Modelling and Optimization of Batch Manufacturing Systems under Environmental and Economic Considerations

by

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A thesis submitted to the Faculty of Graduate and Postdoctoral Studies

in partial fulfillment of the requirements for the degree of

Master of Applied Science

Ottawa-Carleton Institute for Mechanical and Aerospace Engineering

University of Ottawa

Ottawa, Canada

April 2015

Abstract

Nowadays, minimization of the negative environmental impact of manufacturing processes is considered one of the most challenging problems in various industrial fields. Research communities and environmental legislators are continuously working to address these problems by placing significant efforts in devising new strategies to increase environmental sustainability. One of these problems is the lack of a comprehensive framework that can simultaneously improve economic aspects and lessen the impact on the environment. The need for a mathematical model that can assist firms in reaching suitable investment decisions has become of paramount importance. In this context, this study aims at optimizing the environmental and economic sustainability of batch production systems (i.e. a series of workstations where products are manufactured in batches). To this end, a profit maximization model was created by incorporating constraints such as budget, demand, greenhouse gas emissions and hazardous wastes within the manufacturing stage of product life cycle. Moreover, the model provides detailed guidelines on required improvements in a specific manufacturing system and calculates the investment associated with such implementations. This new approach was tested by using two different software packages and results were probed and discussed in different scenarios to investigate its validity. Sensitivity analysis and simulation results proved the consistency of the proposed mathematical model. In particular, in order to further assess the validity of the model, a pharmaceutical plant was selected as a case study, which also permitted discussion on additional aspects of the problem.

Acknowledgement

I would like to thank all of the people who supported me during the undertaking of this research. To begin, I would like to thank my thesis supervisor, Professor Fabio Variola, for his advice, support, and availability. My sincere thanks to Professor Ming Liang who advised me and gave me the motivation to fulfill this research.

I want to express my gratitude to Ashley Hanson and Lanner Company's staff who generously provided me with proper training documents and permitting me to use WITNESS software.

I would like to extend my appreciation to Professor Saeed Zolfaghari, Mr. Gilbert Arbez, and Professor John Chinneck for their supporting words and emails. My thanks to Dr. Amir Monjazeb who patiently answered my research questions. Special Thanks to Goli Monjazeb who was always available for reviewing my work and was with me to the end.

I am deeply thankful to Mrs. Leyla Azmoodeh, Mr. Peyman Parvaneh, and Mr. Manouchehr Monjazeb whose support and care were encouraging me during this research and to my beloved family whose love, patience and financial support were always heartwarming.

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Nomenclature

Indices:

i	module number, i=1,…,I
j	station number, j=1, . . . ,J_i, where J_i is the number of stations in module i
k	machine number, k=1, . . . , K_{ij}, where K_{ij} is the number of machines in the station j of module i
total	this index indicates total value in the market (e.g. p^{LE}_{total} is the total p^{LE} for all the firms in the market under the same environmental taxation plan)
r	parameter type
v	variable abbreviated name

r indices related to local parameters (these parameters are shown in p^{r}_{ijk} form):

AAE	total loss caused by deviation DAE of air emission criterion
AE	initial air emission per operation
AHW	total loss caused by deviation DHW of hazardous waste criterion
ALE	total loss caused by deviation DLE of land emission criterion
AWE	total loss caused by deviation DWE of water emission criterion
CT	cycle time

DAE	Deviation from air emission criterion
DHW	Deviation from Hazardous waste criterion
DLE	Deviation from Land Emission criterion
DWE	deviation from water emission criterion
E	electricity busy use
H	handling time from previous module to current module (min)
HW	initial hazardous waste per operation
NTAE	net payment-air emission decrease constant
NTE	net payment-electricity saving constant
NTHW	net payment-weight of hazardous waste decrease constant
NTLE	net payment-land emission decrease constant
NTWE	net payment-Water emission decrease constant
IVTAE	cost of lowering air emission by one unit
IVTE	cost of lowering electricity consumption by one unit
IVTH	cost of lowering handling time by one unit
IVTHW	cost of lowering hazardous waste by one unit
IVTLE	cost of lowering land emission by one unit
IVTQ	cost of lowering scrap rate by one unit

IVTT cost of reducing cycle time by one unit

IVTWE cost of lowering water emission by one unit

LE initial land emission per operation

MSCp material cost for setup

NOS number of setups per machine

OR operators cost/min

Q initial scrap rate

SEp setup electricity use for the pth setup of the machine

ST setup time

TUEv tax charge per unit of emission ($\forall v \in \{WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\}$, v is the index for different types of emissions: water emission, land emission, air emission and hazardous waste)

VAE target value for air emission

VHW target value for hazardous waste

VLE target value for land emission

VWE target value for water emission

WE initial water emission per operation

General parameters:

η	Market sensitivity to the average emission abatement
Φ	Relative environmental effectiveness
B_T	budget available for improvement
D_T	base demand during time T
ER	unit electricity price
I_{ijk}^{+}	positive sustainability indicator (indicators whose increase has a positive impact on sustainability)
I_{ijk}^{-}	negative sustainability indicator (indicators whose increase has a positive impact on sustainability)
Ji	number of stations in module i
Kj	number of machines in station j
N_{ijk}^{+}	normalized negative sustainability indicator
N_{ijk}^{-}	normalized positive sustainability indicator
SR_s	scrap (failure) rate of the system
T	planning period
T_{ijk}^{v}	target value (lower boundary) related to v, $\forall v \in \{H, CT, A, E, WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\}$
UAE^T	upper bound for air emission during planning period T
UHW^T	upper bound for hazardous waste during planning period T

ULE^T upper bound for land emission during planning period T

UP unit price

UWE^T upper bound for water emission during planning period T

Dependant variables:

CL^v Loss function related to v, $\forall v \in \{WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\}$

dt demand during period t

EC electricity Cost

HC handling cost

NT emission net payment (in general)

NTAE air emission reduction net payment

NTHW hazardous waste reduction net payment

NTWE water emission reduction net payment

IVT investment (in general)

IVTAE air emission reduction investment

IVTE electricity investment

IVTH handling investment

IVTHW hazardous waste reduction investment

IVTLE	land emission reduction investment
IVTP	productivity investment
IVTQ	quality investment
IVTWE	water emission reduction investment
NOP	no of operations
OC	operating cost
SC	setup cost
TBijk	accumulated process time from the beginning of a batch to the end of the process done at machine ijk
TPT	total process time for one batch
TS	total sale

Independent variables:

x_{ijk}^{Q}	accuracy improvement ratio
x_{ijk}^{AE}	air emission abatement ratio
x_{ijk}^{T}	cycle time abatement ratio
x_{ijk}^{E}	electricity efficiency improvement ratio
x_{ijk}^{H}	handling time deduction ratio

x_{ijk}^{HW} hazardous waste deduction ratio

x_{ijk}^{LE} land Emission abatement ratio

x_{ijk}^{WE} water emission abatement ratio

Chapter 1 : Introduction

The "going green" initiative has numerous advantages that permit firms to achieve set goals while remaining environmentally friendly. Cost reduction, increased motivation among employees, higher profit for stakeholders and, most importantly, reduction in the negative environmental impact, can all be attained simultaneously by employing "green" methods. Two systematic approaches have been widely adapted by numerous firms in order to improve specific goals in their manufacturing processes. The first is *lean manufacturing*, a set of operations that focus primarily on waste elimination. The second is *green manufacturing*, a series of protocols and regulations that minimizes waste, pollution and the exploitation of natural resources. Focusing on these issues to find an optimal manufacturing setting will ultimately improve economic and environmental sustainability. A selection of topics related to this area are elaborated and discussed in this section.

1.1. An Overview of Environmental Sustainability

Sustainability is known to lie on three main pillars, namely economy, environment and society. The U.S. Department of Commerce defines sustainable manufacturing as "the creation of manufactured products that use processes that minimize the negative environmental impact, conserve energy and natural resources, are safe for employees, communities and consumers, and are economically sound" (International Trade Administration, 2007). Nowadays, societies have raised their awareness on product sustainability and environmental concerns, by considering factors such as air pollution, depletion of natural resources and global warming. Researchers and legislators have also put much effort into addressing environmental and climate change issues. Their concerns have been regularly brought forth through international summits, held by many organizations such as the United States Environmental Protection Agency (EPA). The committee on manufacturing challenges has predicted six major qualifications in manufacturing for 2020, striving for a reduction of the production waste and a "near zero" environmental impact (National Research Council, 1998). Legislators have been committed to reducing the negative environmental impact from manufacturers by enforcing environmental regulations and the application of performance measurement tools to reward or penalize firms. As a consequence, manufacturers are now required to produce environmental friendly products by exploiting greener processes (Hu & Lu, 2011; National Research Council, 1998). One of the most promising approaches to achieve this objective is the optimization of manufacturing facilities with respect to different aspects of sustainability. Environmental performance has recently been among the main criteria for many customers, a factor that in turn affects production demand (Nouira, Frein, & Hadj-Alouane, 2014). As a result of the above-mentioned implementations, firms can now benefit from financial aid while producing eco-friendly products that are more appealing to customers.

To improve the overall economic and environmental performance of manufacturing processes, lean manufacturing tools are routinely employed by firms. Among them, value stream mapping is a helpful tool that guides decision makers in finding potential improvement areas within the life cycle of a product. The value stream map (VSM) presents a snapshot of the tasks involved in any part of the whole life cycle of a single or group of products. In a VSM, the tasks are divided into two categories: value-added and non-value added. The main manufacturing steps (e.g. granulation of tablets in the model manufacturing process investigated herein, see Section 4.1.3.2) are examples of value-added tasks, while other steps (e.g. transportations and setups between main steps in the model manufacturing process) are non-value added. The main goal of this mapping process is to minimize the time spent on non-value added tasks. Newer approaches in this field add environmental information to the VSM, one of which is the development of environmental value stream maps (EVSM) that include energy and material usage in VSMs (EPA, 2007). Finding efficient methods to present improved results related to emission abatements and cost reductions on a single map can undoubtedly contribute to a more efficient decision making process that promises to enable firms to develop greener processes.

1.2. Thesis Outline

Chapter 1 provides an overview of environmental sustainability in manufacturing systems, as well as the outline of the thesis.

A review of the current state-of-the-art is presented in Chapter 2 through a careful selection of relevant topics. In this section, the gap that this work aims to fill is identified and thoroughly described.

Chapter 3 covers the theoretical background used in this work, which comprises the mathematical model developed based on a batch production manufacturing system. It also shows how the proposed formulation maximizes the profit by considering demand, budget and environmental constraints. Moreover, a numerical example is provided and the model is optimized using a commercial package.

Different scenarios including data analysis of various types of investment functions are presented in Chapter 4. As an alternative approach to optimization, a simulation is performed using the WITNESS software package. Results from the simulation are compared to the optimization outcome followed by an analysis and a series of discussions.

To conclude, Chapter 5 summarizes the results and outlines the contribution of this thesis in relation to the stated objectives.

Chapter 2 : Problem Statement and Literature Review

Global warming, economic recessions and human right advancements have propelled the search of new methods to optimize manufacturing plants while considering environmental, economic and social sustainability. However, previous studies have never focused on the optimization of profit gained from investing in technology enhancements with respect to environmental sustainability of a given manufacturing plant. In particular, the investments required for the improvements in machinery have never been estimated. In this study, environmental and economic sustainability have been taken into account for batch production where the data before and after optimization are depicted in current and projected value stream maps, respectively. Taguchi's *quality loss function* (Taguchi, 1986), which assumes that deviation of product specifications from target values results in customer dissatisfaction and thereby lost profit, was integrated into the model to convert a group of parameter deviations from their target values to cost (Section 2.2.2). In the following sections, the problem, the relevant literature review, and the motivation of this research are elaborated.

2.1. Problem Statement

Environmental concerns have been under the spotlight of many manufacturing firms for a number of years, and environmental goals have been set to address these concerns. For the firms to be motivated to achieve these goals, financial stimuli and incentives that increase the firm's net profit are necessary. The question that underlines this work is whether a mathematical model can be developed to achieve profit maximization while tackling environmental issues. Based on literature review, there is a lack of a comprehensive mathematical model that can potentially guide decision makers in reaching proper investment decisions towards this "greener" direction. Available investment budgets, market demand and the target greenhouse gas emission levels were considered in the development of the proposed model. From an environmental point of view, total demand consists of the demand not only from customers who are not concerned about the environment, but also from that segment of the population that investigates the green factor of the manufacturers.

The life cycle of a product encompasses different stages of pre-manufacturing, manufacturing and post-manufacturing. The pre-manufacturing stage consists of extraction and processing of material. The manufacturing stage covers the tasks involved in transforming material into the final product. The post-manufacturing stage includes the use of the final product by customers, as well as waste management which begins subsequent to the use stage. There are also possibilities of recycling, remanufacturing and reusing of materials and products at different stages of the life cycle.

In this context, the goal of the thesis was to develop a mathematical model for a batch production system. In batch production, a limited amount of input material is processed either continuously or intermittently into the same type of output. Such production is very common in pharmaceutical industry (Karanjkar ,2008). The decision variables of the model are improvement levels on different sustainability indicators of different machines, and the objective is to maximize profit. The model constraints were set in ways that investment budget is respected, and greenhouse gas emissions and hazardous waste levels below the set targets are maintained. To address the demand from potential customers, the proposed model also considers the demand as a function of the reduction in emission levels. It should be noted that the emphasis of this thesis is only on the manufacturing stage of the product life cycle (Figure 2-1), of which, only economic and environmental factors will be considered (Figure 2-2).

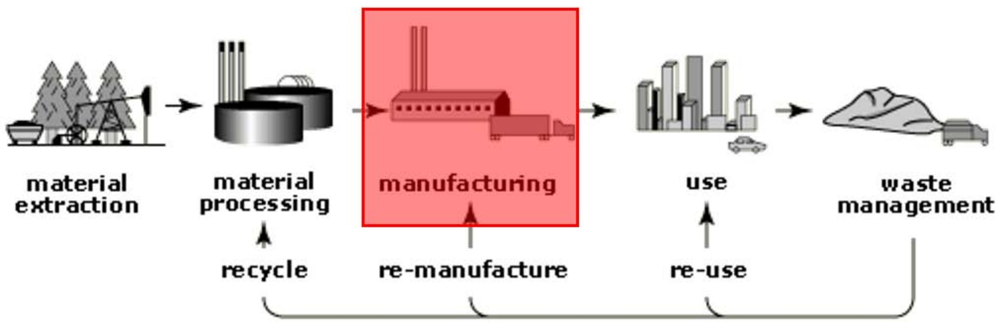

Figure 2-1: The life cycle of a product (Tarr, 2004); the stage addressed in this thesis is highlighted in red.

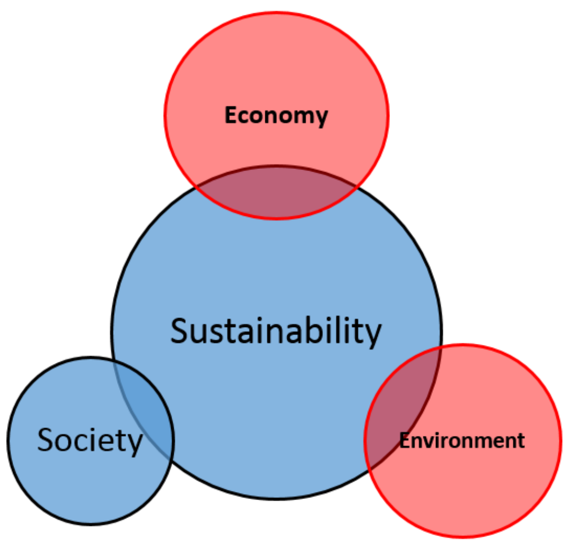

Figure 2-2: The pillars of sustainability. The two addressed in this research are highlighted in red.

2.2. Literature Review

As outlined in the previous section, the goal of this thesis is to provide environmental and economic guidelines to improve a batch production system using a mathematical model. There is a vast number of studies that aim at improving firms' processes and protocols by focusing on one or more pillars of sustainability (Figure 2-2). In the following sections, the most recent studies which address environmental and economic optimization of manufacturing systems and applications of Taguchi' *quality loss function* are presented.

2.2.1. Optimization of Manufacturing Systems

Mathematical modelling is one of the most successful approaches to improve efficiency and industrial production. Wang et al (2011) developed a model that comprised two objective functions, total cost of a life cycle and total CO_2 emission. The focus of their research was to find optimal values for environmental investments while trying to achieve those objectives. The model included long-term strategic decisions related to the selection of distribution centers and warehouse locations, as well as transportation modes and quantity of material transported. The study, however, did not include quality considerations and customer demand was assumed to be a constant.

In parallel, a more recent study addressed manufacturing systems with the consideration of environmental cost while assuming that the demand is a function of product greenness, which, in turn, is a function of three elements (Nouira, Frein, & Hadj-Alouane, 2014), namely (i) total emissions in the existing process used for production of a given product, (ii) the emissions from the least environmentally efficient process available and (iii) the level of environmentally-friendliness of the input material.

In this study, customers were divided into ordinary and green customers and they proved experimentally that firms that offer different variety of products to each group of customers are more successful financially than the ones that offer a single product. They concluded that considering the awareness of customers to the environment can substantially benefit firms.

Another study has suggested that the increased level of greenhouse gas emissions decreases market demand (Letmathe & Balakrishnan, 2005). These studies stand out of other published works in the field of environmental optimization due to the fact that other publications considered demand as a constant or as a stochastic input to the model. However, none of the above-mentioned studies considered demand as a function of greenness enhancement of manufacturing processes. This consideration is important since factories with greener processes and less negative environmental impacts are more valued by societies and can attract greater attention by customers.

2.2.2. Taguchi's Quality Loss Function

Quality Loss Function (QLF) was originally developed by Genichi Taguchi in 1986 (Taguchi, 1986) for the purpose of transforming deviations in product characteristics from target values into cost. In fact, cost can be considered as the financial loss caused by a decreased market demand for the product exhibiting variance from the target specifications provoked by non-optimal manufacturing processes. In other words, that monetary loss can be regarded as a projection of the customer's dissatisfaction (Bentley, 1999). This approach has been used in various studies to quantify performance indicators that are not measurable. For example, Ordeoobadi (2009) applied Taghuchi's loss function as a tool to measure intangible benefits of adopting advanced manufacturing technologies such as increased quality, productivity and customer satisfaction. Another beneficial application area would be to use the transformation to aggregate indicators with different measures into one unified index. QLF has proven to be useful in the integration of conflicting and non-comparable performance indicators towards module selection in finding the optimal design of a modular manufacturing setting (Xu & Liang, 2006). It has also been used to calculate the loss to society by extra CO_2 emission generated by data centres (Pendelberry, Ying Chen Su, & Thurston, 2010; Xu & Liang, 2006).

In this thesis, QLF was employed to calculate the financial loss caused by the deviations of environmental indicators from target values. “The-smaller-the-better with lower limit” loss function was applied. This type of QLF function, as described by Xu and Liang (2006), assumes that only specifications with higher values than the targets can generate profit loss and as the values grow from nominal point (target value), losses increase. Negative environmental impact is of this nature (Krajnc & Glavic, 2005). The lower its value, the lower the loss will be.

2.2.3. Sustainability Improvements Cost Curves

Technological changes can improve manufacturing processes in terms of their environmental and economic parameters. Finding the relationship between the machine investments and the amount of improvements has been the focus of some studies. Vijay (2010) proposed a function that exhibits an exponential relation between the cost of using new technology and the amount of reductions in NO_x (Vijay, DeCarolis and Srivastava, 2010). Another study estimated the abatement cost of CO_2 as an exponential function of emission levels (Ko, Chen, Lai, & Wang, 2013). This relationship between cost and abatement level is used in the current thesis to calculate the investment required for improvements.

2.2.4. Value Stream Mapping (VSM)

The value stream mapping is a tool created to improve the productive systems (Lasa et al., 2008). A value stream encompasses all the actions (both value and non-value added) required to bring a product, or group of products that use many of the same resources in the same way, through the main flow from the raw material to its final form. Monden (1993) believed that in addition to value-added and non-value added activities there are activities which are Necessary but Non-Value Adding (NNVA). These are considered wasteful in nature but they cannot be eliminated due to some limitation (e.g. unpacking of delivered material). However, from a lean manufacturing point of view, these activities are not adding value to the final product. Therefore, there might be methods to shorten their duration and/or simplify their process. VSM is a visualization tool that shows the flow of materials and information as the product makes its way through the value stream. It serves as a starting point to help management, engineers, suppliers, and customers to recognize waste and its sources (Seth et al.,2008). The mapping reviews the flow of information and physical goods, aiming at eliminating waste and thereby improving quality, cost and delivery. There are seven kind of waste that VSM can help identify. The wastes present in any system in form of inventory, overproduction, over capacity, wrong processing methods, non-value adding activities, etc (Seth et al., 2008).

In order to understand the flow, one should first understand the concepts of the value stream. Value stream is the linkage of events or activities which ultimately delivers value to a customer. A value stream crosses functional and, usually, organizational boundaries. Figure 2-3 shows a simple value stream which typical for any given manufacturer. The value stream does not show all the supporting activities, but only the main value adding stages and the key multi-functional teams involved.

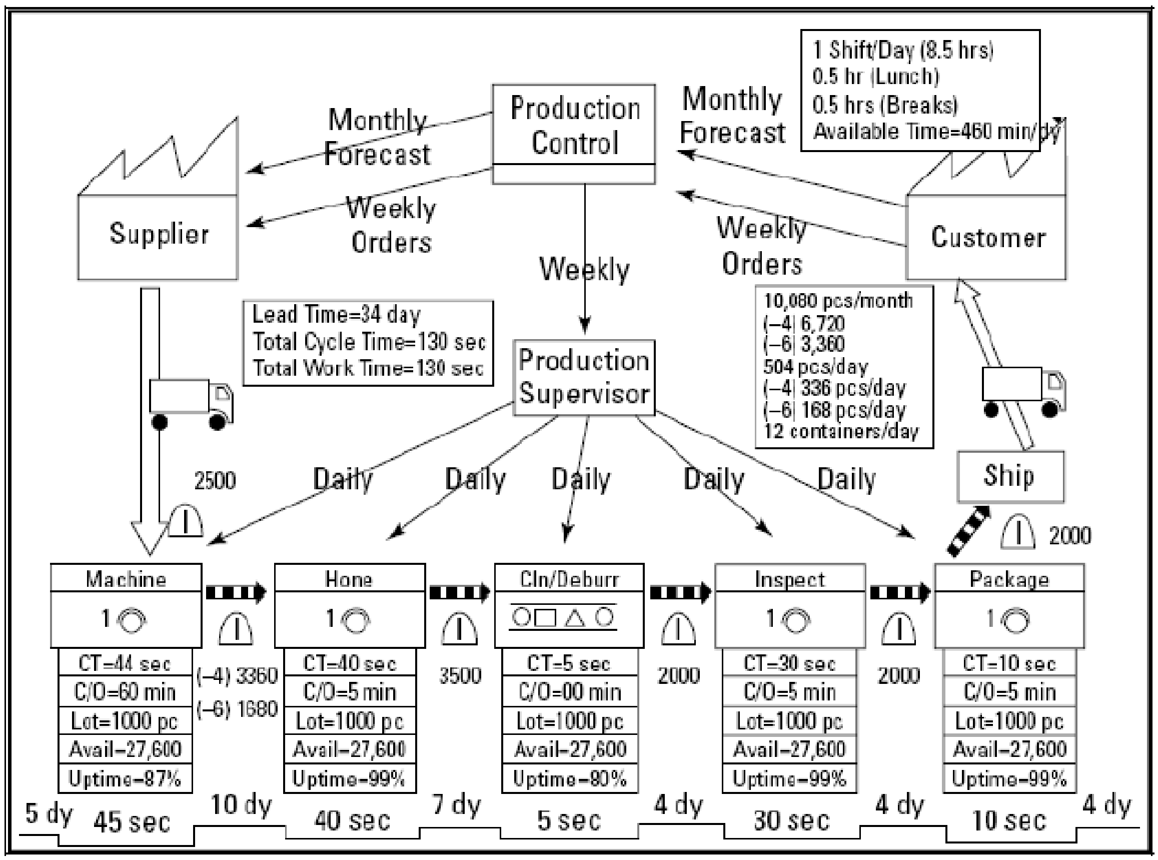

Figure 2-3: A simple value stream map depicting life cycle of a product

As shown in Figure 2-3, VSM contains essential, descriptive process information. Generally, a VSM contains the following (Sayer and Williams, 2007):

i. Process Steps: The VSM shows the process steps in the value stream, including both value-added (VA) and non-value-added (NVA).
ii. Inventory: The VSM highlights storage and the amount and movement of work-in-progress within the process.
iii. Information flow: All supporting information required by the process is shown on the VSM. This can include orders, schedules, specifications, kanban signals (a kanban is a signal to replenish inventory in a pull system), shipping information, and more.
iv. Box score: A VSM includes a summary of the key operational metrics of the process. At a minimum, this includes a summary of the total lead time of a process. The summary may also include such information as distance travelled, parts per shift, scrap, pieces produced per labourhour, changeover time, inventory turns, uptime, downtime, etc.
v. Lead time: Along the bottom of the VSM is the current lead time performance of the value stream. Lead time is the amount of time that one piece takes to flow completely through the process. The time is divided into value-added and non-value-added portions.
vi. Takt time: A box in the upper-right-hand corner of the VSM shows the customer demand rate or takt time. This rate is determined by the customer demand and production time available. Ideally, all steps in the value stream should then produce to this rate.

2.3. Motivation of the Thesis

Development of strategic guidelines is quite critical in the overall economic and environmental performance of industry. As reviewed in this chapter, there have only been a few precise guidelines on how to achieve these specific goals. The motivation of this thesis is thus to provide companies with a model that allows them to locate the necessary improvements for each workstation and estimate the required investment.

In reviewing the results from United States Environmental Protection Agency's (EPA) greenhouse gas emissions database, one can observe that the firms from the automotive sector have lower levels of emissions than ones from the pharmaceutical sector. For instance, one of Ford's largest facilities, with around 5100 employees has reported annual greenhouse gas emissions of 78,045 metric tons of CO_2 in 2013. Conversely, Pfizer's Groton pharmaceutical facility with slightly more than 3100 employees reported 85,678 metric tons of CO_2 for the same year (EPA, 2013). Based on these data, a pharmaceutical plant was selected as case study, to exemplify factories in the pharmaceutical sector which are among the leaders in total negative environmental and societal impact.

2.4. Summary

Recent studies have focused on the financial and environmental optimization of plants; however, there is a lack of a mathematical model which covers technology enhancement decisions under environmental considerations. The problem was identified in detail followed by the research question which is the possibility of development of a mathematical model to tackle environmental issues in order to achieve profit maximization. This model can be developed considering environmental and economic performance. Taguchi's quality loss was identified as a function to be incorporated into the suggested model in order to transform the deviations of water, land and air emissions as well as hazardous waste indicators from their target values into cost.

Chapter 3 : Environmental and Economic Sustainability Model

In this chapter, a framework for a batch production optimization process in terms of environmental and economic sustainability is proposed. The idea is to gather information about the current state of a process based on selected sustainability indicators, draw a current-state value stream map (VSM) and subsequently optimize the data towards the production of a future-state map. A mathematical model was developed by including an objective function that covers:

i. Factory's operating cost;
ii. The net emission payments;
iii. Investment costs related to these improvements;
iv. Quality loss values for environmental indicators; and
v. Revenue from annual sales.

Budget, demand, and greenhouse gases and hazardous waste emissions were the constraints of the model. The values suggested by the optimization process are represented in a future-state map which can be used as a guideline by firms to improve their processes in terms of sustainable manufacturing.

The collected data related to sustainability indicators are based on various units of measurement such as weight, cost and time. Therefore, the data are normalized and tooled together in order to be presented on the current VSMs. The stations with the highest sum of normalized indicators are recognized and referred to as *sustainability* *bottlenecks*. The future-state VSM includes the projected data for each indicator. In this map, the stations requiring the highest percentage of improvement are identified.

This thesis does not aim at providing detailed guidelines on how to practically perform the improvements on each machine to get the new values for the parameters. Instead, it estimates, from a theoretical point of view, the cost for the suggested combination of improvements.

3.1. Research Stages

In this section, the structure of the study is explained in detail. It starts by collecting data from a selected process and product within a specific firm. An optimization of the current data is then performed and the existing and projected data are normalized and displayed in the form of VSM. Improvement decisions are taken based on the VSMs. A flowchart of the working approach related to this process is shown in Figure 3-1.

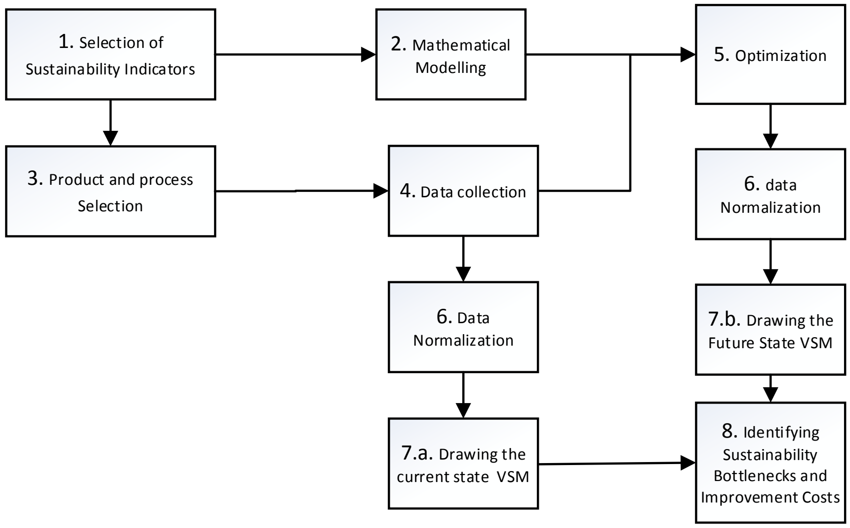

Figure 3-1: Flowchart of the working approach. This chart shows the proposed stages for optimization of a selected manufacturing process.

The following are the definitions of the stages shown in the flowchart:

3.1.1. Selection of Sustainability Indicators

Choosing decision variables is one of the main stages in developing any mathematical model. In this thesis, decision variables are based on a selection of sustainability indicators. There are many indicator sets available in the literature. These indicators are developed for the evaluation of products and processes. Two examples of the available indicator sets are brought in Appendix C, D and E (Global reporting initiatives (GRI), 2006; RobecoSAM Indexes, 2007; Dreher et al, 2009). International standard ISO14031 (1999) is another approach for environmental evaluation of firms. This standard is used to assess firms based on their management and operational performance as well as their direct impact on the environment. The selected indicators used in this thesis are described below:

Indicator name	**Description**	**Associated Decision Variable**
Scrap Rate	The rate at which scrapped product is generated by machinery	Accuracy Improvement Ratio
Air Emissions	Amount of emitted air pollutants including CO_2 and NO_x	Air emission abatement ratios
Land Emissions	Total land emissions from the process(non-hazardous waste)	Land emission abatement ratios
Water Emissions	Total quantity of pollutants in wastewater that is discharged in water source	Water emission abatement ratios
Hazardous Waste	Total amount of ignitable (i.e., burns readily), corrosive, or reactive (e.g., explosive), or toxic material released into the environment	Hazardous waste abatement ratios
Lead Time	Total production and transportation time of a product to be sent to customers	Cycle time reduction ratio
Electricity Use	Total electricity consumption during the production	Electricity efficiency improvement ratio
Handling Cost	Transportation time between workstations within a process	Handling time reduction ratio

Table 3-1: Selected sustainability indicators. The indicators are selected from the ones available in the literature. The decision variables that are used in the model are based on the selected indicators.

3.1.2. Mathematical Modelling

In this section, the proposed mathematical model, as well as the solution method for its optimization, are explained.

The following assumptions have been made in the proposed model:

i. Batch production.

ii. One module includes one or more stations that operate in series. There are I modules in the model and $i \in \{1,..,I\}$.

iii. Every station includes one or more machines that operate in parallel, meaning that the machines do the same type of operations on different parts of the batch at the same time. However, the machines working in parallel can have different sustainability characteristics. The index chosen for station number is j and there are total of J stations in the model and and $j \in \{1,..,J\}$.. The total number of machines in the model is K and the index for machines is k and and $k \in \{1,..,K\}$..

iv. Handling only covers the handling between modules. Therefore, handling between stations and between machines within each station is neglected.

v. If any of the machines generate waste, the whole batch of product is considered as waste.

3.1.2.1. Description of the Cost-revenue Model

Objective Function

The objective function of the cost-revenue model includes five main elements:

i. The operating costs (OC); this term includes handling cost (HC), electricity cost (EC) and setup cost (SC). These terms are shown in Equations (3.10), (3.14) and (3.15).

ii. Improvement investments (IVT); this term includes the investment required for the following sections:

   a) Reduction of machine cycle times (IVTT);

   b) Quality improvement (IVTQ), which results in a smaller waste production;

   c) Energy saving on each machine (IVTE);

   d) Reduction of handling times (IVTH); and

   e) Emissions and hazardous waste abatement (this includes land (IVTLE), water (IVTWE) and air (IVTAE) emissions, as well as hazardous waste).

iii. Net payments (NT); these values show the amount of money the firm will pay or receive based on its relative environmental effectiveness. Environmental effectiveness is the market production share divided by the firm's market emission share. The calculation of relative environmental effectiveness is shown in Equation (3.4). If a firm's relative environmental effectiveness is higher than the regional firms' average, there will be a tax charge; otherwise, an amount is refunded to the firm as an incentive.

iv. Quality loss functions related to emissions (CL); it is assumed that the emission values that are larger than targets result in a loss calculated using *Taguchi loss function*.

v. Total sale from the final products (TS): this value depends on the number of finished goods. The higher the volume of finished and flawless goods, the higher impact on the sale. Therefore, it is assumed that all the final products from the factory are sold to the distributors.

Based on the above-mentioned terms, an objective function is formulated (Equations (3.1) and(3.2)).

Decision Variables

The decision variables that are listed within this section represent the ratio of improvement on each of the selected sustainability indicator. The selection process was more elaborated in Section 3.1.1. The variables range from zero to one where zero indicates zero per cent improvement/abatement while one represents a hundred per cent improvement/abatement.

i. Accuracy improvement ratio (x_{ijk}^{Q}): this is the quality improvement ratio for the machine k of the station j of the module i. For instance, $x_{111}^{Q} = 0.01$ represents 1% improvement in the current value of the accuracy level of the first machine located within the first station of the first module in the process. This improvement induces one per cent decrease in production of the waste.

ii. Air, land, water emission and hazardous waste abatement ratios (x_{ijk}^{AE} , x_{ijk}^{LE} , x_{ijk}^{WE} and x_{ijk}^{HW}): these are the ratios that illustrate the amount of required improvement in the current values of air, land, water emissions and hazardous wastes for each of the machines.

iii. Cycle time reduction ratio (x_{ijk}^{T}): this ratio specifies the required improvement level in the cycle time of each machine within the process. For example,

$x_{211}^{T} = 0.03$ represents 3% improvement in the current value of the cycle time of the first machine of the first station from the second module.

iv. Electricity efficiency improvement ratio (x_{ijk}^{E}): this ratio suggests the required improvement in the level of electricity efficient for each machine.

v. Handling time reduction ratio (x_i^H): as mentioned in the model assumptions, handling covers only the handling between modules and x_i^H is the reduction ratio in the handling time of the input material for module i.

Constraints

The constraints related to the cost-revenue model were defined as follows**:**

i. Demand constraint: this assures that firm’s annual average demand is fulfilled. This means that the total number of flawless final products produced during the planning period must be higher than the total expected demand.

ii. Budget constraint: this guarantees that the investment required for each type of improvement or abatement does not exceed the associated allocated budget (Equation (3.22)).

iii. Emission target: this constraint limits the yearly amount emissions generated by the firm to the strategic emission targets (Equations (3.23) to (3.26)).

3.1.2.2. Mathematical Formulations

Mathematical formulation related to the proposed model is explained. The reader is advised to consult the nomenclature presented on pages x-xv.

Objective Function

Given the description in Section 3.1.2.1, the cost-revenue model for the problem is formulated as:

$$Max\ f = TS\text{-}NT\text{-}OC\text{-}IVT\ \text{-}CL \tag{3.1}$$

Equation (3.1) shows that the objective function is the maximization of the profit. The formula is expanded in Equation (3.2).

$$\begin{aligned} Max\ f &= TS - (NTE + NTLE + NTWE + NTAE + NTHW) - \sum_{i=1}^{I} HC_i - \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}} (EC_{ijk} + SC_{ijk} \\ &+ IVTT_{ijk} + IVTQ_{ijk} + IVTE_{ijk} + IVTH_{ijk} + IVTLE_{ijk} + IVTWE_{ijk} + IVTAE_{ijk} + IVTHW_{ijk}) \\ &- \sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}} (CL_{ijk}^{LE} + CL_{ijk}^{WE} + CL_{ijk}^{AE} + CL_{ijk}^{HW}) \end{aligned} \tag{3.2}$$

Profit is equal to revenue (total sales) minus costs (net payments, operating costs, investments and quality costs).

i. Net Payments

Net payments were modelled by Sterner & Höglund Isaksson (2006) as a function of tax and refund payments. Their study emphasized that factories with a higher-than-average environmental effectiveness (the ratio between production and emission market share) will receive refunds and the ones below average will be charged emission taxes.

Net payments equation consists of two terms: tax and refund (3.3). The first term is the amount of tax paid to the government on the emission level and defined as $\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}} (1-x_{ijk}^{v})\, p_{ijk}^{v}\ (1-x_{ijk}^{v})\, p_{ijk}^{v}$. Parameter p^{TUEv} is the tax charge per unit of emission (v is the index for water, land, air emissions and hazardous waste). The second term includes a multiplication of the firm's output share, the total emission by peer firms(p_{total}^{v}

) and tax charges per unit of emission (p^{TUEv}). It is noteworthy that firm's output share is the number of batches of product produced by the firm or $\left\lfloor (1-\mathrm{SR_s})\frac{T}{TPT} \right\rfloor$ divided by total number of batches produced by the market (Q).

$$NTv_{ijk} = -p^{TUEv}\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(1-x_{ijk}^{v})\,p_{ijk}^{v} + p^{TUEv}\,\frac{\left\lfloor (1-\mathrm{SR_s})\frac{T}{TPT} \right\rfloor}{Q}\,p_{total}^{v}\,,\forall v \;\in\; \{WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\} \tag{3.3}$$

Relative environmental effectiveness is the market production share divided by market emission share (Sterner & Höglund Isaksson, 2006). The version that was adjusted for batch production is shown below:

$$\Phi = \frac{\dfrac{\left\lfloor (1-\mathrm{SR_s})\frac{T}{TPT} \right\rfloor}{Q}}{\dfrac{\sum_{i=1}^{I}\sum_{j=1}^{J_i}\sum_{k=1}^{K_{ij}}(1-x_{ijk}^{v})\,p_{ijk}^{v}}{p_{total}^{v}}} \tag{3.4}$$

As mentioned before, if a firm's environmental effectiveness is higher than the peer firms' average, there will be a tax charge, conversely, if that value is lower than the average, the firm receives an incentive.

ii. Total Sale

Total sale function is defined as:

$$TS = \mathrm{UP}\left\lfloor (1-\mathrm{SR_s})\frac{T}{TPT} \right\rfloor \tag{3.5}$$

where SR_s follows Equation (3.6) and UP is the unit price for one batch of final product. The general form for SR_s equation is shown in Equation (3.8)

$$SR_s = 1 - \prod_{i=1}^{I} (1 - \prod_{j=1}^{J_i} (1 - \prod_{k=1}^{K_{ij}} p_{ijk}^{Q} (1 - x_{ijk}^{Q}))) \tag{3.6}$$

The model under study is comprised of modules that are linked together in series and each module contains one or more stations operating in series and each station contains one or more parallel machines. In reliability studies, the failure rate of a series-parallel system is calculated using the following formula (Dhillon, 1999).

$$F_{series-parallel} = 1 - \prod_{i=1}^{n} (1 - \prod_{k=1}^{K} F_k) \tag{3.7}$$

It follows that, based on this formula, a model with above-mentioned specifications has the following failure rate:

$$F_{system} = 1 - \prod_{i=1}^{I} (1 - \prod_{j=1}^{J_i} (1 - \prod_{k=1}^{K_{ij}} F_{ijk}) \tag{3.8}$$

The total number of flawless products is equal to F_{system} multiplied by the system's scrap rate.

Therefore, the total number of flawless final products is formulated as follow

$$\left\lfloor (1 - \mathrm{SR_s}) \times \frac{T}{TPT}) \right\rfloor \tag{3.9}$$

The number is rounded down ($\lfloor \quad \rfloor$ is the symbol presenting rounding down) so that an integer value is resulted for the number of finished batches. Multiplying this value by the unit price of each batch results in the total sale value (Equation(3.5)).

iii. Operating costs

Operating cost includes electricity and setup costs and can be expressed as follows:

$$HC_i = NOP_{i11}.p_i^H(1-x_i^H) \tag{3.10}$$

The projected handling time required for one operation for module *i* is the current handling time (p_i^H) minus the required decrease in handling time ($p_i^H x_i^H$), which is equal to $p_i^H(1-x_i^H)$. To calculate handling time for all operations performed during the planning period, this value is multiplied by the number of operations (NOP) performed by the first station of the module *i* (NOP_{i11}). The number of operations can be calculated using Equation (3.11).

$$NOP_{ijk} = \begin{cases} \left\lfloor \dfrac{T}{TPT} \right\rfloor + 1 & , \; T - \left\lfloor \dfrac{T}{TPT} \right\rfloor .TPT - TB_{ijk} \geq 0 \\ \left\lfloor \dfrac{T}{TPT} \right\rfloor & , \; T - \left\lfloor \dfrac{T}{TPT} \right\rfloor .TPT - TB_{ijk} < 0 \end{cases} \tag{3.11}$$

NOP_{ijk} is the number of operations performed by each machine during the planning period. In order to obtain the NOP value for each machine, if the planning period (T) is greater than or equal to the total operation time of the machine, T/TPT is rounded up, otherwise it is rounded down (Equation (3.11)). The ratio T/TPT is the ideal number of batches produced during time T. TPT is the total time that takes for one batch to be produced (Equation (3.13)). TB is the accumulated operation time for each machine since the beginning of the batch production (Equation(3.12)).

$$TB_{ijk} = \sum_{i=1}^{i} p_i^H (1 - x_i^H) + \sum_{j=1}^{j} (\max \left\{ (1 - x_{ijk}^T) p_{ijk}^T + p_{ijk}^{ST} + p_{ijk}^{MF} p_{ijk}^{MT}, \mathrm{k} = 1,..K_{ij} \mid \right\}) \tag{3.12}$$

The first term in TB is the accumulated handling time from the first module in the process to the i^{th} module. The second term is the accumulated cycle time from the first machine in the process to the i^{th} machine.

$$TPT = \sum_{i=1}^{I} p_i^H (1 - x_i^{HT}) + \sum_{j=1}^{J_i} (\max \left\{ (1 - x_{ijk}^T) p_{ijk}^T + p_{ijk}^{ST} + p_{ijk}^{MF} p_{ijk}^{MT}, \mathrm{k} = 1,..K_{ij} \mid \right\}) \tag{3.13}$$

TPT follows the same mathematical formulation as TB with an exception that the accumulated times is calculated for the last machine/module in the process sequence.

Electricity cost (EC) is part of the operating cost and is calculated using Equation (3.14).

$$EC_{ijk} = NOP_{ijk} p_{ijk}^E (1 - x_{ijk}^E) ER (1 - x_{ijk}^T) p_{ijk}^T \tag{3.14}$$

Electricity cost for one operation is a multiplication of projected electricity use per busy time ($p_{ijk}^E (1 - x_{ijk}^E)$), price of electricity per time unit (ER) and the projected cycle time ($(1 - x_{ijk}^T) p_{ijk}^T$). NOP is multiplied by this value to get EC for all the operations performed by machine *ijk* during the planning period.

The next term in the operating cost is setup cost. It follows Equation (3.15), which includes material cost along with operating and electricity costs during the setup time for each setup.

$$SC_{ijk} = \sum_{p=1}^{p_{ijk}^{NOS}} [\mathrm{NOP}_{ijk}(p_{ijk}^{MSCp} + p_{ijk}^{STp} . p_{ijk}^{OR} + p_{ijk}^{STp} \; . p_{ijk}^{ER} \; . p_{ijk}^{SEp} \;)] \tag{3.15}$$

iv. Improvement Investments

Investment cost is a function of improvement level, improvement-investment ratio and current value of the corresponding indicator (see Equation(3.16)). The improvement-investment is a proportionality ratio that transforms the amount of improvement into investment value. If the function is assumed linear, the investment cost is equal to the amount of improvement (percentage of improvement multiplied by the current value of the indicator) multiplied by the improvement-investment ratio. This ratio is thus a proportionality ratio (Equation (3.17)).

$$IVTv_{ijk} = f_{ijk}^{IVTv}(x_{ijk}^{v}, p_{ijk}^{IVTv}, p_{ijk}^{v}) , \forall v \in \{\mathrm{T, Q, E, H, WE, LE, AE, HW}\}$$

(3.16)

$$IVTv_{ijk} = x_{ijk}^{v} p_{ijk}^{v} p_{ijk}^{IVTv} , \forall v \in \{\mathrm{T, Q, E, H, WE, LE, AE, HW}\}$$

(3.17)

The same function, if assumed exponential (refer to Section 2.2.3 for the literature background) is represented as

$$IVTv_{ijk} = PIVTv \times P_{ijk}^{v} \times e^{x_{ijk}^{v}}; \qquad \forall v \in \{H, T, A, E, WE, \mathrm{LE, AE, HW}\}$$

(3.18)

v. Quality Loss Functions

The loss functions are of the smaller-the-better type with lower limit T and defined as follows:

$$CL_{ijk}^{v} = \begin{cases} \dfrac{A_{ijk}^{v}}{(\Delta_{ijk}^{v})^2}((1-x_{ijk}^{v})p_{ijk}^{v} - T_{ijk}^{v})^2, & T_{ijk}^{v} \le (1-x_{ijk}^{v})p_{ijk}^{v} \le T_{ijk}^{v} + \Delta_{ijk}^{v} \\ A_{ijk}^{v}, & otherwise \end{cases} \quad \forall v \in \{WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\}$$

The smaller-the-better quality loss function was further discussed by Xu and Liang (2006). These functions which are based on Taguchi's quality loss functions were used in the model to calculate the amount of loss caused by the deviation of each environmental indicator (water emission, land emission, air emission and hazardous waste) from their targets (T_{ijk}^{v}). A_{ijk}^{v} is the total loss caused by the deviation Δ_{ijk}^{v} from target.

Constraints

The mathematical equations that represent the constraints described in Section 3.1.2.1 are presented here:

i. Demand Constraint

$$\left\lfloor (1-\mathrm{SR}_s) \times \left\lfloor \frac{T}{TPT} \right\rfloor \right\rfloor \ge d_t \tag{3.20}$$

where

$$d_t = D_T + \eta\left(\frac{x_{ijk}^{LE} + x_{ijk}^{WE} + x_{ijk}^{AE} + x_{ijk}^{HW}}{4}\right) \tag{3.21}$$

and η is the market sensitivity to average level of abatements.

The Equation (3.21) is based on the assumption that was made by Nouira et al. (2014). The authors assumed that base demand (D_T) is the demand related to ordinary customers but total demand increases according to the firm's levels of abatements. Therefore, the second expression of the Equation (3.21) is related to customers that choose products based on greenness of their manufacturers.

ii. Budget Constraint:

Every firm has a budget for investments and the following inequality assures that the total investment for improvements cannot exceed the budget available for the planning period T.

$$IVTT + IVTQ + IVTE + IVTH + IVTWE + IVTLE + IVTAE + IVTHW \leq B^T \qquad (3.22)$$

Each term in the left hand side of the inequality refers to investment related to improvement of one sustainability indicator.

iii. Greenhouse Gas Emission and Hazardous Waste Constraints:

The firms with emission goals can use the following constraints to set upper limits for total amount of emissions they cause during planning period T.

$$\sum_i \sum_j \sum_k NOP_{ijk}\, p_{ijk}^{WE}(1 - x_{ijk}^{WE}) \leq UWE^T \qquad (3.23)$$

$$\sum_i \sum_j \sum_k NOP_{ijk}\, p_{ijk}^{LE}(1 - x_{ijk}^{LE}) \leq ULE^T \qquad (3.24)$$

$$\sum_i \sum_j \sum_k NOP_{ijk}\, p_{ijk}^{AE}(1 - x_{ijk}^{AE}) \leq UA\mathrm{E}^T \qquad (3.25)$$

$$\sum_i \sum_j \sum_k NOP_{ijk}\, p_{ijk}^{HW}(1 - x_{ijk}^{HW}) \leq UHW^T \qquad (3.26)$$

The projected value for indicators are multiplied by the number of completed operations to result in the left hand side of the constraints which are the total emissions during planning period T. For instance, Equation (3.23) ensures that the total generated water emission by all machines during the planning period (while performing NOP number of operations) is below a decided level (i.e. UWE).

Variable Ranges

Variables vary between zero and one, showing the range for the level of improvement on each factor. As shown in inequality (3.27), the improvements cannot be 100 per cent and this is based on the fact that it is infeasible to reduce an indicator's value by 100 per cent

$$0 \leq x_{ijk}^{v} < 1 \qquad , \forall v \in \{H, T, A, E, WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\} \qquad (3.27)$$

3.1.3. Product and Process Selection

Variety of parameters such as the strategic importance of a certain product/process, prediction of waste in a certain product/process and the contribution of a particular product in the revenue of the firm could be taken into consideration. For the purpose of this study, the process related to the product with the highest value in the firm's revenue is selected.

3.1.4. Data Collection

During the data collection phase, the following stages were performed:

i. Gathering information related to process flow, as well as sequence of operations, such as standard operating procedures (SOP), time sheets related to work measurement and time study, operation process charts (OPC) and flow process charts (FPC);

ii. Measurement of the environmental and economic indicators for each of the stations within the process: indicators that are selected from available indicator sets in the literature in Section 2.2.3 in Chapter 2 are measured and recorded at this stage. Air, land and water emissions exemplify indicators that might be selected for a firm.

iii. Collection of governmental incentives and tax charges related to emissions, hazardous waste and electricity consumption: tax charges and incentives can vary depending on the geographical area. For example, in Sweden, a very high amount of tax (over USD 4000) is charged on emission of every ton of sulphur oxide as that material have had a tremendous negative impact on ecosystems of most Scandinavian countries (Sterner & Höglund Isaksson, 2006).

iv. Assessing parameters related to Taguchi's quality loss functions (QLF) for corresponding indicators: Quality loss function is integrated into the proposed method in ways that the intangible aspects of sustainability are converted into cost. These can be assembled in one objective function along with other costs related to the batch production of a certain product in a set timeframe.

3.1.5. Optimization

The developed model has a nonlinear objective function and nonlinear constraints. Among the available commercial packages to solve problems of this nature, the *sequential quadratic programming* (SQP) algorithm from Matlab's optimization package was employed. While there are many available approaches to solve problems of such nature, SQP has proven to provide near to optimal results in a nonlinear setting. It is an iterative method for nonlinear optimization that uses *Newton's method* in each of the iterations. While Netwon's method is only used for unconstrained problems, SQP employs constraints in each iteration. The original SQP was tested in terms of efficiency, accuracy and percentage of successful solutions over a large number of tested problems (Schittkowski, 1986). Maltlab's SQP algorithm was reformulated and now offers the following advantages (MathWorks, 2014):

i. Strict Feasibility with respect to bounds: this algorithm takes all the iterative steps within the perimeters of the variable bounds. That will guarantee that the final solution is feasible with respect to bounds.
ii. Efficient in both memory usage and speed: this is based on the fact that the linear algebra routines of the algorithm are refactored for the Matlab's package.
iii. Feasibility of solutions; the algorithm can lead to a feasible solution by combining objective and constraint functions into a merit function which is then minimized. In the case that nonlinear constraints are not satisfied, the algorithm attempts to gain feasibility by a second-order approximation to the constraints. This highly precise level of approximation can lead to feasibility.

Noteworthy, the SQP algorithm requires a starting point to run the optimization.

3.1.6. Data Normalization

The two groups of current and suggested values for indicators can include numbers with different units. For example, CO_2 emission is measured in weight units while cycle time is measured in unit of time. A normalization method was applied to create a unified set of data for both the current and optimized values. That set of data is depicted in current and future state VSMs. The normalization formulas used for optimization are as follow (Krajnc and Glavic, 2005):

$$N_{ijk}^{+} = \frac{\overline{I_{ijk}^{+}} - \overline{I_{\min,ijk}^{+}}}{I_{\max,ijk}^{+} - I_{\min,ij}^{+}} \tag{3.28}$$

$$N_{ijk}^{-} = 1 - \frac{\overline{I_{ijk}^{-}} - \overline{I_{\min,ijk}^{-}}}{I_{\max,ijk}^{-} - I_{\min,ij}^{-}} \tag{3.29}$$

Equation (3.28) is related to the indicators whose increase have positive impact on sustainability of the process. Equation (3.29) is used for indicators whose increase have negative impact on sustainability of the process.

3.1.7. Value Stream Mapping

The data from the current and future state of the studied process are presented in two separate VSMs. The main advantage of depicting the data in a map form is to be able to have a general picture of the whole process. The maps presented in this work show the data from two areas of sustainability: economic and environmental. The required improvements for each stage of the process are defined on the future-state VSM.

3.1.8. Identification of the Sustainability Bottlenecks

The stations with the highest sum of normalized sustainability indicators were identified. These stations are referred to as sustainability bottlenecks in this research since improving them improves the whole process in terms of sustainability and they have the highest priority on the improvement list. The future-state map includes the projected data for each of the indicators. In this map, the stations that required the highest improvement are identified.

In the next chapter, the model will be evaluated based on multiple optimization runs, as well as simulation. The mathematical optimization results will be compared with the simulation results and a set of sensitivity analyses will be carried out to validate the mathematical optimization.

3.2. Summary

In this chapter, the optimization process from a batch production point of view was presented to emphasize the environmental and economic sustainability aspects. Different stages involved with the implementation of the optimization model were presented and explained in detail with the main stage, covering structuring and formulation of the proposed mathematical model. The profit maximization objective function was expanded and furthermore the decision variables and constraints were defined. More specifically, Taguchi's quality loss function was integrated into the model in order to transform deviation of sustainability indicators from their target values into cost. In addition, the model incorporated market demand as a function of process greenness enhancement. The output from the approach was presented in the forms of current and future state value stream maps. The machines/stations with the highest potential for improvement could be identified based on the VSMs and the investment required for this improvement could be depicted on the maps. Such maps would potentially guide firm's management in making technology enhancement decisions.

Chapter 4 : Results and Discussion

In order to evaluate the proposed model previously described in Chapter 3, a pharmaceutical plant was selected as a case study. As illustrated in Figure 4-1, the plant encompasses five sequencing modules, each of which includes designated stations that perform a set of tasks. The main modules and stations are listed in Table 4-1, where the numeric arrangement used is based on the current process sequencing. For instance, since granulation occurs prior to the compression step, the module numbers become 2 and 3, respectively. Noteworthy, machines with the same module and station numbers operate in parallel. For example, Press 55 and BB4 are two compressing machines operating in parallel.

Module Name	Module Number(i)	Station Name	Station Number(j)	Machine Name	Machine Number(k)
Warehouse	1	Scaling	1	Scaling	1
Granulation	2	Granulation	1	Granulator	1
Granulation	2	Mixing	2	Agitator	1
Granulation	2	Drying	3	FBD	1
Granulation	2	Sizing	4	Sizing	1
Compression	3	Tablet press machines	1	Press55	1
Compression	3	Tablet press machines	1	BB4	2
Compression	3	Tablet press machines	1	BB3	3
Blister	4	Tablet press machines	1	UPS1260-Blisterpack	1
Blister	4	Tablet press machines	1	UPS600	2
Blister	4	Tablet press machines	1	UPS4	3
Cartoning	5	Cartoning	1	UPS1260-Cartoning	1
Cartoning	5	Final Packaging	2	Shrinkpack Machine	1

Table 4-1: Modules, stations and machines of the example model. The numbering used in the table is based on the sequence of the elements in the process. For example, products go through warehouse (module 1), granulation (module 2) and blister (module 3) subsequently.

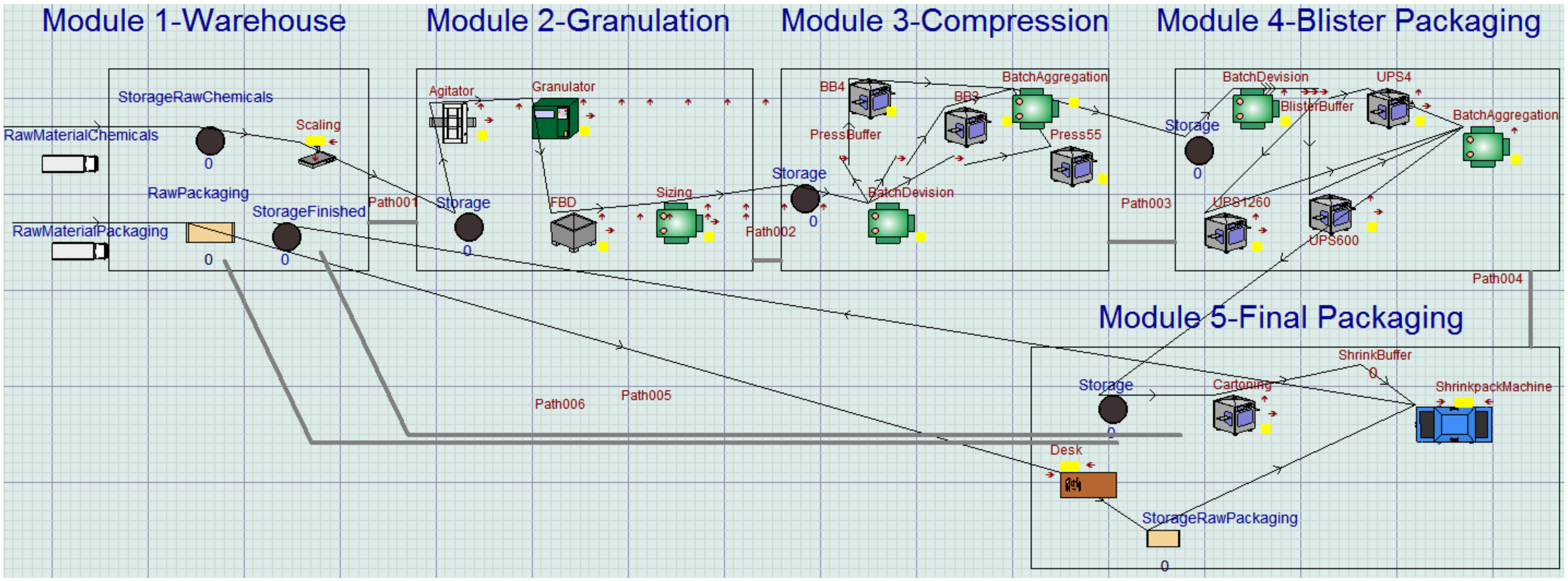

Figure 4-1: WITNESS snapshot of the model of the firm under study. Each module includes some machines and there are paths connecting modules to each other. Module 3 and 4 include three machines that work in parallel. Therefore, there are batch division sections to divide the batch material into three and distribute it to the machines. The three portions are aggregated after the machines perform their process. There is a storage for every module to hold the work-in-process inventory.

4.1. Case Study

A pharmaceutical plant was used for this study. This factory has four categories of products, namely tablets, capsules, lotions and syrups. The production process related to one of the tablet products was selected due its high contribution to the revenue of the firm. The collected data were used for mathematical optimization, as well as optimization using WITNESS software. For both tasks, a set of configurations including setting the planning period, method of optimization and detail settings for the chosen optimization method were selected.

Based on the selected configurations, both methods were run for the duration of the planning period and the results were compared. These results are configured in two different categories: (i) the ones related to optimization process. This included the time it takes for the optimization, the specifications of the hardware, the number of iterations and the speed of convergence to the optimal point. (ii) Output data. This includes values of the decision variables, the values of the objective function and values of all the subsections of the objective function.

For the purpose of aggregation, since the outputs are based on various measurement units, a normalization of data was performed. The aggregated data are shown in a VSM as single numbers for each machine or set of parallel machines. This additional data can extend the traditional VSM that only covered the details related to cycle times and number of units produced.

In accordance with the working approach (refer to Figure 3-1 in Chapter 3), prior to optimization of the model plant, and as a matter of fact, the two stages of product and process selection, as well as data collection need to be performed. These stages are briefly discussed in the following sections:

4.1.1. Product and Process Selection in the Example Factory

The process with the highest value in the revenue of the company was selected. The top two revenue making products of the factory selected as a model are listed in Table 4-2 (IranDaru, 2010). Folic acid tablet production is the highest revenue making process, and therefore was selected for the current thesis.

Product name	**Average Annual Production Budget**		**Total Expected Average Annual Sale (Million dollars)**
	(boxes)	(tablets)	
Folic Acid production	1625000	162500000	8.125
Trihexyphenidyl production	520000	52000000	6.24

Table 4-2: Top two high revenue making processes in the plant (IranDaru, 2010). Production budget is the amount of products that are planned to be produced in the following year. Folic acid production with the highest expected sale is the selected process for optimization.

4.1.2. Data collection

Data collection is one of the most complex and sensitive stages of any sustainability assessment project. In fact, the variety of the data for this step is substantial and numerous observation days in the manufacturing facility are required. In addition, non-stop communication with the engineering and production personnel is a key factor. A list of required parameters for the model is presented in Table 4-3 and the collected data are listed in Appendix A.

Parameters Required	Unit
Initial scrap rate	%
Electricity Busy use	Kwh/min
Initial water emission per operation	Kg
Initial land emission per operation	Kg
initial air emission per operation	Kg
Initial hazardous waste per operation	Kg
Transportation cost per travel	$
Electricity price cost per Kwh	$
Handling time from previous module to current module	min
Setup time	min
Cost of reducing cycle time by one unit	$
Cost of lowering scrap rate by 1 unit	$
Cost of lowering handling time by 1 unit	$
Cost of lowering electricity consumption by 1 unit	$
Cost of lowering water emission by 1 unit	$
Cost of lowering land emission by 1 unit	$
Cost of lowering air emission by 1 unit	$
Cost of lowering hazardous waste by 1 unit	Kg
Operators cost	Min
Cycle time	Min
Number of setups per machine	-
Material cost for setup	$
Setup electricity use for the pth setup of the machine	Kwh/min
Net payment-electricity saving constant	$
Net payment-Water emission constant	$
Net payment-land emission constant	$
Net payment-air emission constant	$
Net payment-weight of hazardous waste constant	$
Target value for water emission	Kg
Target value for land emission	Kg
Target value for air emission	Kg
Target value for hazardous waste	Kg
Total loss caused by deviation DWE of Water emission criterion	$
Total loss caused by deviation DLE of Land emission criterion	$
Total loss caused by deviation DAE of Air emission criterion	$
Total loss caused by deviation DHW of Hazardous waste criterion	$
Deviation from Water emission criterion(Taguchi parameter)	Kg
Deviation from Land Emission criterion(Taguchi parameter)	Kg
Deviation from air emission criterion(Taguchi parameter)	Kg
Deviation from Hazardous waste criterion(Taguchi parameter)	Kg

Table 4-3: Required parameters for the developed model

4.1.3. Manufacturing Process in the Case Study

Based on the collected data, the modules involved in the folic acid tablet production are depicted in Figure 4-2 and described below:

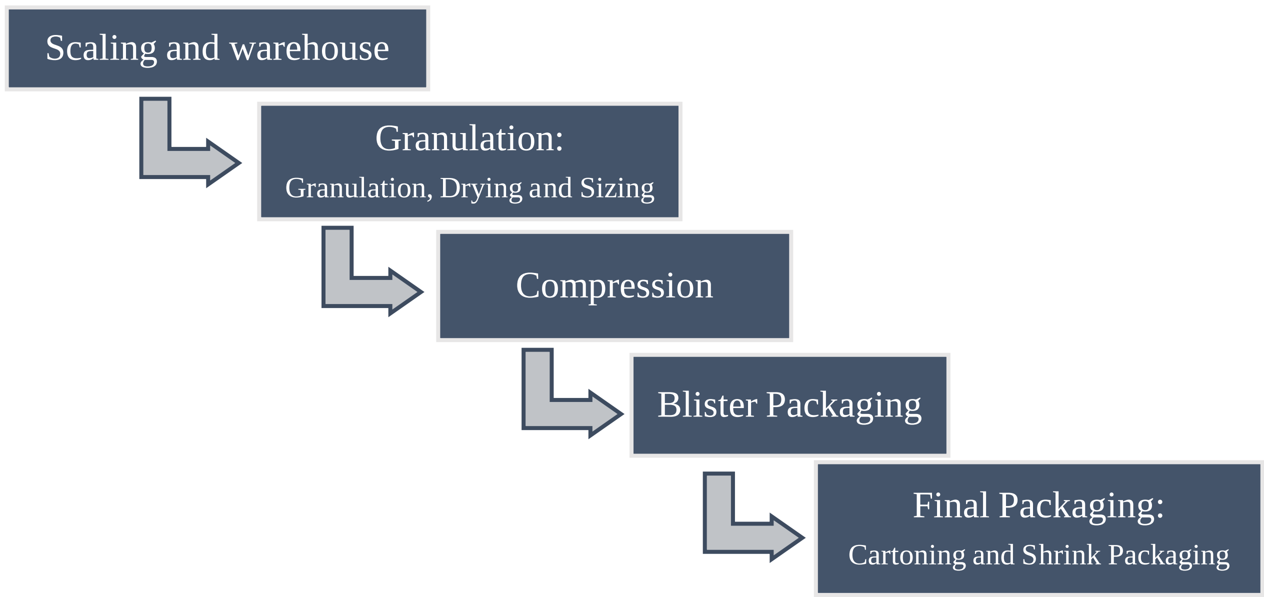

Figure 4-2: The five modules involved in the tablet manufacturing using granulation method.

4.1.3.1.Scaling and Warehouse

This module represents the warehouse through which raw material is fed to the factory. Next, the quality of materials is checked followed by scaling in accordance to the standard operating procedure (SOP). The scaling step involves portioning raw materials for the production section.

4.1.3.2. Granulation

Granulation has been used as the main approach in preparing the granulated powders for a variety of tablets and capsules. Granulation involves mixing the active pharmaceutical ingredients (API) with the excipient material and using binder materials to produce formulations that contain fixed composition of active ingredients. The mixing is performed using an agitator and a granulation machine. The output material is subsequently dried by using a fluid bed dryer (FBD) and is finally sized using a milling machine to ensure that the powder's size distribution is acceptable for the compression process.

4.1.3.3. Compression

In this module, the powder produced in the granulation module is compressed into tablets using a number of tablet presses.

4.1.3.4. Blister Packaging

Blister packs are a common form of packaging used for a wide variety of tablets and capsule products. This packaging method requires holding layers of aluminum foils and transparent films together using pressure and heat.

4.1.3.5. Final Packaging

The final packaging consists of placing the blister packs in their designated packages through automated or manual methods in the cartooning station, and using packaging machines to collate certain number of packages into large shrink packs. The final products are then transferred into a section of the warehouse assigned to the finished products.

4.1.4. Optimization of the Model Using Simulation Software

The model proposed was simulated and optimized using WITNESS software package. This simulation software consists of a high performance tool that models and simulates business processes with various complexities (Lanner, 2013). A snapshot of the model developed by WITNESS was provided in Figure 4-1.

The simulation and optimization using WITNESS involves the following main steps:

4.1.4.1. Designing Model Elements

At this step two groups of elements are added to the WITNESS model:

i. Physical elements (such as parts, paths, machines and labor cost); and

ii. Logical Elements (such as shifts, attributes and variables).

4.1.4.2. Determining Parts Flow through the Model

Using input and output rules for each machine and part, elements were linked to each other. As a result, the parts that enter the model are processed by each machine following a specific sequence.

4.1.4.3. Defining Attributes and Details Related to Each Element

This step involves applying the input data from the studied factory (Appendix A) to the model elements. All cycle times, handling times, energy, costing and other sustainability related information are added to the model.

4.1.4.4. Optimization

The main steps for the optimization are outlined below:

Optimization of the model begins with integrating decision variables into the model. For example, the projected values are used for the cycle time of each machine. This value incorporates the decision variable related to cycle time. Therefore, the cycle time for each machine is defined as $(1 - x_{ijk}^{T})\, p_{ijk}^{T}$.

The next stage is the initialization of the decision variables. It is assumed that no improvements are initially performed on the model, which implies that all the decision variables are initially set to zero.

Following the initialization stage, optimization is performed using WITNESS experimenter. This tool is an evolved version of the previous scenario manager tool in the former WITNESS versions. The parameters of the experimenter (decision variables), constraints and a response (total profit) are defined using this tool and the model is optimized using the following settings (Table 4-4):

Property	Value	Description
Simulation algorithm	All combinations	This method tries all the algorithms available in WITNESS including: Simulated Annealing, Six Sigma, Min/Mid/Max, Hill Climb and Random solutions
Run length	624,000 minutes	Run length for each iteration
Replications	1	The number of replications for each run
Target	Maximum	Specifies whether the objective function is a maximization or minimization function
Hardware used	Intel i5 650 processor and 4GB of RAM	Computer configuration used to run the optimization

Table 4-4: Selected optimization properties and hardware for the experimenter. These settings are used in the optimization using WITNESS. All combinations of algorithms available in WITNESS are tested to improve results. There is only one replication, since there is no randomness in the input data. The target is to maximize the profit.

4.2. Optimization Results and Analysis

The model was optimized by considering different scenarios. A number of sensitivity analyses were performed to see the impact of varying selected input parameters in the model. Additionally, the results from the initial run or the original scenario were compared with the ones obtained by the WITNESS optimization.

Noteworthy, generated results were based on the assumption that investment functions are exponential, as illustrated in Equation (4.1). This assumption is based on the equation expanded by Vijay (2010) and Ko (2013) and described in Section 2.2.3 in Chapter 2.

$$f_{ijk}^{IVTv} = PIVTv \times P_{ijk}^{v} \times e^{x_{ijk}^{v}}; \qquad \forall v \in \{H, T, A, E, WE, \mathrm{LE}, \mathrm{AE}, \mathrm{HW}\} \tag{4.1}$$

This function transforms the amount of improvement on each indicator into the required investment by using a proportionality value (*PIVTv*).

4.2.1. Initial Run Using Matlab

Sequential quadratic programming (SQP) algorithm was employed to solve the model and the coding was done in Matlab. The code can be found in Appendix B. The starting point for the algorithm is presented in Part 0 of the Appendix B.

In the original run, base demand was set to 120 batches, the investment budget equals to \$2M and the market sensitivity to average improvements in emission levels was assumed to be 40 batches. The chosen values are based on an interview with the planning manager of the firm. This results in iteration details shown in Figure 4-3 and the run stopped after 19069 function evaluations (Figure 4-4). Final constraint violation was close to zero as depicted in Figure 4-5. Although in the first set of iterations this value was approximately 1500, the algorithm lowered the number by finding a feasible final solution. The first-order optimality of the results was shown to be zero.

The optimal profit in this scenario was \$3.29 × 10^{7} as shown in Figure 4-6. This value is presented in the chart as a negative value due the fact that profit maximization is presented as the cost minimization according to the requirements of the Matlab's SQP algorithm.

The optimal values for decision variables are shown in Table 4-5. The cells that are highlighted with darker shades show higher potential for improvement. For example, the machine that is located in the second station of the second module (i=2, j=2, k=1) requires as high as 90% improvement in the value of hazardous waste (x_{ijk}^{HW}). Other variables listed are the ratio for improvement of handling time (x_{ijk}^{H}), cycle time (x_{ijk}^{T}), accuracy (x_{ijk}^{Q}), electricity efficiency (x_{ijk}^{E}), and water (x_{ijk}^{WE}), land (x_{ijk}^{LE}) and air (x_{ijk}^{AE}) emissions.

I	J	k	x_{ijk}^{H}	x_{ijk}^{T}	x_{ijk}^{Q}	x_{ijk}^{E}	x_{ijk}^{WE}	x_{ijk}^{LE}	x_{ijk}^{AE}	x_{ijk}^{WE}
1	1	1	0.000	0.016	0.304	0.826	0.727	0.011	0.017	0.018
2	1	1	0.620	0.695	0.403	0.000	0.000	0.007	0.665	0.865
2	2	1	0.000	0.474	0.304	0.003	0.000	0.016	0.845	0.900
2	3	1	0.000	0.262	0.333	0.000	0.000	0.007	0.000	0.886
2	4	1	0.000	0.839	0.769	0.010	0.011	0.014	0.757	0.020
3	1	1	0.091	0.000	0.333	0.004	0.000	0.000	0.000	0.018
3	1	2	0.000	0.000	0.564	0.146	0.000	0.009	0.536	0.880
3	1	3	0.000	0.000	0.819	0.000	0.001	0.453	0.589	0.019
4	1	1	0.227	0.000	0.261	0.150	0.015	0.774	0.000	0.900
4	1	2	0.000	0.000	0.738	0.175	0.498	0.826	0.000	0.000
4	1	3	0.000	0.000	0.251	0.000	0.423	0.495	0.000	0.001
5	1	1	0.000	0.000	0.778	0.500	0.000	0.555	0.576	0.000
5	2	1	0.000	0.133	0.000	0.725	0.000	0.316	0.628	0.900

Table 4-5: Results from the optimization of the mathematical model, including the values for decision variables. The data present the level of improvement on each area and each machine. For instance, $x_{111}^{WE} = 0.727$ denotes 72.7 per cent reduction in water emission of the machine 1 of the station 1 of the module 1.

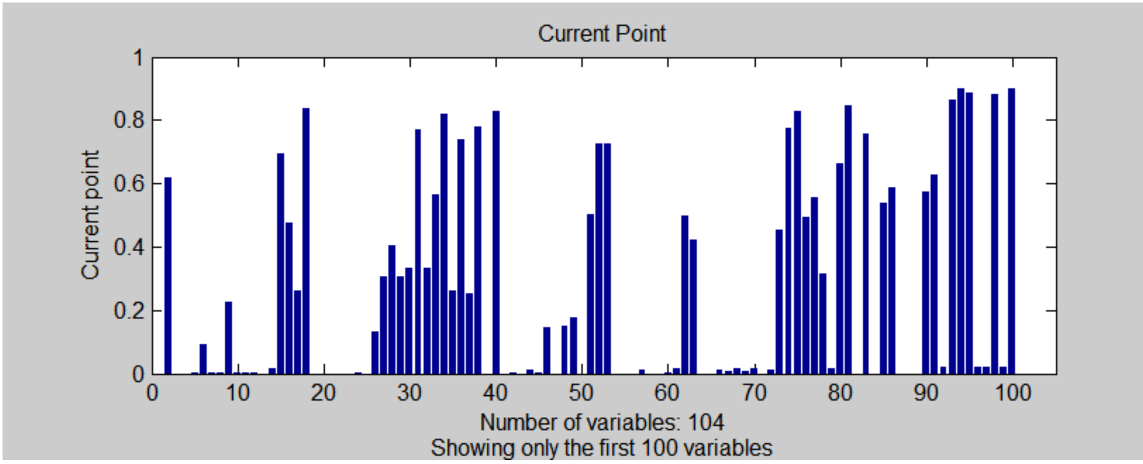

Figure 4-3: Optimal values for decision variables (initial run). The first 52 variables are related to economic indicators, including handling time (x_{ijk}^{H}), cycle time (x_{ijk}^{T}), accuracy (x_{ijk}^{Q}), electricity efficiency (x_{ijk}^{E}) and the rest are environmental variables specifically water emission (x_{ijk}^{WE}), land emissions (x_{ijk}^{LE}), air emission (x_{ijk}^{AE}) and hazardous waste (x_{ijk}^{HW}).

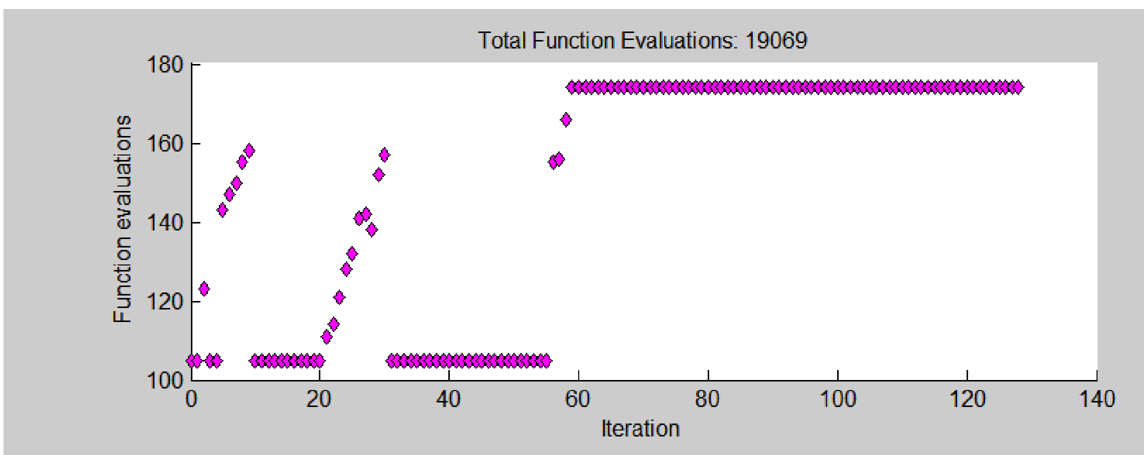

Figure 4-4: Function evaluations (initial run), which includes evaluations of objective functions and constraints at every iteration.

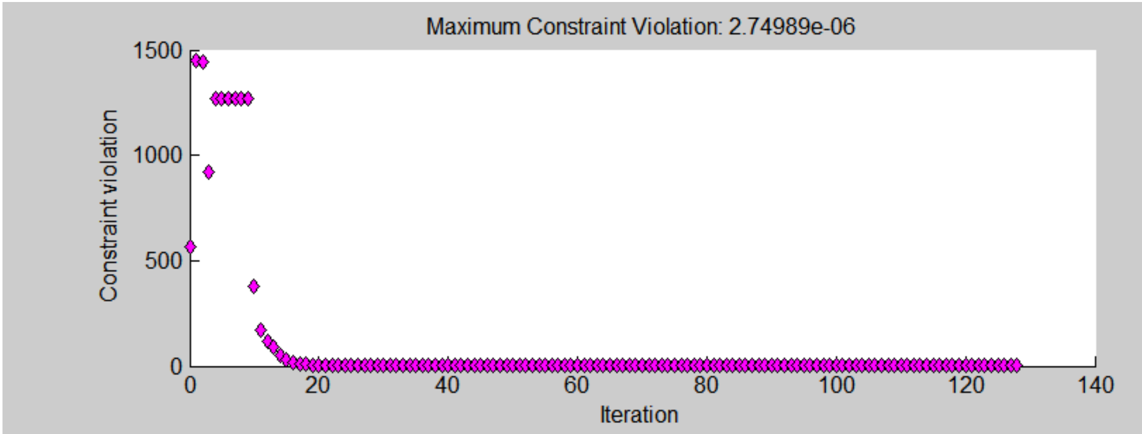

Figure 4-5: Constraint violation (initial run) at each iteration and the value approaches zero after the 17^{th} iteration.

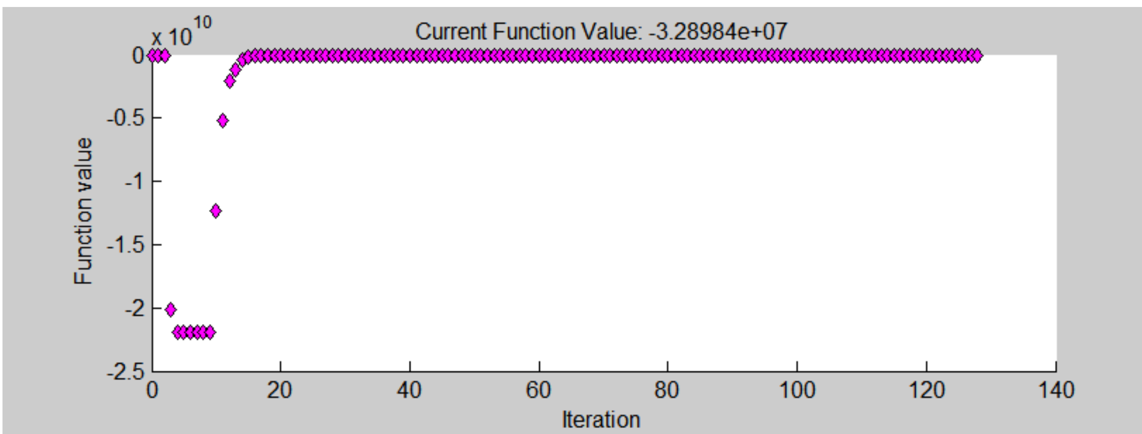

Figure 4-6: Values for objective function (cost minus revenue) in dollars (initial run) at each iteration. The values are negative, since, due to the limitations of Matlab optimization, the profit maximization function was converted into cost minimization.

The goal of the SQP algorithm used is to optimize the objective function while simultaneously ensuring near-to-zero constraint violation, zero first-order optimality and solution feasibility in terms of bounds. First-order optimality is a measure of how close a point x is to optimal. As shown in , the constraint violation begins to converge to zero starting at the 11^{th} iteration and immediately after the 16^{th} iteration drops to a near-to-zero value. Zero constraint violation and respecting bounds assure a feasible optimal solution in any optimization procedure.

4.2.2. Initial Run Using WITNESS

Based on the steps described in Section 4.1.4, an optimization of the model was performed. The input data used were identical to the original data used in Section 4.2.1. The optimal values for decision variables suggested by the WITNESS optimization are shown in Table 4-6. These values are used to validate the results obtained from the proposed mathematical model and presented in Section 4.2.1. The statistical comparison of the two sets of data is presented in Section 4.2.3.

i	J	k	x_{ijk}^{H}	x_{ijk}^{T}	x_{ijk}^{Q}	x_{ijk}^{E}	x_{ijk}^{WE}	x_{ijk}^{LE}	x_{ijk}^{AE}	x_{ijk}^{WE}
1	1	1	0.100	0.010	0.160	0.670	0.680	0.190	0.030	0.070
2	1	1	0.580	0.630	0.360	0.050	0.090	0.090	0.660	0.810
2	2	1	0.040	0.430	0.260	0.090	0.090	0.080	0.840	0.790
2	3	1	0.040	0.190	0.360	0.090	0.180	0.090	0.000	0.810
2	4	1	0.170	0.710	0.650	0.090	0.130	0.010	0.660	0.050
3	1	1	0.050	0.070	0.230	0.080	0.070	0.180	0.000	0.050
3	1	2	0.180	0.020	0.540	0.040	0.040	0.140	0.480	0.860
3	1	3	0.020	0.170	0.670	0.000	0.190	0.270	0.490	0.030
4	1	1	0.090	0.150	0.180	0.060	0.060	0.760	0.060	0.970
4	1	2	0.030	0.180	0.670	0.090	0.410	0.890	0.160	0.060
4	1	3	0.010	0.030	0.310	0.040	0.420	0.460	0.050	0.010
5	1	1	0.050	0.090	0.770	0.510	0.000	0.400	0.570	0.090
5	2	1	0.080	0.130	0.030	0.570	0.080	0.270	0.430	0.760

Table 4-6: Results from optimization using WITNESS which include the values for decision variables. The data present the level of improvement on each area and each machine. For instance, $x_{111}^{WE} = 0.680$ denotes 68% reduction in water emission of the machine 1 of the station 1 of the module 1.

4.2.3. Comparison between Matlab and WITNESS Optimization Results

A comparison between the two datasets using single-factor ANOVA[1] with a significance level of 0.05 shows that the difference between results produced by Matlab's mathematical optimization and the ones from WITNESS simulation is insignificant and therefore can be ignored. As illustrated in

[1] Single-factor ANOVA is a statistical test that compares two samples and to check for differences between their variances. It starts with calculating the F-ratio and critical value and comparing them. The critical value is the number that the F value (i.e. the ratio between the two groups' mean squares) must exceed to reject the test.

F-Test for xHW of mathematical modelling and xH from simulation		
Source of Variation	*F*	*F crit*
Between Groups	2.223	4.260
Total		
F-Test for xCT of mathematical modelling and xCT from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.644	4.260
F-Test for xA of mathematical modelling and xA from simulation		
Source of Variation	*F*	*F crit*
Between Groups	3.309	4.260
F-Test for xE of mathematical modelling and xE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	3.990	4.260
F-Test for xWE of mathematical modelling and xWE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.203	4.260
F-Test for xLE of mathematical modelling and xLE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	1.123	4.260
F-Test for xAE of mathematical modelling and xAE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.380	4.260
F-Test for xHW of mathematical modelling and xHW from simulation		
Source of Variation	*F*	*F crit*
Between Groups	1.883	4.260

Table 4-7, the $F_{Critical}$ in all rows is larger than the corresponding F value. For instance, the F value for xA is approximately 3.31 which is smaller than $F_{Critical}$ with the value of around 4.26. This analysis proves the validity of the results obtained from Matlab.

A visual comparison will also show that the focus areas of both the methods are identical. The figure below (Figure 4-7) shows the areas of improvement suggested by both the simulation and Matlab methods. The darker the cells are, the higher the suggested level of improvements are.

Module	Station	Machine	Decision Variables							
i	j	k	x_{ijk}^{H}	x_{ijk}^{T}	x_{ijk}^{Q}	x_{ijk}^{E}	x_{ijk}^{WE}	x_{ijk}^{IE}	x_{ijk}^{AE}	x_{ijk}^{HW}
1	1	1								
2	1	1								
2	2	1								
2	3	1								
2	4	1								
3	1	1								
3	1	2								
3	1	3								
4	1	1								
4	1	2								
4	1	3								
5	1	1								
5	2	1								

Figure 4-7: A visual comparison between Matlab and simulation results, The focus areas of both the methods are the same. The higher the suggested improvements are, the darker the cells.

F-Test for xHW of mathematical modelling and xH from simulation		
Source of Variation	*F*	*F crit*
Between Groups	2.223	4.260
Total		
F-Test for xCT of mathematical modelling and xCT from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.644	4.260
F-Test for xA of mathematical modelling and xA from simulation		
Source of Variation	*F*	*F crit*
Between Groups	3.309	4.260
F-Test for xE of mathematical modelling and xE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	3.990	4.260
F-Test for xWE of mathematical modelling and xWE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.203	4.260
F-Test for xLE of mathematical modelling and xLE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	1.123	4.260
F-Test for xAE of mathematical modelling and xAE from simulation		
Source of Variation	*F*	*F crit*
Between Groups	0.380	4.260
F-Test for xHW of mathematical modelling and xHW from simulation		
Source of Variation	*F*	*F crit*
Between Groups	1.883	4.260

Table 4-7: Single factor ANOVA between Matlab and WITNESS. The result shows that the difference between the results is insignificance level at a significance level of 0.05.

4.2.4. Presenting the Initial Results in Value Stream Maps

Using equations from Section 3.1.6 in Chapter 3, parameters of the current and future states were normalized (Table 4-9 and Table 4-10). The data obtained from mathematical optimization were successively used in the development of the maps (Figure 4-8 and Figure 4-9).

Machine	Average Required Improvement	Handling Time (mins)	Cycle Time (mins)	Scrap Rate (%)	Electicity Use(Kwh)	Water Emission (KG)	Land Emission (KG)	Air Emission (KG)	Hazardous Waste (KG)	Improvement Cost($1000)	Sum of Normal values
Scaling	0.11	0.20	0.00	0.86	1.00	1.00	0.98	0.94	1.00	28.81	5.98
Granulator	0.25	0.87	0.72	0.71	0.83	0.49	0.85	0.00	1.00	24.91	5.47
Agitator	0.08	1.00	0.00	0.91	0.98	0.90	0.99	0.98	1.00	12.51	6.76
FBD	0.12	1.00	0.00	0.95	0.98	0.88	0.98	0.97	1.00	36.03	6.76
Sizing	0.12	1.04	0.00	0.91	0.95	0.90	0.99	0.49	1.00	7.44	6.28
Press55	0.20									116.78	
BB4	0.17									124.07	
BB3	0.19									65.22	
Press	0.20	0.99	0.00	0.98	0.99	0.96	0.99	0.95	1.00	306.06	6.87
UPS1260	0.19									447.43	
UPS600	0.22									416.66	
UPS4	0.18									156.88	
Blistering	0.22	1.00	0.00	0.99	1.00	1.00	1.00	0.98	1.00	1020.97	6.96
Cartoning	0.11	0.88	0.00	1.00	1.00	1.00	1.00	0.97	1.00	52.85	6.84
ShrinkpackMachine	0.09	1.00	0.00	1.00	1.00	0.98	0.99	0.84	1.00	10.15	6.80

Table 4-8: Normalized values for the current state of the process.These show the normalized values for sustainability indicators related to each machine. This way the data from machines can be compared to each other. For instance, one can observe that the sum of the normalized values for the granulator is greater than that of the agitator. This shows a higher improvement potential for the granulator. *The handling time between machines within each station is neglected based on the model assumptions. **In the normalized data table, the data for “Press row” is the summation of the values for three machines within the compression module. Also, the data for “Blistering row” represents the data from the whole module since there are machines operating in parallel in this module.

Machine	Handling Time (mins)	Cycle Time (mins)	Scrap rate (%)	Electicity Use(Kwh)	Water Emission (KG)	Land Emission (KG)	Air Emission (KG)	Hazardous waste (KG)	Sum of Normal values
Scaling	0.18	0.00	0.85	1.00	1.00	0.98	0.94	1.00	5.96
Granulator	0.97	0.00	0.92	0.96	0.88	0.97	0.75	1.00	6.45
Agitator	*	0.00	0.90	0.98	0.90	0.99	0.98	1.00	5.75
FBD		0.00	0.95	0.98	0.88	0.99	0.97	1.00	5.77
Sizing		0.00	0.92	0.96	0.92	1.00	0.54	1.00	5.34
Press55	**								
BB4									
BB3									
Press	0.99	0.00	0.99	1.00	0.98	0.99	0.95	1.00	6.90
UPS1260									
UPS600									
UPS4									
Blistering	1.00	0.00	0.99	1.00	1.00	1.00	0.98	1.00	6.97
Cartoning	0.89	0.00	1.00	1.00	1.00	1.00	0.97	1.00	6.85
Shrinkpack Machine		0.00	1.00	1.00	0.98	0.99	0.83	1.00	5.79

Table 4-9: Normalized values for the current state of the process for sustainability indicators related to each machine. One can observe that the sum of the normalized values for the granulator is greater than that of the agitator. This shows a higher improvement potential for the granulator. *The handling time between machines within each station is neglected based on the model assumptions. **The data for "Press row" is the summation of the values for three machines within the compression module. Also, the data for "Blistering row" represents the data from the whole module since there are machines operating in parallel in this module.

Machine	Average Required Improvement	Handling Time (mins)	Cycle Time (mins)	Scrap Rate (%)	Electicity Use(Kwh)	Water Emission (KG)	Land Emission (KG)	Air Emission (KG)	Hazardous Waste (KG)	Improvement Cost($1000)	Sum of Normal values
Scaling	0.11	0.20	0.00	0.86	1.00	1.00	0.98	0.94	1.00	28.81	5.98
Granulator	0.25	0.87	0.72	0.71	0.83	0.49	0.85	0.00	1.00	24.91	5.47
Agitator	0.08	1.00	0.00	0.91	0.98	0.90	0.99	0.98	1.00	12.51	6.76
FBD	0.12	1.00	0.00	0.95	0.98	0.88	0.98	0.97	1.00	36.03	6.76
Sizing	0.12	1.04	0.00	0.91	0.95	0.90	0.99	0.49	1.00	7.44	6.28
Press55	0.20									116.78	
BB4	0.17									124.07	
BB3	0.19									65.22	
Press	0.20	0.99	0.00	0.98	0.99	0.96	0.99	0.95	1.00	306.06	6.87
UPS1260	0.19									447.43	
UPS600	0.22									416.66	
UPS4	0.18									156.88	
Blistering	0.22	1.00	0.00	0.99	1.00	1.00	1.00	0.98	1.00	1020.97	6.96
Cartoning	0.11	0.88	0.00	1.00	1.00	1.00	1.00	0.97	1.00	52.85	6.84
ShrinkpackMachine	0.09	1.00	0.00	1.00	1.00	0.98	0.99	0.84	1.00	10.15	6.80

Table 4-10: Normalized values for the future state of the process for sustainability indicators after optimization that were initially of different measurement units. The data from each indicator can be compared to the other ones. For instance, one can observe that the difference between total normalized values for scaling and that of granulator has shrunk due to the fact that cycle time values have been improved.

Based on the normalized data, the VSMs are drawn (Figure 4-8 and Figure 4-9).

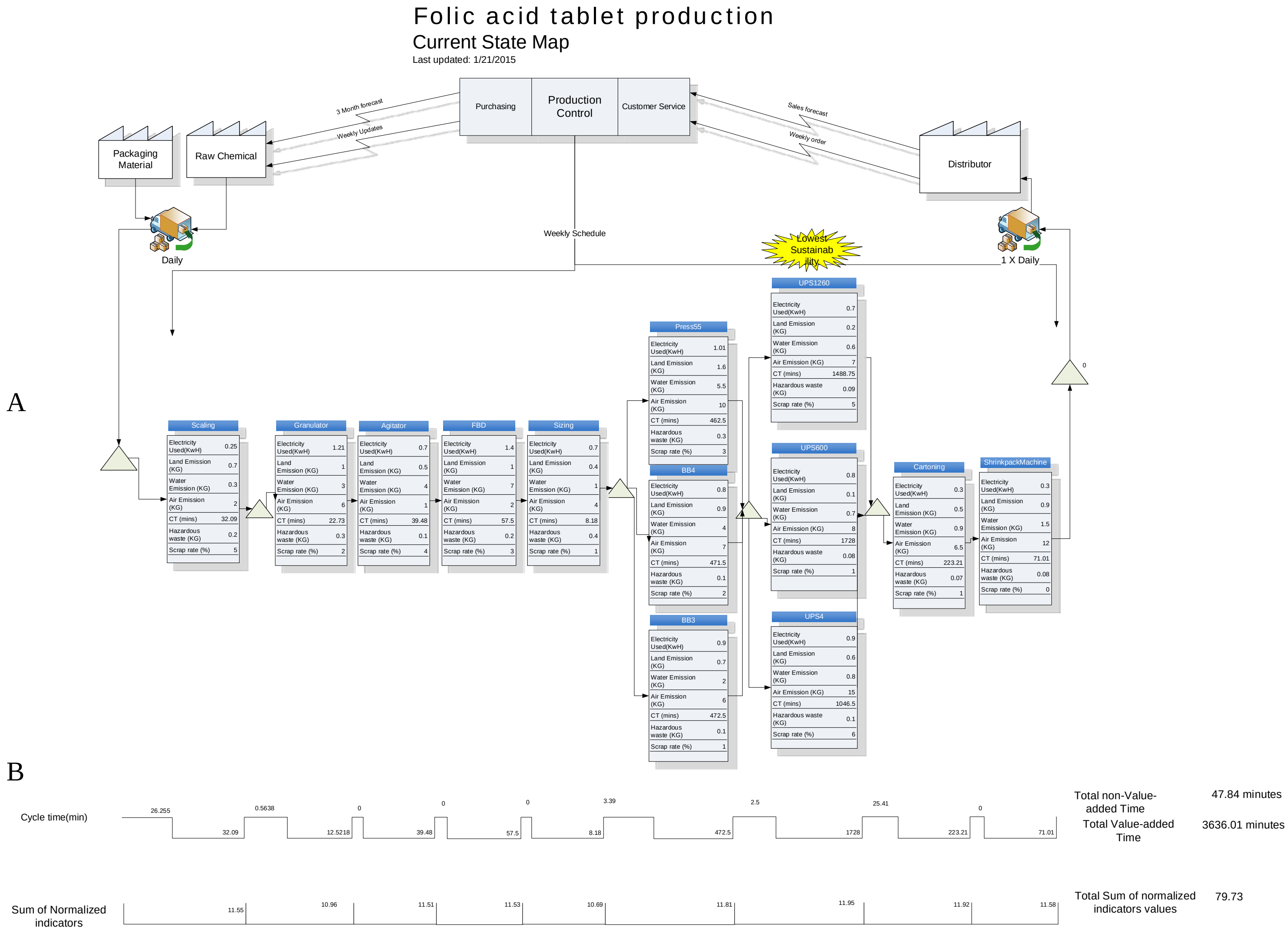

Figure 4-8: Current-state value stream map. (A) Each box contains the values for selected indicators and is related to a task involved in the tablet production. These values are related to the current state of the process. Blisterpackaging module (including UPS4, UPS600 and UPS1260 machines) has the highest indicator values and therefore is the sustainability bottleneck of the process. (B) Cycle time related to value-added and non-value added tasks are shown in different heights on the bar. For example, it takes 8.18 minutes for a batch to go through the sizing machine and this is considered as a value-added task. An example of non-value added tasks is the handling time between granulation module (encompassing granulator, agitator, FBD and sizing machines) and compression module (including press 55, BB4 and BB3 machines) which is 3.39 minutes. Total sum of normalized indicators which are related to both value-added and non-value added are shown at the bottom.

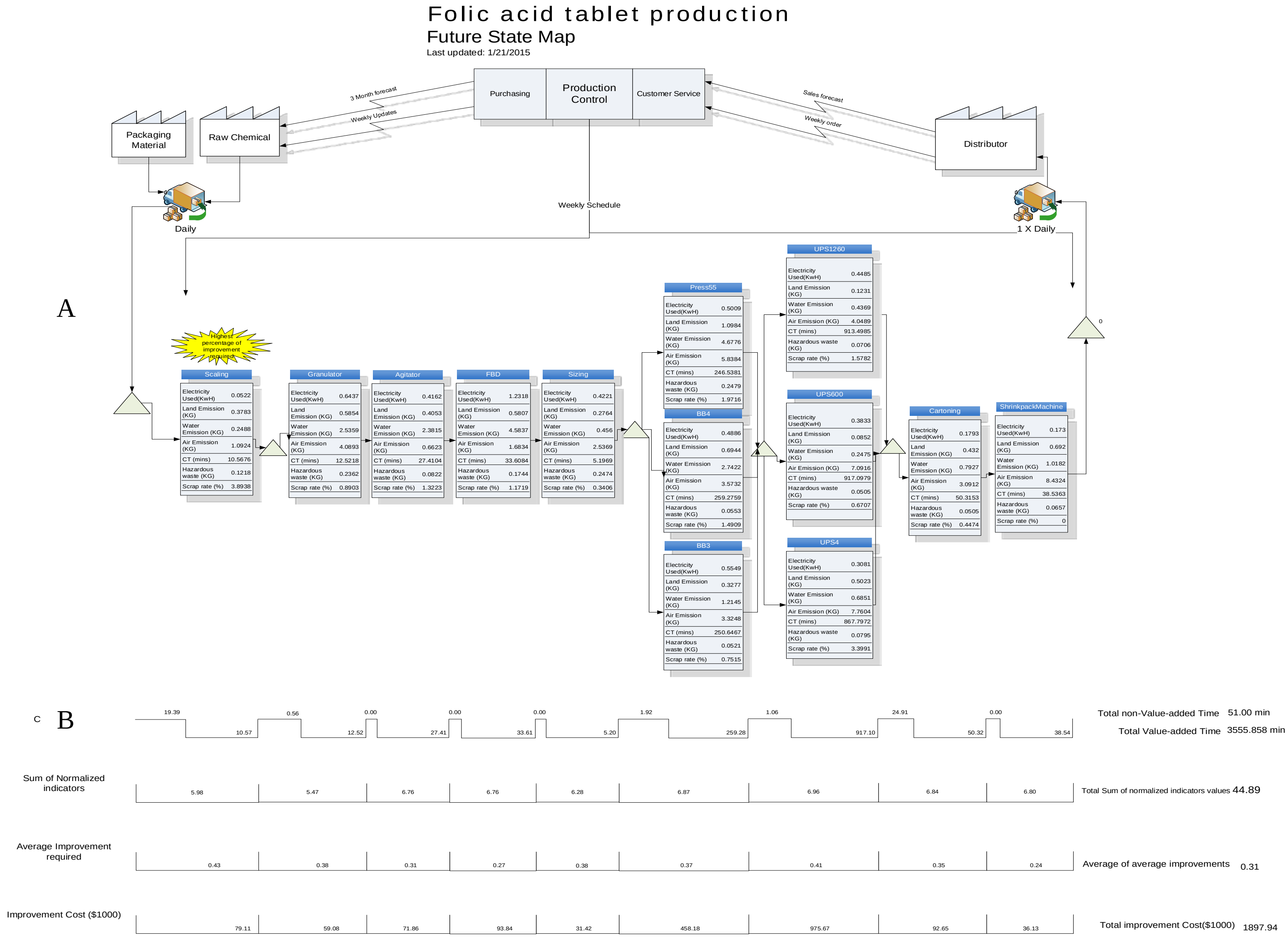

Figure 4-9: Future-state value stream map(A)The values suggested by the optimization for the selected indicators are shown in boxes. Each box is related to a task involved with the model process. (B)The optimal values for cycle times are shown in two different groups of value-added and non-value-added groups. The average improvement required is the average of all the improvement ratios related to one module/machine. For example, press requires 37% improvements on different areas (indicators). The total estimated costs for the suggested improvements are also depicted. One can observe that the blisterpackaging module requires the highest amount of investment. .

The current-state map includes the data from the existing state of the production line. The blister packaging module has the lowest sustainability level and therefore, it is identified as a sustainability bottleneck.

The results from the future-state map suggest that an average of 41% improvement is required in the blister packaging module. This percentage is the average for the required improvements on different indicators (water emission, land emission and etc.). More details are available on each box on the maps. As shown in Figure 4-9 (B), the total cost for the suggested improvement is estimated to be $1.897 million which includes an estimated improvement cost of around $975,670 for the bottleneck station.

4.2.5. Sensitivity Analysis for Investment Budget

The model was initially run with the investment budget of $2 million as described in Section 4.2.1. To test the validity of the model, different values were arbitrarily assigned to the investment budget and the model was applied to each value. The multiple runs resulted in different values in profit. A few examples of model run details are shown in the following sections:

4.2.5.1. Investment Budget of $1.8 Million:

Changing the value of investment budget to $1.8M while keeping all other model inputs unchanged, results in a total profit of $\$2.39 \times 10^{7}$ (Figure 4-12). The profit increases by 25% and that is due to less investment budget available. Visual comparison between optimal points for variables in this scenario (Figure 4-10) with the initial scenario shown in Figure 4-3, indicates that there are less improvements suggested in this scenario. This is also as a result of a lower available budget in comparison to the original run.

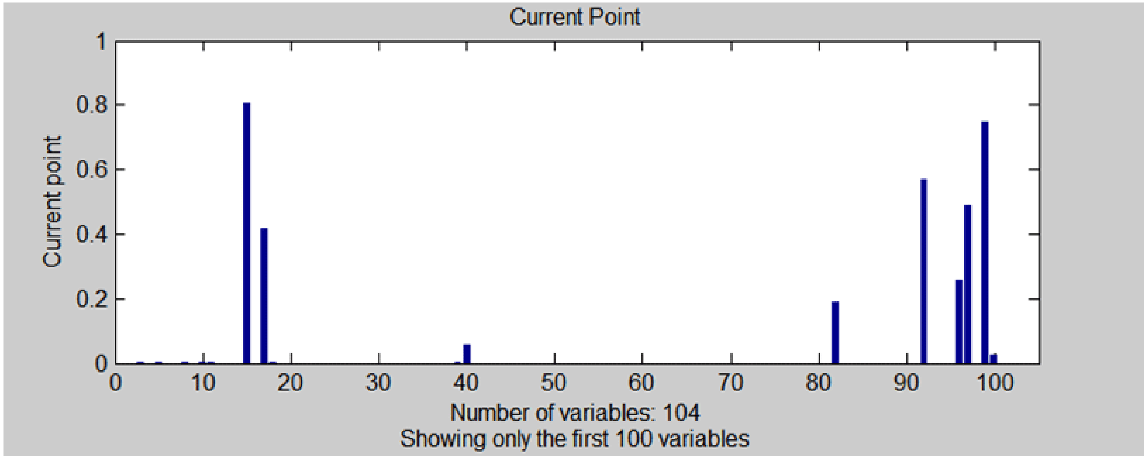

Figure 4-10: Optimal values for decision variables (investment budget=$1.8M)

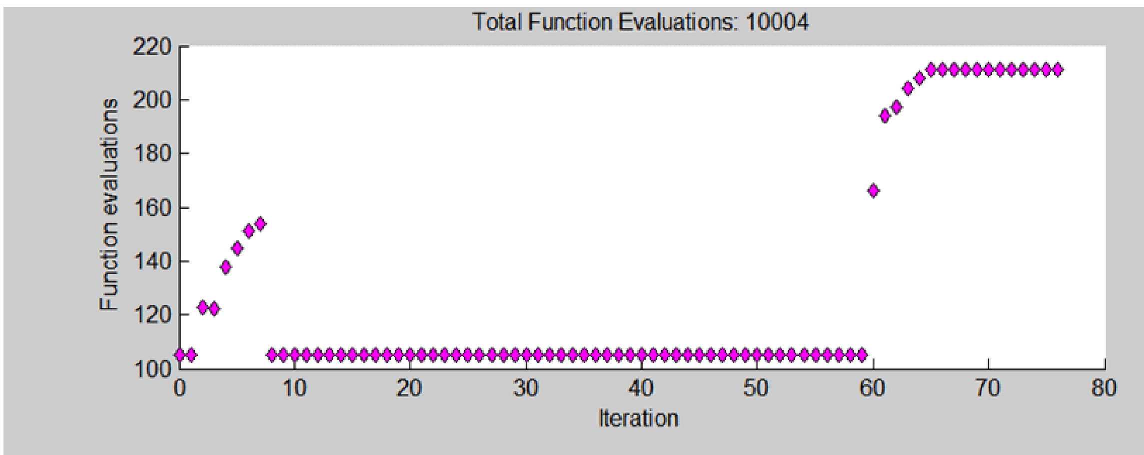

Figure 4-11: Function evaluations (investment budget=$1.8M). Total number of evaluations on the objective and constraint functions is depicted in the plot. It is clear that the algorithm increased the number of evaluations on the iterations close to the optimal solution. The algorithm reaches the optimum point after 10004 function evaluations.

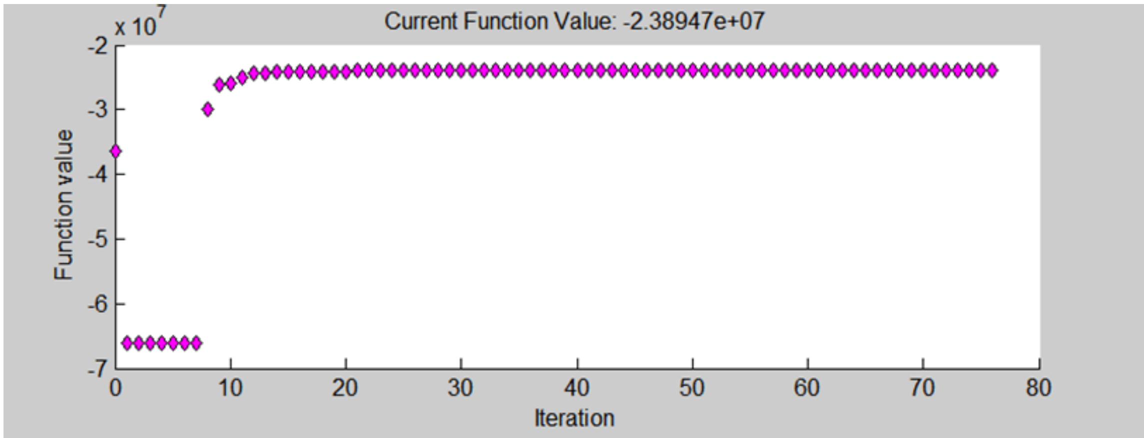

Figure 4-12: Values for objective function (investment budget=$1.8M).The algorithm started converging to the optimal point at the 10th iteration.

4.2.5.2. Investment Budget of $1.55 Million:

In this scenario, the budget was decreased to $1.55 Million while keeping all other parameters unchanged. This is particularly interesting as this reduction has an impact in limiting the model's available resources while it has a minimal impact on lowering the profit (Figure 4-15).

By looking at the data presented in Figure 4-13, one can observe that the model reacted to the shortage of investment budget by focusing on more vital indicators including life cycle improvements. This was while the model focused less on the improvement of environmental indicators.

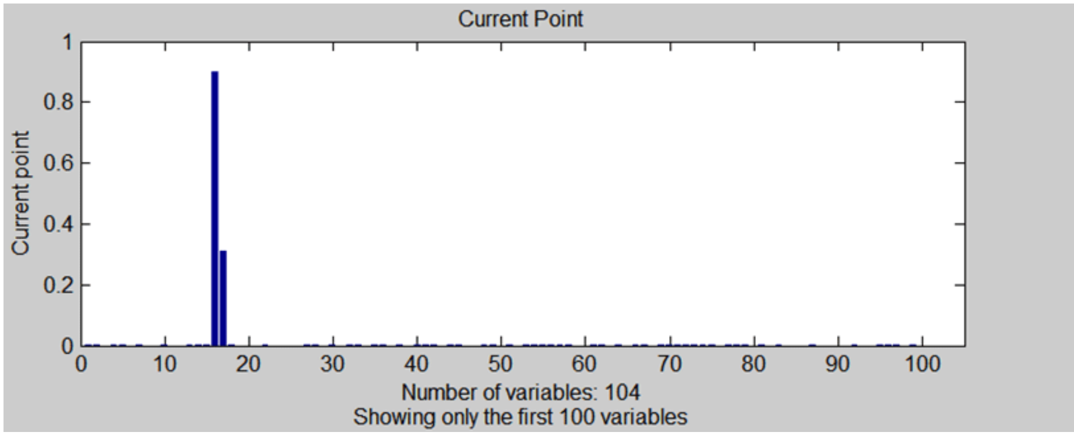

Figure 4-13: Optimal values for decision variables (investment budget=$1.55M)

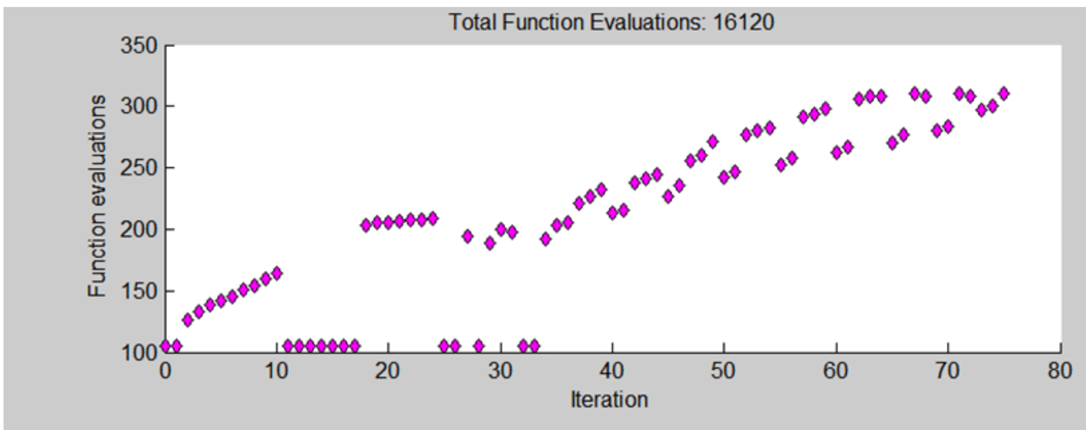

Figure 4-14: Function evaluations (investment budget=$1.55M)

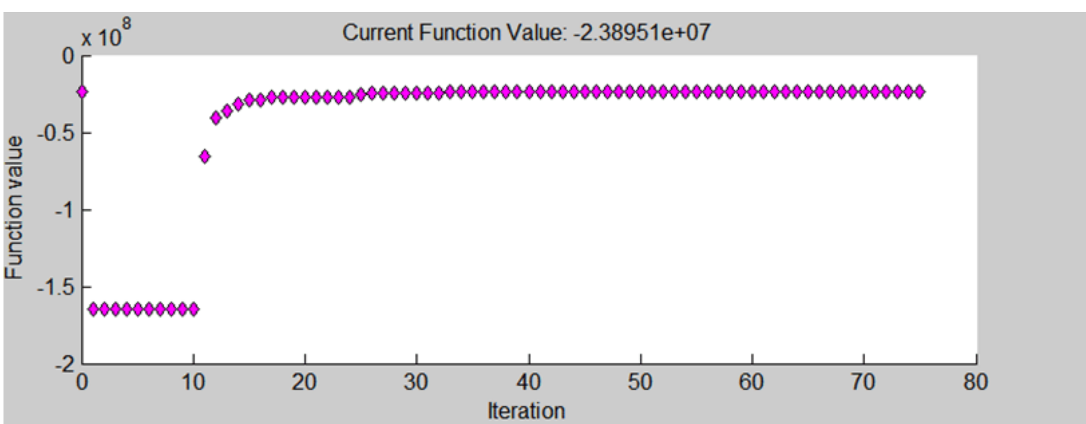

Figure 4-15: Values for objective function (investment budget=$1.55M)

4.2.5.3. Investment Budget in a Range of \$1.5M and \$2M:

By running the model with different budget values ranging from of \$1.5M and \$2M, one can observe that increasing the investment budget escalates the profit (Figure 4-16). The results show high potential in increasing the profit by approximately 25% through only adding \$0.1M to the investment budget.

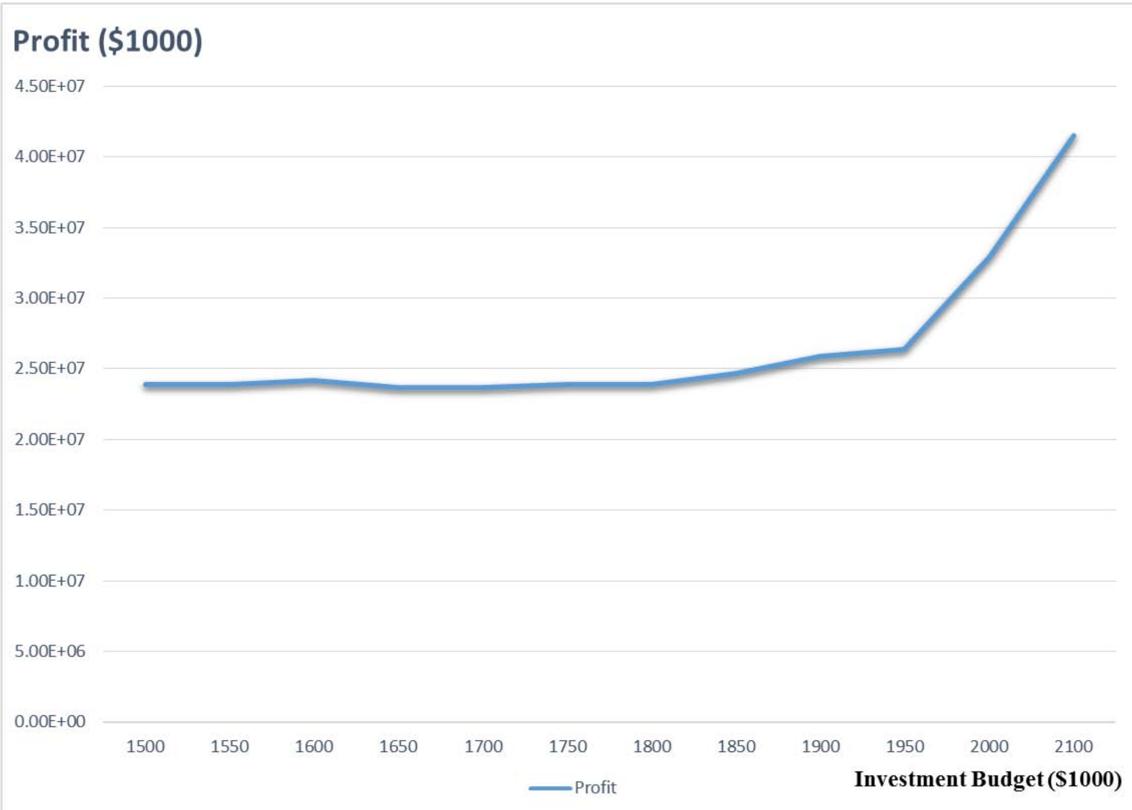

Figure 4-16: Investment budget sensitivity analysis

4.2.6. Sensitivity Analysis for Base Demand

Different values for base market demand can result in different profit values. An optimization run was performed for each value given to base demand.

4.2.6.1. Increasing Base Demand from 120 to 155 Batches

Changing the demand from 120 to 155 batches did not show a significant change in the profit. After 15710 function evaluations (Figure 4-18), the resultant optimal profit value for this scenario was $2.59 × 10^{7} (Figure 4-19). The reason for such result is the fact that an increase in demand changes the focus of the optimization model from environmental issues to investing its resources on cycle time improvements. It is shown in Table 4-12 and Figure 4-17 that the increased ratios for cycle times (x_{ijk}^{T} values) have grown on the machines with high cycle times and low associated improvement cost while the investments on environmental indicators has dropped to zero (Table 4-11). It is evident that increasing the base demand can force the firm to concentrate most of the resource on lead time reduction to satisfy the extra market demand.

i	J	k	x_{ijk}^{H}	x_{ijk}^{T}	x_{ijk}^{Q}	x_{ijk}^{E}	x_{ijk}^{WE}	x_{ijk}^{LE}	x_{ijk}^{AE}	x_{ijk}^{WE}
1	1	1	0.149	0.000	0.000	0.891	0.000	0.000	0.000	0.000
2	1	1	0.864	0.871	0.868	0.000	0.000	0.000	0.000	0.000
2	2	1	0.000	0.843	0.000	0.771	0.000	0.000	0.000	0.000
2	3	1	0.000	0.807	0.000	0.671	0.000	0.000	0.000	0.000
2	4	1	0.000	0.890	0.881	0.811	0.000	0.000	0.000	0.000
3	1	1	0.778	0.000	0.000	0.747	0.000	0.000	0.000	0.000
3	1	2	0.000	0.000	0.000	0.788	0.000	0.000	0.000	0.000
3	1	3	0.000	0.822	0.000	0.709	0.000	0.000	0.000	0.000
4	1	1	0.801	0.000	0.000	0.792	0.000	0.000	0.000	0.000
4	1	2	0.000	0.000	0.877	0.796	0.000	0.000	0.000	0.000
4	1	3	0.000	0.000	0.000	0.744	0.000	0.000	0.000	0.000
5	1	1	0.082	0.000	0.000	0.847	0.000	0.000	0.000	0.000
5	2	1	0.000	0.782	0.000	0.878	0.000	0.000	0.000	0.000

Table 4-11: Optimal values for decision variables (base demand=155 batches)

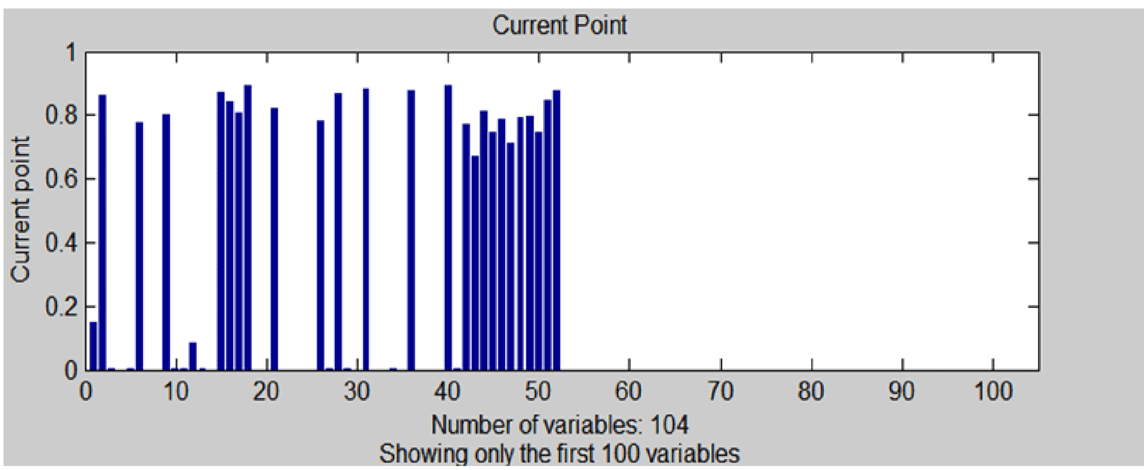

Figure 4-17: Optimal values for decision variables (base demand=155 batches). The improvements are all focused on the first half of the variables which are related to economic indicators.

i	j	k	PCT	PIVTT	x_{ijk}^{T}
1	1	1	32.09	0.3	0.000
2	1	1	22.73	0.35	0.871
2	2	1	39.48	0.4	0.843
2	3	1	57.5	0.45	0.807
2	4	1	8.18	0.34	0.890
3	1	1	462.5	0.45	0.000
3	1	2	471.5	0.55	0.000
3	1	3	472.5	0.24	0.822
4	1	1	1488.75	0.7	0.000
4	1	2	1728	0.45	0.000
4	1	3	1046.5	0.34	0.000
5	1	1	223.21	0.4	0.000
5	2	1	71.01	0.45	0.782

Table 4-12: Current cycle time (PCT in minutes), improvement cost (PIVT) and cycle time decision variable (base demand=155 Batches)

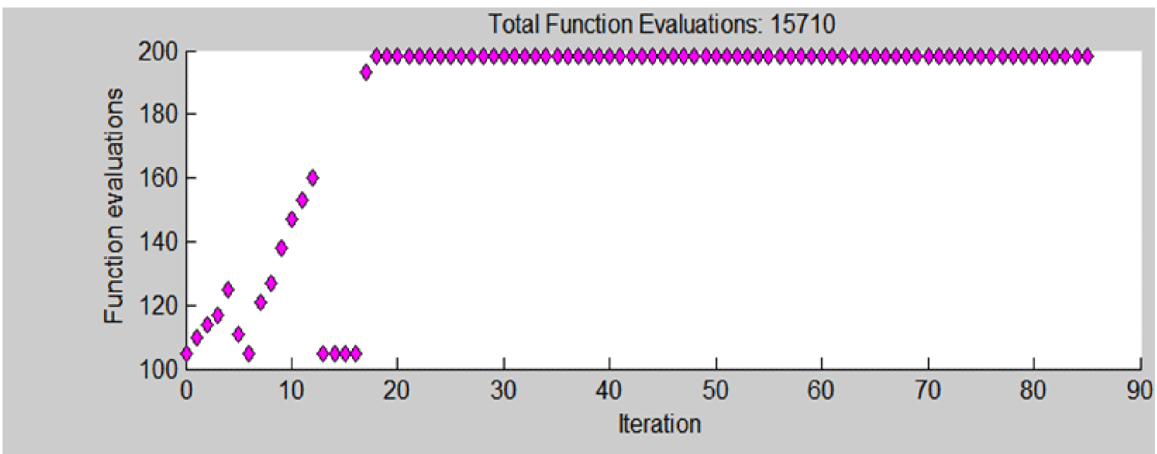

Figure 4-18: Function evaluations (base demand=155 batches)

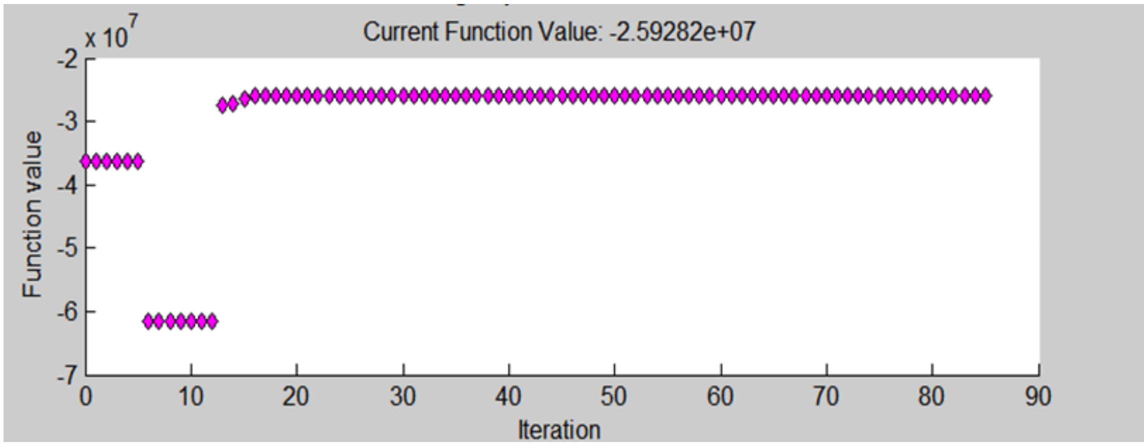

Figure 4-19: Values for objective function (base demand=155 batches)

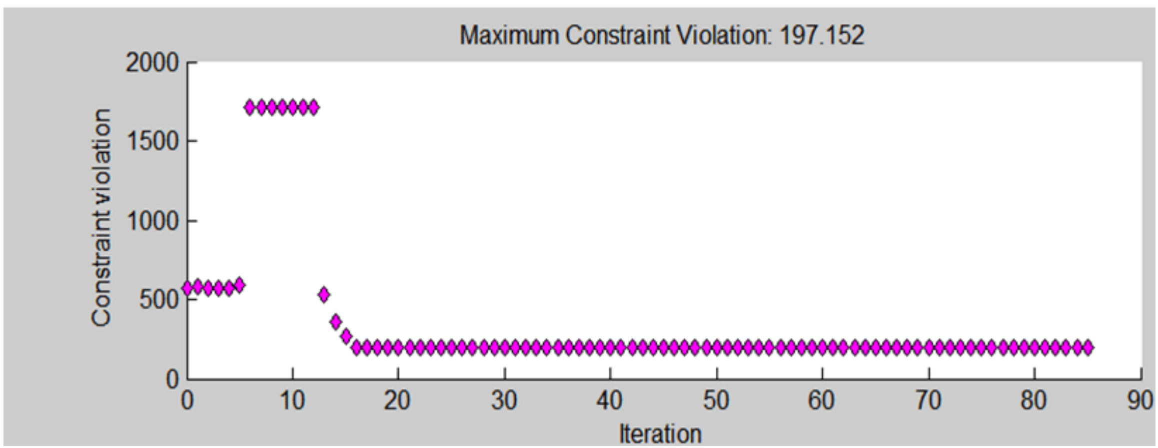

Figure 4-20: Constraint violation for each iterations (base demand=155 batches)

4.2.6.2. Decreasing Base Demand from 120 to 115 Batches

Decreasing base demand to 115 resulted in a profit value of $\$3.14 \times 10^{7}$ (Figure 4-23), slightly lower than the initial profit of $\$3.29 \times 10^{7}$. Due to the lower demand, the sales decreased and thus lowered the revenue and ultimately resulted in a lower profit. The optimal values for the decision variables are shown in Figure 4-21. The total constraint violation reached a value near zero after 20709 function evaluations which proves that the model is still consistent and creating feasible solutions (Figure 4-22 to Figure 4-22).

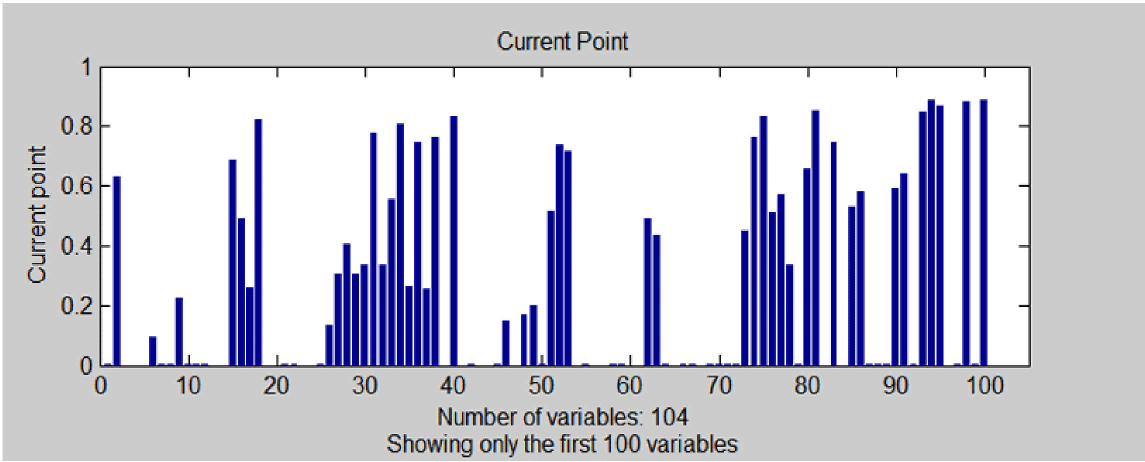

Figure 4-21: Optimal values for decision variables (demand=115 batches)

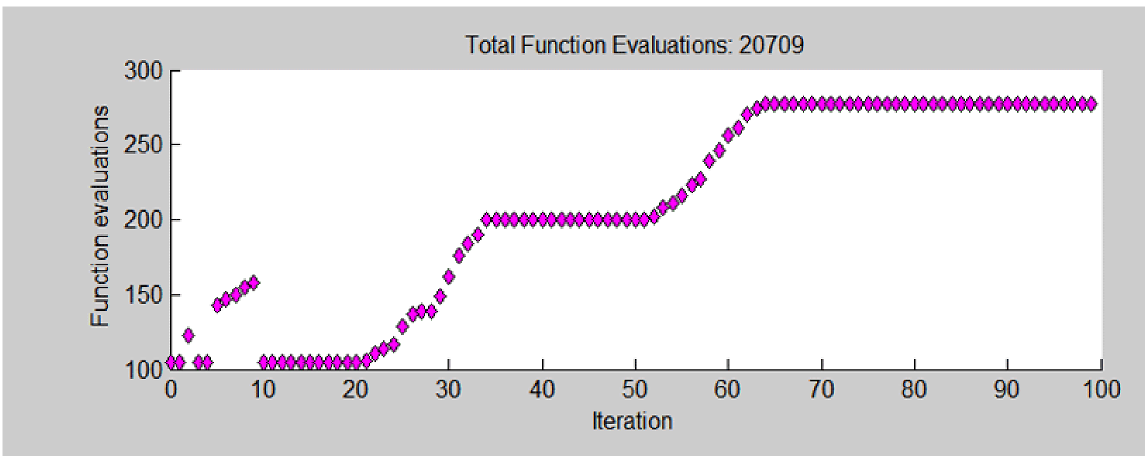

Figure 4-22: Function evaluations (base demand=115 batches)

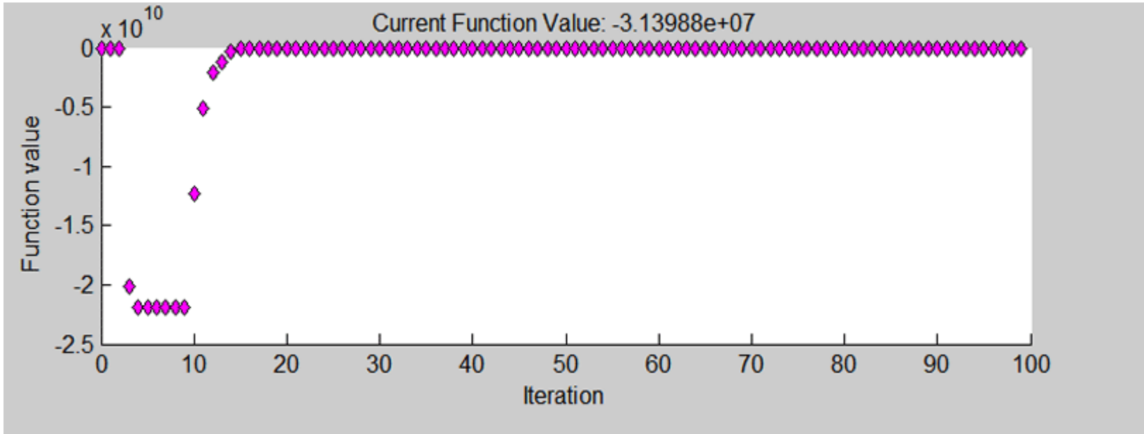

Figure 4-23: Values for objective function (base demand=115 batches)

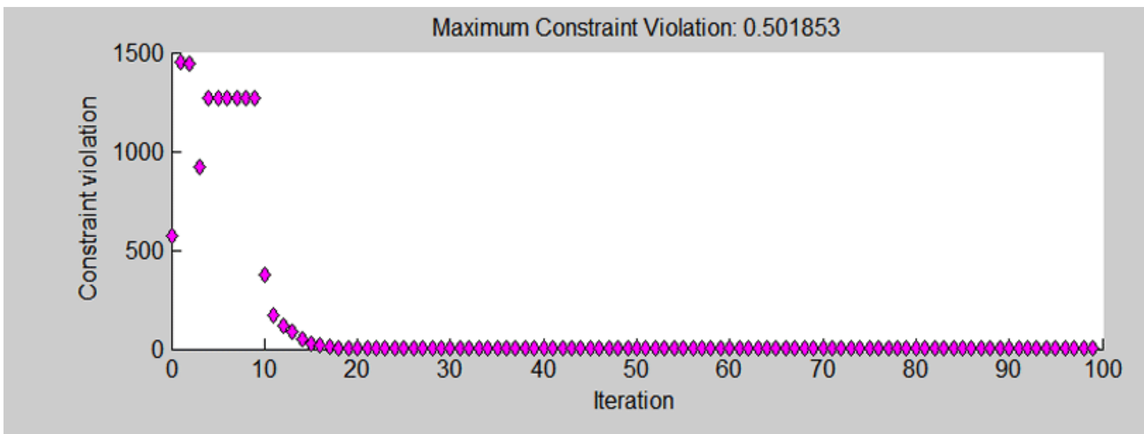

Figure 4-24: Constraint violation for each iterations (base demand=115 batches)

4.2.6.3. Further Decreasing Base Demand to 105

The profit was \$6.13 × 10^{8} (Figure 4-27), and the total constraint violation was close to zero (Figure 4-28). This significant increase in profit is based on the fact that a lower base demand can increase monetary resources for the firm, enabling it to focus on the environmental factors, ultimately causing a higher level of tax refund and thus higher profit. The optimal values for decision variables are listed in Table 4-13 and depicted in Figure 4-25. It can be observed that the cycle time improvements are zero for most of the machines, while the improvement levels of environmental indicators (especially xHW) have increased.

i	J	k	x_{ijk}^{H}	x_{ijk}^{T}	x_{ijk}^{Q}	x_{ijk}^{E}	x_{ijk}^{WE}	x_{ijk}^{LE}	x_{ijk}^{AE}	x_{ijk}^{WE}
1	1	1	0.001	0.000	0.058	0.832	0.726	0.000	0.000	0.000
2	1	1	0.651	0.697	0.177	0.000	0.000	0.000	0.673	0.851
2	2	1	0.000	0.527	0.058	0.000	0.000	0.000	0.852	0.888
2	3	1	0.000	0.338	0.092	0.000	0.000	0.000	0.000	0.870
2	4	1	0.000	0.825	0.784	0.000	0.000	0.000	0.754	0.000
3	1	1	0.205	0.000	0.092	0.001	0.000	0.000	0.000	0.000
3	1	2	0.000	0.000	0.585	0.248	0.000	0.000	0.564	0.882
3	1	3	0.000	0.000	0.809	0.000	0.000	0.493	0.606	0.000
4	1	1	0.310	0.000	0.012	0.266	0.000	0.769	0.000	0.888
4	1	2	0.000	0.000	0.756	0.288	0.528	0.832	0.000	0.000
4	1	3	0.000	0.000	0.000	0.001	0.483	0.543	0.000	0.000
5	1	1	0.000	0.000	0.769	0.549	0.000	0.596	0.613	0.000
5	2	1	0.000	0.236	0.000	0.744	0.000	0.398	0.659	0.888

Table 4-13: Optimal values for decision variables (demand=105 batches)

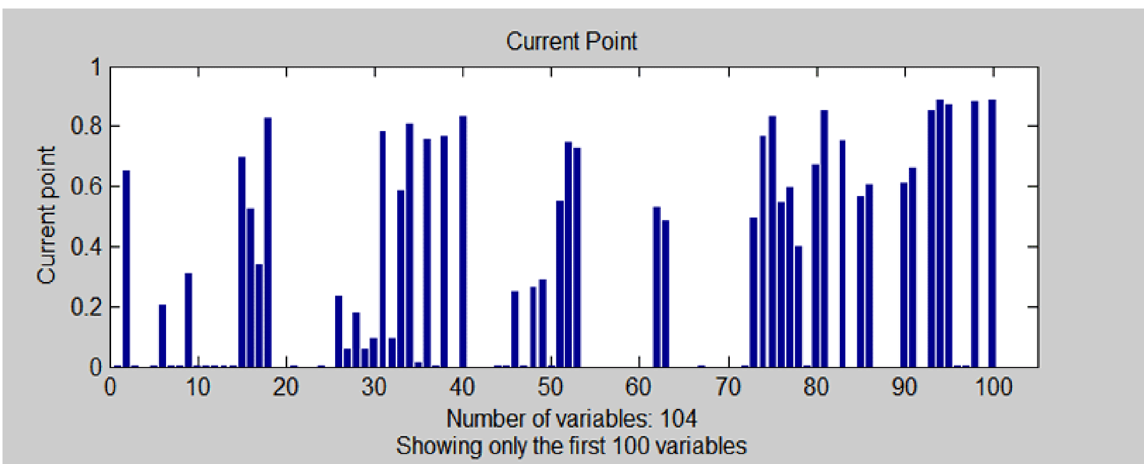

Figure 4-25: Optimal values for decision variables (demand=105 batches)

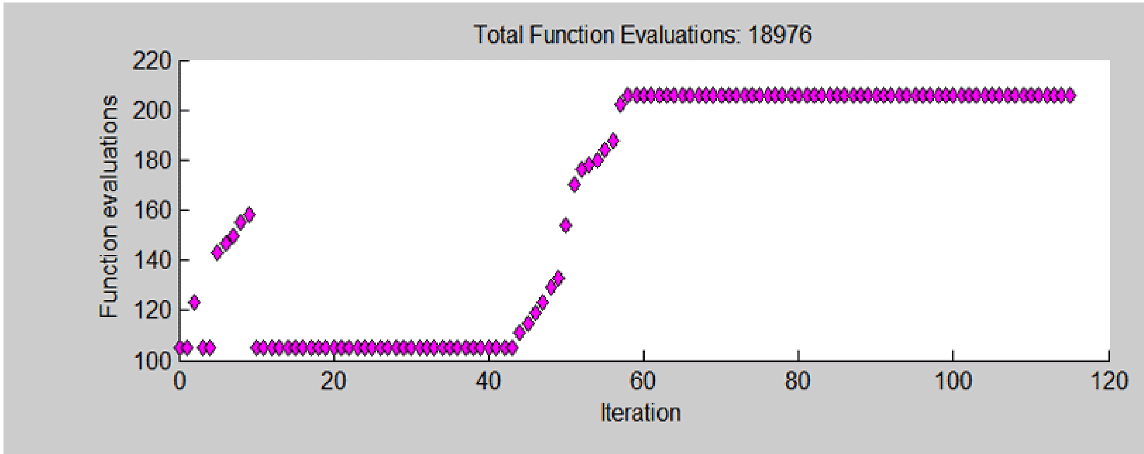

Figure 4-26: Function evaluations (base demand=105 batches)

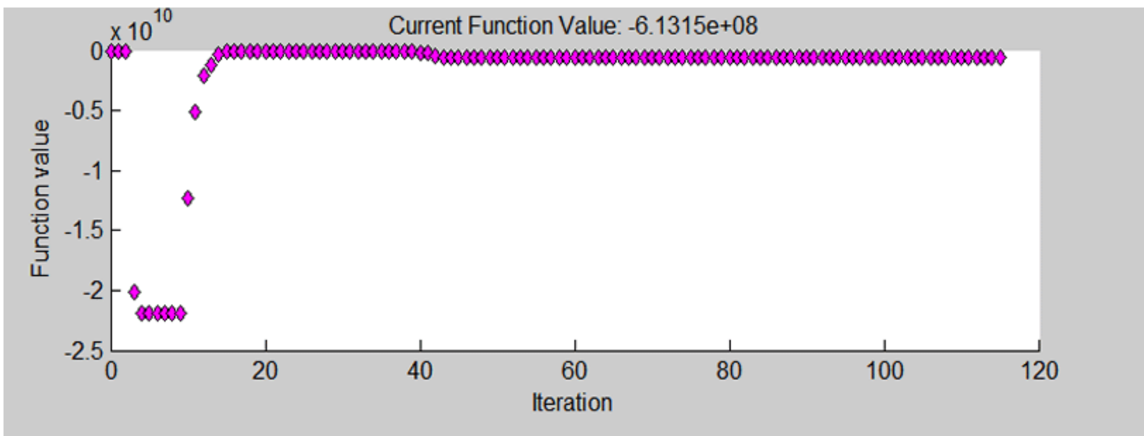

Figure 4-27: Values for objective function (base demand=105 batches)

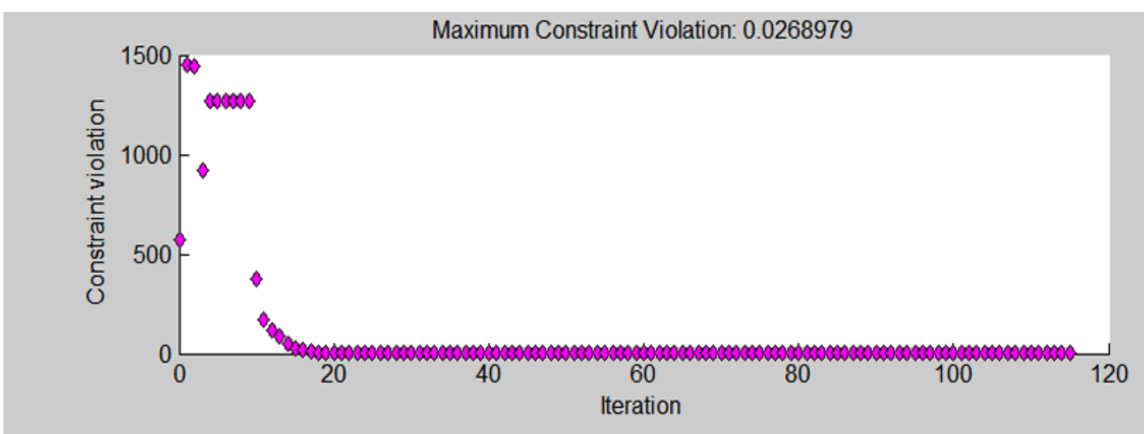

Figure 4-28: Constraint violation for each iterations (base demand=105 batches)

4.2.6.4. Base Demand in a Range of 100 to 155 Batches:

Based on the analysis in Sections 4.2.6.1, 4.2.6.2 and 4.2.6.3, an increase in base demand slightly improved the profit of the plant, by influencing the way investments were focused. This occurred while a decrease in demand level caused a significant increase in the profit. This trend is shown in Figure 4-29. Results from this sensitivity analysis demonstrate that a slight decrease in base market demand can result in high profitability, if the plant devotes the unutilized resources to environmental enhancements.

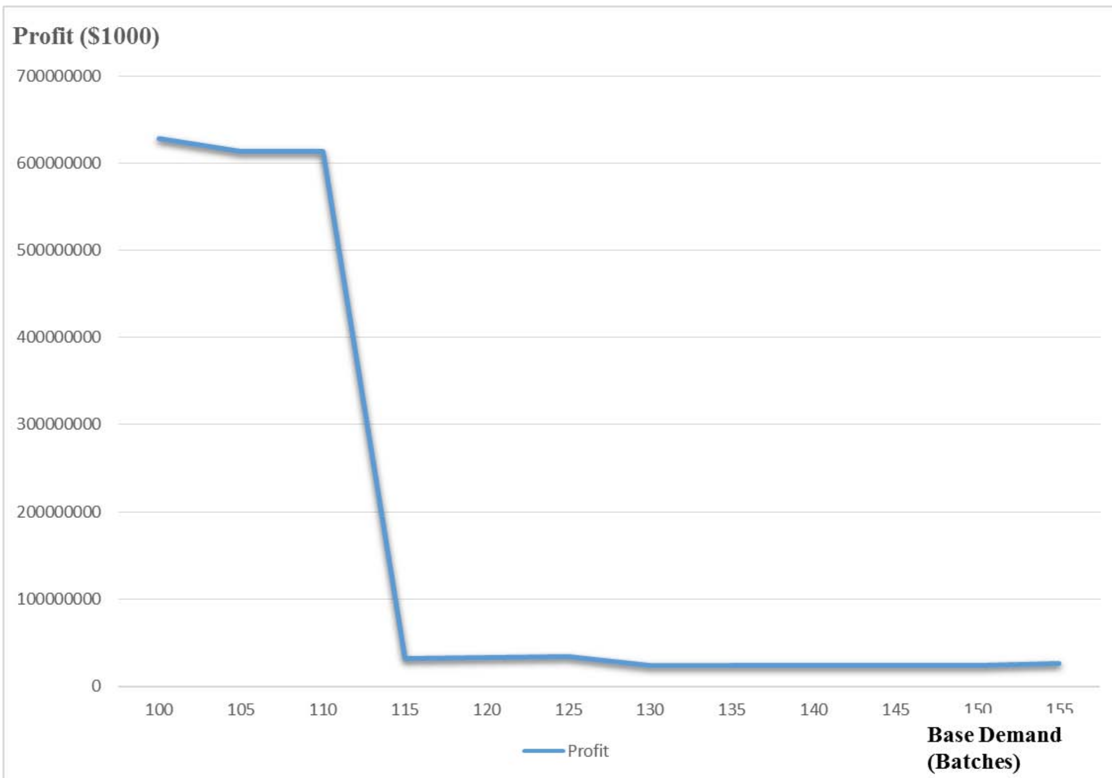

Figure 4-29: Sensitivity analysis for base demand. A decrease in demand, while keeping investment budget unchanged, improves the firm's profit significantly especially at the values lower than 115 batches.

Chapter 5 : Conclusion

5.1. Contributions

The main contribution of this thesis is the creation of an approach that optimizes a batch production system. The method focuses on the development of a mathematical model that takes into account environmental sustainability while maximizing the firm's profit. It also provides detailed guidelines on how to make effective technology enhancement decisions while estimating the required investments. Furthermore, the proposed model takes into consideration selected environmental indicators and offers the amount of improvements required on each indicator.

Another contribution is that a new approach was used in the calculation of market demand. Demand was considered as a function of enhancement of the greenness of the process.

In addition, a payment-and-refund approach was used in the calculation of the firm's net environmental tax payments. To show the results from the optimization model, current and future state value stream maps were developed using real data from a pharmaceutical plant, providing the firm's management with a snapshot of the manufacturing process and its potential improvement points. More specifically, the snapshot covered details on environmental and economic sustainability and it also detected sustainability bottlenecks where bottlenecks are the least sustainable station/module in the model requiring greatest attention.

Finally, two approaches of sensitivity analysis and comparison of the results with the outcome from a popular simulation package were used for validating the data obtained from the optimization model. Based on these results, it was determined that the amount of improvements/abatements on each of the firm's stations could potentially contribute towards making efficient decisions. Through different scenarios, it is concluded that the proposed model is reliable for practical implementations.

5.2. Future Work

This study can be used as both practical and theoretical basis for further studies in the development of model that include setup and factory maintenance programs, as well as randomness in input data. Firstly, setup and maintenance aspects in this and any model could increase the results' accuracy and be considered as starting points for further readings even for various manufacturing systems. Secondly, in order to further increase the accuracy in results, one may find it rather difficult for the proposed model to be developed using fixed parameters. As a result, it may be more practicable if random data based on probability distributions were applied. Thus, the model can include dynamic parameters to cover uncertainty in demand, cycle times, emission amounts, etc.

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Appendix A: Numerical Example Model Parameters

Model Parameters (IranDaru, 2010)	Module number(i)	1		2	2	2	2		3	3	3		4	4	4		5	5	5
	Station Number(j)	1		1	2	3	4		1	1	1		1	1	1		1	2	3
	Machine Number(k)	1		1	1	1	1		1	2	3		1	2	3		1	1	1
Parameter Desc.	Machine / r, Parameter	Scaling	path for finished products	Granulator	Agitator	FBD	Sizing	Granulation Path	Press55	BB4	BB3	Compression Path	UPS1260	UPS600	UPS4	Blister Path	Cartoning	Shrinkpack	Cartoning Path
Initial scrap rate(5)	SR	5		2	4	3	1		3	2	1		5	1	6		1	0	
Electricity Busy use(Kwh/min)	EBU	0.25		1.21	0.7	1.4	0.7		1.01	0.8	0.9		0.7	0.8	0.9		0.3	0.3	
Initial water emission(kg) per operation	WE	0.3		3	4	7	1		5.5	4	2		0.6	0.7	0.8		0.9	1.5	
Initial land emission(kg)per operation	LE	0.7		1	0.5	1	0.4		1.6	0.9	0.7		0.2	0.1	0.6		0.5	0.9	
initial air emission(kg)per operation	AE	2		6	1	2	4		10	7	6		7	8	15		6.5	12	
Initial hazardous waste per operation	HW	0.2	0.2	0.3	0.1	0.2	0.4		0.3	0.1	0.1		0.09	0.08	0.1		0.07	0.08	0.1
Transportation (cost / travel)	HR		13					15				10				5			2.5
Electricity price (Cost $/Kwh)	ER	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08	0.08
Handling time from previous module to current module(min)	HT		26.3					1				3.39				2.5			25.4
Maintenance time(min)	MT	34.6		9	14.7	16.2	14.7		9	9	9		15	15	6.6		15	4.88	
Setup time(min)	ST			62.8	14.7	62.4	15.1												
Cost of reducing cycle time by one unit.($1000)	IVTT	0.3		0.35	0.4	0.45	0.34		0.45	0.55	0.24		0.7	0.45	0.34		0.4	0.45	
Cost of lowering scrap rate by 1 unit	IVTQ	4		4	5	5.5	4.4		5.5	6.5	3.4		5	5.5	4.4		5	5.5	
Cost of lowering handling time by 1 unit	IVTH		8					10				10				11			9
cost of lowering electricity consumption by 1 unit($1000)	IVTE	10		40	50	45	34		42	39	59		43	36	48		49	20	
Cost of lowering water emission by 1 unit	IVTWE	22.5		22.5	22.5	22.5	22.5		22.5	22.5	22.5		22.5	22.5	22.5		22.5	22.5	
Cost of lowering land emission by 1 unit	IVTLE	25		25	25	25	25		25	25	25		25	25	25		25	25	
Cost of lowering air emission by 1 unit	IVTAE	2		1.5	1.77	1.5	1.4		2	2	2		2.5	2.1	2.22		1.8	0.8	
Cost of lowering hazardous waste by 1 unit(kilo gram)	IVTHW	4	3	6	4.3	5.5	4.4		3.4	6.5	3.4		5	5.5	4.4		5	5.5	4.2
Operators cost/min	OR	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13	0.13
Cycle time	CT	32.1		22.7	39.5	57.5	8.18		463	472	473		1489	1728	1047		223	71	
Number of setups per machine	NOS	1		1	1	1	1		1	1	1		1	1	1		1	1	
Material cost for setup	MSCp																		
Setup electricity use for the pth setup of the machine	SEp	0.1		0.48	0.28	0.56	0.28		0.4	0.32	0.36		0.28	0.32	0.36		0.12	0.12	
Net payment-electricity saving constant	NTE	6		6	6	6	6		6	6	6		6	6	6		6	6	
Net payment-Water emission constant	NTWE	4		4	4	4	4		4	4	4		4	4	4		4	4	
Net payment-land emission constant	NTLE	3		3	3	3	3		3	3	3		3	3	3		3	3	
Net payment-air emission constant	NTAE	0.2		0.2	0.2	0.2	0.2		0.2	0.2	0.2		0.2	0.2	0.2		0.2	0.2	
Net payment-weight of hazardous waste constant	NTHW	0.3		0.3	0.3	0.3	0.3		0.3	0.3	0.3		0.3	0.3	0.3		0.3	0.3	
Target value for water emission	VWE	0.17		2.18	1.18	2.77	0.29		3.69	0.94	0.74		0.32	0.14	0.49		0.67	0.87	
Target value for land emission	VLE	0.13		0.16	0.19	0.07	0.07		0.33	0.42	0.21		0.03	0.07	0.04		0.29	0.25	
Target value for air emission	VAE	0.15		2.93	0.31	1.5	2.16		2.71	1.75	1.58		2.03	5.84	5.17		2.01	4.77	
Target value for hazardous waste	VHW	0.07		0.18	0.06	0.16	0.13		0.19	0.02	0.03		0.04	0.02	0.05		0.01	0.06	
total loss caused by deviation DWE of Water emission criterion	AWE	2.66		2.23	2.5	2.14	2.27		2.95	2.22	2.54		2.59	2.13	2.47		2.98	2.91	
total loss caused by deviation DLE of Land emission criterion	ALE	2.64		2.3	2.45	2.19	2.33		2.29	2.2	2.12		2.93	2.58	2.96		2.14	2.33	
total loss caused by deviation DAE of Air emission criterion	AAE	2.16		2.21	2.71	2.27	2.17		2.33	2.14	2.12		2.19	2.76	2.08		2.91	2.33	
total loss caused by deviation DHW of Hazardous waste criterion	AHW	2.25		2.67	2.37	2.22	2.76		2.42	2.78	2.59		2.15	2.67	2.97		2.97	2.86	
Deviation from Water emission criterion	DWE	0.7		0.58	0.57	0.76	0.36		0.51	0.47	0.71		0.73	0.69	0.67		0.78	0.49	
Deviation from Land Emission criterion	DLE	0.45		0.6	0.71	0.35	0.7		0.57	0.78	0.73		0.66	0.55	0.74		0.64	0.67	
Deviation from air emission criterion	DAE	0.75		0.64	0.57	0.42	0.43		0.3	0.46	0.39		0.8	0.72	0.4		0.59	0.56	
Deviation from Hazardous waste criterion	DHW	0.62		0.69	0.8	0.41	0.68		0.62	0.8	0.66		0.59	0.56	0.36		0.34	0.42	

Appendix B: Matlab Code and Settings for the Optimization

Part 0: The starting point for the SQP algorithm

Module	Station	Machine	Decision Variables							
i	j	k	X_{ijk}^{H}	X_{ijk}^{T}	X_{ijk}^{Q}	X_{ijk}^{E}	X_{ijk}^{WE}	X_{ijk}^{LE}	X_{ijk}^{AE}	X_{ijk}^{HW}
1	1	1	0.109	0.086	0.151	0.182	0.095	0.034	0.042	0.196
2	1	1	0.147	0.928	0.161	0.132	0.072	0.070	0.117	0.392
2	2	1	0.000	0.086	0.152	0.098	0.046	0.021	0.118	0.111
2	3	1	0.000	0.146	0.147	0.153	0.113	0.071	0.144	0.218
2	4	1	0.000	0.142	0.117	0.118	0.068	0.125	0.072	0.306
3	1	1	0.155	0.413	0.183	0.085	0.048	0.096	0.447	0.174
3	1	2	0.000	0.422	0.094	0.084	0.028	0.105	0.412	0.181
3	1	3	0.000	0.436	0.164	0.127	0.013	0.126	0.466	0.161
4	1	1	0.098	0.412	0.139	0.114	0.020	0.124	0.431	0.177
4	1	2	0.000	0.516	0.191	0.161	0.087	0.120	0.461	0.184
4	1	3	0.000	0.365	0.155	0.070	0.040	0.153	0.508	0.149
5	1	1	0.149	0.162	0.151	0.058	0.025	0.091	0.100	0.112
5	2	1	0.000	0.164	0.000	0.113	0.017	0.065	0.222	0.102

Part 1: Initializing optimization parameters (param.m)

```
UP= 250000;%Unit price (UP) for a batch of products
T=624000;
D=120; % Annual demand
IL=2000;% Investment budget ($1000)
LEL= 3500;   %Total land emission upper limit
WEL=10000;   %total water emission upper limit
AEL=50000;   %total air emission upper limit
HWL=900;     %total hazardous waste upper limit
U1=1; %unit conversion for net payment and investment
values
U2=1;  %unit conversion for quality loss values
PTLE=50000; %assumed value for total market Land Emission
PTWE=50000;%assumed value for total market Water Emission
PTAE=50000;%assumed value for total market Air Emission
PTHW=50000;%assumed value for total market Hazardous Waste
eta=120/3; %  is the market sensitity to average level of
improvement in emissions

Q=10^4; % Total market output

V=8; %number of variables
UL=0.99999; %upper limit for variables
```

```
LL=0 ;   %lower limit for variables

fileName   = 'Parameters.xlsx'; %Excel file related to
modelling parameters
sheetName  = 'p'  ; %excel sheet related to parameters
ParameterRange='A1:AU14' ; %cell range for the parameter
data in the excel file

parameterData=xlsread(fileName, sheetName  ,ParameterRange)
;%loading from parameter Excel file

I=parameterData(:,2);  %Module number
J=parameterData(:,3);  %Station number
K=parameterData(:,4);  %Machine number
SU=strcat(num2str(I),num2str(J));

%Creating zero matrices for all the parameters:
PSR=zeros(numel(I));
PEBU=zeros(numel(I));
PWE=zeros(numel(I));
PLE=zeros(numel(I));
PAE=zeros(numel(I));
PHW=zeros(numel(I));
PHR=zeros(numel(I));
PER=zeros(numel(I));
PHT=zeros(numel(I));
PMT=zeros(numel(I));
PST=zeros(numel(I));
PIVTT=zeros(numel(I));
PIVTQ=zeros(numel(I));
PIVTH=zeros(numel(I));
PIVTE=zeros(numel(I));
PIVTWE=zeros(numel(I));
PIVTLE=zeros(numel(I));
PIVTAE=zeros(numel(I));
PIVTHW=zeros(numel(I));
POR=zeros(numel(I));
PCT=zeros(numel(I));
PNOS=zeros(numel(I));
PMSCp=zeros(numel(I));
PSEp=zeros(numel(I));
PICTE=zeros(numel(I));
PICTWE=zeros(numel(I));
PICTLE=zeros(numel(I));
PICTAE=zeros(numel(I));
PICTHW=zeros(numel(I));
AWE=zeros(numel(I));
```

```
ALE=zeros(numel(I));
AAE=zeros(numel(I));
AHW=zeros(numel(I));
DWE=zeros(numel(I));
DLE=zeros(numel(I));
DAE=zeros(numel(I));
DHW=zeros(numel(I));
VWE=zeros(numel(I));
VLE=zeros(numel(I));
VAE=zeros(numel(I));
VHW=zeros(numel(I));
 CCLE=zeros(numel(I));
CCWE=zeros(numel(I));
CCAE=zeros(numel(I));
CCHW=zeros(numel(I));

%NOP=zeros(numel(I));


%Pluging in numbers in the parameter matrices :

PSR=parameterData(:,7);
PEBU=parameterData(:,8);
PWE=parameterData(:,9);
PLE=parameterData(:,10);
PAE=parameterData(:,11);
PHW=parameterData(:,12);
PHR=parameterData(:,13);
PER=parameterData(:,14);
PHT=parameterData(:,15);
PMT=parameterData(:,16);
PST=parameterData(:,17);
PIVTT=parameterData(:,18);
PIVTQ=parameterData(:,19);
PIVTH=parameterData(:,20);
PIVTE=parameterData(:,21);
PIVTWE=parameterData(:,22);
PIVTLE=parameterData(:,23);
PIVTAE=parameterData(:,24);
PIVTHW=parameterData(:,25);
POR=parameterData(:,26);
PCT=parameterData(:,27);
PNOS=parameterData(:,28);
PMSCp=parameterData(:,29);
PSEp=parameterData(:,30);
PNTE=parameterData(:,31);
PNTWE=parameterData(:,32);
```

```
PNTLE=parameterData(:,33);
PNTAE=parameterData(:,34);
PNTHW=parameterData(:,35);
AWE=parameterData(:,36);
ALE=parameterData(:,37);
AAE=parameterData(:,38);
AHW=parameterData(:,39);
DWE=parameterData(:,40);
DLE=parameterData(:,41);
DAE=parameterData(:,42);
DHW=parameterData(:,43);
VWE=parameterData(:,44);
VLE=parameterData(:,45);
VAE=parameterData(:,46);
VHW=parameterData(:,47);
```

Part 2: functions

TT function(TT.m):

```
function f = TT(x,PCT,PST,PMT )


f=(1-x(:,2)).*PCT +PST+PMT;


end
```

TB function(TB.m)

```
function f = TB(x,PCT,PST,PMT,PHT,I)
   maxTT=(TT(x,PCT,PST,PMT ));


    for i=numel(I):2
        if SU(i)==SU(i-1)
        maxTT(i-1)=max(maxTT(i),maxTT(i-1));
        maxTT(i)=0;


        end
    end
```

```
f=(1-x(:,1)).*PHT +maxTT;

end
```

QLF function(QLF.m)

```
function f = QLF(a,d,Pf,v)

 F=(Pf >= v) .* (Pf <= v + d).*(a./(d.*d)).*(Pf-v).*(Pf-
v)+abs(1-(Pf >= v) .* (Pf <= v + d)).*a;
Fnan= isnan(F);
F(Fnan)=0;
 f=F;
    %loss function for the smaller-the-better type with
lower limit
 end
```

PSRf function(PSRf.m)

```
function y = PSRf(x,PSR,I)
%calculates the reliability of the system
PSRi=PSR.*(1-x(:,3));

 for i=numel(I):2
     if SU(i)==SU(i-1)
     PSRi(i-1)=PSRi(i)*PSRi(i-1);
     PSRi(i)=0;

     end
 end
 y=1-prod(1-PSRi);
end
```

NP function(NP.m):

```
function f = NP(x,T,PCT,PST,PMT,PHT,I,J,K)
        % Calculates the no. of operations by machine K
of the station J of the module I


NOPt=zeros(max(I),max(J),max(K));


    for n=1:size(I)
        if((T-TPT(x, PHT,PCT,PST,PMT)*floor(T/TPT(x,
PHT,PCT,PST,PMT))-TB(x,PHT,PCT,PST,PMT,I,J,K))<0)
            NOPt(I(n),J(n),K(n))=floor(T/TPT(x,
PHT,PCT,PST,PMT));
        else
            NOPt(I(n),J(n),K(n))=floor(T/TPT(x,
PHT,PCT,PST,PMT))+1;
        end
    end
    f=NOPt;
end
```

Part 3: Output Scripts

```
IVTT    =U1*PIVTT.*exp(x(:,2)-1).*PCT;  %IVTT
IVTQ    =U1*PIVTQ.*exp(x(:,3)-1).*PSR;  %IVTQ
IVTE    =U1*PIVTE.*exp(x(:,4)-1).*PEBU; %IVTE
IVTH    =U1*PIVTH.*exp(x(:,1)-1).*PHT;  %IVTH
IVTWE   =U1*PIVTWE.*exp(x(:,5)-1).*PWE; %IVTWE
IVTLE   =U1*PIVTLE.*exp(x(:,6)-1).*PLE; %IVTLE
IVTAE   =U1*PIVTAE.*exp(x(:,7)-1).*PAE; %IVTAE
IVTHW   =U1*PIVTHW.*exp(x(:,8)-1).*PHW; %IVTHW

TIVT=sum(IVTH+IVTT+IVTQ+IVTE+IVTWE+IVTLE+IVTAE+IVTHW); %total
investment
IVT=cat(2,IVTH,IVTT,IVTQ,IVTE,IVTWE,IVTLE,IVTAE,IVTHW); %concantenating
all the investment arrays into one matrix
filename = 'outPollution.xlsx';
sheet = 'IVT_witness';
    header =
{'i','j','k','IVTH','IVTT','IVTQ','IVTE','IVTWE','IVTLE','IVTAE','IVTHW
'};
```

```
      colnames = strcat(num2str(I),num2str(J),num2str(K));
     xlswrite(filename,IVT,sheet,'D2');
xlswrite(filename,header,sheet,'A1');
xlswrite(filename,colnames,sheet,'A2')


filename = 'out.xlsx'; %outputting x values
x=optimresults.x;
sheet = 'x';
    header = {'i','j','k','xH','xT','xA','xE','xWE','xLE','xAE','xHW'};
      colnames = strcat(num2str(I),num2str(J),num2str(K));
     xlswrite(filename,x,sheet,'D2');
xlswrite(filename,header,sheet,'A1');
xlswrite(filename,colnames,sheet,'A2');
```

Part 4 :Objective function and constraints

objective function(myOF.m)

```
function y =
myOFNT(x,PSR,PEBU,PWE,PLE,PAE,PHW,PTLE,PTWE,PTAE,PTHW,PHT,P
MT,PST,PHR,PIVTT,PIVTQ,PIVTH,PIVTE,PIVTWE,PIVTLE,PIVTAE,PIV
THW,PCT,PMSCp,POR,PER,PSEp,PICTWE,PICTLE,PICTAE,PICTHW,AHW,
DHW,VHW,AWE,DWE,VWE,AAE,DAE,VAE,ALE,DLE,VLE,U1,U2,UP,T,I,Q)

HC  =NP(x,T,PCT,PST,PMT,PHT,I).*PHR.*(1-x(:,1)).*PHT;
EC  =NP(x,T,PCT,PST,PMT,PHT,I).*PER.*(1-x(:,2)).*PCT.*(1-
x(:,4)).*PEBU ;
SC
=NP(x,T,PCT,PST,PMT,PHT,I).*(PMSCp+PST+POR+PST.*PER.*PSEp);
IVTT    =U1*PIVTT.*exp(x(:,2)-1).*PCT;
IVTQ    =U1*PIVTQ.*exp(x(:,3)-1).*PSR;
IVTE    =U1*PIVTE.*exp(x(:,4)-1).*PEBU;
IVTH    =U1*PIVTH.*exp(x(:,1)-1).*PHT;
IVTWE   =U1*PIVTWE.*exp(x(:,5)-1).*PWE;
IVTLE   =U1*PIVTLE.*exp(x(:,6)-1).*PLE;
IVTAE   =U1*PIVTAE.*exp(x(:,7)-1).*PAE;
IVTHW   =U1*PIVTHW.*exp(x(:,8)-1).*PHW;
floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))))

ICTLE   =-PICTLE.*(1-
x(:,6)).*PLE+PTLE*(floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))))/Q)*PICTLE;
ICTWE   =-PICTWE.*(1-
x(:,6)).*PWE+PTWE*(floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))))/Q)*PICTWE;
ICTAE   =-PICTAE.*(1-
x(:,6)).*PAE+PTAE*(floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))))/Q)*PICTAE;
```

```
ICTHW   =-PICTHW.*(1-
x(:,6)).*PLE+PTHW*(floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))))/Q)*PICTHW;

% ICTWE =U2*PICTWE.*x(:,5).*PWE;
% ICTLE =U2*PICTLE.*x(:,6).*PLE;
% ICTAE =U2*PICTAE.*x(:,7).*PAE;
% ICTHW =U2*PICTHW.*x(:,8).*PHW;
TS  =UP*floor((PSRf(x,PSR,I))*floor(T/
sum(TB(x,PCT,PST,PMT,PHT,I))));
CCWE    =U2*QLF(AWE,DWE,(1-x(:,5)).*PWE,VWE);
CCLE    =U2*QLF(ALE,DLE,(1-x(:,6)).*PLE,VLE);
CCAE    =U2*QLF(AAE,DAE,(1-x(:,7)).*PAE,VAE);
CCHW    =U2*QLF(AHW,DHW,(1-x(:,8)).*PHW,VHW);

y=sum(sum(sum(HC+EC+SC+IVTT+IVTQ+IVTE+IVTH+IVTWE+IVTLE+IVTA
E+IVTHW+ICTLE+ICTWE+ICTAE+ICTHW+CCLE+CCWE+CCAE+CCHW)))-TS;
end
```

Constraints(Constraints.m)

```
function
[c,ceq]=constraints(x,PSR,PEBU,PWE,PLE,PAE,PHW,PHT,PMT,PST,PIVTH,PIVTT,
PIVTQ,PIVTE,PIVTWE,PIVTLE,PIVTAE,PIVTHW,PCT,U1,D,IL,LEL,WEL,AEL,HWL,T,I
,eta)

IVTT    =U1*PIVTT.*exp(x(:,2)-1).*PCT;
IVTQ    =U1*PIVTQ.*exp(x(:,3)-1).*PSR;
IVTE    =U1*PIVTE.*exp(x(:,4)-1).*PEBU;
IVTH    =U1*PIVTH.*exp(x(:,1)-1).*PHT;
IVTWE   =U1*PIVTWE.*exp(x(:,5)-1).*PWE;
IVTLE   =U1*PIVTLE.*exp(x(:,6)-1).*PLE;
IVTAE   =U1*PIVTAE.*exp(x(:,7)-1).*PAE;
IVTHW   =U1*PIVTHW.*exp(x(:,8)-1).*PHW;


TUS =floor((PSRf(x,PSR,I))*floor(T/ sum(TB(x,PCT,PST,PMT,PHT,I))));
%Total Unit Sold


% Nonlinear inequality constraints
c=[D+eta*(mean((x(:,5)+x(:,6)+x(:,7)+x(:,8))/4))-TUS
sum(IVTT+IVTQ+IVTE+IVTH+IVTWE+IVTLE+IVTAE+IVTHW)-IL
sum(NP(x,T,PCT,PST,PMT,PHT,I).*(1-x(:,6)).*PLE)-LEL
sum(NP(x,T,PCT,PST,PMT,PHT,I).*(1-x(:,5)).*PWE)-WEL
sum(NP(x,T,PCT,PST,PMT,PHT,I).*(1-x(:,7)).*PAE)-AEL
sum(NP(x,T,PCT,PST,PMT,PHT,I).*(1-x(:,8)).*PHW)-HWL];
ceq=[];
end
```

Part 4 Matlab optimization settings

Algorithm:	SQP
Max iteration:	10000
Max function evaluation:	100000
X tolerance:	1e-33
Function Tolerance:	1e-22
Non-linear constraint tolerance:	10

Appendix C: GRI's environmental indicators- (GRI, 2006)

Environmental Performance Indicators

ASPECT: MATERIALS

CORE **EN1** Materials used by weight or volume.

CORE **EN2** Percentage of materials used that are recycled input materials.

ASPECT: ENERGY

CORE **EN3** Direct energy consumption by primary energy source.

CORE **EN4** Indirect energy consumption by primary source.

ADD **EN5** Energy saved due to conservation and efficiency improvements.

ADD **EN6** Initiatives to provide energy-efficient or renewable energy based products and services, and reductions in energy requirements as a result of these initiatives.

ADD **EN7** Initiatives to reduce indirect energy consumption and reductions achieved.

ASPECT: WATER

CORE **EN8** Total water withdrawal by source.

ADD **EN9** Water sources significantly affected by withdrawal of water.

ADD **EN10** Percentage and total volume of water recycled and reused.

ASPECT: BIODIVERSITY

CORE **EN11** Location and size of land owned, leased, managed in, or adjacent to, protected areas and areas of high biodiversity value outside protected areas.

CORE **EN12** Description of significant impacts of activities, products, and services on biodiversity in protected areas and areas of high biodiversity value outside protected areas.

ADD **EN13** Habitats protected or restored.

ADD **EN14** Strategies, current actions, and future plans for managing impacts on biodiversity.

ADD **EN15** Number of IUCN Red List species and national conservation list species with habitats in areas affected by operations, by level of extinction risk.

ASPECT: EMISSIONS, EFFLUENTS, AND WASTE

CORE **EN16** Total direct and indirect greenhouse gas emissions by weight.

CORE **EN17** Other relevant indirect greenhouse gas emissions by weight.

ADD **EN18** Initiatives to reduce greenhouse gas emissions and reductions achieved.

CORE **EN19** Emissions of ozone-depleting substances by weight.

CORE **EN20** NO, SO, and other significant air emissions by type and weight.

CORE **EN21** Total water discharge by quality and destination.

CORE **EN22** Total weight of waste by type and disposal method.

CORE **EN23** Total number and volume of significant spills.

ADD **EN24** Weight of transported, imported, exported, or treated waste deemed hazardous under the terms of the Basel Convention Annex I, II, III, and VIII, and percentage of transported waste shipped internationally.

ADD **EN25** Identity, size, protected status, and biodiversity value of water bodies and related habitats significantly affected by the reporting organization's discharges of water and runoff.

Appendix D: Indicators Proposed by Global Reporting Initiative (GRI, 2006)

Customer Relationship Management	X	X	X	industry-specific
Innovation Management			X	industry-specific
Market Opportunities		X		industry-specific
Marketing Practices			X	industry-specific
Price Risk Management		X		industry-specific
Research & Development			X	industry-specific
Risk & Crisis Management	X	X	X	general
Stakeholder Engagement	X			industry-specific
Scorecards/Measurement Systems		X		industry-specific
Total Economic Dimension Weight	**38%**	**35%**	**40%**	
Environmental Dimension				
Biodiversity		X		industry-specific
Business Opportunities Financial Services/Products	X			industry-specific
Business Risks Large Projects / Export Finance	X			industry-specific
Climate Change Governance	X			industry-specific
Climate Strategy		X	X	industry-specific
Electricity Generation		X		industry-specific
Environmental Footprint	X			industry-specific
Environmental Policy/Management System	X	X	X	general
Environmental Reporting	X	X	X	general
Operational Eco-Efficiency		X	X	industry-specific
Transmission & Distribution		X		industry-specific
Water-Related Risks		X		industry-specific
Total Environmental Dimension Weight	**24%**	**35%**	**10%**	
Social Dimension				
Addressing Cost Burden			X	industry-specific
Bioethics			X	industry-specific
Corporate Citizenship and Philanthropy	X	X	X	general
Controversial Issues, Dilemmas in lending/financing	X			industry-specific
Financial Inclusion/Capacity Building	X			industry-specific
Health Outcome Contribution			X	industry-specific
Human Capital Development	X	X	X	general
Labor Practice Indicators	X	X	X	general

Appendix E: Proposed Sustainability Indicators by GM

(Dreher et al (2009)