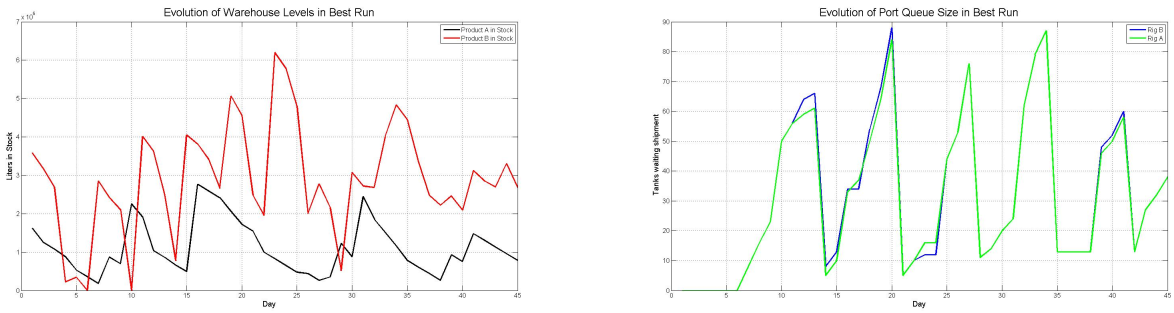


Figure 5.23: Evolution of Warehouse levels (in Liters) and Port Queue Size (number of tanks) using PID-APVIOPBCS Controller

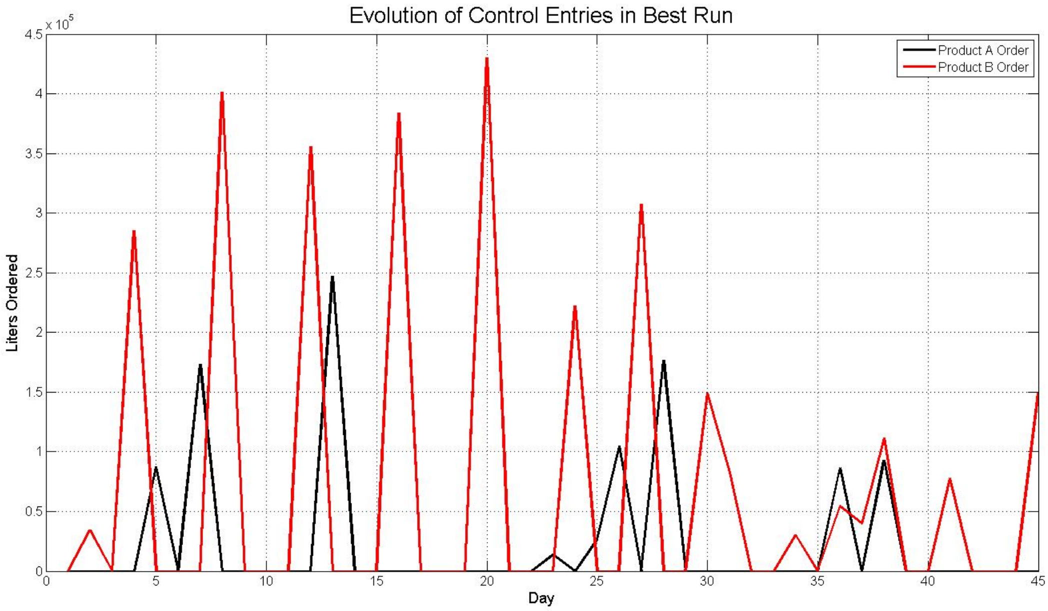


Figure 5.24: Evolution of Controlled variable level for the PID-APVIOBPCS Controller

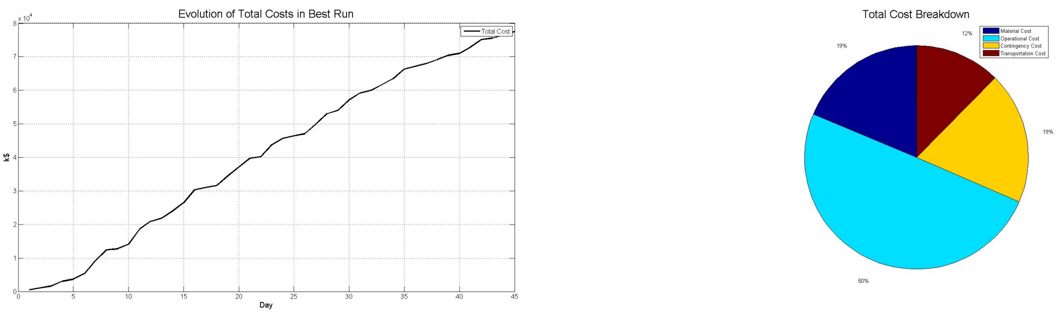


Figure 5.25: Total Cost Evolution and Final Day Total Cost Breakdown for the PID-APVIOBPCS Controller

Table 5.15: Final Day Cost Breakdown for the PID-APVIOBPCS Controller

Type of Cost	Value	Color
Material Cost	14476	Dark Blue
Transportation Cost	9600	Brown
Operational Cost	38643	Cyan
Contingency Cost	14805	Yellow
Total Cost	77524	-

Table 5.16: Cost Comparison Between all Control Strategies

Controller	Best Run	Mean	Standard Deviation
P-IBPCS	84288	89437	431.14
P-IOBPCS	78196	81756	438.91
P-VIOBPCS	88613	91726	223.74
P-APIOBPCS	77212	81940	245.72
PID-APIOBPCS	76629	83593	343.99
P-APVIOBPCS	80039	87738	303.92
PID-APVIOBPCS	77524	89147	868.57

5.3 Discussion of Results

It is noticeable that Costs from the best strategy ($76692.00) to the worst one ($88613.00), show a variation of 15%. Choosing the right controller is important to keep costs low even with optimized parameters.

Furthermore, it is observed that, despite being more complex, APVIOBPCS controllers does not perform better than APIOBPCS controllers. In the presented study, this happens due to a demand that is not well predicted by ADF. Recalling figure 5.4, we have shown using automatic demand prediction that the better predictor is the simpler one, or a (M,N,N) predictor. If the demand had more recognizable trends or seasonality, controllers with variable set-points would likely outperform the ones with fixed set-points.

There is an obvious trade-off between Operations and Contingency Costs. Controllers with best performance had higher operational costs compared with the other ones, but significantly lower Contingency Costs. Contingency Costs never drop below $10000.00 on the other hand, which implies that the relation between these two variables is not as simple as a constant ratio, but rather a more complicated relationship.

Compared to other control strategies, APIOBPCS is not only the one that provides lower Total Costs, but also low Mean Total cost and low Standard Deviation. That suggests that APIOBPCS is the most robust controller for this model with the demand being investigated.

If both APIOBPCS strategies are compared, PID-APIOBPCS wins on best run, but P-APIOBPCS or just APIOBPCS strategy performs better on both mean and standard deviation criteria. The fact that the controller has fewer parameters to adjust is certainly an advantage and it is shown by those two last statistics. This can be observed in table 5.16.

The fact that the APIOBPCS controller fares better than the APVIOBPCS controller and the IOBPCS controller achieves a better result, when compared to VIOBPCS, agrees with the conclusions in [15] regarding demand forecasting and its possible negative effect on control, since the variable set-point strategies rely more heavily on demand prediction than the fixed set-point strategies.

Chapter Summary: This chapter presented methodology to compare different controllers from the IOBPCS family. A flowchart describes the use of the plant model, predictor and genetic algorithm to find optimal controller parameters and calculate corresponding performance in terms of the cost function. Finally, the simulation results are discussed to obtain a perspective on the comparison of the different controllers studied.

Chapter 6

Conclusion

It is certainly not a easy task to model a real world process of a supply chain in terms of a dynamic system. Information is not always accessible, from both process itself and for model validation purposes, flow sheets may not reflect exactly how the process is performed and the whole process encompasses several people from different areas in the company, which means there is no single person that is familiar with the whole process from start to finish.

The model proposed and studied in this dissertation focused on an important part of the whole upstream supply chain for which data became available. The experience gained during the modeling process indicated that the porposed model could be modified, without much additional work, to encompass other types of bulk cargo, which were not modeled due to lack of data and detailed process information.

The controllers used in this dissertation were based on the production control literature and are more advanced than the classic MRP relay controller. Some modifications of the IOBPCS family of controllers were also studied.

In particular, the simulation results show that the PID-APIOBPCS and the P-APIOBPCS controller are good choices for this LSBC plant model. Their reliance on derivative control to track the trend of the disturbance in the former and the simplicity and the smaller amount of parameters to be optimized in the latter controller confers advantage in a real world demand scenario in which there are no obvious trends and seasonality and, for which, even the optimal ADF predictor did not turn out to deliver good performance.

6.1 Future Work

This dissertation presented a model of the liquid bulk supply chain to offshore rigs, but the model is general enough to be applied to other types of bulk material, with minor modifications, In the liquid bulk control, a feature of practical interest, that should be added in future work, is the consideration of backload (i.e. the return of empty tanks to land).

For reasons of practicality and simplicity the controllers studied in this dissertation used inventory level control based on the IOBPCS family, with parameters set through optimization of a cost functional.

While this approach provide guidelines for controller design, solving the optimal control problem with traditional optimization tools or using more sophisticated control schemes such as Model Predictive Control (MPC) or Economic Model Predictive Control (EMPC) is certainly an interesting option, that should be investigated.

The functional being optimized in this dissertation is the overall cost of the operation, and it was chosen as the simplest option with economic significance. It is also possible to calculate costs based on the value of items supplied and subsequently calculate how these items (or the lack of them) impact production revenues. In other words, a cost function reflecting Profit or even *Economic Value Added* or EVA should be of greater financial interest and thus influence future design of (upstream) supply chains.

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