Lean Accounting: Measuring Target Costs

Adil Salam

A Thesis

in

The Department

of

Mechanical and Industrial Engineering

Presented in Partial Fulfillment of the Requirements
for the Degree of Doctor of Philosophy (Mechanical Engineering) at
Concordia University
Montréal, Québec, Canada

April 2012

CONCORDIA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: **Adil Salam**

Entitled: **Lean Accounting: Measuring Target Costs**

and submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY (Mechanical Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

______________________________ Chair
Dr. A. Schiffauerova

______________________________ External Examiner
Dr. J.E. Niosi

______________________________ External to Program
Dr. I. Dostaler

______________________________ Examiner
Dr. G. Gouw

______________________________ Examiner
Dr. M.Y. Chen

______________________________ Thesis Supervisor
Dr. N. Bhuiyan

Approved by ______________________________
Dr. W-F. Xie, Graduate Program Director

April 4, 2012 ______________________________
Dr. Robin A.L. Drew, Dean
Faculty of Engineering & Computer Science

ABSTRACT

Lean Accounting: Measuring Target Costs

Adil Salam, Ph.D.

Concordia University, 2012

Aerospace is very important to the Canadian economy, with over 80,000 employees; generating over $20 billion dollars in revenue. However, the industry is facing many challenges. With the economic downturn, sales have been decreasing. Competition is growing with emerging countries entering the market, with the aid of government subsidies, as well as lower costs of production. Companies are struggling to stay competitive, and they are adopting various practices to deliver value to their customers. The principles of lean manufacturing strive to do just that, and while enjoying much success in production environments, lean principles have been found to be applicable in other areas of the enterprise, including accounting. This thesis presents the notion of target costing for new products, which is one of the pillars of lean accounting. In comparison to traditional costing of products, where the desired profit is added to the cost required to develop the product, target costing is 'lean' in the sense that it puts the focus on creating value for the customer by setting the price of the product based on the cost. A number of methods exist for determining target costs, however, the accuracy of such methods are critical. In this thesis, various types of target cost models are developed and compared to one another in terms of their accuracy. The models are based on parametric models, neural networks and data envelopment analysis. The models are then applied to predict the cost of commodities at a major Canadian aerospace company.

ACKNOWLEDGMENTS

All praise is to God, who allowed me to complete this thesis.

I would like to thank my thesis supervisor, Dr. Nadia Bhuiyan. Apart from the financial support, I have gained much from "Dr. Nadia". Over the years, she has been very compassionate and has gone out of her way on countless occasions to provide guidance in my research, at work, and in life. I would like to take this opportunity to say, "thank you."

I would like thank my friend, Dr. Defersha, who provided valuable advice for this research.

I would like to thank my parents, Abdul and Sajeela Salam, for their moral support.

I would like to thank my wife, my son, and my daughter Aisha, Omar, and Arwa. They were understanding, and patiently waited for me many an evening when I would get home late, as I worked on this thesis.

Finally, I would like to thank the personnel at Bombardier Aerospace, where this research was applied.

This thesis is dedicated to my father, Abdul Salam who had to abandon completing his PhD to care for his family

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ACRONYMS

ADT	-	Advanced design team
ANN	-	Artificial neural networks
ANOVA	-	Analysis of variance
BA	-	Bombardier Aerospace
BP		Back propagation
CER	-	Cost estimation relationship
CERs	-	Cost estimating relationships
CNLM	-	Complex non-linear model
DEA	-	Data envelopment analysis
DMU	-	Decision making unit
GA	-	Genetic algorithm
ISPA	-	International society of parametric analysis
IT	-	Information Technology
JIT	-	Just in Time
KPI	-	Key performance indicator
LB	-	Lower bound
LCC	-	Life cycle costing
LCL	-	Lower control limits
LG	-	Landing gear
LR	-	Linear regression
MLG	-	Main landing gear
MLG	-	Main landing gear
MLRM	-	Multiple linear regression model
MTOW	-	Maximum takeoff weight
NL	-	Non-linear
NLG	-	Nose landing gear
NLM	-	Non-linear model
NN	-	Neural networks
PA	-	Path analysis

PC	-	Product complexity
RM	-	Regression models
SC	-	Supply chain
SPC	-	Statistical process control
SPCO	-	Single-point-crossover-operator
SSR	-	Regression sum of squares
SSTO	-	Total sum of squares
SwCO	-	Swap-crossover-operator
TC	-	Target cost
T-Price	-	Target price
TP	-	Target profit
TPS	-	Toyota production system
TQM	-	Total quality management
UB	-	Upper bound
UCL	-	Upper control limits
UK LAI	-	UK Lean Aerospace Initiative
VSC	-	Value stream costing

LIST OF SYMBOLS

a, b, c_m	:	Constants (weights) estimated from historical data
y	:	Target cost
β_0	:	Intercept
β_1	:	Slope
ε	:	Error
β_j, β_m	:	Regression coefficients
X_k	:	k^{th} dependent variable
$\hat{y}$	:	Target cost
σ	:	Standard deviation of the residuals
R^2	:	Coefficient of determination
r_L	:	Correlation coefficient
H_o	:	The error has a normal behaviour
H_1	:	The error not to have a normal behaviour
r	:	The resulting correlation coefficient
Ps_i	:	Pseudo-value for the entire sample, omitting sub-sample i
n	:	Population size
ns	:	Number of sub-samples
$\hat{\beta}$	:	Least-squares estimator of the whole sample
$\hat{\beta}_{-i}$,	:	Least-squares estimator for the entire sample, omitting sub sample i
$\widetilde{\beta}$	:	The jackknife estimator
U	:	The un-correlated value of the function
p_{0i}	:	The direct and indirect effects that the independent variables
r_{ij}	:	The inter-relationships
a_i	:	Regression coefficient of the independent variable *i*
p_{0U}	:	The value of path coefficient
y_n	:	Actual value for sample number *n*
σ^2_y	:	Variance of the sample data of the dependent variable

$\sigma^2_{\hat{y}}$	:	Variance of the predicted output value
σ^2_e	:	Variance of the residuals
$w_{j,i,l}$	:	The weight for the connection between j^{th} neuron of layer $l-1$ and i^{th} neuron of layer l
$f(net)$	:	Nonlinear activation function
Q	:	The temperature of the neuron
η	:	The learning rate
∇	:	Gradient
$o_{p,j,l}$	:	The output of the j^{th} neuron of layer, l
$\delta_{p,j,l}$	:	The error signal at the j^{th} neuron of layer l
$t_{p,1,2}$	:	The desired value at the neuron in the output layer (layer 2)
α	:	Small Probability
I	:	The number of inputs
O	:	The number of outputs
E_k	:	The efficiency measure
$u_{i,k}$, $v_{o,k}$	:	Non-negative weights
c	:	A positive constant
$x_{i,k}$	:	An input quantity
D_m	:	Effort Driver (factor m)
$\hat{E}$	:	Estimated design effort
PC	:	Product complexity
X_1	:	Weight of the MLG
X_2	:	MTOW
X_3	:	Height of the MLG
y_i	:	Masked cost of the MLG
δ	:	The maximum value for the stopping criterion
θ_{max}	:	Maximum step size
k	:	*k-way* tournament factor
α_1	:	Probability of SwCO-1
α_2	:	Probability of SwCO-2
α_3	:	Probability of SPCO-1

α_4	:	Probability of SPCO-1
α_5	:	Probability of chromosome being mutated
α_6	:	Probability of gene being mutated

1. Introduction

Canada is a world leader in aerospace. There are more than 400 firms across the nation. Canada is a global leader in producing business and regional jets, helicopters, commercial helicopters, engines, amongst others (AIAC, 2012). The Canadian Aerospace industries employed 81,050 Canadians in 2010, and according to Statistics Canada (2009), 55% of the jobs in 2007 were in the province of Quebec. The aerospace industry is an important element of the Canadian economy: in 2010, it generated $21 billion dollars of revenue, and has exported over $15 billion dollars (AIAC, 2012).

Bombardier Aerospace (BA) has significantly contributed to the revenue generated in Canada. According to their 2011 annual report, their annual revenue was $8.6 billion dollars. They specialize in the manufacturing and assembly of business and regional jets. They employ over 30,000 people worldwide (2011 BA Annual Report, 2012)

However, in the current global economy, BA amongst the other aerospace companies is struggling to remain competitive. During this economic downturn, resulting in the reduction of revenue coupled with the advent of emerging countries, the aerospace companies are facing many challenges. Furthermore, the volatility of the fuel prices has impacted the economics of the airline, and has reduced the demand for new products (2011 BA Annual Report, 2012).

One of the major challenges for companies in this difficult era is to identify value and deliver it to its stakeholders. To meet this challenge, many philosophies and principles were developed and have evolved over the last few decades. These principles, such as Just in Time (JIT), Total Quality Management (TQM), Statistical Process Control

(SPC) and Lean Manufacturing, are applied to both manufacturing and engineering environments to meet the company's requirements in providing value to their stakeholders (Bicheno, 2001; Rother and Shook, 1999). The principles of lean manufacturing in particular focus on the creation of value through the elimination of waste. The roots of lean are in the automotive industry (Womack *et al.*, 1990). It began with Henry Ford who introduced the notion of mass production in automobile assembly, which evolved into the Toyota Production System (TPS), introduced by Taichi Ohno in Japan and now better known as lean manufacturing. The application of lean principles has gained much impetus in the recent past, and has found success in areas other than manufacturing, such as in engineering, administration, and even at the enterprise level, which extends beyond the company itself. The term 'lean' is now used to apply to the more general case.

Accounting is one area in which lean principles have been applied. Since the application of lean requires a very different way of working, accounting procedures must also adapt to these new methods. Researchers such as Ahlstrom and Carlson (1996), DeFilippo (1996), Womack and Jones (1996), and Bahadir (2011) have pointed out how companies have realized that their current (traditional) costing and account management principles conflict with the principles of lean. Traditional costing methods refers to methodology of the allocation of manufacturing overhead to the products produced thereof (Maskell, 2004; Fang, 2011). Because these traditional methods are designed to accommodate the financial accounting requirements, the overhead costs have no relation to the resources allocated to the individual demand of each product. In other words, the costs allocated to a specific product are not causally related to the value of the mentioned product. Traditional accounting practices focus primarily on lowering product costs. Such limitations have called for the implementation of new management accounting systems that focus on the profitability of the entire value stream of the product (Maskell and Baggaley, 2002; 2006).

The introduction of new products in many industries, including the aerospace industry, can be characterized by long development cycles and can account for major costs to the company. The technique that can be used to quantify the cost of these products over the length of their total life is by evaluating the total life cycle cost.

Life cycle costing (LCC) focuses on a detailed total acquisition cost starting from development, research, maintenance, production, operations, etc. in order to determine the cost of a product. A modified version of the LCC equation presented by Rahman and Vanier (2004) is as follows.

$$\text{LCC} = \text{Acquisition Cost} + \text{Ownership Cost} \tag{1}$$

The acquisition cost refers to the direct and indirect costs of procuring the product, whereas ownership cost refers to the costs of utilizing and maintaining the product. In order to estimate the acquisition cost, one must understand its target cost (TC). The TC is the financial goal of the full cost of a given product, derived from the estimate of its selling and the desired profit Rhodes (2006). It uses the competitive market price and works backwards to achieve the desired cost. The equation for TC is as follows:

$$\text{Target Cost} = \text{Market-driven Target Price} - \text{Demand Profit Margin} \tag{2}$$

Estimating the cost (or target cost) is a key element of many engineering and managerial decisions (Smith and Mason, 1997). As target costing focuses on the product and its characteristics, (Kocakülâh and Austill, 2011), those characteristics will be the basis of estimating the cost. Therefore, in order to develop an accurate cost model, the cost drivers have to be defined. The cost drivers are those factors or characteristics of the product that will influence the cost (Elragal and Haddara, 2010), hence the premise of the cost model. In a regression based model they are used to develop the final target cost model, or the cost estimating relationship (CER). These models are critical for the strategic planning of an organization. Furthermore, it will help in budgeting, negotiating, and selecting suppliers when considering the introduction of a new product. The focus of this research is on target costing in a lean environment.

1.1 Thesis Objectives

Traditionally, companies set the price of their product on the basis of what it cost to develop the product, otherwise known as cost plus pricing. The desired profit is then added to the cost based on required margins. However, this is not a very competitive method as the end price may be higher than the market price. In a lean environment, the opposite takes place. The cost of the product is based on the selling price; hence the focus is on the value created for the customer. Thus, if a company knows the price at which it wishes to sell its product in order to be competitive, then they can determine the cost at which this product needs to be developed, which in turn can turn the focus on designing and developing the product in order to meet that cost. This is the target costing method. It is used in new product introduction and requires highly integrative processes which are all designed to create value for the customer. This is the essence of lean.

The objective of this thesis will be to develop models to predict target cost based on cost drivers. The models will be developed for the introduction of new products in the market. The focus of this study will be on a particular product or commodity, but the findings can be applied to other commodities and used in a general fashion. Several methodologies will be used to approach the problem at hand.

1.2 Methodology

With the cost drivers, several models are developed to estimate the target cost. The models will be based upon parametric, neural networks, and data envelopment analysis. Several tools and techniques such as path analysis, and analysis of variance will be used to validate the cost models. Two types of training algorithms will be used to develop the neural network models. Finally, a modified version of the traditional data envelopment method will be developed for estimation purposes. A conceptual diagram of the methodology is shown below.

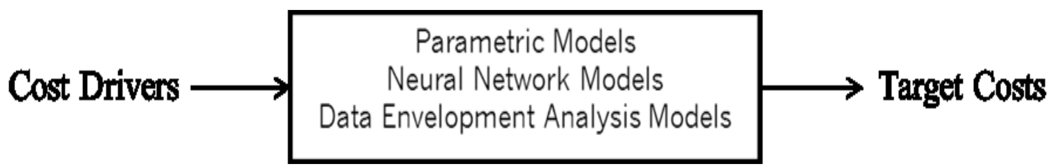


Figure 1.1: Conceptual diagram of methodology

The three types of models will be analyzed and compared in order to determine which model will most accurately predict the cost. The models are then applied to the costing of an aircraft component at Bombardier Aerospace.

1.3 Organization of Thesis

This thesis is organized as follows. A review of existing work on traditional cost accounting, lean accounting and models developed to predict the cost is presented in Chapter 2. Chapter 3 discusses the models developed to estimate the target cost. The company and its corresponding case are presented in Chapter 4. Chapter 5 presents the results and analysis. The summary of findings, practical application and managerial implications are presented in Chapter 6. Finally, Chapter 7 presents conclusions and limitations of the thesis, and discusses potential future research.

2. Literature Review

Much research has been conducted on traditional costing methods. According to Kaplan (1988), a major problem with traditional cost management (accounting) practices is the incorrect allocation of overhead. Kaplan (1998) states that companies are using their direct labour to allocate overhead, when in fact the direct labour only represents a minor portion (about 10%) of the manufacturing costs. The incorrect allocation of costs can result in losing competitive strategy (Cooper, 1995; Maskell, 1996).

Traditional cost management principles may also misguide many managers due to the reliance on procedures put in place to reduce the unit cost of a product. As the overhead will typically be allocated over the total number of units produced, it would push for the high production of units, with the intent of fully utilizing labour and machines. Even though, based on cost allocation practices, it would reduce the average overhead per unit, it would result in over production, hence a great amount of inventory. Therefore researchers state that traditional methods are appropriate when dealing with standard mass production industries of the 1960's, but not of those today (Johnson and Kaplan, 1987; Johnson, 1990; Turney, 1991; Johnson, 1992; Maskell and Lilly, 2006; Stenzel, 2007; Cooper and Maskell, 2008).

Moreover, traditional methods can push management, by not understanding the cost drivers, to develop products that are over engineered and do not meet the needs of the customer (Butscher *et* al., 2000). It can also lead management to develop performance measures that do not reflect the priority, as they do not focus on the right things, i.e. the product, its characteristics, and ultimately the customer (Maskell and Baggaley, 2002).

Zbib *et al.* (2003) summarize the drawbacks of traditional accounting principles for companies driven by their supply chain. Some of the disadvantages reported are the following:

1. Do not account for the changes in the cost structure
2. Over emphasize the relevance of direct labour cost
3. Not fully aligned with just in time (JIT) principles
4. Inconsistency in the continuous improvement activities
5. Ignores the needs of the customer
6. Purchasing decision based upon the lowest price
7. Too many suppliers
8. Performance measurements on cost alone, can overlook quality and on time delivery

Many shortcomings of traditional practices have been highlighted by several researchers. Fritzch (1998) proposed two methods to establish product cost: activity-based costing (ABC) and the theory of constraints (TOC). TOC focuses on increasing the profitability of an organization by adjusting the scheduling to maximize the manufacturing output (Goldratt and Fox 1992, 1996; Goldratt, 1999). Goldratt and Fox (1992) argue that focusing on the product cost is a way of the past and the focus should be on maximizing the throughput (manufacturing production). Their underlying assumption is that there are negligible (or minimal) variable costs, and the majority of the costs are fixed.

According to Ifandoudas and Gurd (2010), the premise of the TOC model is to focus on the global efficiency, rather than any local efficiency. Moreover, they state that the throughput, the inventory, and the operating expense are the measures for activities for a business using the TOC model. Razaee and Elmore (1997) state that if the TOC model is properly implemented in an organization, it can result in a reduction in inventory, lead-time and cycle-time, while increasing the productivity and quality.

However, Kaplan (1998) states that the TOC is flawed due to wrongfully classifying parameters, such as price and labour rates as fixed costs. Moreover, Kaplan (1998) challenges the TOC model, due to it conglomerating many of the costs as operating expenses, which results in a larger portion of unallocated costs then that even of traditional costing.

According to Fritzch (1998), apart from the TOCs model, the other methodology of establishing the product cost is activity-based costing (ABC). ABC, also known as activity-based accounting focuses on the manufacturing processes related to the development of a product (Johnson and Kaplan, 1997). All the incurred costs from the direct and indirect processes are allocated to a product to establish its unit cost. Thus, according to Carmo and Padovani (2012), its objective is to reduce the distortion caused by arbitrarily allocating the indirect costs. The benefit of ABC is that is provides a precise view of the consumption of resources by activities, which corresponds to the costs (Cokin *et al*., 2012).

Even though the ABC method has overcome some of the obstacles of traditional accounting, it has its drawbacks. Benjamin *et al*. (2009) argue that ABC is simply an extension of traditional accounting, as they state that ABC simply splits (allocates) the overhead into several bases instead of one, as is the case in traditional accounting. For this reason, Benjamin *et* al. (2009) proposed the methodology of efficiency based absorption costing (EBAC). They state EBAC is an improvement to ABC by considering the element of overhead utilization efficiency when allocating the costs. They define efficiency as the ratio of input required to produce an output. They further explain the efficiency rate as a division of the number of cost drivers of a particular product, by the number of units produced thereof.

Other researchers such as Womack and Jones (1996), who are strong promoters of lean manufacturing, have also questioned the principles of ABC. They argue that it requires many resources to implement, and is costly to maintain. Furthermore, they state as ABC will solely focus on cost minimization, it will not focus on continuous improvement, waste reduction, and most importantly, the customer and the value created for them. Finally, they state that ABC is simply another method of allocating costs, which is a pivotal flaw in the principles of traditional accounting.

Some of the shortcomings of traditional accounting have been overcome through the use of lean manufacturing principles. Lean manufacturing has had great success in production environments (Lander and Liker, 2007) through a focus on the creation of value through the elimination of waste. Taichi Ohno (1912 - 1990) was a Toyota executive who had identified seven types of deadly wastes, which are referred to as *muda* in Japanese. The seven wastes are: Excessive Motion, Waiting Time, Over Engineering, Unnecessary Processing Time, Defects, Excessive Resources and Unnecessary Handoffs (Womack and Jones, 1996). The objective of lean is to act as an antidote to eliminating these wastes. Oakland and Marosszeky (2007) quote James Womack, president and founder of Lean Enterprise Institute, who said, “None of us have seen a perfect process, nor will most of us ever see one. Lean thinkers still believe in perfection, the never ending journey towards the truly lean process." Womack and Jones (1996) defined the five basic principles of lean; Value, Value Stream, Flow, Pull, and Perfection. Since the focus of lean thinking is on the customer, it is important to understand what the customer perceives as value. After the value to the customer is identified, the value stream of the product should be identified. The value stream includes taking a product through the design, make and order phase. All the processes in the value stream should flow to avoid interruptions. Wherever continuous flow is not possible, a pull system should be introduced. The pull system is created so that a product is produced just in time, when it is required from the customer. Lean principles are a continuous process of improvement which always seeks the fifth principle, perfection. In short, lean thinking is employed because it provides a method to do more with less (Womack and Jones, 1996).

More recently, the success of lean manufacturing principles has led to their application in other areas of the enterprise, such as to the supply chain (Miao and Xu, 2011), engineering (Black and Philips, 2012; Beauregard, 2010; Schulze and Störmer, 2012) and even accounting (DeBusk, 2012).

DeFilippo (1996), Womack and Jones (1996), Maskell and Baggaley (2002), Cooper and Maskell (2008), and Bahadir (2011) indicated the urgency of aligning accounting principles with a lean philosophy. Lean accounting focuses on eliminating waste in the accounting process. There are many sources of such waste such as unnecessary transactions, meetings, and approval processes that are time consuming, costly and serve no value (Maskell and Lilly, 2006). Some of the many benefits of lean accounting that Maskell and Baggaley (2004) stated are the following:

1. Provides information in order to make better (lean) decisions

2. Eliminate redundant systems and unnecessary transactions which will reduce time and cost
3. Provides information and statistics focused on lean
4. Directly addresses customer value

Ward and Graves (2004) in conjunction with the UK Lean Aerospace Initiative (UK LAI) developed a theoretical framework for supporting lean thinking with respect to cost management in the following three dimensions:

1. Manufacturing
2. Extended Value Stream
3. New product introduction

In the dimension of manufacturing, they identified the following three parameters for consideration.

1. Product costing and overhead allocation
2. Operational control
3. Costing for continuous improvement

They proposed using the notion of value stream costing, the process of allocating all the costs to the product or value stream, rather than a department (Stenzel, 2007). Furthermore, for operational control, they proposed using lean performance measures, such as the *takt* time, which, also referred to as the output rate, is the synchronization of the paces of different processes (Seth and Gupta, 2005). Ward and Graves (2004) discussed several techniques such as kaizen costing, cost of quality, cost of waste, and activity based costing for continuous improvement, where kaizen costing refers to finding opportunities and proposing alternative techniques for the manufacturing of the part to reduce the cost (Mondem and Hamada, 1991). Wang (2011) describe the two elements of kaizen costing being the accounting and physical control system. The accounting control systems are those of continuously setting and deducing cost reduction targets, whereas the responsibility of achieving the targets and placed upon the shop floor, is known as the physical control system. As kaizen costing focuses on the continuous reduction in cost, it is aligned with the principles of lean accounting (Modarress *et al.*, 2005).

In terms of the extended value stream, which is the entire supply chain from raw material provider to the end customer (Womack and Jones, 2003), they (Ward and Graves, 2004) proposed kaizen costing and target costing (TC) with the intent of reducing the costs. Similarly target costing along with life cycle costing, was proposed for cost management techniques for the introduction of new products.

Target costing originated in Japan in the 1960's (Ellram, 1999; 2000; 2006) and was originally known as G*enka Kikaku* (Nicolini *et al*, 2000). Target costing is defined as a methodology of using a systematic process of managing the cost of a product during its design phase (Ibusuki and Kaminski (2007); Iranmanesh and Thomson (2008); Ax *et al.,* (2008); Filomena *et al.* (2009); and Kee (2010). Target costing is more simply defined as the process of deducing the target cost (TC) from the difference of desired target profit (TP) and the target price (T-Price) of the market (ie. TC = TP – T-price). The TC is defined as the financial goal of the full cost of a given product, from derived from the estimate of its selling and the desired profit (Rhodes *et al*., 2006). Ulrich and Eppinger (2012) define TC as the manufacturing cost at which a company and all of its associated stakeholders for the given distribution channel, while make sufficient profit at a competitive price. Yazdifar and Askarany (2012) summarize the two objectives of target costing as:

1. Reducing the cost of the new product so the required amount of profit can be achieved (Target Profit = Target Price – Target Cost). Furthermore, this is to be coupled with satisfying the following three conditions
    i. Quality
    ii. Development time
    iii. Price demanded from the global market
2. Motivating employees up front, during the development phase, to achieve the target profit.

As the intent of TC is to reduce the cost to obtain the target profit, it has been applied in many domains. Some of the recent research in TC has been in the domains of IT (Choe, 2011), construction (Pennanen *et al*., 2011; Chan *et al.* 2010; 2011), rail transportation (Mathaisel *et al*., 2011), food (Bertolini and Romagnoli, 2012), automotive (Slater, 2010), and aerospace (Bi and Wei, 2011).

According to Lorino (1995), over 80% of the large Japanese assembly companies had adopted TC. This is not the case in the rest of the world. According to a recent study, Yazdiffar and Ashkarany (2012) conducted a study on manufacturing firms in Australia, New Zealand, and the United Kingdom, and found that less than 20% of the firms adopted the practice of TC.

Jenson et al. (1996) studied several case studies and found that those that incorporated lean accounting principles to pursue excellence all possessed the following characteristics:

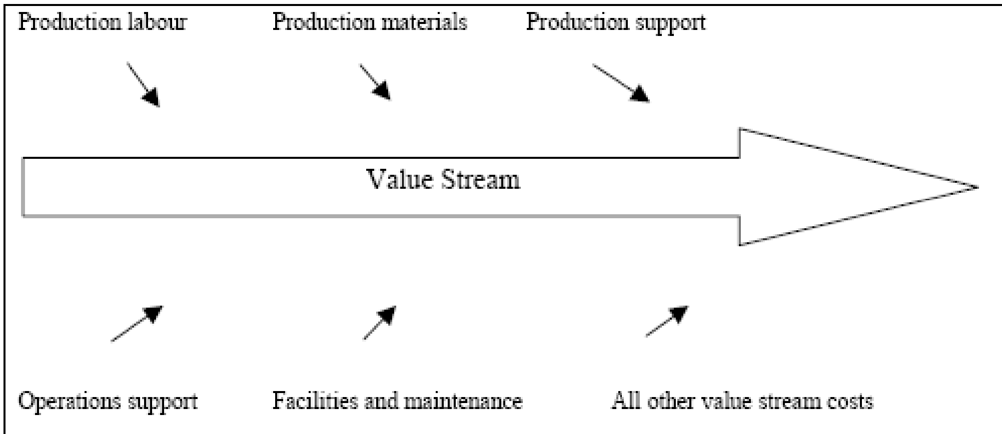
1. Integration of business and manufacturing cultures
2. Recognized lean manufacturing and its effect of management accounting
3. Emphasize on continuously improving their accounting methods
4. Strive to eliminate waste in accounting
5. Encourage a pro-active management culture

Maskell (1996, 2000) developed a theoretical framework to show how companies adopting the principles of lean can move away from the traditional cost management techniques. Maskell's 4-Step lean accounting maturity model provides a framework that shows the various levels of maturity of organizations incorporating lean costing principles.

The first level of maturity is to address the low-hanging fruit in which current accounting and control system is maintained by minimizing waste from the system. Secondly, by removing unnecessary transactions, the redundant cost of excessive financial reporting will be eliminated. Thereafter the 3rd level of maturity will eliminate waste. The operations are independent from the accounting reporting periods. Finally, the fourth level of maturity is lean accounting. It focuses on minimizing transactions such as in product completion and product shipment.

Other more recent models have been developed based on the principles of lean. Gamal (2011) applied the principles of lean accounting to develop a Value Stream

Costing (VSC) model. According to Cooper and Maskell (2008), utilizing the VSC methodology will result in a transparent accounting system. This system will be used to track the value streams of a particular product. Figure 2.1 presents a conceptual diagram of VSC. VSC enables the proper allocation of cost to a product, or value stream. This allocation will reflect a realistic picture of the cost of the product, without having costs arbitrarily allocated to them, as was the case in traditional accounting.



Source: Maskell and Baggaley (www.maskell.com)

Figure 2.1 Conceptual Diagram of VSC

As can be seen from VSC the emphasis is on the actual cost of the product. In order to estimate the cost of the product, one can develop a target cost. Odedairo and Bell (2009) have pointed out that TC is the cost the customer is willing to pay for a product. Lean accounting focuses on the product and its characteristics (Kocakülâh and Austill, 2011). These characteristics can be the basis of making an estimate. Foussier (2006) describes how estimates can be quantitative or qualitative. The qualitative analysis is based upon heuristic rules or the judgment of experts. According to Layer *et al.* (2002), the quantitative estimates can be further divided into the following three categories;

analytical, analogous, and statistical models. The statistical models contain both regression models (RM) and models using neural networks (NN).

In recent years, research has been conducted on cost estimation using both RM and NN. Salam *et al.* (2008, 2009) developed RM using both linear and non-linear models to estimate the design effort for an aircraft component. The estimated cost can easily be derived by multiply the effort by the labour rate. Furthermore they utilized the jackknife technique, which is a sub-sampling technique to reduce the bias. Moreover, an analysis of variance (ANOVA) was conducted to determine the significant cost drivers. It was found the estimate based upon a non-linear model yielded better results.

Sayadi *et al*. (2012) conducted a comparative study between single point and multiple non-linear (NL) RM. Their findings were that the NL RM has a better outcome to predict the costs.

Caputo *et al.* (2008) compared the use of NN models trained using back propagation, to that of a non-linear regression model to estimate the cost of a pressure vessel. The term training using back-propagation (BP) refers to a systemic process of adjusting the weights of the NN in order to reduce the square error (Pandya and Macy, 1996). They found the estimation based upon NN to outperform those using the non-linear regression model. They as well as Chou *et al*. (2010) pointed out the requirement of a large sample size in order to have meaningful results using NN.

Chou *et al*. (2010) conducted a comparative analysis of RM to NN trained using BP to NLM, In order to estimate the development cost of manufacturing equipment. Their findings, similar to Caputo *et al*. (2008), was that the NN models using BP outperforms the NLM. In recent years, other researchers, such as Ju and Xi (2008) and Zangeneh *et al*. (2011) have used the NN trained using BP to estimate the cost.

NN can also be trained using the genetic algorithm (GA). Even though the NN based upon GA have been used in many domains, there is little literature found on comparing the use of the GA versus BP for the training algorithm on cost estimation.

Table 2.1, summarizes the research found on comparing the methodologies of cost estimation, as well as the tools and techniques they used for estimation thereof, and shows the analysis to be conducted in this thesis.

Table 2.1: Comparison of developed models

	Linear Model	Non-Linear Model	NN trained using BP	NN trained using GA
Thesis' models and techniques	✓	✓	✓	✓
Salam *et al.* (2008; 2009)	✓	✓		
Sayadi *et al*. (2012)		✓	✓	
Caputo *et* al. (2010); Chou *et al*. (2010)		✓	✓	
Ju and Xi (2008), Zangeneh *et al.* (2011)			✓	

As there has not been research conducted using an exhaustive approach to compare all estimation techniques, this thesis takes a holistic approach by using the above-mentioned methods to estimate target costs. It will also present a complex non-linear model (CNLM) used to estimate the cost. Furthermore, it will discuss the development of an adapted mathematical model, namely data envelopment analysis, which is typically used to calculate efficiency; however it is modified to serve as a target costing model. All models will be applied in a case study on a commodity in the aerospace sector.

3. Target Costing Models

In this chapter, the models developed to estimate the targets costs are described in detail. There are three types of models that are developed. This first type is a parametric cost estimation model. Two types of regression models and a complex non-linear model are developed. The second model is based on neural networks. Two types of neural network models relying on different training algorithms are presented. Finally, the third model presented is a data envelopment analysis model.

3.1 Parametric Cost Estimation

Parametric cost estimation is a technique that can be used to develop a cost estimate based on the statistical relationship of the input variables, (PMI, 2000; ISPA, 2009). Parametric cost estimation has many applications. It is a tool that is deemed essential for project management (PMI, 2000). In the context of projects, parametric estimation determines estimates for parameters (e.g. cost or duration) using historical data and/or other variables. It can be used to determine the feasibility of a project, to determine a budget, and to compare projects (products), amongst others (Fragkakis *et al.*, 2011). The input variables, which are the cost drivers, will be used to formulate the cost model or the cost estimating relation (CER). The parametric CERs are commonly utilized to estimate the cost during the design phase of a product, when only the few, yet key design parameters or input variables (in this case, cost drivers) are known. CERs can be parametric or non-parametric. The generic formula is as follows:

$$\text{CER}\ (y) = f(x_i) \tag{3}$$

The CER, or the target cost is a function of its input variable(s). CERs can be simple or complex. The simple CERs depend on a single cost driver, whereas the complex CERs depend on multiple cost drivers (ISPA, 2009). By identifying the cost drivers, parametric models can be developed. Parametric models can be linear, non-linear, log-normal, and exponential, amongst others.

In this thesis, two models based on linear regression are selected to formulate the CER. The reason for selecting the regression models are because they are commonly used in practice today, and they will formulate the basis of comparison to the other more complex models developed and discussed in the sections to come.

The simple CER based on a linear regression (LR) model can be denoted as following.

$$y = \beta_0 + \beta_1 X_1 + \varepsilon \tag{4}$$

where,

y, Target cost

β_0, Intercept

β_1, Slope

X_1, cost drivers

ε, Error

As can be seen, the element of error is introduced. The error, or noise, represents the element of the cost not described by its cost driver. As can be seen from the standard form there is only one independent variable, hence only one cost driver. However in many cases, such as that of this case study, several cost drivers are selected, thus the CER will be complex. The complex form of the CER using regression can be denoted by the multiple linear regression model (MLRM). The MLRM function is as follows:

$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \varepsilon \tag{5}$$

where,

y, Target cost dependent on k predictor values

β_j , Regression coefficients

X_k, k^{th} independent variable

ε, Error

The regression coefficients are deduced by the method of least squares. The least squares estimation generates an equation that will minimize the sum of the square errors (Kutner *et al*., 2004). As the method of least squares has been commonly used for several years, it will not be further described.

Another complex CER will be developed based upon a standard non-linear model (NLM). The purpose of developing another parametric CER will be used as a comparison mechanism to that based upon the MLRM, in terms of accuracy of prediction. In statistics, the NLM is a type of regression that utilizes data modeled in the form of non-linear combinations (Montgomery, 2005). Below is the formula for the NLM used in this study.

$$\hat{y} = \beta_0 X_1^{\beta_1} X_2^{\beta_2} X_3^{\beta_3} \tag{6}$$

where,

$\hat{y}$, Target cost

X_m, Specified cost driver

β_m, Regression coefficient

Since Equation (6) is represented in a non-linear form, it must be transformed into a linear model to conduct the regression analysis. The manner to transform the model in a linear form is simple, the natural log (ln) on both sides of the equation are taken. The resulting equation will thus be suitable for linear regression. The linear equation generated is shown below.

$$\ln \hat{y} = \ln (\beta_o) + \beta_1 \ln (X_1) + \beta_2 \ln (X_2) + \beta_3 \ln (X_3) \tag{7}$$

Thereafter, as the equation is in the standard linear regression form, the least squares method will be utilized to calculate the regression coefficients. As the units for the input and output variables are not identical, the units will have be addressed, and this will be done through dimensional analysis. Dimensional analysis is a tool used to verify relations between physical quantities by checking their dimensions (Palmer, 2008). In the case where all the input variables do not have the same units, the simplest way to remove them would be to divide each input value by a reference value of unity having the same units. The procedure would be the following.

Step 1

Categorize all the input data, by their given dimensions.

Step 2

Divide all the reference data of the ith variable for sample *n*, with dimension d_i by the reference value of 1 having the same d_i.

$$x_{ij} = \frac{x^{old}{}_{ij} d_i}{1 d_i} \tag{8}$$

If this procedure is repeated for all the variables, none of the values will have any dimensions, hence be dimensionless. The analysis can be carried out without the constraint of different dimensions of variables.

Even though the units have been removed using the dimensional analysis technique, the models are linear. As the models described in Section 3.1 are based upon linear regression, it is important that the linearity and normal assumptions are met.

3.1.1 MLRM Assumptions

In order to use the MLRM the following two assumptions need to be satisfied.

1. Linearity assumption

2. Normality assumption

3.1.1.1 Linearity assumption

In order to determine if the function is linear for a given case of the MLRM, scatter plots or residual plots can be made. In the case of the scatter plot, the standardized residuals could be plotted against the non-standardized predicted value. For a linear function, the scatter plot should not have any curvilinear patterns.

Another graphical manner to statistically prove the validity of the MLRM is to create statistical process control (SPC) charts. In the context of this research, the predicted values against the actual values of target cost will are plotted. The errors or residuals will be the deviation from the line ln (Predicted) = ln (Actual) + ε. The expected error, assuming a normal distribution, is zero, i.e. $E(\varepsilon) = 0$. Thus, the mean of the function f(x), will simply be f(x). The equations for the upper control limits (UCL) and lower control limits (LCL) are shown below.

$$UCL = f(x) + 3\sigma \tag{9}$$

$$LCL = f(x) - 3\sigma \tag{10}$$

where,

f(x), Masked Cost = Target Cost + ε

σ, Standard deviation of the residuals

As can be seen from equations (9) and (10), the notion of masked cost is introduced. As can be understood, Bombardier, similar to any other company, is sensitive to proprietary information. The company will not divulge the commercial terms they have with their suppliers. On the other hand, it is important for the regression to have meaningful results. Thus, the use of a proper data masking technique is important. A masking technique described by Muralidhar *et al*. (1999) was applied to the company raw data and will be described in a later section.

According to Montgomery (1985), if the residuals are within 3σ of the expected value of the function, then the function is considered to be statistically in control. In other words, the assumption of linearity holds.

3.1.1.2 Normality assumption

The second assumption that must be validated is that the error values follow a normal distribution. The test to determine error normality requires the coefficient of correlation, *r*. The value of r is calculated from the following equation.

$$r = \pm\sqrt{\mathrm{R}^2} \tag{11}$$

where,

R^2, Coefficient of determination

The value of R^2 is calculated from the following equation.

$$R^2 = \frac{\mathrm{SSR}}{\mathrm{SSTO}} \tag{12}$$

where,

SSR, Regression sum of squares

SSTO, Total sum of squares

This will also involve a hypothesis test in which the critical values for the correlation coefficient, r_L prepared by Looney and Gulledge (1985) are to be compared against the resulting correlation coefficient, *r*, from the generated regression model. The H_o assumes the error has a normal behaviour. The H_1 assumes the error not to have a normal behaviour. The outcome of the test is as follows:

$$\text{If r} \geq r_L(1\text{-}\alpha), \text{conclude}\, H_0$$

$$\text{If } r < r_L(1\text{-}\alpha), \text{conclude}\, H_1 \tag{13}$$

In contrast to Looney and Gulledge (1985), derived from ISPA (2009), if the value of r is greater or equal to ~0.837 ($R^2 \geq 0.70$) the model is good, whereas if the value of *r* is between ~0.592 and ~0.837 (0.35 ≥ R^2 0.70) the model has marginal results. Anything below the previous mentioned values for *r* would not be considered as an acceptable value, highlighting little worth of the generated model. These values will be used to fulfill the normality assumption.

As previously mentioned, the regression model uses the method of squares for error to calculate the regression coefficients. It is therefore understood that the more data points available for the model, the more robust the generated model will be. However, as this methodology is being applied in a case study at BA, there are limited data points, 13 to be precise. The manner of overcoming this constraint is by creating more data points. In order to do this, a sub-sampling technique, namely the jack knife technique, is utilized.

3.1.2 Jackknife Technique

The jackknife technique is used to determine the regression coefficients of each of the model parameters. This technique was originally a computer-based method for estimating biases and the standard errors. According to Efron and Tibshirani (1993), this technique is commonly used not only to improve the problem of biased estimation due to small sample size, but also in situations where the distribution of the data is hard to analyze. In this technique, the data are divided into sub-samples, and the sub-samples are obtained by deleting one observation at a time. The calculations are carried out for each sub sample. Given a data set x = (x_1, x_2, x_3,…,x_n), the i^{th} jackknife sample x_i is defined to be x with the i^{th} data point removed. The pseudo-values, Ps_i, are determined using the following equation:

$$Ps_i = ns\hat{\beta} - (ns-1)\hat{\beta}_{-i} \tag{14}$$

where,

Ps_i, Pseudo-value for the entire sample, omitting sub-sample i.

ns, Number of sub-samples

$\hat{\beta}$, Least-squares estimator of the whole sample

$\hat{\beta}_{-i}$, Least-squares estimator for the entire sample, omitting sub sample i

The jackknife estimator $\tilde{\beta}$ is determined as follows:

$$\tilde{\beta} = \frac{\sum_{i=1}^{ns} Ps_i}{ns} \tag{15}$$

3.1.3 Selection of Cost Drivers for the Final Regression Model

This section discusses two techniques that determines which selected cost drivers will be kept in the final CERs, one for the MLRM, and the other for the adapted version of the NLM. The techniques are path analysis (PA) and analysis of variance (ANOVA).

The first technique, PA, is very visual. It is usually used to reduce the number of selected cost drivers to keep in the final CER, with the intent of ensuring that the model has meaningful results. It will result in showing the individual effects of each of the cost drivers, and how they interact with one another, and with the cost. Contrary to PA, ANOVA will not try to minimize the number of cost drivers. Rather, it will only retain the selected cost drivers that are statistically significant in the final regression model.

3.1.3.1 Path Analysis

Path analysis, developed by Wright (1934), was an approach used to study the direct and indirect effects of variables. This approach takes a confirmatory, rather than exploratory, approach to data analysis and requires that the inter-variable relations be specified beforehand. This type of model will enable one to understand the effects that each of the cost drivers will have on the output of the equation. Therefore, in this applied research, the PA model will determine the direct impact and indirect impact that the cost drivers have on the target cost. The reference to the impacts will be denoted as path coefficients from this point onwards. A conceptual diagram of the PA model can be seen in Figure 3.1 below.

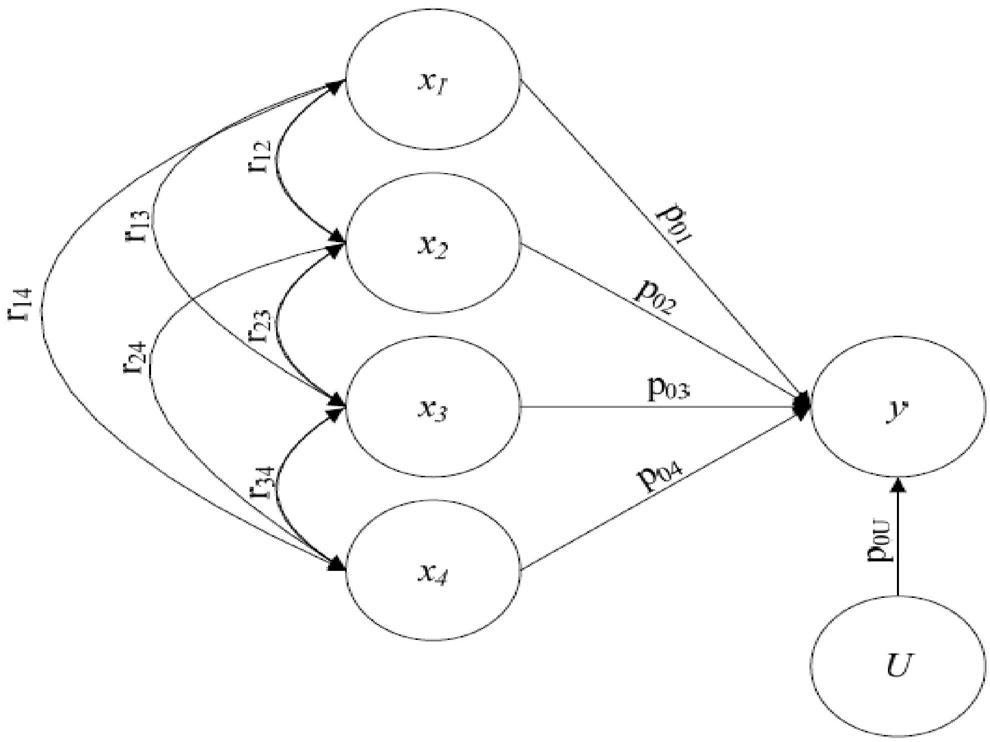


Figure 3.1: Conceptual PA diagram

As can be seen in Figure 3.1, x_i represents the cost drivers. The circle containing the letter "*y*" represents the dependent variable, the cost. The circles containing the letter "U" represents the un-correlated value of the function. The term correlation refers to dependency of a variable on another one. As previously mentioned, the path coefficients, p_{0i} are the direct and indirect effects that the independent variables have on the output of the equation. The inter-relationships (r_{ij}) that can be seen in Figure 3.1 are simply the correlations of the factors (cost drivers and cost), which can be derived from the correlation matrix. The correlation matrix for the conceptual PA presented in Figure 3.1 is depicted in Table 3.1 below.

Table 3.1: Conceptual Correlation Matrix

	x_2	x_3	x_4	y
x_1	r_{12}	r_{13}	r_{14}	r_{10}
x_2		r_{23}	r_{24}	r_{20}
x_3			r_{34}	r_{30}
x_4				r_{40}

It should be noted that the correlation matrix also contains the values of r_{i0}, which is the relationship between each individual factor and the output. The utilization of these values will be explained later. It should also be noted that no coefficient is compared to itself as it is evaluated at 1. More precisely refer to the equation below.

$$\mathrm{r}_{ij} = 1 \text{ , for } i = j \tag{16}$$

The values for the path coefficients for the four variables as shown in Li (1975) will be calculated as follows:

$$\begin{bmatrix} r_{11} & r_{12} & r_{13} & r_{14} \\ r_{21} & r_{22} & r_{23} & r_{24} \\ r_{31} & r_{32} & r_{33} & r_{34} \\ r_{41} & r_{42} & r_{43} & r_{44} \end{bmatrix} \begin{bmatrix} p_{01} \\ p_{02} \\ p_{03} \\ p_{04} \end{bmatrix} = \begin{bmatrix} r_{10} \\ r_{20} \\ r_{30} \\ r_{40} \end{bmatrix} \tag{17}$$

If the equation were to be expanded the sets of equations in standard form will be as follows:

$$p_{01} + r_{12}p_{02} + r_{13}p_{03} + r_{14}p_{04} = r_{10} \tag{18}$$

$$r_{21}p_{01} + p_{02} + r_{23}\, p_{03} + r_{24}p_{04} = r_{20} \tag{19}$$

$$r_{31}p_{01} + r_{32}p_{02} + p_{03} + r_{34p04} = r_{30} \tag{20}$$

$$r_{41}p_{01} + r_{42}p_{02} + r_{43}p_{03} + p_{04} = r_{40} \tag{21}$$

As can be seen in Equations (18-21), the number of unknowns is equal to the number of equations, thus deriving the path coefficients, p_{0i} will require simple analysis.

Building on the work of Wright (1934), Li (1975) derived another manner to calculate the path coefficients. The derived equation is as follows:

$$p_{0i} = \frac{a_i \sigma_i}{\sigma_y}, i \neq y \tag{22}$$

where,

a_i, Regression coefficient of the independent variable i

σ_i, Standard deviation of the sample data of the independent variable i

σ_y, Standard deviation of the sample data of the dependent variable

If Figure 3.1 representing the conceptual PA diagram is recalled, the variable U represents the un-correlated value of the function. The value of path coefficient, p_{0U} is calculated from the following equation:

$$p_{0U} = \frac{\sigma_y}{\sigma_e} \tag{23}$$

where,

σ_y, Standard deviation of the i^{th} cost driver

σ_e, Standard deviation of the residuals

The residuals, e_i are calculated from the following equation.

$$e_i = y_n - \hat{y}_n \tag{24}$$

where,

y_n, Actual cost for sample number n

$\hat{y}_n$, Output (predicted cost) value for sample number n

It should be recalled that the predicted value of the output will be obtained from the resulting CER derived from Equation (5) for the standard MLRM and from Equation (7) for the MLRM that was transformed from a non–linear state.

The variance, σ^2 refers to the measuring the spread out the data. The total variance of the actual cost is a combination of the variance of the predicted cost and the variance of the residuals. This is mathematically represented in Equation (25).

$$\sigma^2{}_y = \sigma^2{}_{\hat{y}} + \sigma^2{}_e \tag{25}$$

where,

$\sigma^2{}_y$, Variance of the sample data of the dependent variable

$\sigma^2{}_{\hat{y}}$, Variance of the predicted output value

σ^2_e , Variance of the residuals

Once the variance and the path coefficients are obtained, the total effect that the cost drivers have on the predicted cost can be calculated from either one of the following equations.

$$R^2{}_{0(1234)} = p_{01}r_{10} + p_{02}r_{20} + p_{03}r_{30} + p_{04}r_{40} \tag{26}$$

$$R^2{}_{0(1234)} = \frac{\sigma^2{}_{\hat{y}}}{\sigma^2{}_y} \tag{27}$$

As can be seen from the notation, the total effect the cost drivers have on the predicted cost is simply the coefficient of determination derived from the linear regression model.

The PA model can serve as a tool to try to reduce the number of cost drivers, while still having meaningful results. Keeping this objective in mind, the first step would be to see if the model can be based solely upon a single cost driver. The procedure is as follows:

Step 1

Having the data readily available is important. One would refer to the correlation matrix. In this case, for the conceptual model, this could be found in Table 3.1

Step 2

In order to pick the best cost driver, the single cost driver that has the greatest effect on the predicted cost, in other words, the variable with the greatest value of r_{iy}, is selected.

Step 3

As only 1 cost driver is considered at this point, the new value of R^2 is calculated from the following equation.

$$R^2{}_{0(i)} = \left(r_{(i)0}\right)^2 \tag{28}$$

Step 4

The next step requires intuition to determine if the revised R^2 is still acceptable. This could be calculated as a percent change of the previous value, or it also could be based upon a certain threshold value for R^2 as shown in ISPA (2009) or derived from Looney and Gulledge (1985). There could also be other methods adopted in industry to be utilized depending on the context and application of the model.

Step 5

If the resulting R^2 value is acceptable based upon an established acceptance criteria, the resulting model will be solely be based upon a cost driver. However, if the resulting model is not acceptable the PA has to be recomputed by adding another factor. The next best cost driver identified in **Step 2** should be selected.

Step 6

Repeat **Step 1 to Step 5** until an acceptable value of R^2, as described in **Step 4,** is obtained. It should be noted that this procedure may repeat several times. Even though PA may keep or eliminate cost drivers, it does not indicate whether the cost drivers are significant. In order to determine the significant cost drivers, further analysis must be conducted, and this is done in this research using ANOVA.

3.1.3.2 Analysis of Variance

ANOVA for an MLRM will help to determine which cost drivers have a statistical significance (Kutner *et al.*, 2004). The ANOVA will indicate, with the use of the F-test for linear regression, if the CER only contains statistical significant cost drivers (Weisberg, 2005). When conducting a regression analysis on computer software as Microsoft Excel, the ANOVA table can be automatically generated by utilizing the statistical application. The ANOVA table would include the *p-value* for any given regression coefficient (cost driver). According to Kutner *et al.* (2004), the *p-value* will indicate the statistical significance of a given parameter, which in this case, the cost drivers. The following set of equations will be utilized to determine if the selected input variables are statistically significant.

$$\text{If } p_i \geq 1 - Confidence\ Level, Factor\ is\ statistically\ significant \quad (29)$$

$$\text{If } p_i < 1 - Confidence\ Level, Factor\ is\ not\ statistically\ significant \quad (30)$$

For the purpose of this thesis, the selected confidence level, which would relate to the reliability of the estimate, is set at 90%. It should be noted that the subscript, i for the term, p_i represents the i^{th} cost drivers, as several cost are considered in the complex CER.

After creating the regression model and computing the ANOVA, if there is a single value of $p_i > 0.1$, the regression will have to be repeated by eliminating the selected cost driver with the greatest value of p_i. This procedure will repeat itself until the all the values of $p_i \geq 0.1$. The resultant equation will be utilized to predict the target cost solely upon statistically significant cost drivers at a specified confidence level, 90% in this case.

All the tools and techniques discussed in the previous sections will be used to support the methodology of linear regression. However, it only compares the standard MLRM and a simple non-linear model for the development of a cost model. A more complex parametric CER to be used for estimating the target cost is referred to from this point forward the complex non-linear model.

3.1.4 Complex Non-Linear Model

The CNLM used in this thesis has the following notation.

$$\hat{y} = a_0 x_1^{b_0} + a_1 x_2^{b_1} + a_2 x_3^{b_2} + c_0 x_1^{d_0} x_2^{d_1} + c_1 x_1^{d_2} x_3^{d_3} + c_2 x_2^{d_4} x_3^{d_5} + e_0 x_1^{f_0} x_2^{f_1} x_3^{f_2} \quad (31)$$

As was the case in the regression models, the terms x_i represent the cost drivers, and remaining terms are the constants. As this equation is not in the form of a regression model, the constants will have to be determined analytically. The manner is determining the constants will be using the gradient descent algorithm (GDA). The GDA is an optimization tool to find the local minima of a function (Snyman, 2005). In order to determine the constants, the function to be minimized is the square error of the predicted versus the actual costs (ie. $\sum(y - \hat{y})^2$). The gradient, ∇ for each of the constants will calculate the amount the constant has to be changed (ie. delta) in order to minimize the function, the square error. Furthermore, the value of the constant will be adjusted by multiplying it by a step rate, η. Each of the constants will be adjusted each iteration until the specified stopping criterion (ie. acceptable change in error) is fulfilled.

Parametric CERs depend on a pre-determined cost function to establish the target cost. However, using non-parametric models such as the models based upon artificial intelligence, such as neural networks (NN) does not require pre-determined relationships. NN models have the ability of self-determining relationships of the variables to predict the cost. Therefore, the next model developed is based upon NN, and is discussed in the following section.

3.2 Neural Networks

Neural networks (NN) traditionally refer to a network of biological neurons that are functionally related in the central nervous system. Neural networks may be used for solving artificial intelligence problems without necessarily creating a model of a real biological system (Pandya and Macy, 1996). Since biological neural networks are quite complex, the term artificial neural networks (ANN, or simply NN) is used when a somewhat simplified version is studied. They are nevertheless used to model complex relationships between inputs and outputs in an effort to find data patterns. A NN is essentially a number of interconnected elements that work together to solve a problem. Through a learning process, whereby it learns by example, it can be configured for a specific application. They can be utilized in many applications, such as data processing, classification, and function approximation to name a few (Pandya and Macy, 1996, Bishop, 1996).

Several researchers such as Tu (1996), Cavalieri *et* al. (2004), and Caputo (2008) have commended neural networks (NN) models for their ability to characterize complex relationships. The benefit of developing CERs from neural networks is that it does not need a pre-determined function. This means that, unlike the case of the parametric CERs, where the type of parametric model had to be pre-selected, NN models have the ability to classify and extrapolate data, hence not requiring a predetermined function (Pandya and Macy, 1996). This is the primary impetus for selecting this methodology for the cost model, as these relationships cannot be detected using linear regression.

A conceptual diagram showing a simple CER (1 cost variable) can be seen below.

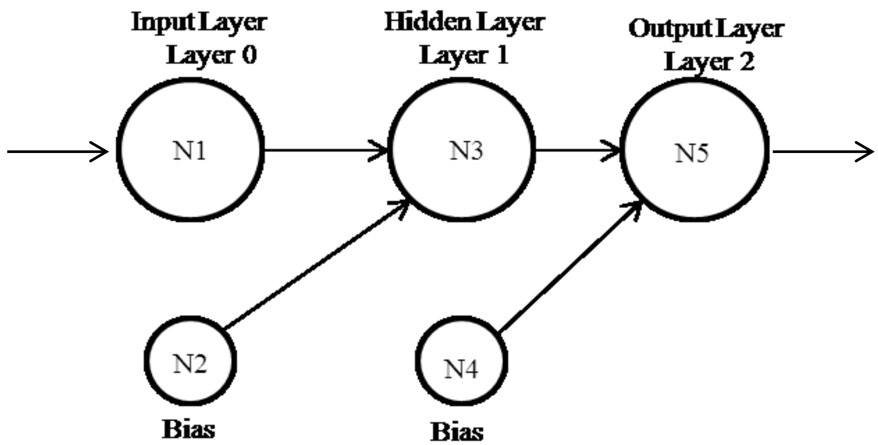


Figure 3.2: Conceptual NN diagram with a simple CER

As can be seen from the diagram, there are layers, bias neurons, and arrows which represent weights. The input and output arrows on the extremities represent the input value of the cost driver and the predicted cost, respectively. These elements will now be described.

3.2.1 Layers

The generic ANN for both simple and complex CER consists of three layers: the input layer, which is connected to the hidden layer(s), which is connected to the layer of outputs.

Input layer: For this problem, an input vector representing the cost driver is incident to the input layer. This represents the raw information that is fed into the network.

Hidden layer: The input layer is distributed (or sends data) to the hidden layer. What goes on in this layer depends on the input and the weights on the connection between the input and hidden units.

Output layer: The hidden layer is distributed to the output layer via weighted connections, and what goes on in this layer depends on the hidden units and the weights between the hidden and output units.

3.2.2 Weights

The weights are the links between the layers. All the neurons have input vectors containing the weight the exception of the bias neuron. The bias neuron tries to influence the desired output by shifting the value of the activation function, which will be discussed shortly, to output values close to those provided in the training data. According to Kecman (2001), without the element of the bias, the training mechanism may be impeded, or even stopped (Kecman, 2001).

Figure 3.2 presented a conceptual model of a simple NN CER. A complex CER is shown in the following diagram.

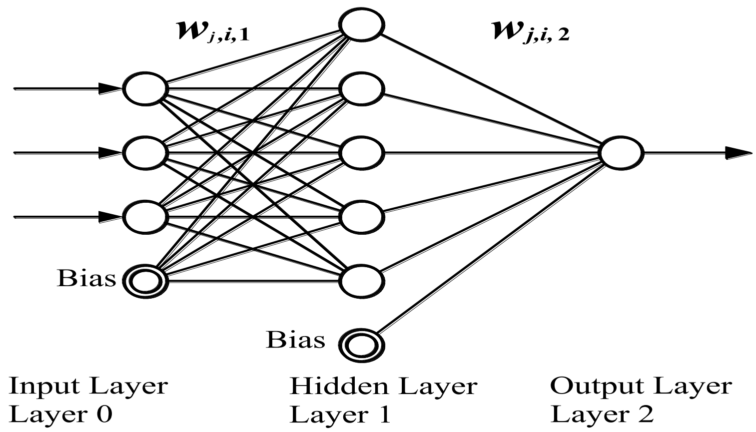


Figure 3.3: Conceptual NN diagram with a complex CER

As can be seen from the diagram, there are 3 input vectors, representing 3 cost drivers, as in this case. Moreover, the number of neurons in the hidden layer has increased to 5 excluding the bias neuron. The number of neurons in the hidden layer has to be determined by trial and error. Thus, a sensitivity analysis is conducted to determine the number of neurons to use. The output of every vector is calculated using an activation function.

3.2.3 Activation function

All the neurons in the network, with the exception of the bias, operate by taking the sum of its weighted inputs and passing the result through a nonlinear activation function. The non-linear activation function is mathematically computed as follows.

$$out_{i,l} = f(net_i) = f\left(\sum_j w_{j,i,l} out_{j,l-1}\right) \tag{32}$$

In this equation, $out_{i,l}$ is the output of i^{th} neuron in layer l, $w_{j,i,l}$ is the weight for the connection between j^{th} neuron of layer *l-1* and i^{th} neuron of layer *l*, and f is a nonlinear activation function. There are several conventionally used choices for this activation function. One of the most frequently used functions, also used in this study, is the sigmoid function given below.

$$f(net_i) = \frac{1}{1 + e^{\frac{-net_i}{Q}}} \tag{32}$$

The computational simplicity of the derivative of this function simplifies the formulation of the equations needed for the training process. The training process is where a NN is taught, or trained, to perform a task.

It should be noted that Equation (32) in its form in bounded, ensuring that certain signals remain within a range and introduces non-linearity to the model. The term Q in this equation is referred to as the temperature of the neuron and it determines the shape of the sigmoid. It is used to tune the network in order to improve its convergence behaviour.

There are various methods for obtaining the weights via training mechanisms for NN. The two methods investigated for training will be the following:

1. Training trained with the back propagation algorithm
2. Training trained with the genetic algorithm

3.2.4 Neural Networks trained with the Back Propagation Algorithm

Training is the process of a successive and a systematic adjustment of the weights in order to minimize a defined measure of error, which is typically the square error. Multilayer NNs trained by back propagation are among the most popular and versatile forms of NNs. They are able to classify data and approximate functions based on a set of sample data. In the literature, it is shown that a NN with a single hidden layer and a non-linear activation function can approximate the decision boundaries of arbitrary complexity (Kecman, 2001). In this thesis, this property is used to investigate the applicability of neural networks for cost estimation of a major aircraft component.

For the NN to be able to predict the cost given the selected cost drivers as inputs, it must first be trained using a training set. In the training process, each time an input vector p (the three cost drivers) from the training set is presented to the network, the difference between the desired and the actual output is computed and the each weight is adjusted by an amount $\Delta w_{j,i,l}$, given in Equation (33).

$$\Delta w_{j,i,l} = \eta \times \delta_{p,i,l} \times O_{p,i,l} \tag{33}$$

In this equation, η refers to the learning rate; $o_{p,j,l}$ refers to the output of the j^{th} neuron of layer, l; and $\delta_{p,j,l}$ refers to the error signal at the j^{th} neuron of layer l. The error signal is computed using Equation (34) for the neuron in the output layer and using Equation (35) for the neurons in the hidden layer. The term $t_{p,1,2}$ in Equation (34) is the desired value at the neuron in the output layer (layer 2), corresponding to the p^{th} presentation of the vector from the training set.

$$\delta_{p,1,2} = (t_{p,1,2} - O_{p,1,2}) \times O_{p,1,2} \times (1 - O_{p,1,2}) \tag{34}$$

$$\delta_{p,j,1} = O_{p,j,1} \times (1 - O_{p,j,1}) \times \delta_{p,1,2} \times w_{j,1,2} \tag{35}$$

This training algorithm is called "training by back-propagation," and the complete derivation of the algorithm can be found in Pandya and Macy (1996).

3.2.5 Neural Networks trained with the Genetic Algorithm

Genetic algorithm (GA) was introduced in the 1970s by Holland (1975) has gained increasing popularity in solving many optimization problems. It is an iterative procedure maintaining a population of structures (chromosomes) that encode candidate solutions of a problem under consideration. Computation is performed through the creation of an initial population of individuals followed by the evaluation, synthesis, creation and elimination of individuals over successive generations until a satisfactory solution is found. Using the principle of survival of the fittest, GAs have the ability to guide their search to the most promising areas of the state space. This property can be used to find the connection weights of the back propagation neural network presented later.

The chromosomal encoding of a solution is the first task in applying a genetic algorithm in any problem. Figure 2 below represents the NN model used for the GA.

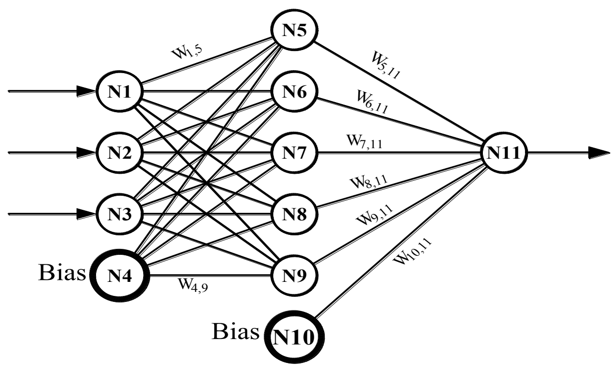


Figure 3.4: NN model used for training with the GA

Consider a chromosomal representation of a NN (with a fixed number of layers, number of neurons per layer, sigmoid function constants) to be a string of connection weights ordered as shown in Figure 3.5.

Input Layer Segment				Hidden Layer Segment					
N1	N2	N3	N4	N5	N6	N7	N8	N9	N10
$w_{1,5}$ $w_{1,6}$ $w_{1,7}$ $w_{1,8}$ $w_{1,9}$	$w_{2,5}$ $\cdots$ $w_{2,9}$	$w_{3,5}$ $\cdots$ $w_{3,9}$	$w_{4,5}$ $\cdots$ $w_{4,9}$	$w_{5,11}$	$w_{6,11}$	$w_{7,11}$	$w_{8,11}$	$w_{9,11}$	$w_{10,11}$

Figure 3.5: A Chromosomal Representation of the NN shown in Figure 3.4

The gene $w_{i,j}$ represents the connection weight between neurons i and j. This gene can assume any value between pre-specified upper bound UB and lower bound LB. These bounds on the weights can be treated as parameters of the algorithm that can be adjusted during algorithm tuning.

The purpose of the fitness function is to measure the fitness of candidate solutions in the population. To calculate the fitness of an individual chromosome, first one will set the values of the weights of the various connection of the NN to those values that can be obtained from the chromosome under consideration. Thereafter use the resulting NN to forecast the output on all of the training data sets. Once the output is forecasted, the sum of the square errors is calculated. The error is the difference in percent between the desired and forecasted values. The resulting sum of the square error is used as the fitness of the individual. Hence, the smaller this value is, the more fit is the individual chromosome.

3.2.5.1 Genetic operators

Genetic operators make the population evolve by creating promising candidate solutions to replace the less promising ones. These operators are generally categorized as selection, crossover, and mutation operators.

A simple way to simulate the natural selection process in a GA is through tournament selection. In the proposed GA, we use a k-way tournament selection operator. In this operator, k individuals are randomly selected and the one presenting the highest fitness is declared the winner and a copy of this individual is added to the mating pool to form the next generation. Then, the k individuals in the tournament are placed back to the current population and the process is repeated. This continues until the number of individuals added to the mating pool is equal to the population size.

Once the mating pool is generated using the selection operator, the individuals in the pool are randomly paired to form parents for the next generation. Then for each pair, the algorithm arbitrarily selects one of the available crossover operators and applies it with certain probability to create two child individuals by exchanging information contained in the parents. The crossover operators are (i) swap-crossover-operator-1 (SwCO-1), (ii) swap-crossover-operator-2 (SwCO-2), (iii) single-point-crossover-operator-1 (SPCO-1), and (iv) single-point-crossover-operator-2 (SPCO-2).

The crossover operator SwCO-1 arbitrarily selects a neuron (N1, N2, N3 or N4) in the input layer segment of the parent chromosomes and exchange the weights associated to this neuron between the parent chromosomes. The SwCO-2 crossover operator exchanges the Hidden-Layer Segments of the parent chromosomes. SPCO-1 arbitral selects a crossover point in the Input-Layer-Segment of the parent chromosomes and exchange the part of this segment lying to the left of the crossover point. SPCO-2 exchanges the part of the Hidden Layer Segment lying to the right of an arbitrarily selected crossover point on this segment. The above four crossover operators are applied with probabilities α_1, α_2, α_3, and $\alpha_{4.}$

Selection and crossover do not introduce new genetic material into the population pool. This task is performed by the mutation operators acting at the gene level to alter information contained in the gene. In this research we consider a single mutation operator. This operator is applied with a small probability α_5 on a given chromosome and gets affected on each gene with another a small probability α_6. Whenever this operator gets effected on a particular gene, it steps up or down the value of this gene by a step amount θ using the equations $w_{i,j} = min\ (UB,\ w_{i,j} + \theta)$, or $w_{i,j} = max\ (LB,\ w_{i,j} - \theta)$, respectively. The step amount θ is calculated every time this operator is applied on a given $w_{i,j}$ with the equation $\theta = \theta_{max} * rand\ ()$, where $\theta_{\max}$ is a parameter to be set and *rand ()* is random number generator in [0, 1].

3.2.5.2 Implementation

Once the solution representation, fitness function, and genetic operators are defined, the genetic algorithm can be implemented following the general steps shown in Figure 4.

```
Initialize Population
Repeat
    Get a weight for the neural network from a chromosome
    Evaluate the neural network and assign a fitness to the chromosome
    Repeat the above two steps for each chromosome
    Perform competitive selection
    Randomly for Pair Individuals
    Apply Crossover and obtain two children from each pair
    Apply Mutation operator on each child chromosome
    Constitute the next generation from the new chromosomes
Until stopping criterion is reached
```

Figure 3.6: A pseudo-code for genetic algorithm

The stopping criterion used is the maximum allowable average square error of prediction on the training data set using the best NN so far found. Once stopping criterion is reached, the algorithm is stopped and we then evaluate each NN in the final population both on the training and validation data sets and select the one that outperforms the other neural networks. This is one significant advantage of the genetic algorithm based approach than the simple gradient decent based back propagation. At the end of its iteration, the genetic algorithm approach can provide several thousands of neural networks from which the one that provides a good prediction not only on the training data set but also on the validation can be chosen.

The procedure in initializing the models is complete. It is important to understand the advantages and the disadvantages of using non-parametric NN CERs versus CERs based upon parametric.

3.2.5.3 Parametric versus Non-Parametric CERs

There are several advantages and disadvantages of using NNs as compared to parametric models for CERs. The findings of Tu (1996) in comparing the two methodologies are as follows:

Advantages of NN

1. Less statistical training required
2. Ability to detect complex nonlinear relationships between variables
3. Can detect all possible interactions between the predictor variables
4. Many forms of training algorithms

Disadvantages of NN

1. Calculations are in a “black box” thus limited ability to explicitly identify causal relationships.
2. Neural networks models may be more difficult to apply in a particular field.
3. Require great computational resources
4. Are prone to over-fitting.
5. As the model development is empirical, relatively limited research with possibly many methodological issues remaining

3.3 Data Envelopment Analysis

In recent times, data envelopment analysis (DEA), which was introduced by Charnes *et al.* (1978), has become a popular management tool. It is commonly used to rank the efficiency of products; one example is in the electrical (utilities) sector, in which the government can compare different suppliers (Berg, 2010). As the models output the efficiency, the efficiency, in turn, can be used to predict the target cost. Depending on the application, the target cost can be extrapolated from the best, worst, or average efficiency.

DEA is a mathematical technique used to measure the relative efficiency of homogeneous decision-making units (DMUs) with multiple inputs and outputs. It is applied when there is no obvious unit price information for some or all of the inputs and the outputs to aggregate them into a single equivalent input and a single equivalent output, respectively. In DEA, the relative efficiency of a DMU is defined as the ratio of total weighted output to total weighted input. By considering a set of homogeneous N decision making units (DMU_n for $n = 1, 2, \cdot\cdot\cdot, N$) each having I number of inputs ($x_{i,n}$ for $i = 1, \cdot\cdot\cdot, I$), and O number of outputs ($y_{o,n}$ for $o = 1, \cdot\cdot\cdot, O$), the efficiency measure E_k for DMU_k is given by Equation (34), where the weights $u_{i,k}$ and $v_{o,k}$ are non-negative and unknown until they are determined by the DEA procedure.

$$E_k = \frac{\sum_{o=1}^{O} u_{o,k} y_{o,k}}{\sum_{o=1}^{O} v_{i,k} x_{i,k}} \tag{36}$$

The weights $u_{i,k}$ and $v_{o,k}$ corresponding to DMU_k are determined in such a way that the efficiency E_k of this decision making unit can be maximized subject to the following constraints. The first one is, when these weights are applied to all DMUs they should not provide any DMU with efficiency greater than one. The second one requires the weights to be non-negative. This problem can be formulated for DMU$_k$ as fractional linear programming mathematical model as follows.

Maximize:

$$E_k = \frac{\sum_{o=1}^{O} v_{o,k} y_{o,k}}{\sum_{o=1}^{O} u_{i,k} x_{i,k}} \tag{37}$$

Subject to:

$$\frac{\sum_{o=1}^{O} v_{o,k} y_{o,n}}{\sum_{o=1}^{O} u_{i,k} x_{i,n}} \leq 1; \forall n \tag{38}$$

$$u_{i,k}, v_{o,k} \geq 0; \forall o, \forall i \tag{39}$$

DMU$_k$ will choose weights $u_{i,k}$ and $v_{o,k}$ so as to maximize its efficiency, given the constraints in Equations (38) and (39). The fractional linear programming described above can be transformed into a simple linear programming by multiplying both the numerators and denominators of the fractions with a positive constant c and choosing the constant c such that the following holds; $c \sum_{o=1}^{O} u_{i,k} v_{i,k} = 1$. The products of the constant c and the variables $u_{i,k}$ and $v_{o,k}$ can be replaced by new variables $p_{i,k}$ and $q_{o,k}$, respectively. The resulting linear programming is shown below.

Maximize:

$$E_k = \sum_{o=1}^{O} q_{o,k} y_{o,k} \tag{40}$$

Subject to:

$$\sum_{o=1}^{O} q_{o,k} y_{o,n} - \sum_{i=1}^{I} p_{i,k} x_{i,n} \leq 0; \forall n \tag{41}$$

$$\sum_{i=1}^{I} p_{i,k} x_{i,k} = 1 \tag{42}$$

$$p_{o,k}, q_{o,k} \geq \varepsilon; \forall o, \forall i \tag{43}$$

A computed DEA solves the above linear programming model n times, one for each k. The DMUs having $E_k = 1$ are deemed efficient, whiles those having $E_k < 1$ are deemed inefficient. One of the limitations of this method is that if there are several DMUs having $E_k = 1$, the method cannot provide a comparison among these efficient DMUs. To overcome this limitation, Andersen and Petersen (1993) developed a procedure for ranking efficient units. The methodology enables an extreme efficient unit k to achieve an efficiency score greater than one by removing the k^{th} constraint in the set of n constraints given by Equation (41). Moreover, they slightly adjusted the non-negativity constraint in Equation (42) by imposing the variable $p_{i,k}$ and $v_{o,k}$ to be greater than or equal to a small positive number ε. This increases the sensitivity of the result of the DEA analysis to the changes of the levels of the input and the output ($x_{i,n}$ and $y_{o,n}$). The technique is known as super-efficiency ranking technique and its model is given by Equations (44-47).

Maximize:

$$E_k = \sum_{o=1}^{O} q_{o,k} y_{o,k} \tag{44}$$

Subject to:

$$\sum_{o=1}^{O} q_{o,k} y_{o,n} - \sum_{i=1}^{I} p_{i,k} x_{i,n} \leq 0;\ \forall n | n \neq k \tag{45}$$

$$\sum_{i=1}^{I} p_{i,k} x_{i,k} = 1 \tag{46}$$

$$p_{o,k}, q_{o,k} \geq \varepsilon; \forall o, \forall i \tag{47}$$

This model is used as the basis for the study on cost estimation.

3.3.1 Advantages and Disadvantages of DEA

Upon studying the research of Berg and Lin (2008), Berg (2010), and Harton (2011), the following strengths and weaknesses were identified.

Advantages of DEA

1. Mathematical function does need to be explicitly specified.
2. Discovers relationships that are limited in other methodologies.
3. Able to compute analyses with several inputs and output variables.
4. Easy to apply with any input – output measurement.
5. Inefficiency can be analyzed and quantified for every evaluated unit.

Disadvantages of DEA

1. Results are sensitive to the selection of inputs and output variables.
2. Limited application
3. Number of efficient samples tends to increase as the number of inputs and output variables increase.

3.4 Chapter Summary

This chapter presents the target cost models or the cost estimating relationships (CERs) developed in this thesis. The first two models presented are based upon regression. The next models presented are neural network models trained using back-propagation and the genetic algorithm. Finally, the chapter concludes by presenting the data envelopment analysis models developed and applied in the case. The case study is presented in the following chapter.

4. Case Study at Bombardier Aerospace

The models developed in this thesis were applied at a case study conducted at a major aerospace company. Bombardier Aerospace (BA) is a unit of Bombardier Inc. and its headquarters are in Montreal, Quebec. Bombardier specializes in the design and manufacture of innovative aviation products. Bombardier has about 30,000 employees worldwide. Their large work force coupled with their annual revenues of over $8 Billion dollars (BA 2011 Annual Report, 2012) highlight their significance to the Canadian economy.

Bombardier has a large portfolio of business and regional jets. Their products in business jets include the Challenger, Global Express, and Lear jet. The commercial jets include the CRJs, Q-series, and they will soon be introducing the C-Series on the market. Despite their achievements, they, like other aerospace companies, are facing many challenges.

The extreme volatility of the fuel price in recent years has played an integral role in their current financial difficulties. Moreover the competition is fierce; other airframes such as Embraer are developing products in direct competition with BA. To makes matters even more difficult other countries such as India and China are developing their own aircrafts with subsidies from their respective governments.

Lin Ai, economist at the Conference Board of Canada states “The Canadian aerospace industry must continue to improve the quality of its products and to develop leading technology if it is to compete more effectively in the global marketplace” (Conference Board of Canada, 2012). Bombardier is well aware of this predicament, and they are constantly seeking to develop new programs, such as the C-Series and the Global 5000, in order to remain competitive and to gain new market segments.

Due to the economic situation at the time of this study, the emergence of cost understanding initiatives had become critical, even at an early conceptual stage. Having an accurate understanding of the cost of a new program was among the company's main priorities. Crucial to the supply chain was to accurately predict a target cost for all major structures and commodities in order to launch a new aircraft program, especially since some of these commodities cost several millions of dollars. The models developed in this thesis were therefore applied to BA to predict the target cost to help BA in bidding, forecasting and strategic initiatives. This chapter will present the steps undertaken to apply the cost model. It will discuss the data collection process, the product studied in this case, and the identification of its cost drivers.

4.1 Data Collection

According to ISPA (2009), the sources of data can be primary, secondary, or both. The primary data are derived from basic accounting records. The secondary data can be extracted from contracts and cost proposals. Finally, the data that is classified as either primary or secondary is cost reports, historical and technical databases, specialists, and other information systems. In this study data was collected for 13 programs from the following sources: technical databases, design drawings, specialists, historical databases, contracts, extrapolation of data from the contracts, estimates based upon experts inputs, and attendance at workshops. These sources of data helped to identify the commodity to study, the cost drivers of that commodity, and collect pertinent details about the cost drivers required for the model. Interviews were conducted and attendance at team meetings helped to substantiate and validate some of the data collected. Challenges specific to data collection are highlighted in the sections that follow.

4.1.1 Landing Gear

During the time of this study, research was already underway at BA to develop models to determine target costs. Several commodities had already been identified for study. The first commodity selected was the landing gear (LG). The LG, also known as the undercarriage, is utilized as an interface between the aircraft and the ground. The landing gear can be divided into different sub-systems such as: main landing gear (MLG), nose landing gear (NLG), extension and retraction system, alternate release system, steering system and brake control system. The main functions of the landing gear are to absorb loads upon landing, taxiing and braking. The load during landing is absorbed by the gears and it is proportional to the maximum takeoff weight (MTOW). The MTOW, typically measured in pounds, is the heaviest weight at which the aircraft can takeoff and fly and meets all the applicable airworthiness requirements. Figure 4.1 below shows an MLG.

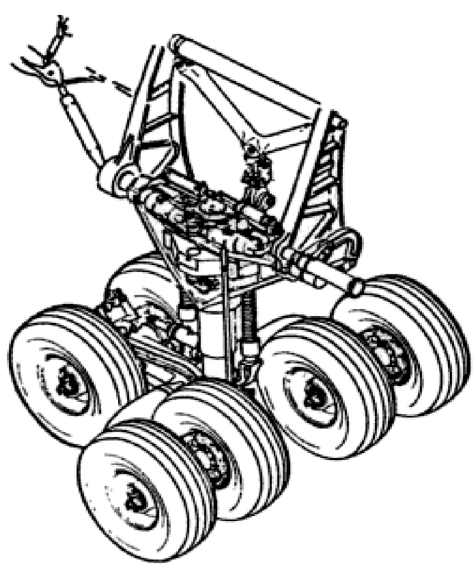


Figure 4.1: Lockheed C-5A MLG (Currey, 1988)

In this research, target cost models were applied to the MLGs based upon a select number of cost drivers.

4.1.2 Cost Drivers

Lean accounting focuses on the product, its characteristics, and the customer (Maskell and Baggaley, 2002). The characteristics of the products are the design parameters, which will be used to formulate the cost model or the cost estimating relation (CER). The design parameters that influence the cost of the product are the cost drivers. Recalling Equation (3): CER (y) = f(x_i), it can be seen that the cost drivers, x_i are those variables that will determine the cost of the product. Thus, selecting the right cost drivers are of upmost importance.

As some of the design parameters can be the cost drivers, the technical specialists responsible for the design of the aircraft were used as the primary source for establishing the cost drivers. The cost drivers were selected through interviews with the technical specialists in the advanced design team (ADT). The ADT is responsible for the configuration and design of the aircraft from the conceptual phase of the design process. They design the aircraft to meet the needs of the market, and the customer.

At a conceptual phase of design, only a few characteristics of the aircraft such as the range, required thrust, maximum take-off weight (MTOW) are known. As the selected product was the landing gear, and the aircraft had a defined MTOW, the engineers had some characteristics about the component. Of the known characteristics, upon extensive interviews, the following three design parameters were selected as the cost drivers.

1. Maximum Take Off Weight (MTOW)
2. Height of the MLG
3. Weight of the MLG

The first parameter is the MTOW. As mentioned in Section 4.1.1, the MTOW is an airworthiness requirement and will ultimately be primal factor in designing the MLG. Thus, it being selected as a cost driver was deemed important. The selection of the height of the MLG is due to the amount of material that will be required to construct the MLG. The more material required, the greater the impact on the overall cost. Similarly, the weight was also believed to have an impact on the cost. Depending on the weight requirements, the selection of the material used to fabricate the MLG would differ. The prices of typical materials used in MLGs such as aluminum, titanium, and composite are significantly different, thus the reason for assuming the weight to be the other potential cost driver. As previously mentioned, as there is very little information known in the conceptual design phase, the list of potential factors are scarce, and based upon the information known, the engineers felt these to the best factors to be selected as the cost drivers.

The technical databases had limited information; more importantly its credibility was not certain. The only information to be extracted was that of the MTOW. To validate the data, the public information, such as the company or suppliers website, disclosing the MTOW was reviewed.

The assistance of the technical specialists was required in extracting the weights and heights of the MLG, as the technical data did not have the data for all the 13 programs considered to develop the cost models. The information was gathered in the form of workshops. During the workshops, the computer aided design (CAD) drawings were reviewed. From the drawings, the heights of the programs were extracted. Moreover, the specialists were also able to extract the weight based upon the material and volume of the MLG. However, in some cases there were no CAD drawings, due to legacy systems, and only technical drawings available. For those programs, much effort was put in reviewing the drawings, and estimating the weights, once again, based upon their weights and their volume.

The cost data of the historical programs were extracted from the historical databases and cross validated with the contracts. The reason for cross validating the contract was mainly due to the manner in which the cost was stored in the database. In some instances the database did not have the cost of the MLG but of the entire landing gear (LG). In those cases the cost had to be extracted from the contracts. However the contracts are not real time and are a static picture of the agreed upon price at contract signature. As the contracts were for many years, a price adjustment formula was used as a mechanism to adjust the price, typically upon an annual basis. Therefore, the cost of the MLG would have to be extrapolated to the year of study.

Finally in one of the cases, the cost of the MLG was not broken down in the contract as well. Therefore based upon inputs from experts and the comparison of the cost structure other LGs, the cost of one MLG was estimated.

4.2 Chapter Summary

In this chapter, the case company in which the target cost models were applied, Bombardier Aerospace is introduced. Thereafter, the particular commodity selected for study is described. Next, the manner in which the selected cost drivers is discussed. Finally, the steps followed to gather the data are outlined. The results and analysis are presented in the following chapter.

5. Results and Analysis

This chapter presents the results and analyses for the target cost models for the main landing gear (MLG). The chapter has four main sections. The first three sections present the results and analysis of the linear regression, neural networks (NN), and data envelopment analysis (DEA) models. The final section provides a comparative study of the results of the three models.

5.1 Parametric Analysis

As mentioned in Chapter 4, three cost drivers were identified for the MLG: weight, maximum take-off weight (MTOW), and height of the MLG. For this type of parametric model, having several cost drivers is considered complex and therefore the multiple linear regression model (MLRM) shown in Equation (3) will be employed to predict the target cost (Kutner *et al.*, 2004).

The section starts with an analysis of the linear model, followed by the non-linear one and will then provide a comparative study between the two. Due to the scarcity of data, the jackknife technique was utilized. An analysis showing the linearity and normality assumptions fulfilled are also presented. This section will also describe the use of path analysis and analysis of variance to determine the factors to be retained for the final target cost models.

5.1.1 Linear Model

The following historical data was obtained from BA for the MLG. It should be noted that the cost data is masked to protect BA's proprietary information. A masking technique described in Muralidhar *et al*. (1999) was used for this purpose.

Table 5.1: Historical Data

Program	X_1: Weight	X_2: MTOW	X_3: Height	y_i: Masked Cost
1	335.77	33,000	111.16	63,816
2	335.77	36,300	111.16	69,465
3	389.97	43,000	111.54	73,794
4	490.58	64,500	124.58	125,657
5	199.58	37,850	43.29	78,516
6	265.62	47,600	43.30	117,834
7	328.81	53,000	40.85	104,635
8	333.00	51,000	42.00	103,552
9	532.00	72,750	54.80	103,173
10	532.00	80,500	54.80	114,082
11	594.00	85,970	55.00	102,595
12	526.97	92,500	75.17	104,400
13	526.97	98,000	75.17	104,408

where,

X_1, Weight of the MLG

X_2, MTOW

X_3, Height of the MLG

y_i, Masked cost of the MLG

As can be seen from Table 5.1, the variables do not have any units since, as discussed in Section 3.1.1 dimensional analysis was used to make the variables dimensionless. Furthermore, it should be noted that the term 'masked cost' will be referred to simply as 'cost' from this point forward.

The regression models will be developed using the method of least squares discussed in Chapter 3. The cost drivers will serve and those parameters are used to model the cost. The data for all the cost drivers are used in the regression models. As there are a total of thirteen programs, three programs were randomly removed to validate the results. The sample removed programs 6, 7, and 13, and is referenced as Trial 1 from this point forward. Similarly, another 2 sub-samples were created, namely Trial 2 and

Trial 3. Trial 2 omitted programs 2, 8, and 12, whereas Trial 3 omitted programs 3, 7, and 9. As previously mentioned, due to the limited data, the jackknife technique is utilized.

As required by the jackknife method, a regression analysis was conducted for each sub sample. The following table summarizes the resulting equations from the regression analysis of Trial 1 without the jackknife technique (y_3) and for each sub-sample utilizing jackknife ($y_{3A\text{-}J,}$ where the subscripts A to J refer to the sample in question).

Table 5.2: Summary of LG jackknife equations for 3 factors

$$ln\,\hat{y}_3 = 50726 - 16.27X_1\ + 0.81X_2 + 20.23X_3$$

$$\hat{y}_{3A} = 54125 + 2.12X_1\ + 0.63X_2 + 32.58X_3$$

$$\hat{y}_{3B} = 52221 - 15.09X_1\ + 0.77X_2 + 44.01X_3$$

$$\hat{y}_{3C} = 50806 - 5.73X_1\ + 0.73X_2 + 37.76X_3$$

$$\hat{y}_{3D} = 80171 + 35.90X_1\ + 0.32X_2 - 322.24X_3$$

$$\hat{y}_{3E} = 52587 - 22.80X_1 + 0.83X_2 + 17.55X_3$$

$$\hat{y}_{3F} = 32871 - 15.51X_1\ + 0.92X_2 + 135.09X_3$$

$$\hat{y}_{3G} = 50491 - 21.06X_1\ + 0.84X_2 + 28.81X_3$$

$$\hat{y}_{3H} = 50772 - 22.70X_1\ + 0.82X_2 + 38.61X_3$$

$$\hat{y}_{3I} = 49029 + 24.70X_1\ + 0.66X_2 - 46.40X_3$$

$$\hat{y}_{3J} = 19061 - 281.86.2X_1\ + 2.79X_2 + 439.60X_3$$

Recall that in Section 3.1.2, the linearity and normality assumptions must be fulfilled. The following set of figures (Figures 5.1 - 5.10), are the SPC charts were used validate the fulfillment of the linearity assumption. Furthermore, it should be recalled from Section 3.1.2.1, the control limits are ±3σ of the residuals.

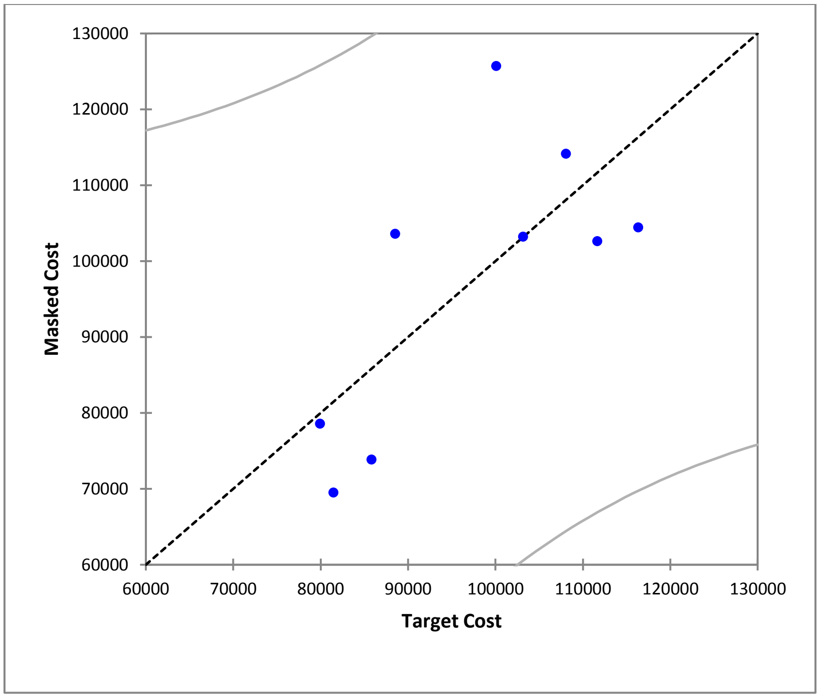


Figure 5.1: SPC chart for LR, 3 factors, sample A

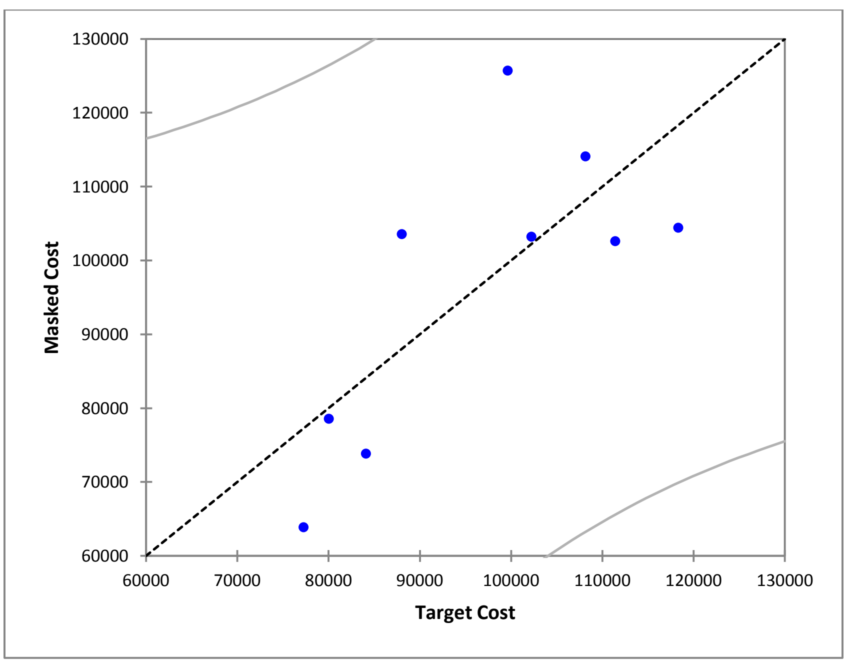


Figure 5.2: SPC chart for LR, 3 factors, sample B

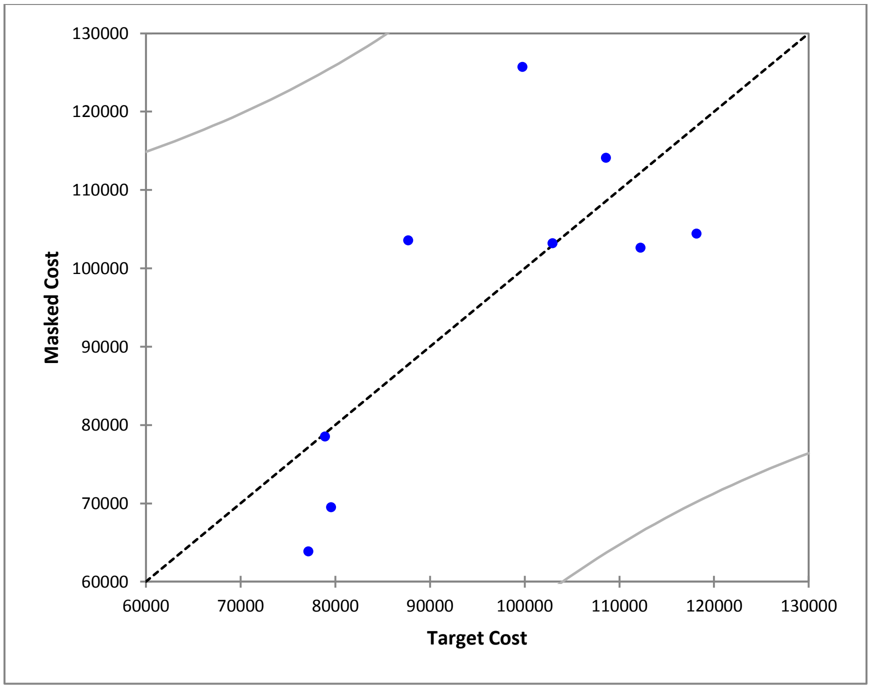


Figure 5.3: SPC chart for LR, 3 factors, sample C

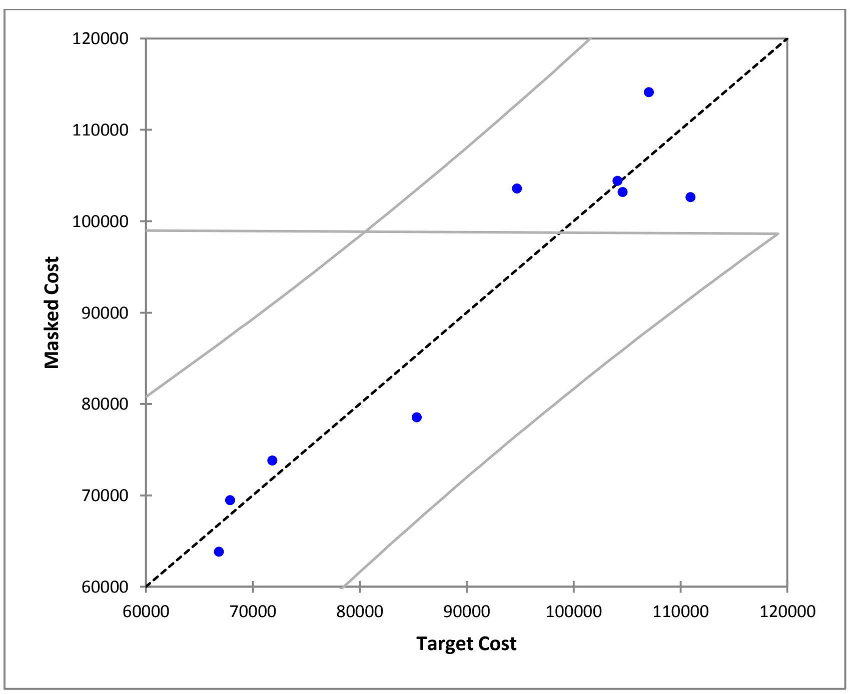


Figure 5.4: SPC chart for LR, 3 factors, sample D

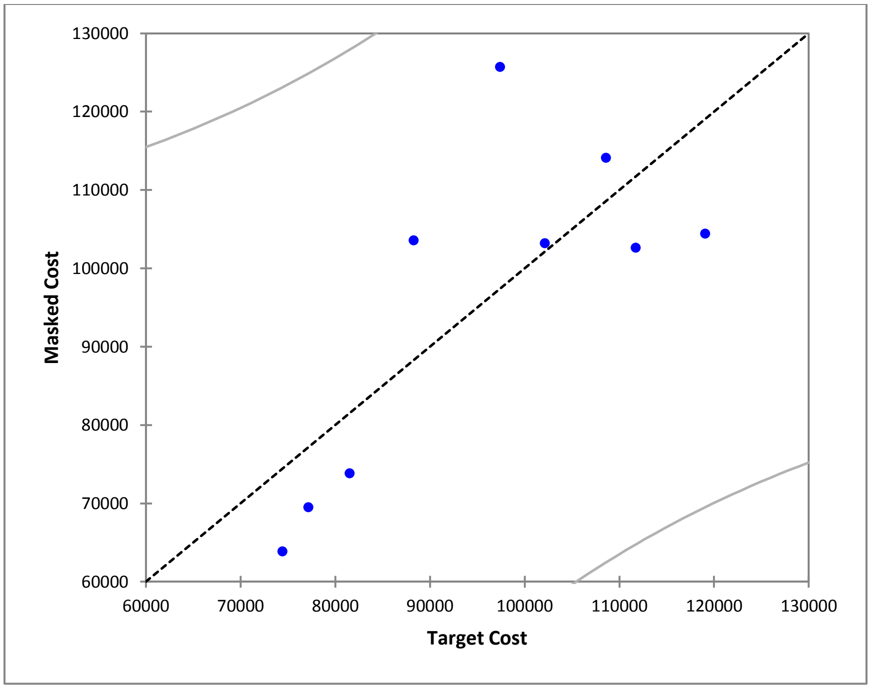


Figure 5.5: SPC chart for LR, 3 factors, sample E

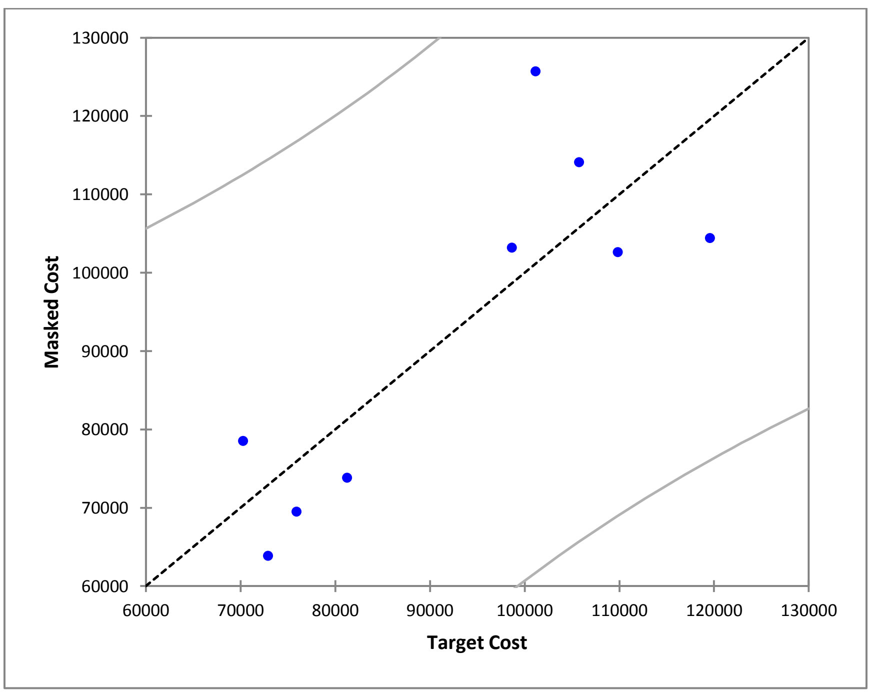


Figure 5.6: SPC chart for LR, 3 factors, sample F

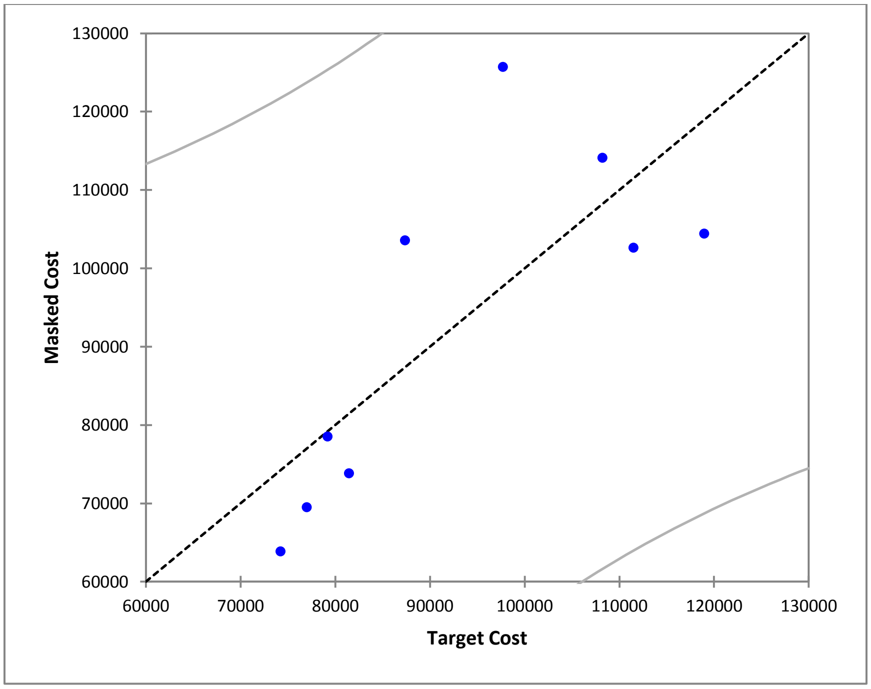


Figure 5.7: SPC chart for LR, 3 factors, sample G

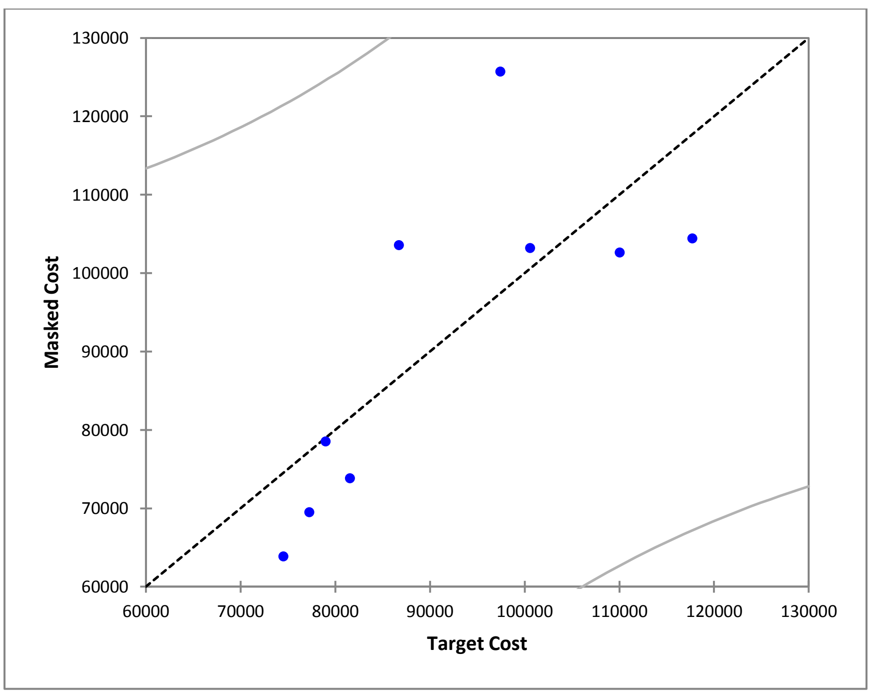


Figure 5.8: SPC chart for LR, 3 factors, sample H

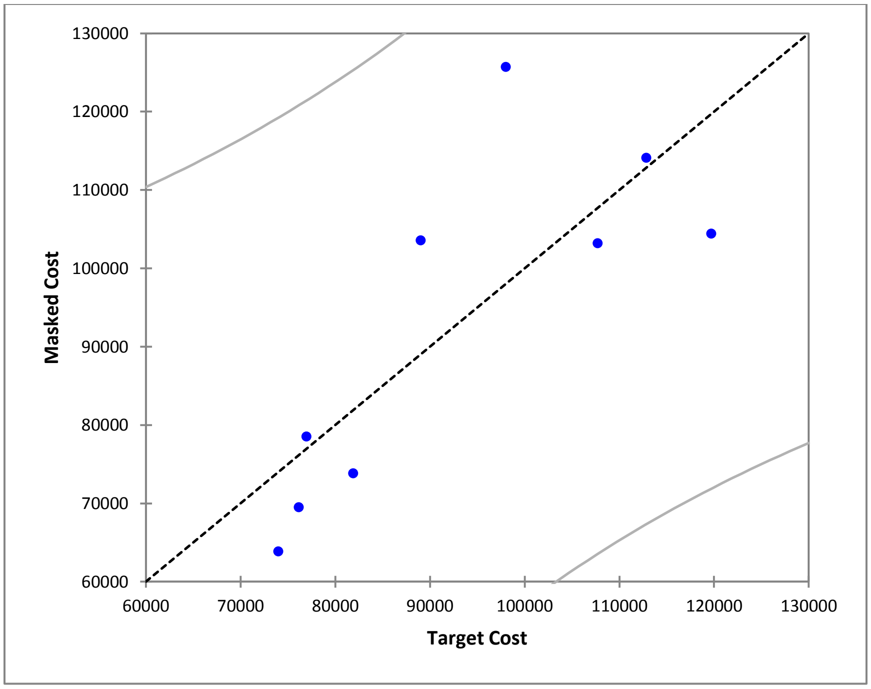


Figure 5.9: SPC chart for LR, 3 factors, sample I

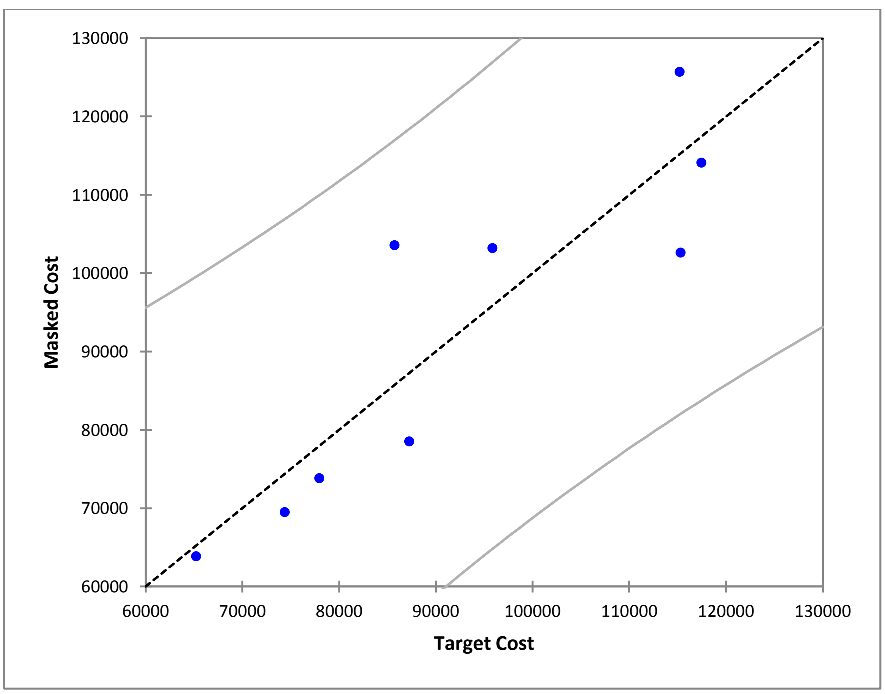


Figure 5.10: SPC chart for LR, 3 factors, sample J

As can be seen from Figures 5.1 to 5.10, all of the points fall within the control limits, which suggests that the linearity assumption to be fulfilled. The next test to fulfill is the normality test. The R^2 values, from all the sub-samples are tabulated below.

Table 5.3: Summary of R^2 values for LR, 3 factors

Sub-Sample	R^2
NO $JACK_3$	0.5937
$JACK_{3A}$	0.5097
$JACK_{3B}$	0.5350
$JACK_{3C}$	0.5645
$JACK_{3D}$	0.9067
$JACK_{3E}$	0.5648
$JACK_{3F}$	0.6807
$JACK_{3G}$	0.5839
$JACK_{3H}$	0.5521
$JACK_{3I}$	0.6227
$JACK_{3J}$	0.7967
$JACK_{3AVG}$	0.6317

As can be seen from Table 5.3, the average and minimum values of R^2 are 0.6317 and 0.5350, respectively. Accordingly to ISPA (2008), this would indicate the resulting model is marginal, yet acceptable. Moreover, as expected, the R^2 of the average sub-samples are greater than the R^2 without using the jackknife technique.

The resulting target cost model averaged from all the equation in Table 5.2 is as follows.

$$\hat{y}_{3AVG,LR} = 49213 - 32.20X_1 + 0.93X_2 + 40.54X_3 \quad (48)$$

The errors generated for all the programs are tabulated below.

Table 5.4: Errors for Trial 1 LR, 3 factors

Program	Error (%)
1	15.34
2	10.38
3	10.01
4	21.64
5	1.58
8	15.37
9	1.15
10	4.29
11	9.45
12	16.23

Recall Trial 1 omitted three data points, as they were kept for validation. If Equation (47) is used to predict the target cost of those programs, and then compared to their actual costs, it generates the following errors (percent deviation). It other words, it is an indicator of the models accuracy.

Table 5.5: Errors for Trial 1 validation data of LR, 3 factors

Program	Error (%)
6	26.42
7	14.38
13	21.12

The model is currently using 3 cost drivers to predict the target cost. The path analysis (PA) technique will now be utilized to understand the inter-relationships of the variables. It will also try to reduce the number of cost drivers.

The following table, Table 5.6, which is similar to Table 5.1, contains all the parameters required for the PA technique. There are two additions columns added from the original data set. The first variable $\hat{y}$ represents the predicted cost, and e represents the residuals, which is the difference of the cost and their predictions.

Table 5.6: Data for PA in LR, 3 factors

N	x_1	x_2	x_3	y	$\hat{y}$	*e*
1	335.77	33,000	111.16	63,816	74,327	-10,511
2	335.77	36,300	111.16	69,465	77,009	-7,544
3	389.97	43,000	111.54	73,794	81,579	-7,785
4	490.58	64,500	124.58	125,657	97,676	27,981
5	199.58	37,850	43.29	78,516	79,110	-594
8	333.00	51,000	42	103,552	87,599	15,953
9	532.00	72,750	54.8	103,173	102,294	879
10	532.00	80,500	54.8	114,082	108,591	5,491
11	594.00	85,970	55	102,595	112,031	-9,436
12	526.97	92,500	75.17	104,400	118,835	-14,435
σ^2	15,839	498,263,801	1,067	435,984,173	258,856,698	177,127,475
σ	125.85	22,322	32.66	20880	16089	13309

It should be noted, that Table 5.6, contains the results without the jackknife technique. As the jackknife technique is used to reduce the bias, the underlying inter-relations of the cost and their drivers are derived from the data without using the jackknife technique.

Table 5.7: Correlation matrix LR

	x_2	x_3	*Y*
x_1	0.890	-0.055	0.673
x_2		-0.367	0.770
x_3			-0.282

From Equations (20) and (21), the path coefficients would be calculated as the following.

Table 5.8: Path coefficients for LR, 3 factors

Path Coefficients	Value
p_{01}	-0.0980
p_{02}	0.8686
p_{03}	0.0317
p_{0U}	0.6374

The resulting PA diagram is shown in Figure 5.11.

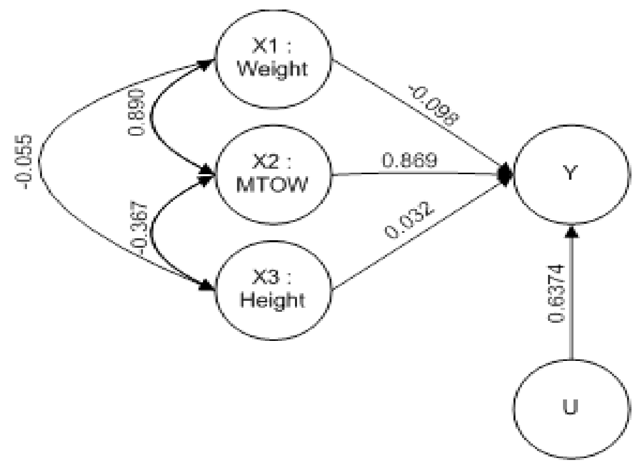


Figure 5.11: PA for LR, 3 factors

As can be seen in the diagram the effects of each of the cost drivers have on the cost is shown. The higher the value of the arrow connecting the cost drivers to the cost, in order words the path coefficient, the more importance it will have in determining the cost. In this diagram, it is clearly shown that the cost driver that most influences the cost, is the MTOW.

Moreover, the arrows connecting the cost drivers to one another are the correlations. In other words, it shows the degree of dependency the cost drivers have one another. It also represents the direct of the relationship. For example, in this instance as the correlation between the MTOW and the weight is positive, it would indicate that as the MTOW would increase, the weight would also follow. Finally, the variable U represents the value of the cost function not being represented by its drivers. The lower the value, the greater the cost drivers represent the cost.

In order to minimize the number of cost drivers, the procedure stipulated in Section 3.1.4.1 is followed. By utilizing Equation (26) and by cross validating with Equation (27), to calculate the coefficient of determination, R^2, the following result are obtained.

$$R^2_{0(123)LR} = 0.5937 \tag{49}$$

The next step in the procedure would be to select the input variable that is most correlated to the output variable. The variable x_2 is selected, and by computing Equation (26) the following result is obtained.

$$R^2_{0(2)LR} = 0.5925 \tag{50}$$

Referring to Step 4 of the procedure, the stopping criteria decided was that the value of R^2 does not change by more than 10% relative to its previous value. It this case, the value has only changed by 0.20%, thus the stopping criterion has been met. The final PA diagram is as follows.

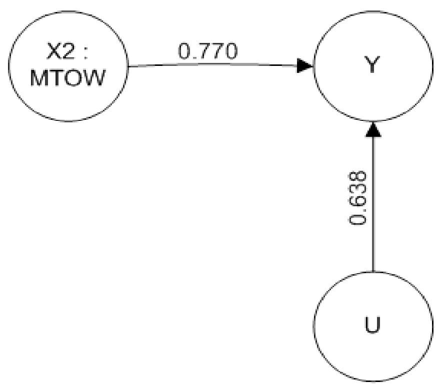


Figure 5.12: PA for LR, 1 factor

The next technique utilized to select the cost drivers is based upon statistical significance by the use of ANOVA. The resulting *p-values* for all the coefficients of all the jackknife sub-samples considering all three potential cost drivers are tabulated below.

Table 5.9: *p-values* for LR, 3 factors

	p - values										
	$JACK_{3A}$	$JACK_{3B}$	$JACK_{3C}$	$JACK_{3D}$	$JACK_{3E}$	$JACK_{3F}$	$JACK_{3G}$	$JACK_{3H}$	$JACK_{3I}$	$JACK_{3J}$	$JACK_{3AVG}$
X_0	0.096	0.110	0.116	0.001	0.263	0.294	0.128	0.120	0.121	0.455	0.170
X_1	**0.988**	0.913	0.967	0.547	0.901	0.901	0.897	0.873	0.868	0.116	**0.797**
X_2	0.468	0.384	0.409	0.401	0.395	0.259	0.398	0.355	0.450	0.042	0.356
X_3	0.898	0.869	0.886	0.048	0.949	0.600	0.925	0.886	0.866	0.144	0.707

As can be derived from Equations (27) and (28), currently none of the factors are significant. The factor to be removed is the one with the highest *p-value*. Incidentally, as can be seen in bold the above table, x_1 has the highest average as well as the highest individual *p-value*. Therefore, the regression analysis must be repeated, while omitting the weight of the MLG.

Table 5.10 summarizes the resulting equations with the omission of x_1.

Table 5.10: Summary of LG jackknife equations for 2 factors

$$\hat{y}_{2,LR} = 50826 + 0.72X_2 + 0.59X_3$$

$$\hat{y}_{2A,LR} = 54099 + 0.65X_2 + 35.00X_3$$

$$\hat{y}_{2B,LR} = 52319 + 0.68X_2 + 25.89X_3$$

$$\hat{y}_{3C,LR} = 50841 + 0.70X_2 + 31.23X_3$$

$$\hat{y}_{2D,LR} = 79258 + 0.52X_2 - 272.25X_3$$

$$\hat{y}_{2E,LR} = 50063 + 0.73X_2 + 4.83X_3$$

$$\hat{y}_{2F,LR} = 32956 + 0.83X_2 + 116.42X_3$$

$$\hat{y}_{2G,LR} = 50842 + 0.72X_2 + 0.37X_3$$

$$\hat{y}_{2H,LR} = 50905 + 0.69X_2 + 10.53X_3$$

$$\hat{y}_{2I,LR} = 49075 + 0.79X_2 - 14.83X_3$$

$$\hat{y}_{2J,LR} = 39941 + 0.89X_2 + 36.35X_3$$

Similar to the analysis containing three cost drivers, the linearity and normality assumptions must upheld. The SPC charts for this analysis can be found in APPENDIX A. As can be seen from Figures A.1-A.10, all of the points fall within the control limits, inferring the linearity assumption to be fulfilled. The next test to fulfill is the normality test. The R^2 values, from all the sub-samples are tabulated below.

Table 5.11: Summary of R^2 values for LR, 2 factors

Sub-Sample	R^2
NO $JACK_{2,LR}$	0.5925
$JACK_{2A,LR}$	0.5097
$JACK_{2B,LR}$	0.5338
$JACK_{2C,LR}$	0.5643
$JACK_{2D,LR}$	0.8989
$JACK_{2E,LR}$	0.5633
$JACK_{2F,LR}$	0.6795
$JACK_{2G,LR}$	0.5824
$JACK_{2H,LR}$	0.5495
$JACK_{2I,LR}$	0.6204
$JACK_{2J,LR}$	0.6505
$JACK_{2AVG}$	0.6152

As can be seen from Table 5.11, the average and minimum values of R^2 are 0.6152 and 0.5097, respectively. Accordingly to ISPA (2009), this would indicate the resulting model to be marginal, yet acceptable. The resulting equation (target cost model) from the jackknife equations in Table 5.11 is as follows.

$$\hat{y}_{2AVG,LR} = 51012 + 0.72X_2 - 2.35X_3 \qquad (51)$$

The errors generated for all the programs are tabulated below.

Table 5.12: Errors for Trial 1 LR, 2 factors

Program	Error (%)
1	16.8
2	10.7
3	10.7
4	22.7
5	0.4
8	15.4
9	0.1
10	4.6
11	9.9
12	12.5

By computing Equation (50) predict the target cost of the validation programs, and then compared to their actual costs, it would generate the following errors (percent deviation).

Table 5.13: Errors for Trial 1 validation data of LR, 2 factors

Program	Error (%)
6	27.70
7	14.86
13	16.28

The ANOVA has to be repeated to determine the statistical significance of the remaining factors. The resulting *p-values* for all the coefficients of all the jackknife sub-samples considering two potential cost drivers are tabulated below.

Table 5.14: *p-values* for LR, 2 factors

	p - values										
	$JACK_{2A}$	$JACK_{2B}$	$JACK_{2C}$	$JACK_{2D}$	$JACK_{2E}$	$JACK_{2F}$	$JACK_{2G}$	$JACK_{2H}$	$JACK_{2I}$	$JACK_{2J}$	$JACK_{2AVG}$
X_0	0.066	0.078	0.082	0.001	0.190	0.246	0.091	0.086	0.088	0.160	0.109
X_2	0.049	0.043	0.035	0.004	0.061	0.014	0.034	0.041	0.025	0.020	**0.033**
X_3	0.847	0.891	0.869	0.025	0.983	0.538	**0.998**	0.955	0.934	0.834	**0.788**

As can be derived from Equations (27) and (28), only x_2 has a value (in green) that may be considered significant at the 90% confidence interval. The factor to be removed is the one with the highest *p-value*. Incidentally, as can be seen in bold the above Table, x_3 has the highest average as well as the highest individual *p-value*. Therefore, the regression analysis must be repeated again, while omitting the height of the MLG.

Table 5.15 summarizes the resulting equations with the omission of x_1, and x_3.

Table 5.15: Summary of LG jackknife equations for 1 factor

$$\hat{y}_{1,LR} = 50891 + 0.72X_2$$

$$\hat{y}_{1A,LR} = 57566 + 0.63X_2$$

$$\hat{y}_{1B,LR} = 54901 + 0.67X_2$$

$$\hat{y}_{1C,LR} = 53999 + 0.68X_2$$

$$\hat{y}_{1D,LR} = 49734 + 0.69X_2$$

$$\hat{y}_{1E,LR} = 50708 + 0.72X_2$$

$$\hat{y}_{1F,LR} = 46985 + 0.76X_2$$

$$\hat{y}_{1G,LR} = 50882 + 0.72X_2$$

$$\hat{y}_{1H,LR} = 52039 + 0.69X_2$$

$$\hat{y}_{1\mathrm{I},LR} = 47483 + 0.80X_2$$

$$\hat{y}_{1J,LR} = 44221 + 0.86X_2$$

The SPC charts for this analysis can be found in APPENDIX B. As can be seen from Figures B.1 - B.10, all of the points fall within the control limits, inferring the linearity assumption to be fulfilled. The next test to fulfill is the normality test. The R^2 values, from all the sub-samples are tabulated below.

Table 5.16: Summary of R^2 values for LR, 1 factor

Sample	R^2
NO JACK$_{1,LR}$	0.5925
JACK$_{1A,LR}$	0.5064
JACK$_{1B,LR}$	0.5322
JACK$_{1C,LR}$	0.5622
JACK$_{1D,LR}$	0.7494
JACK$_{1E,LR}$	0.5633
JACK$_{1F,LR}$	0.6568
JACK$_{1G,LR}$	0.5824
JACK$_{1H,LR}$	0.5492
JACK$_{1I,LR}$	0.6199
JACK$_{1J,LR}$	0.6477
JACK$_{1AVG,LR}$	0.5970

As can be seen from Table 5.16, the average and minimum values of R^2 are 0.5970 and 0.5064, respectively. Accordingly to ISPA (2008), this would indicate the resulting model to be marginal, yet acceptable.

The resulting equation (target cost model) from the jackknife equations in Table 5.15 would be as follows.

$$\hat{y}_{1,LR} = 50852 + 0.72X_2 \tag{52}$$

The errors generated for all the programs are tabulated below.

Table 5.17: Errors for Trial 1 LR, 1 factor

Program	Error (%)
1	17.0
2	11.0
3	11.0
4	22.4
5	0.40
8	15.3
9	0.2
10	4.4
11	10.1
12	12.7

By computing Equation (52) predict the target cost of the validation programs, and then compared to their actual costs, it would generate the following errors (percent deviation).

Table 5.18: Errors for Trial 1 validation data of LR, 1 factor

Program	Error (%)
6	27.66
7	14.80
13	16.52

The ANOVA is repeated to determine the statistical significance of the remaining factors. The resulting *p-values* for all the coefficients of all the jackknife sub-samples considering one potential cost driver are tabulated below.

Table 5.19: *p-values* for LR, 1 factor

	p - values										
	$JACK_{1A}$	$JACK_{1B}$	$JACK_{1C}$	$JACK_{1D}$	$JACK_{1E}$	$JACK_{1F}$	$JACK_{1G}$	$JACK_{1H}$	$JACK_{1I}$	$JACK_{1J}$	$JACK_{1AVG}$
X_0	0.008	0.010	0.008	0.001	0.015	0.010	0.009	0.009	0.013	0.013	0.009
X_2	0.032	0.026	0.020	0.003	0.020	0.008	0.017	0.022	0.012	0.012	0.017

As can be derived from Equations (27) and (28), both x_0 and x_2 have values (in green) that may be considered significant at the 90% confidence interval.

The analysis for the LR is now complete. The model has collapsed on one significant factor, x_2 (MTOW). This is also the same finding for PA. The next analysis to be conducted is to see how the results impact the non-linear target cost model.

5.1.2 Analysis Based on a Non-Linear Model

As discussed in Section 3.1, as the target cost will be in the form of Equation (4), it will have to be transformed into a linear format (Equation 5) to conduct regression analysis. In order to convert the data into proper form for the analysis, the natural log (ln) will have to be taken for all input and output data. The transformed data can be seen in Table 5.20.

Table 5.20: Historical Data (*ln* values)

Program	$ln\ x_1$	$ln\ x_2$	$ln\ x_3$	$ln\ y$
1	5.8164	10.4043	4.7110	11.0638
2	5.8164	10.4996	4.7110	11.1486
3	5.9661	10.6690	4.7144	11.2090
4	6.1956	11.0744	4.8249	11.7413
5	5.2962	10.5414	3.7679	11.2711
6	5.5821	10.7706	3.7682	11.6770
7	5.7955	10.8780	3.7099	11.5582
8	5.8081	10.8396	3.7377	11.5478
9	6.2766	11.1948	4.0037	11.5442
10	6.2766	11.2960	4.0037	11.6447
11	6.3869	11.3618	4.0073	11.5385
12	6.2671	11.4350	4.3198	11.5560
13	6.2671	11.4927	4.3198	11.5561

The methodology applied for the linear model will be applied. Trial 1 will be used for the analysis, which will omit the programs 6, 7, and 13, as they will be kept for the validation. Table 5.21 summarizes the resulting equations from the regression analysis of Trial 1 without the jackknife technique and for each sub-sample utilizing jackknife.

Table 5.21: Summary of LG jackknife equations for 3 factors

$$ln\hat{y}_3 = 5.22 - 0.22\ ln\ X_1 + 0.68\ lnX_2 + 0.03\ lnX_3$$

$$ln\hat{y}_{3A} = 5.90 - 0.14\ lnX_1 + 0.58\ lnX_2 + 0.02\ lnX_3$$

$$ln\hat{y}_{3B} = 5.39 - 0.21\ lnX_1 + 0.65\ lnX_2 + 0.04\ lnX_3$$

$$ln\hat{y}_{3C} = 5.33 - 0.20\ lnX_1 + 0.65\ lnX_2 + 0.04\ lnX_3$$

$$ln\hat{y}_{3D} = 8.77 + 0.14\ lnX_1 + 0.27\ lnX_2 - 0.27\ lnX_3$$

$$ln\hat{y}_{3E} = 5.17 - 0.54\ lnX_1 + 0.85\ lnX_2 + 0.05\ lnX_3$$

$$ln\hat{y}_{3F} = 3.85 - 0.32\ lnX_1 + 0.80\ lnX_2 + 0.15\ lnX_3$$

$$ln\hat{y}_{3G} = 5.19 - 0.23\ lnX_1 + 0.68\ lnX_2 + 0.03\ lnX_3$$

$$ln\hat{y}_{3H} = 5.24 - 0.24\ lnX_1 + 0.68\ lnX_2 + 0.04\ lnX_3$$

$$ln\hat{y}_{3I} = 5.32 - 0.12\ lnX_1 + 0.63\ lnX_2 - 0.01\ lnX_3$$

$$ln\hat{y}_{3J} = 1.48 - 0.66\ lnX_1 + 1.19\ lnX_2 + 0.22\ lnX_3$$

The SPC charts, to fulfill the linearity assumptions are in APPENDIX C. As can be seen from Figures C.1 –C.10 all of the values fall within the control limits implying the model to be statistically linear.

The R^2 values, to fulfill the normality test are as follows.

Table 5.22: Summary of R^2 values for NLM, 3 factors

Sub-Sample	R^2
NO $JACK_{3,NLM}$	0.7380
$JACK_{3A,NLM}$	0.6442
$JACK_{3B,NLM}$	0.6877
$JACK_{3C,NLM}$	0.7180
$JACK3_{D,NLM}$	0.9464
$JACK_{3E,NLM}$	0.7382
$JACK_{3F,NLM}$	0.8078
$JACK_{3G,NLM}$	0.7296
$JACK_{3H,NLM}$	0.7105
$JACK_{3I,NLM}$	0.7545
$JACK_{3J,NLM}$	0.8421
$JACK_{3AVG,NLM}$	0.7579

As can be seen from Table 5.22, the average value of R^2 is 0.7579. Accordingly to ISPA (2008), this would indicate that the resulting model is good.

The resulting equation (target cost model) from all the equation in Table 5.21 is as follows.

$$\hat{y}_{3,NLM} = 5.16 - 0.25\, lnX_1 + 0.70\, lnX_2 + 0.03\, lnX_3 \tag{53}$$

The errors generated from Equation (53) for all the programs in Trial 1 are tabulated below.

Table 5.23: Errors for Trial 1 NLM, 3 factors

Program	Error (%)
1	6.03
2	4.13
3	6.26
4	21.53
5	5.01
8	13.92
9	0.78
10	3.68
11	9.07
12	17.46

Using Equation (53) on the validation to predict the target cost of those programs, and then comparing them to the actual costs generates the following errors (percent deviation).

Table 5.24: Errors for Trial 1 validation data of NLM, 3 factors

Program	Error (%)
6	23.60
7	12.28
13	22.29

The model is currently using 3 cost drivers to predict the target cost. The PA technique will now be utilized to understand the inter-relationships of the variables. It will also try to reduce the number of cost drivers.

The following Table, Table 5.25, which is similar to Table 5.20, contains all the parameters required for the path analysis technique.

Table 5.25: Data for PA in NLM, 3 factors

n	x_1	x_2	x_3	y	$\hat{y}$	e
1	5.8164	10.4043	4.7110	11.0638	11.1251	-0.0613
2	5.8164	10.4996	4.7110	11.1486	11.1897	-0.0411
3	5.9661	10.6690	4.7144	11.2090	11.2713	-0.0623
4	6.1956	11.0744	4.8249	11.7413	11.4985	0.2428
5	5.2962	10.5414	3.7679	11.2711	11.3057	-0.0346
8	5.8081	10.8396	3.7377	11.5478	11.3929	0.1549
9	6.2766	11.1948	4.0037	11.5442	11.5374	0.0067
10	6.2766	11.2960	4.0037	11.6447	11.6061	0.0386
11	6.3869	11.3618	4.0073	11.5385	11.6262	-0.0877
12	6.2671	11.4350	4.3198	11.5560	11.7120	-0.1560
σ^2	0.1124	0.1506	0.1825	0.0539	0.0398	0.0141
σ	0.3353	0.3881	0.4271	0.2321	0.1994	0.1188

Similar to the case of LR, Table 5.25 contains the results of the predicted cost and their associated residuals, without utilizing the jackknife technique. If recalled from Section 3.1, the covariance matrix (Table 5.26) will be used on the PA diagram, to map out the inter-relationships between the variables.

Table 5.26: Correlation matrix NLM

	ln x_2	*ln* x_3	*ln y*
ln x_1	0.837	0.117	0.633
ln x_2		-0.316	0.847
ln x_3			-0.340

Recalling Equations (20) and (21), the path coefficients would be the following.

Table 5.27: Path coefficients for NLM, 3 factors

Path Coefficients	Value
p_{01}	-0.0980
p_{02}	0.8686
p_{03}	0.0317
p_{0U}	0.6374

The resulting PA diagram is shown in Figure 5.13.

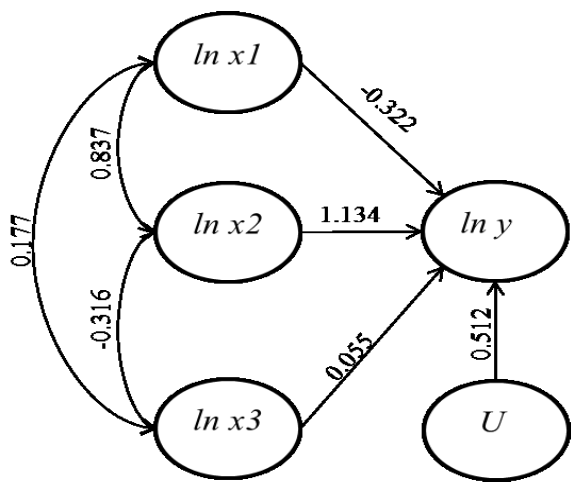


Figure 5.13: PA for NLM, 3 factors

In order to minimize the number of cost drivers, the procedure stipulated in Section 3.1.4.1 is followed. By utilizing Equation (24) and by cross validating with Equation (25), the following result is obtained.

$$R^2_{0(123)NLM} = 0.7380 \tag{54}$$

The next step in the procedure would be to select the input variable that is most correlated to the output variable. The variable *ln* x_2 is selected, and by computing Equation (26) the following result is obtained.

$$R^2_{0(2)LR} = 0.7177 \tag{55}$$

Referring to Step 4 of the procedure, the stopping criteria decided was that the value of R^2 does not change by more than 10% relative to its previous value. It this case, the value has changed less than 3% (~2.75%), thus the stopping criterion has been met. The final path analysis diagram is below.

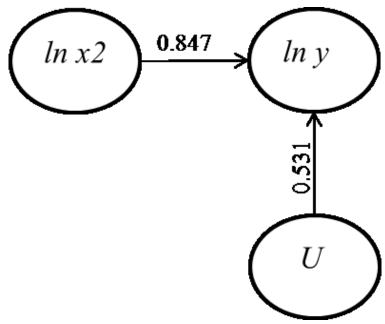


Figure 5.14: PA for NLM, 1 factor

As was the case in LR, the statistical significance is tested using ANOVA. The resulting *p-values* for all the coefficients of all the jackknife sub-samples considering all three potential cost drivers are tabulated below.

Table 5.28: *p-values* for NLM, 3 factors

	p - values										
	$JACK_{3A}$	$JACK_{3B}$	$JACK_{3C}$	$JACK_{3D}$	$JACK_{3E}$	$JACK_{3F}$	$JACK_{3G}$	$JACK_{3H}$	$JACK_{3I}$	$JACK_{3J}$	$JACK_{3AVG}$
$ln\ x_0$	0.098	0.102	0.098	0.001	0.103	0.176	0.118	0.105	0.091	0.622	0.151
$ln\ x_1$	0.758	0.636	0.645	0.484	0.483	0.425	0.638	0.596	0.783	0.158	0.560
$ln\ x_2$	0.230	0.152	0.146	0.181	0.144	0.062	0.151	0.134	0.149	0.030	0.138
$ln\ x_3$	0.913	0.852	0.831	0.039	0.820	0.441	0.877	0.841	**0.947**	0.265	**0.683**

In the present form, none of the cost drivers are significant at the 90% confidence interval. The regression analysis is repeated with the omission of $ln\ x_3$ (height of MLG), and the resulting equations are tabulated below.

Table 5.29: Summary of NLM jackknife equations for 2 factors

$$ln\hat{y}_{2,\mathrm{N}LM} = 5.56 - 0.17\ lnx_1 + 0.63\ lnx_2$$

$$ln\hat{y}_{2\mathrm{A},\mathrm{N}LM} = 6.16 - 0.11\ lnx_1 + 0.54\ lnx_2$$

$$ln\hat{y}_{2\mathrm{B},\mathrm{N}LM} = 5.79 - 0.15\ lnx_1 + 0.60\ lnx_2$$

$$ln\hat{y}_{2\mathrm{C},\mathrm{N}LM} = 5.79 - 0.14\ lnx_1 + 0.59\ lnx_2$$

$$ln\hat{y}_{2\mathrm{D},\mathrm{N}LM} = 5.72 - 0.25\ lnx_1 + 0.66\ lnx_2$$

$$ln\hat{y}_{2\mathrm{E},\mathrm{N}LM} = 5.66 - 0.45\ lnx_1 + 0.78\ lnx_2$$

$$ln\hat{y}_{2\mathrm{F},\mathrm{N}LM} = 5.56 - 0.10\ lnx_1 + 0.59\ lnx_2$$

$$ln\hat{y}_{2\mathrm{G},\mathrm{N}LM} = 5.55 - 0.17\ lnx_1 + 0.63\ lnx_2$$

$$ln\hat{y}_{2\mathrm{H},\mathrm{N}LM} = 5.68 - 0.17\ lnx_1 + 0.62\ lnx_2$$

$$ln\hat{y}_{2\mathrm{I},\mathrm{N}LM} = 5.18 - 0.15\ lnx_1 + 0.65\ lnx_2$$

$$ln\hat{y}_{2\mathrm{J},\mathrm{N}LM} = 4.57 - 0.25\ lnx_1 + 0.77\ lnx_2$$

The SPC charts for the linearity test can be found in APPENDIX D. Figures D.1-D.10 infer the linearity constraint to be upheld as all the points are within the control limits. The R^2 values, for the normality test are as follows.

Table 5.30: Summary of R^2 values for LR, 2 factors

Sub-Sample	R^2
NO $\mathrm{JACK}_{2,\mathrm{NLM}}$	0.7368
$\mathrm{JACK}_{2\mathrm{A},\mathrm{NLM}}$	0.6433
$\mathrm{JACK}_{2\mathrm{B},\mathrm{NLM}}$	0.6853
$\mathrm{JACK}_{2\mathrm{C},\mathrm{NLM}}$	0.7151
$\mathrm{JACK}_{2\mathrm{D},\mathrm{NLM}}$	0.8631
$\mathrm{JACK}_{2\mathrm{E},\mathrm{NLM}}$	0.7352
$\mathrm{JACK}_{2\mathrm{F},\mathrm{NLM}}$	0.7809
$\mathrm{JACK}_{2\mathrm{G},\mathrm{NLM}}$	0.7282
$\mathrm{JACK}_{2\mathrm{H},\mathrm{NLM}}$	0.7079
$\mathrm{JACK}_{2\mathrm{I},\mathrm{NLM}}$	0.7543
$\mathrm{JACK}_{2\mathrm{J},\mathrm{NLM}}$	0.7924
$\mathrm{JACK}_{2\mathrm{AVG},\mathrm{NLM}}$	0.7406

As the average values are above 0.70, the model is considered good (ISPA, 2008). The resulting equation (target cost model) from the jackknife equations in Table 5.30 would be as follows.

$$ln\hat{y}_{2,\mathrm{AVG}} = 5.57 - 0.19\ lnx_1 + 0.64\ lnx_2 \tag{56}$$

The errors generated for all the programs are tabulated below.

Table 5.31: Errors for Trial 1 NLM, 2 factors

Program	Error (%)
1	6.60
2	4.12
3	6.16
4	22.61
5	4.70
8	23.52
9	11.46
10	12.94
11	0.25
12	3.23

Table 5.32 gives the errors of the validation data.

Table 5.32: Errors for Trial 1 validation data of NLM, 2 factors

Program	Error (%)
6	23.52
7	11.46
13	20.21

The ANOVA for the two remaining factors are as follows.

Table 5.33: *p-values* for NLM, 2 factors

	p - values										
	$JACK_{3A}$	$JACK_{3B}$	$JACK_{3C}$	$JACK_{3D}$	$JACK_{3E}$	$JACK_{3F}$	$JACK_{3G}$	$JACK_{3H}$	$JACK_{3I}$	$JACK_{3J}$	$JACK_{3AVG}$
ln x_0	0.013	0.012	0.009	0.001	0.008	0.005	0.009	0.010	0.012	0.020	0.010
ln x_1	**0.716**	0.591	0.629	0.185	0.448	0.707	0.541	0.531	0.584	0.332	**0.526**
ln x_2	0.093	0.052	0.049	0.004	0.062	0.030	0.033	0.036	0.025	0.013	0.040

From Table 5.33, it would indicate the insignificance of the weight of the MLG. Thus, the analysis is repeated again with only the MTOW as the potential cost driver. The resulting equations are as follows.

Table 5.34: Summary of LG jackknife equations for 1 factor

$$ln\hat{y}_{1,\mathrm{N}LM} = 5.89 + 0.51\ lnx_2$$

$$ln\hat{y}_{1\mathrm{A},\mathrm{N}LM} = 6.49\_0.45\ lnx_2$$

$$ln\hat{y}_{1\mathrm{B},\mathrm{N}LM} = 6.16 + 0.48\ lnx_2$$

$$ln\hat{y}_{1\mathrm{C},\mathrm{N}LM} = 6.11 + 0.49\ lnx_2$$

$$ln\hat{y}_{1\mathrm{D},\mathrm{N}LM} = 6.18 + 0.48\ lnx_2$$

$$ln\hat{y}_{1\mathrm{E},\mathrm{N}LM} = 5.71 + 0.52\ lnx_2$$

$$ln\hat{y}_{1\mathrm{F},\mathrm{N}LM} = 5.73 + 0.52\ lnx_2$$

$$ln\hat{y}_{1\mathrm{G},\mathrm{N}LM} = 5.85 + 0.51\ lnx_2$$

$$ln\hat{y}_{1\mathrm{H},\mathrm{N}LM} = 6.01 + 0.50\ lnx_2$$

$$ln\hat{y}_{1,\mathrm{N}LM} = 5.42 + 0.55\ lnx_2$$

$$ln\hat{y}_{1\mathrm{J},\mathrm{N}LM} = 5.19 + 0.57\ lnx_2$$

The SPC charts found in APPENDIX E (Figures E1-E.10) infer the linearity assumption to be fulfilled. The R^2 values for the linearity test are as follows.

Table 5.35: Summary of R^2 values for NLM, 1 factor

Sub-Sample	R^2
NO $\mathrm{JACK}_{1,\mathrm{NLM}}$	0.7177
$\mathrm{JACK}_{1\mathrm{A},\mathrm{NLM}}$	0.6347
$\mathrm{JACK}_{1\mathrm{B},\mathrm{NLM}}$	0.6685
$\mathrm{JACK}_{1\mathrm{C},\mathrm{NLM}}$	0.7028
$\mathrm{JACK}_{1\mathrm{D},\mathrm{NLM}}$	0.8120
$\mathrm{JACK}_{1\mathrm{E},\mathrm{NLM}}$	0.7061
$\mathrm{JACK}_{1\mathrm{F},\mathrm{NLM}}$	0.7752
$\mathrm{JACK}_{1\mathrm{G},\mathrm{NLM}}$	0.7091
$\mathrm{JACK}_{1\mathrm{H},\mathrm{NLM}}$	0.6864
$\mathrm{JACK}_{1\mathrm{I},\mathrm{NLM}}$	0.7406
$\mathrm{JACK1}_{\mathrm{J},\mathrm{NLM}}$	0.7539
$\mathrm{JACK1}_{1\mathrm{AVG},\mathrm{NLM}}$	0.7189

As the average value is greater than 0.70, the model is acceptable.

The resulting equation (target cost model) from the jackknife equations in Table 5.34 is as follows.

$$ln\hat{y}_{\text{AVG},NLM} = 5.88 + 0.51\ lnx_2 \tag{57}$$

The errors generated for all the programs are tabulated below.

Table 5.36: Errors for Trial 1 NLM, 1 factor

Program	Error (%)
1	10.10
2	6.16
3	8.89
4	21.45
5	4.07
8	28.20
9	14.61
10	15.39
11	1.69
12	3.19

Table 5.37: Errors for Trial 1validation data of NLM, 1 factor

Program	Error (%)
6	28.20
7	14.61
13	16.87

The ANOVA analysis is presented below.

Table 5.38: *p-values* for NLM, 1 factor

	p - values										
	$JACK_{1A}$	$JACK_{1B}$	$JACK_{1C}$	$JACK_{1D}$	$JACK_{1E}$	$JACK_{1F}$	$JACK_{1G}$	$JACK_{1H}$	$JACK_{1I}$	$JACK_{1J}$	$JACK_{1AVG}$
ln x_0	0.003	0.003	0.002	0.000	0.005	0.002	0.003	0.003	0.005	0.006	**0.003**
ln x_2	0.010	0.007	0.005	0.001	0.005	0.002	0.004	0.006	0.003	0.002	**0.004**

As can be derived from Equations (27) and (28), both *ln* x_0 and *ln* x_2 have values (in green) that may be considered significant at the 90% confidence interval. The analysis is complete for Trial 1.

5.1.3 Analysis for Trials 2 and 3: Linear and Non-Linear Model

The analysis was repeated Trials 2 and 3. For both trials, the CERs were solely using the MTOW as the significant cost driver. The errors for the LR and NLM are presented below.

Table 5.39: Errors for Trial 2 LR, 1 factor

Program	Error (%)
1	31.06
3	20.54
4	20.11
5	9.81
6	22.43
7	9.91
9	1.55
10	4.55
11	8.97
13	13.20

Table 5.40: Error for Trial 2 validation data of LR, 1 factor

Program	Error (%)
2	22.93
8	9.99
12	10.41

Table 5.41: Errors for Trial 2 NLM, 1 factor

Program	Error (%)
1	19.76
3	15.71
4	19.46
5	3.10
6	24.38
7	10.92
9	3.16
10	2.66
11	11.26
13	15.49

Table 5.42: Errors for Trial 2 validation data of NLM, 1 factor

Program	Error (%)
2	14.51
8	11.43
12	12.74

Table 5.43: Errors for Trial 3 LR, 1 factor

Program	Error (%)
1	31.21
2	27.66
4	20.97
5	9.70
6	22.81
8	9.59
10	9.37
11	4.51
12	5.30
13	10.99

Table 5.44: Errors for Trial 3 validation data of LR, 1 factor

Program	Error (%)
3	15.68
7	11.47
9	9.68

Table 5.45: Errors for Trial 3 NLM, 1 factor

Program	Error (%)
1	20.40
2	22.86
4	20.23
5	3.33
6	24.59
8	10.46
10	7.83
11	6.68
12	7.61
13	13.34

Table 5.46: Errors for Trial 3 validation data of NLM, 1 factor

Program	Error (%)
3	8.13
7	12.73
9	12.10

The regression analysis is now complete. The next section shows the analysis of the complex non-linear model (CNLM).

5.1.4 Analysis Based on a Complex Non-Linear Model

The CNLM selected to model the target cost is that shown in Equation (40).

$$\hat{y} = a_0 x_1^{b_0} + a_1 x_2^{b_1} + a_2 x_3^{b_2} + c_0 x_1^{d_0} x_2^{d_1} + c_1 x_1^{d_2} x_3^{d_3} + c_2 x_2^{d_4} x_3^{d_5} + e_0 x_1^{f_0} x_2^{f_1} x_3^{f_2}$$

It should be noted the values of input and cost data was normalized to facilitate in the convergence of the model.

$$x_1 \rightarrow x_{1(original)}/1{,}000$$

$$x_2 \rightarrow x_{2(original)}/100{,}000$$

$$x_3 \rightarrow x_{3(original)}/1{,}000$$

$$y \rightarrow y_{(original)}/1{,}000{,}000$$

As mentioned in Section 3, the gradient descent algorithm (GDA) was used to determine the coefficients of the model. For all 3 Trials, using the GDA, the models converged and resulted in the following equations.

$$\hat{y}_{CNLM,Trial\ 1} = 0.053x_1^{0.664} + 0.189x_2^{0.464} - 0.314x_3^{0.590} - 0.176x_1^{0.605}x_2^{0.678} + 0.179x_1^{0.623}x_3^{0.728} + 0.180x_2^{0.592}x_3^{0.725} + 0.331x_1^{0.574}x_2^{0.544}x_3^{0.697} \quad (58)$$

$$\hat{y}_{CNLM,Trial\ 2} = 0.104x_1^{0.682} + 0.304x_2^{0.523} - 0.428x_3^{0.408} - 0.339x_1^{0.671}x_2^{0.913} + 0.242x_1^{0.623}x_3^{0.722} + 0.254x_2^{0.584}x_3^{0.714} + 0.402x_1^{0.560}x_2^{0.521}x_3^{0.684} \quad (59)$$

$$\hat{y}_{CNLM,Trial\ 3} = 0.139x_1^{0.693} + 0.257x_2^{0.516} - 0.408x_3^{0.453} - 0.319x_1^{0.664}x_2^{0.875} + 0.223x_1^{0.622}x_3^{0.718} + 0.208x_2^{0.574}x_3^{0.715} + 0.364x_1^{0.565}x_2^{0.520}x_3^{0.688} \quad (60)$$

The corresponding errors for all the Trials are shown in Tables 5.47 -5.49.

Table 5.47: Errors for Trial 1 CNLM

Program	Error (%)
1	7.01
2	4.75
3	12.33
4	14.79
5	3.09
8	10.32
9	0.07
10	6.51
11	4.35
12	11.56
6	23.08
7	9.61
13	13.95

Table 5.48: Errors for Trial 2 CNLM

Program	Error (%)
1	1.40
3	1.79
4	0.42
5	0.27
6	0.41
7	1.20
9	2.79
10	1.49
11	0.20
13	1.67
2	0.01
8	1.54
12	0.91

Table 5.49: Errors for Trial 3 CNLM

Program	Error (%)
1	11.28
2	9.05
4	19.81
5	12.61
6	10.88
8	1.85
10	5.45
11	4.74
12	2.19
13	5.48
3	14.33
7	2.45
9	5.17

The analysis of the parametric CERs is complete. The next section of this thesis discusses the results obtained to predict the target cost using neural network models.

5.2 Neural Network Model

Several researchers such as Tu (1996), Cavalieri *et* al. (2004), and Caputo (2008) have commended neural networks (NN) models for their ability to characterize complex relationships. Neural network models will be used to estimate the target cost of the MLG based upon the selected cost drivers. This section will present the results and analysis of two types of NN models that are trained using 1-back propagation and 2- the genetic algorithm (GA).

5.2.1 Neural Network Model Trained using Back Propagation

In order use NN, the input and output data must range between 0 and 1. Table 5.50 presents a normalized version of Table 5.1, i.e., the given data.

Table 5.50: Data for NNs

Program	x_{1NN}	x_{2NN}	x_{3NN}	y_{NN}
1	0.3184	0.0724	0.6718	0.1280
2	0.4164	0.1820	0.6751	0.2280
3	0.5983	0.4178	0.7867	0.7480
4	0.0722	0.1255	0.0909	0.2754
5	0.1916	0.2325	0.0909	0.6696
6	0.3058	0.2917	0.0699	0.5372
7	0.6731	0.5082	0.1894	0.5226
8	0.6731	0.5932	0.1894	0.6320
9	0.7852	0.6532	0.1911	0.5168
10	0.6640	0.7851	0.3638	0.5350
11	0.3184	0.1086	0.6718	0.1846
12	0.3134	0.2697	0.0798	0.5264
13	0.6640	0.7248	0.3638	0.5349

In order to predict the costs, the final weights are set, via training of the NN model. The training takes place by using the training data. The first set of training data is the same as Trial 1 for LR, which omits programs 6, 7, and 13. Similarly, Trials 2 and 3 were used as two sets of training data for the NN models. Following the procedure of Pandya and Macy (1996), to code the NN model, the model parameters mentioned in Section 3.2.1 have to be set.

5.2.1.1 Model parameters for back propagation trained neural networks

The following parameters must be defined to compile the model.

- Temperature, $\mathbb{Q}$
- Learning Rate, η
- Number of Hidden Layers
- The maximum value for the stopping criterion, δ
- Maximum number of iterations
- Neurons in hidden layer

Recall from Chapter 3 that the value of $\mathbb{Q}$ is utilized for the activation function in Equation (29) in order to obtain the output of a given neuron. A higher value of $\mathbb{Q}$ would result in a smoother activation function. Therefore, its value is set at 0.8. The learning rate, η is used to determine the steps of the change in weight. The value is set high to avoid low minima with the intent of obtaining a better solution.

The maximum value for stopping cannot be set at a very low value. If the value is too low, over fitting will occur (Pandya and Macy, 1996). Over fitting, also referred to as over-training, is the notion of having a very good model (i.e. small errors) on the validation data, yet when used to forecast using the validation data, the results are meaningless (i.e. high errors). Thus, based upon trial and error, the value of δ was set at 0.10. The maximum number of iterations is set at a high value, in this case, 192 000 000, in order to allow the model to stop if the other stopping criteria is not met.

The number of neurons in the hidden layer has to be obtained by trial and error. The following figure presents a sensitivity analysis to showing how the maximum error on the validation data changes depending of the number of neurons selected in the hidden layer.

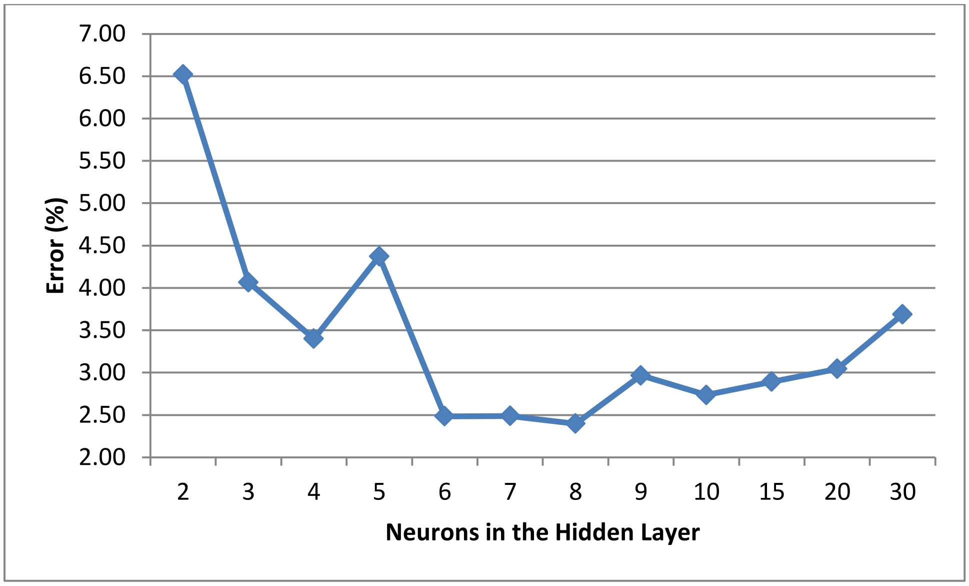


Figure 5.15: Sensitivity Analysis on Neurons in Hidden Layer, Trial 1

All the errors for the sensitivity analysis of Trial 1 are found Table 5.51.

Table 5.51: Sensitivity Analysis of errors for hidden layer, Trial 1

		Number of Neurons in the Hidden Layer (N)											
		2	3	4	5	6	7	**8**	9	10	15	20	30
Training	Max Error	7.15	7.24	7.30	0.00	2.15	3.58	**0.93**	4.26	5.73	3.78	4.57	6.15
	Average Error	1.53	2.18	2.01	0.00	0.47	0.78	**0.20**	0.94	1.23	0.83	0.99	2.04
Validation	Max Error	6.52	4.07	3.40	4.37	2.49	2.49	**2.40**	2.97	2.74	2.89	3.04	3.69
	Average Error	2.90	3.83	3.31	3.64	2.10	2.08	**2.07**	2.86	2.70	2.59	2.71	2.00
Overall Average Error		1.84	2.56	2.31	0.84	0.85	1.08	**0.63**	1.39	1.57	1.24	1.39	2.03

The sensitivity analysis is replicated for Trials 2 and 3. The results of the analysis are in the following figures and tables.

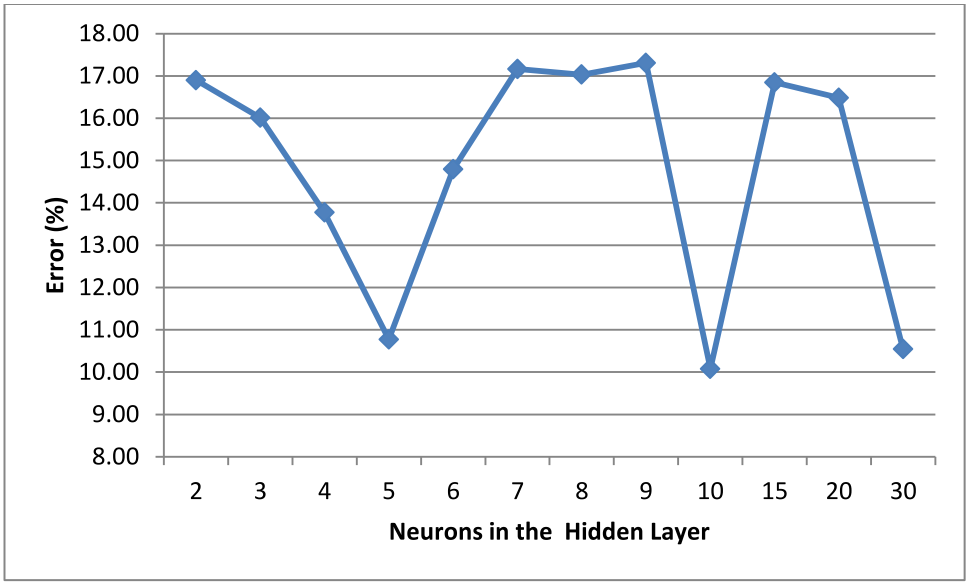


Figure 5.16: Sensitivity Analysis on Neurons in Hidden Layer, Trial 2

Table 5.52: Sensitivity Analysis of errors for hidden layer, Trial 2

		Number of Neurons in the Hidden Layer (N)											
		2	3	4	5	6	7	8	9	10	15	20	30
Training	Max Error	17.19	7.07	5.86	4.91	0.00	18.46	18.79	19.40	**2.85**	19.54	0.00	2.51
	Average Error	9.25	1.53	1.48	1.21	0.00	9.76	9.54	10.15	**1.11**	9.70	0.00	0.94
Validation	Max Error	16.90	16.01	13.77	10.77	14.79	17.16	17.03	17.31	**10.08**	16.84	16.48	10.54
	Average Error	8.39	7.33	8.89	8.11	8.59	8.46	8.46	8.49	**8.08**	8.06	9.50	7.15
Overall Average Error		9.05	2.87	3.19	2.80	1.98	9.46	9.29	9.76	**2.72**	9.32	2.19	2.37

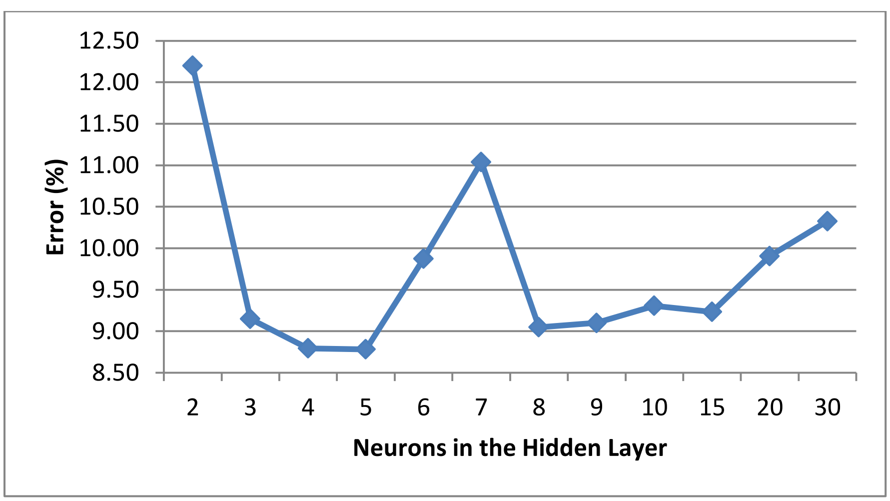


Figure 5.17: Sensitivity Analysis on Neurons in Hidden Layer, Trial 3

Table 5.53: Sensitivity Analysis of errors for hidden layer, Trial 3

		Number of Neurons in the Hidden Layer (N)											
		2	3	4	5	6	7	8	9	10	15	20	30
Training	Max Error	12.71	4.51	5.27	2.88	0.35	0.18	1.43	1.20	1.32	1.32	0.08	0.24
	Average Error	4.28	1.65	1.65	0.87	0.15	0.08	0.44	0.41	0.41	0.39	0.04	0.10
Validation	Max Error	12.20	9.15	8.79	8.78	9.87	11.04	9.05	9.10	9.31	9.23	9.91	10.33
	Average Error	6.47	6.39	6.30	5.55	6.99	7.87	6.32	6.33	6.45	6.63	7.37	7.51
Overall Average Error		4.79	2.75	2.72	1.95	1.73	1.87	1.80	1.77	1.80	1.83	1.73	1.81

As can be seen from the sensitivity analysis, the number of neurons to select based upon the validation errors for Trials 1-3 would be 8, 10, and 5, respectively. In order to conduct the comparative analysis, one value is to be used for the number of neurons in the hidden layer. The value is set to 5 to minimize the number of weights created to avoid over training. With the model parameters set, the next step is to run the model and obtain the results.

5.2.1.2 Model results for back propagation trained neural network

Upon running the NN model, the stopping criterion was met for Trial 1. The following Tables 5.54 presents the final weights.

Table 5.54: 1st layer weights Trial 1 BP

w	5	6	7	8	9
1	2.390	1.336	1.638	9.731	-1.052
2	12.583	1.153	1.168	2.265	1.132
3	-1.246	-1.650	-1.984	-4.089	2.743
Bias1	-2.751	0.888	0.356	-2.094	-1.237

Table 5.55: 2nd layer weights Trial 1 BP

w	11
5	8.262
6	-0.774
7	-1.277
8	-5.699
9	-1.144
Bias2	-0.125

The resulting errors of Trial 1 are the following.

Table 5.56: Errors for Trial 1 BP

Program	Error (%)
1	0.50
2	0.96
3	0.38
4	0.21
5	0.63
8	0.84
9	4.25
10	4.26
11	0.01
12	1.13
6	10.33
7	5.65
13	0.51

The analysis was repeated for both Trials 2, and 3 and the model was able to meet the stopping criterion in both cases. Tables 5.57-5.62 present the weights and errors of Trials 2 and 3, respectively.

Table 5.57: 1st layer weights Trial 2 BP

w	5	6	7	8	9
1	-0.924	2.226	1.909	2.450	-1.319
2	9.724	2.652	0.769	2.833	-3.457
3	-0.979	-3.121	1.514	-3.608	0.575
Bias1	-1.234	0.426	-1.781	0.367	-1.789

Table 5.58: 2st layer weights Trial 2 BP

w	11
5	8.262
6	-0.774
7	-1.277
8	-5.699
9	-1.144
Bias2	-0.125

Table 5.59 Errors for Trial 2 BP

Program	Error (%)
1	0.11
3	0.05
4	0.00
5	0.19
6	0.18
7	0.31
9	2.04
10	4.30
11	1.84
13	0.60
2	4.93
8	1.72
12	0.81

Table 5.60: 1st layer weights Trial 3 BP

w	5	6	7	8	9
1	7.232	-2.540	3.576	2.616	9.188
2	15.659	0.961	4.812	1.660	3.591
3	-5.855	-3.069	0.462	-3.435	-5.418
Bias1	-2.616	1.708	-2.631	1.135	-1.366

Table 5.61: 2st layer weights Trial 3 BP

w	11
5	6.937
6	3.363
7	3.511
8	-3.81
9	-6.701
Bias2	-1.253

Table 5.62 Errors for Trial 3 BP

Program	Error (%)
1	0.01
2	0.24
4	0.18
5	0.32
6	0.34
8	0.38
10	4.91
11	4.56
12	0.74
13	0.40
3	10.77
7	7.61
9	5.96

As all 3 trials were able to meet the stopping criterion, the analysis is complete. The next analysis to be conducted is using a NN trained by the genetic algorithm.

5.2.2 Neural Network Model Trained using the Genetic Algorithm

The data set presented in Table 5.50 will be used for this analysis. For analysis purposes the same 3 Trials will be utilized. Similar to back propagation, the model parameters described in Section 3.2.2 are set, with the exception of the learning rate, η.

5.2.2.1 Model parameters for neural networks trained using the GA

In addition to the parameters already set in Section 5.2.1.2, the following parameters must be defined to compile the model using the genetic algorithm as defined in Section 3.2.2.

- Maximum step size θ_{max}
- Selection Operator
  - Population size, *n*
  - *k-way* tournament factor, *k*
- Cross over operator
  - Probability of SwCO-1, α_1
  - Probability of SwCO-2, α_2
  - Probability of SPCO-1, α_3
  - Probability of SPCO-1, α_4
- Mutation operator
  - Probability of chromosome being mutated , α_5
  - Probability of gene being mutated, α_6

The maximum step is discussed in Section 3.2.2. It is similar to the learning rated in the NN using back propagation. The value of θ_{max} is set at 0.50. The population size, n should be a large number in order for the model to develop enough pairs (parents). Since the GA is compared to the notion of "survival of the fittest," the selected value of *k* is small, in this case 0.001, as it is the multiplicative factor to the population to select the amount of the chromosomes to be randomly selected from the population. The "fittest" or the one that estimates the cost most accurately will be kept and the remaining will be discarded, at each iteration.

The crossover operator is the key operator to generate the new population (Dawid, 1996). The probability of all four of the above mentioned operators discussed in detail in Section 3.2 will have a value of 0.85. Dawid (1996) further explains the mutation operators should have low probabilities. The probability of a chromosome being mutated is set at 0.30. Given that the chromosome is mutated, the probability of any given gene being mutated is 0.15. The model is initialized and the following section presents the results.

5.2.2.2 Model results for neural network model using the GA

Upon running the model, it converged for all of the Trials. Figures 5.18–5.20 displays the masked cost versus the prediction for Trials 1–3, respectively.

Figure 5.18: Masked Cost versus Prediction for Trial 1 GA

Figure 5.19: Cost versus Prediction for Trial 2 GA

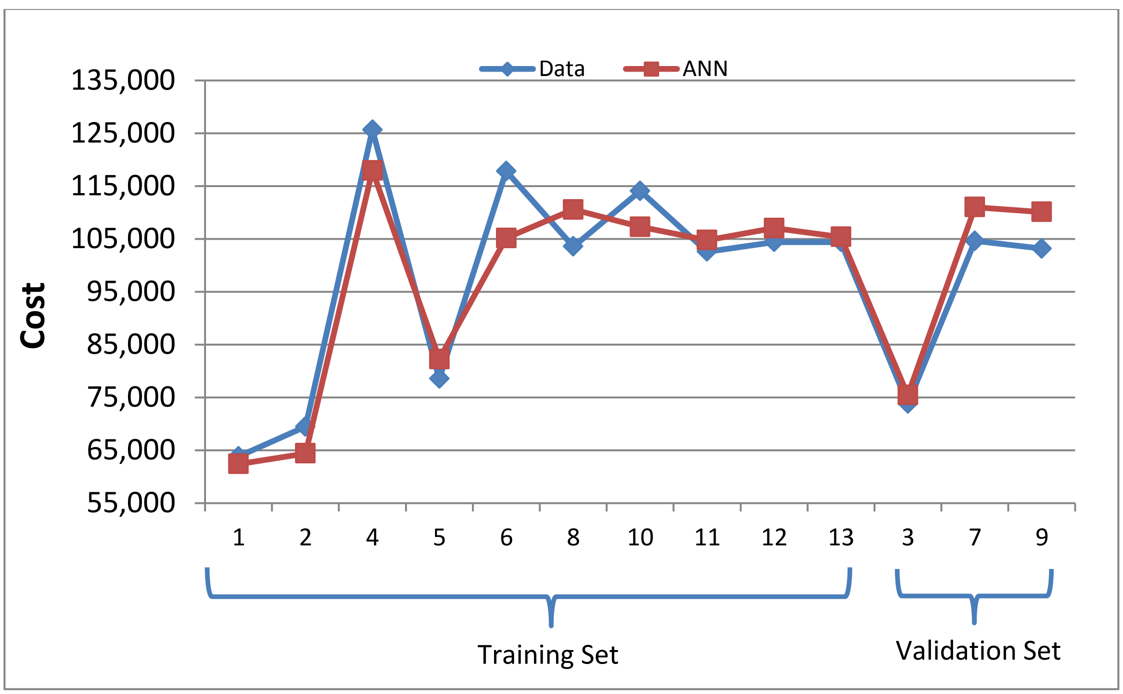


Figure 5.20: Cost versus Prediction for Trial 3 GA

Tables 5.63 – 5.65 present the errors for all of the trials.

Table 5.63 Errors for Trial 1 GA

Program	Error (%)
1	6.88
2	4.49
3	10.25
4	2.02
5	10.89
8	2.78
9	0.56
10	2.02
11	0.56
12	0.52
6	9.94
7	4.98
13	0.08

Table 5.64 Errors for Trial 2 GA

Program	Error (%)
1	1.40
3	1.79
4	0.42
5	0.27
6	0.41
7	1.20
9	2.79
10	1.49
11	0.20
13	1.67
2	0.01
8	1.54
12	0.91

Table 5.65 Errors for Trial 3 GA

Program	Error (%)
1	2.22
2	7.28
4	6.12
5	4.76
6	10.74
8	6.77
10	5.94
11	2.12
12	2.54
13	0.93
3	2.21
7	6.10
9	6.72

The analysis for the NN is complete; the next section will present the results of the data envelopment analysis model.

5.3 Data Envelopment Analysis

Prior to utilize the model, it was adapted to be applied in the studied case. This section explains how the model was adapted, and the results thereof.

5.3.1 Problem Adaption

In the last decades, several DEA models have been proposed in operations research and in the economics literature as tools for the estimation of relative efficiencies and ranking DMUs. In this section, the use of DEA is extended beyond this traditional application to cost estimation of products that may either be procured from external suppliers or manufactured in house in a built-to-order environment. In such an environment, when an order is placed, only a few generic design, manufacturing and operational attributes of the products will be known, which are referred to as cost drivers. However, it can be assumed that the manufacturer has historical data from similar products with varying degrees of the cost drivers and the costs that have been procured or manufactured in the past. This assumption is in agreement with the vast amount of literature both in parametric and non-parametric cost estimation methods. As it is the case in both parametric and non-parametric cost estimation methods in literature, it is further assumed that in the historical data there are *n* products such that each product has *i* number of cost drivers that can be quantified. These cost drivers can be denoted as $\hat{x}_{1,n}, \hat{x}_{2,n}, \cdots, \hat{x}_{r,n}$ for product *n*. Without loss of generality, in this thesis we further assume that the first *r* cost drivers $\hat{x}_{1,n}, \hat{x}_{2,n}, \cdots, \hat{x}_{r,n}$ correspond to desirable attributes and the remaining $i - r$ *cost* drivers $\hat{x}_{r+1,n}, \hat{x}_{r+2,n}, \cdots, \hat{x}_{i,n}$ correspond to undesirable attributes. A desirable attribute means, that given all other attributes kept unchanged, the higher the value of this attribute, the better it is (e.g. load carrying capacity) and the opposite applies for undesirable attributes (e.g. weight of a sub-assembly). With the above introduction, an adapted version of the problem is presented. The analogy between a DMU and a product is used for the purpose of using DEA as a cost estimation tool.

5.3.1.1 Input Adaptation

For DMU$_k$, given all else is equal, the lesser an input quantity $x_{i,k}$ is the more efficient this DMU. For PRODUCT$_k$, given all else is equal, the higher a desirable attribute $\hat{x}_{i,k}$ (for $i \leq r$) or the lesser an undesirable attribute $\hat{x}_{i,k}$ (for $i > r$), the better is the product. If we make an analogy between DMU$_k$ and PRODUCT$_k$, then the inputs to the product should be $x_{i,k} = 1/\hat{x}_{i,k}$ for $i \leq r$ and $x_{i,k} = \hat{x}_{i,k}$ for $i > r$ so that the lesser an input can be interpreted as the better product as is the case for DMU$_k$. This input adaptation is summarized in Equation (61).

$$x_{i,n} = \begin{cases} \frac{1}{\hat{x}_{i,n}} & for\ i = 1, 2, \cdots, r \\ \frac{1}{\hat{x}_{i,n}} & for\ i = r+1, r+2, \cdots, I \end{cases} \tag{61}$$

5.3.1.2 Output Adaption

For DMU$_k$, given all other inputs and outputs the same, the higher an output $y_{o,k}$ is, the more efficient the DMU. For PRODUCT$_k$, given all other inputs the same, the lower the cost is the better the product. If we make an analogy between DMU$_k$ and PRODUCT$_k$, then the output from PRODUCT$_k$ should be $y_{1,k}$ = 1/cost. Thus for this product, given a set of inputs, the higher the output (which is now the ratio 1/cost), the better is the product. This analogy is shown in Figure 5.17 below.

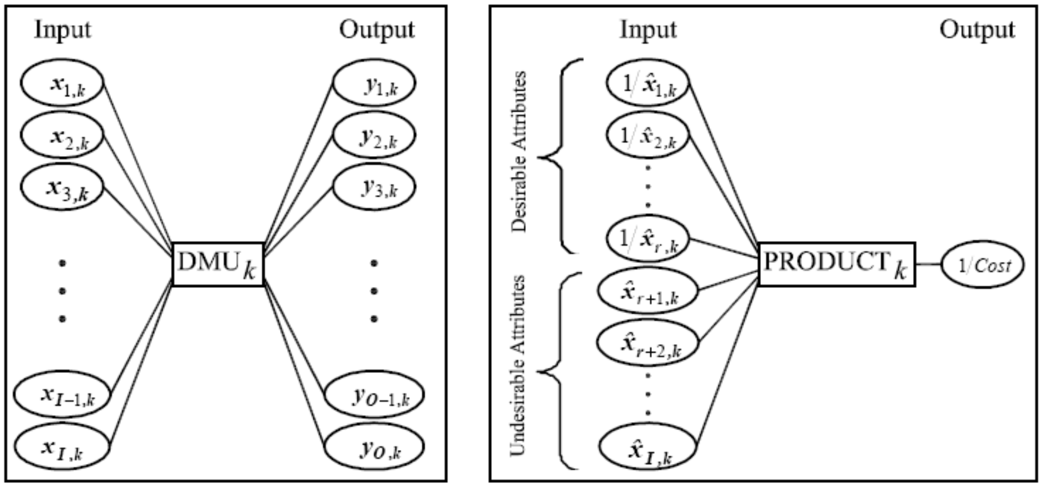


Figure 5.21: Analogy between the DMU and the product

5.3.2 Implementation

After problem adaptation, each product n in the historic data has inputs $x_{1,n}$, $x_{2,n}, \ldots, x_{I,n}$ and an output $y_{1,n}$ = 1/Cost$_n$ having the same interpretation as inputs and outputs of a DMU. Thus, these products in the historic data can be ranked using any DEA model available in the literature. In this thesis we use the super-efficiency DEA model presented in Section 3.3. Once the products are ranked, the one with the highest E_k is considered as the benchmark product. The benchmark can then be used for estimating the cost of a new product with known inputs $x_{1,N+1}$, $x_{2,N+1}$, · · ·, $x_{I,N+1}$ and unknown output $y_{1,N+1}$ = 1/Cost$_{N+1}$ where N is the total number of products in the historic data. This cost estimation is accomplished by repeatedly solving the super-efficiency DEA model for k = $N + 1$ and for different trial values of the output $y_{1,N+1}$. If the efficiency of the new product becomes equal to that of the efficiency of the benchmark product for a certain trial value of $y_{1,N+1}$, then this trial value is used to estimate the cost of the new product as

$Cost_{N+1} = 1/ y_{1,N+1}$. The cost found in this way will render the new product as efficient as the benchmark product.

5.3.3 Analysis using DEA

As discussed in the previous sections the data will have to be presented in a different manner for the analysis.

Table 5.66 Data for DEA

Program	x_1	$1/x_2$	$1/x_3$	1/y
1	335.77	3.03E-05	9.00E-03	1.57E-05
2	335.77	2.75E-05	9.00E-03	1.44E-05
3	389.97	2.33E-05	8.97E-03	1.36E-05
4	490.58	1.55E-05	8.03E-03	7.96E-06
5	199.58	2.64E-05	2.31E-02	1.27E-05
6	265.62	2.1E-05	2.31E-02	8.49E-06
7	328.81	1.89E-05	2.45E-02	9.56E-06
8	333.00	1.96E-05	2.38E-02	9.66E-06
9	532.00	1.37E-05	1.82E-02	9.69E-06
10	532.00	1.24E-05	1.82E-02	8.77E-06
11	594.00	1.16E-05	1.82E-02	9.75E-06
12	526.97	1.08E-05	1.33E-02	9.58E-06
13	526.97	1.02E-05	1.33E-02	9.58E-06

From the developed model presented in Equations (44-47), the resulting efficiencies are tabulated below.

Table 5.67: Program efficiencies using DEA

Program	Efficiency
1	1.089
2	0.978
3	0.974
4	0.673
5	1.367
6	0.748
7	0.855
8	0.833
9	0.836
10	0.819
11	0.858
12	0.975
13	1.028

From the output of the model, it can be seen that Program 5 has the highest efficiency of 1.367, whereas program 4 has the lowest efficiency of 0.673. The average efficiency is 0.926. Figures 5.18 – 5.21, presents the sensitivity analysis of the impact of the input and output variables on the efficiency.

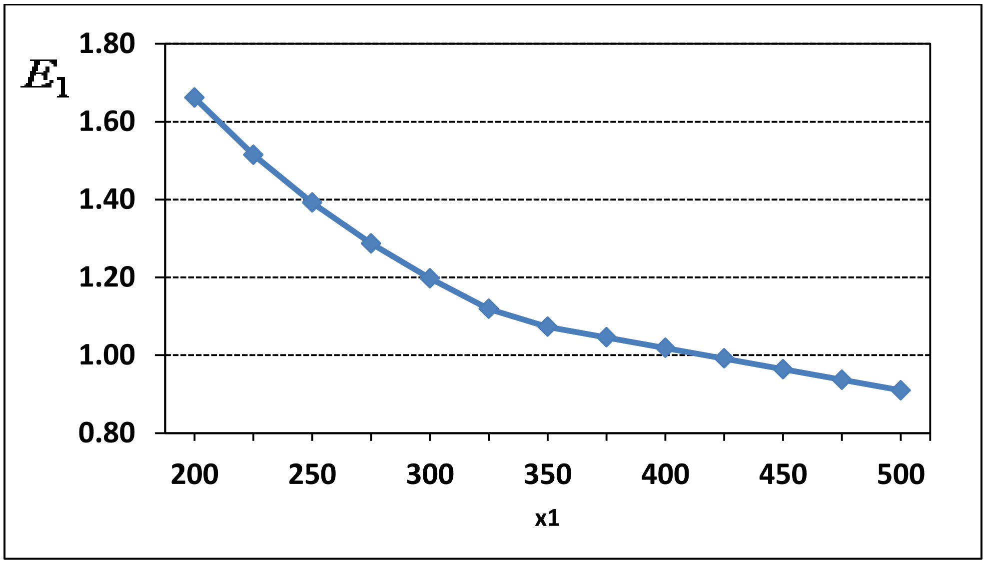


Figure 5.22: Sensitivity analysis of Weight on Efficiency

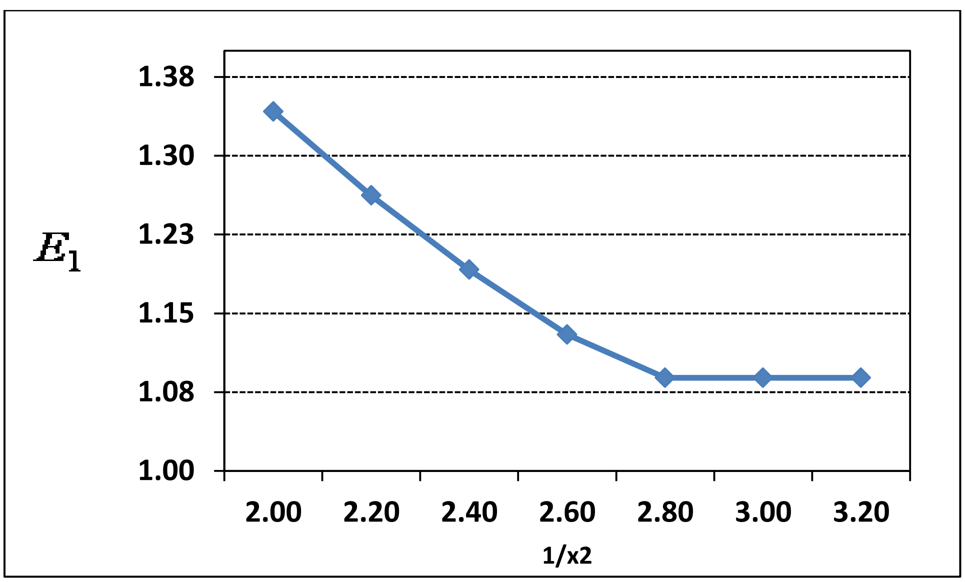


Figure 5.23: Sensitivity analysis of MTOW (1/MTOW) on Efficiency

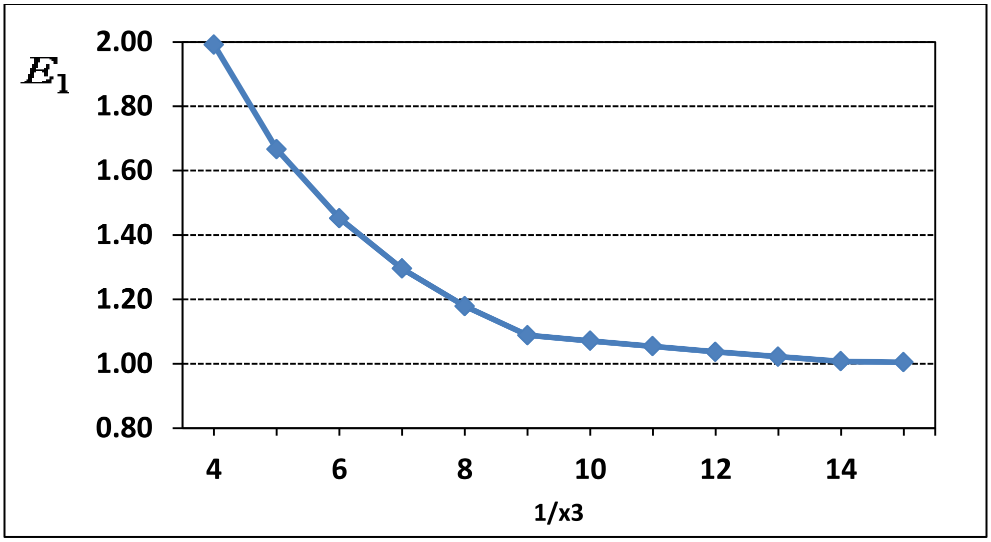


Figure 5.24: Sensitivity analysis of Height (1/Height) on Efficiency

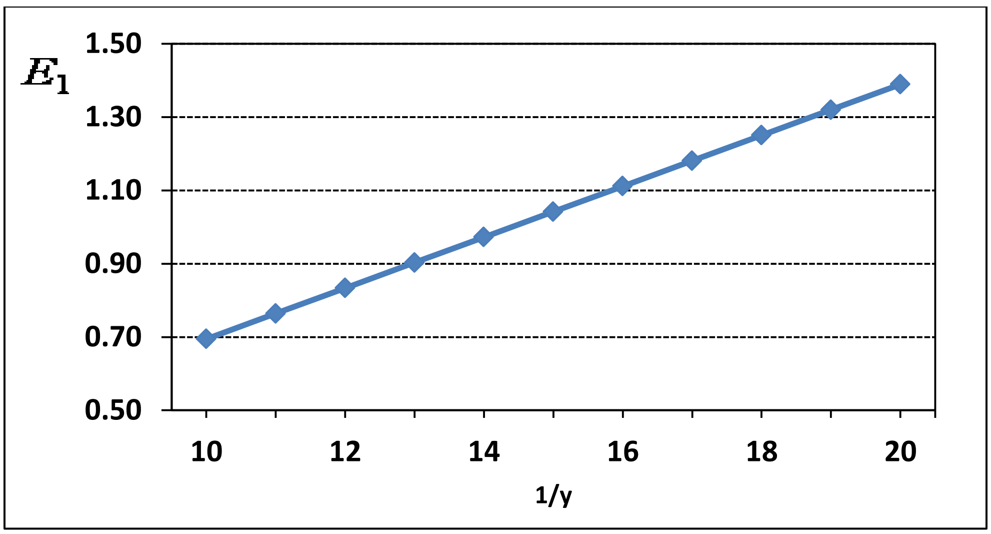


Figure 5.25: Sensitivity analysis of Cost (1/Cost) on Efficiency

As can be seen from the sensitivity analysis, the increase of the MTOW and the Height of the MLG will have a positive impact on the efficiency. On the other hand, the increase of the weight and the cost of the MLG will have a negative impact on the overall efficiency. The analysis of using the all three models stipulated in the methodology is complete. The next section will present a comparative analysis of all the findings.

5.4 Comparative Analysis

The following section will compare the results of all the findings in the developed models. It will first compare the regression models, followed by the NN models, and finish with the DEA.

As can be seen from the regression models, both models converged on one significant factor, the MTOW. Furthermore, by using path analysis, both models obtained the same conclusions. The following table provides a summary for the errors for both the regression models compared to the errors of the complex non-linear model.

Table 5.68: Comparison of Errors of Parametric CERs

Trial 1				Trial 2				Trial 3			
Program	LR	NLM	CNLM	Program	LR	NLM	CNLM	Program	LR	NLM	CNLM
1	10.02	10.10	7.01	1	31.06	19.76	2.02	1	31.21	20.40	11.28
2	6.08	6.16	4.75	3	20.54	15.71	2.75	2	27.66	22.86	9.05
3	8.81	8.89	12.33	4	20.11	19.46	15.55	4	20.97	20.23	19.81
4	21.53	21.45	14.79	5	9.81	3.10	11.29	5	9.70	3.33	12.61
5	4.14	4.07	3.09	6	22.43	24.38	10.47	6	22.81	24.59	10.88
8	15.46	28.20	10.32	7	9.91	10.92	1.20	8	9.59	10.46	1.85
9	1.58	14.61	0.07	9	1.55	3.16	3.27	10	9.37	7.83	5.45
10	3.30	15.39	6.51	10	4.55	2.66	5.49	11	4.51	6.68	4.74
11	11.17	1.69	4.35	11	8.97	11.26	0.14	12	5.30	7.61	2.19
12	13.38	3.19	11.56	13	13.20	15.49	8.10	13	10.99	13.34	5.48
6	28.26	28.20	23.08	2	22.93	14.51	13.69	3	15.68	8.13	14.33
7	14.69	14.61	9.61	8	9.99	11.43	2.52	7	11.47	12.73	2.45
13	16.74	16.87	13.95	12	10.41	12.74	8.59	9	9.68	12.10	5.17
Trial$_{AVG}$	9.55	11.38	7.48	Trial$_{AVG}$	14.21	12.59	6.03	Trial$_{AVG}$	15.21	13.73	8.33
Val.$_{AVG}$	19.90	19.89	15.55	Val.$_{AVG}$	14.44	12.89	8.27	Val.$_{AVG}$	12.28	10.99	7.31

It can be seen the results of the LR and NLM are comparable for the validation data. The CNLM outperforms both of the regression models.

The NN models significantly outperformed the regression models in terms of generated error for prediction of the target cost. Tables 5.69 - 5.71 provides a summary of the errors of the NN models for Trials 1, 2, and 3, respectively.

Table 5.69: Comparison of Errors on NN models, Trial 1

	BP	GA
Program	Error %	Error %
1	0.50	6.88
2	0.96	4.49
3	0.38	10.25
4	0.21	2.02
5	0.63	10.89
8	0.84	2.78
9	4.25	0.56
10	4.26	2.02
11	0.01	0.56
12	1.13	0.52
6	10.33	9.94
7	5.65	4.98
13	0.51	0.08
$Trial_{AVG}$	1.32	4.10
$Validation_{AVG}$	5.50	5.00

Table 5.70: Comparison of Errors on NN models, Trial 2

	BP	GA
Program	Error %	Error %
1	0.11	1.40
3	0.05	1.79
4	0.00	0.42
5	0.19	0.27
6	0.18	0.41
7	0.31	1.20
9	2.04	2.79
10	4.30	1.49
11	1.84	0.20
13	0.60	1.67
2	4.93	0.01
8	1.72	1.54
12	0.81	0.91
$Trial_{AVG}$	0.96	1.16
$Validation_{AVG}$	2.49	0.82

Table 5.71: Comparison of Errors on NN models, Trial 3

Program	BP Error %	GA Error %
1	0.01	2.22
2	0.24	7.28
4	0.18	6.12
5	0.32	4.76
6	0.34	10.74
8	0.38	6.77
10	4.91	5.94
11	4.56	2.12
12	0.74	2.54
13	0.40	0.93
3	10.77	2.21
7	7.61	6.10
9	5.96	6.72
$Trial_{AVG}$	1.21	4.94
$Validation_{AVG}$	8.11	5.01

As can be seen from Tables 5.69 – 5.71, the NN trained based upon the GA, has better results in terms of error on validation data than that trained using BP for all the trials.

The DEA model shows the ranking of all the programs as can be seen below.

Table 5.72: Ranking of MLGs using DEA

Rank	Program	Efficiency of the Equivalent DMU
1	5	1.367
2	1	1.089
3	13	1.028
4	2	0.978
5	12	0.975
6	3	0.974
7	11	0.858
8	7	0.855
9	9	0.836
10	8	0.833
11	10	0.819
12	6	0.748
13	4	0.673

As can be seen from Table 5.60, Program 5 has the highest efficiency, $E_{k,max}$ of 1.367. Program 4 has the lowest efficiency, $E_{k,min}$ with a value of 0.673, and the average efficiency, $E_{k,avg}$ of all the programs is 0.926. With the efficiencies stated above, for all programs the actual cost, y is compared to the target cost, $\hat{y}$ based upon the different efficiencies, and is shown in Table 73.

Table 5.73: Cost based upon varying Efficiencies

Program	y	$\hat{y}_{E_{k,max}}$	$\hat{y}_{E_{k,min}}$	$\hat{y}_{E_{k,avg}}$
1	63,816	50,801	103,235	75,046
2	69,465	49,687	100,971	73,400
3	73,794	52,549	106,787	77,628
4	125,657	61,835	125,657	91,344
5	78,516	78,516	159,555	115,987
6	117,834	64,491	131,054	95,268
7	104,635	65,426	132,954	96,649
8	103,552	63,065	128,157	93,162
9	103,173	63,110	128,250	93,229
10	114,082	68,327	138,851	100,936
11	102,595	64,410	130,890	95,149
12	104,400	74,416	151,223	109,930
13	104,408	78,498	159,519	115,960

This concludes the comparative analysis of the models.

5.5 Chapter Summary

This chapter presented the results of the three methodologies used in this thesis. It presents the results on regression analysis, which was followed by the analysis of neural networks, followed by the findings on data envelopment analysis. Finally, it presents a comparative analysis of the aforementioned models. The next chapter will present a general discussion of the findings in this thesis.

6. Discussion and Implications

This chapter discusses how the results of the models can be applied in a more generalizable way, and the implications thereof. This chapter will begin by presenting the summary of findings, followed by practical applications, and concluded by the managerial implications.

6.1 Summary of Findings

Many qualitative and quantitative studies have been conducted pertaining to the cost of commodities. Research in this area has been even more emphasized over the last two decades with the increased advent of low cost countries in the global economy. In order to reduce or contain total acquisition costs, much emphasis has been placed on target costing.

This thesis presents three different methodologies for determining target costs and compares the performance of each. Even though this research is applied to a specific commodity, the findings and approach utilized can be applied in a general fashion.

The first methodology under study was utilizing parametric based analysis to develop two regression models, one based on a multiple linear regression equation, and the second based on a non-linear equation. From Section 5.1 it was found that the results of both models were comparable. However, these findings are not in line with Salam *et al.* (2008, 2009), in which the non-linear models clearly outperformed the linear ones. This analysis highlights the sensitivity of parametric models based on linear regression. These findings suggest that there is no general rule for which a model is better, in or other words, "One size does not fit all."

The findings also demonstrate the mediocre results in predicting costs, highlighting the need for more accurate models which can take into account the intricate relationships of the given variables, in this case, the cost drivers. Finally, it may question regression models in general as being the sole reference point in establishing the target cost. The manner of overcoming the shortcomings of the regression models was to develop models based upon neural networks.

The models based on neural networks had more meaningful results. Two types of training techniques were applied in developing the models. The first model was trained using the back propagation method, and the second model was trained using the genetic algorithm. Compared to the regression models, the NN models trained using BP reduced the overall prediction error roughly by a factor of four. These findings were in line with the results of Chou *et al*. (2010). However, it was not in line with their perception of questioning the validity of NN models with small sample sizes, as to overcome this hurdle several trials were conducted, and they all yielded meaningful results.

When NN model using BP was compared to that using the GA, it was found that the latter yielded superior results. As there was no real benchmark found in cost estimation in the comparison of the two models, the research was compared to the findings applied in other domains. The other domains used for comparison were those of data classification, manufacturing, and healthcare. The research findings in these domains all concurred with those found in this thesis (Örkcü and Bal, 2011; Provorovs and Borisov, 2011; Fu and Liu, 2011; Zhang *et al*., 2012; Ahmad *et al*., 2010). This suggests in general that NN models trained using the GA have better and more meaningful results than those trained with the BP training algorithm.

The final model that was developed based on data envelopment analysis was created to calculate the efficiency of the programs. Based upon the findings of the efficiencies, the programs were ranked. Moreover the efficiencies can be used to predict the target cost for development programs. Based on the analysis, the ranking, in terms of efficiency using the cost and their associated drivers was established, and comparable to the research of Sueyoshia and Goto (2011) and Kao (2012). The findings of the DEA models as well the findings of the regression and neural network models can have several practical applications, as well as managerial implications, which are discussed in the following section.

6.2 Practical Applications and Managerial Implications

There can be several applications of the findings of this research in an industrial setting. After developing the target cost model and successfully applying it for the MLG, BA wanted to apply them to several other commodities. The other commodities include the engines, the auxiliary power unit (APU), and the wings. The models were accurate in the range of 10%, which is considered reasonable given the estimates are to be used for development programs. Given the successful application of these models on several real components, it can be suggested that they are applicable to products in any industry. Any product generally will have key characteristics that influence its cost. Upon identifying these cost drivers, the methodology used in this thesis can be followed.

Furthermore, the analysis of this case can be applied in trade-off studies, budget allocation, supplier negotiations, and can even further be extended into supplier selection, given support for management.

6.2.1 Trade-off Studies

When designing a product, several trade-off studies have to be conducted usually to optimize the performance and dimensions of the particular product. According to the FAA, (2006), a trade or trade-off study is the process of selecting an optimal solution given several viable solutions. A trade-off study is usually initiated at the request of the market, or the customer.

An example where the target cost was applied in the case company to a trade-off study was to respond to needs of the market to increase the flying distance (range) of the aircraft. A trade study was conducted and two of the viable solutions presented were to either increase the aerodynamic properties of the wing, or to increase the thrust of the engines. The cost drivers of both the wings and the engines were established. Based on these, the target costs of the modified design of the wing and the higher performing engines were calculated. With the target cost models, engineers were able propose a solution that meets the requirements of the market, while minimizing the associated costs.

These findings can also be applied in a general fashion when trade-off studies must be conducted; having accurate cost models will help to propose an optimal technical solution while considering the associated costs thereof.

6.2.2 Budget Allocation

It is of utmost important to understand the total acquisition cost when purchasing a product or service. The target cost is a key value of the total acquisition cost. It would allow the proper planning and allocation of the budget, if feasible, for the product or service to be procured. Using the DEA model would support the notion of "Plan for the worst, and hope for the best." By varying the efficiency, a price range could be established to estimate the most and least they should expect to pay for a particular product. This price range would allow the personnel responsible for the budget to allocate the higher price point in their budget. However, the lower price can be set as targets for suppliers.

6.2.3 Negotiation with Suppliers

"Any negotiation is 80% preparation and only 20% execution" is a phrase commonly stated by executives at Bombardier Aerospace. In any given industry, historical negotiations with suppliers have been based on the market price for a given commodity, with little focus on the actual cost of the product or service. Having an accurate cost model completely changes the dynamics of the negotiation at hand. Using the developed target cost models, the company was able to have fact-based negotiations with their suppliers.

Establishing targets for suppliers had significant benefits in the outcome of commercial negotiations. As the target cost will be a key element in the total life cycle cost model, the company was able to measure the suppliers against the targets and rank them for comparison purposes. Without divulging any proprietary information, using this methodology for several commodities resulted in significant savings on the total life cycle cost from the suppliers initial bid to the signed agreement. For some commodities, the savings could be in range of 50%, which is rather significant, considering that these commodities cost thousands, or even millions of dollars per unit.

6.2.4 Supply Base Optimization

This research can also be extended and applied to reducing the number of considered suppliers. In the aerospace industry depending on the commodity, the range of potential suppliers vastly varies anywhere from 1 to thousands. Having too many suppliers may be difficult to manage and moreover may be very costly, such as in indirect services like facilities maintenance, consulting, and recruitment, where dozens of potentials suppliers may exist. From the findings of the DEA model, along with the associated target cost models, an organization may be able to determine with suppliers will be able to meet the target cost. Furthermore, with the intent of reducing the effort in procuring a product (or service), the organization can shortlist suppliers to only those they believe will be able to meet the target costs.

6.2.5 Managerial Implications and Support

In order to derive the most benefits out of the outcomes of this research, there has to be support from management. As this case was applied for a particular commodity, it was also applied for other commodities, and the findings had several implications

As discussed in the previous section, with the data envelopment analysis model, suppliers that will not be able to meet the cost targets can be identified. Based on the findings in this thesis, management may suggest eliminating the dealings or consideration of those suppliers for future products that are unable to meet the targets. Management may want to consolidate their list of suppliers to develop a preferred supplier list. However, internal stakeholders may have their own preferred or favourites, and may be emotionally or personally involved in the decision process, making it very difficult for management to decide and execute the elimination of those suppliers for future dealings, as the decision may become very political.

Another challenge as was faced in this case in getting the buy in from management to rely on the target cost models derived from neural networks. Even though the NN models outperform the regression models, the regression models will be more readily accepted for application to other commodities. There are several reasons for the push back from management. Linear regression models may not be the best predictors but the cost estimating relationships are clearly defined. It is relatively easy to understand the relationship that a cost driver has on the cost while using a linear, or even a non-linear model, when compared to neural networks.

The costs drivers in the regression model are tangible and are easy to get a grasp of, whereas, neural network models are intangible and the calculations taking place in the "black box" cannot be seen, thus it intuitively becomes difficult to rely on or comprehend the resulting target cost models. Due to the above-mentioned reasons, coupled with the difficulty in replicating the results on the NN models, and because of its random component, it is a tough sell and will be a paradigm shift for management to solely rely on target cost models utilizing neural networks. When management accepts the models, they will also face similar challenges in convincing their internal stakeholders as well as their suppliers with whom they have an open book approach. This dilemma still exists today and was highlighted by Smith and Mason (1997).

Finally, as the importance of identifying the cost drivers has been highlighted several times throughout this thesis, due its direct relation to the credibility and accuracy of its associated cost model effort and time will have to be allocated by management, for any given study, in properly identifying the cost drivers. Moreover, as was seen in this case, the process of identifying the cost drivers, along with data collection, will require the support of many stakeholders from several parts of the organization. Management will need to align the internal priorities to support this endeavour.

6.3 Chapter summary

This chapter discussed the findings of the target cost models developed in this thesis. Furthermore, the practical applications in terms of trade-off studies, budget allocation, negotiation and even extending into supplier selection were discussed. Moreover, it highlights the implication of using, and implementing, the developed models. Finally it ends by describing the tactical issues management may face in the development of the target cost models.

7. Conclusions

The aerospace industry is very important for Canada. Currently the market is facing many challenges; the economic downturns coupled with the advent of emerging countries entering the market have made it very difficult for companies in Canada to keep a competitive advantage. Their revenues have dropped over the last few years and they are trying to survive the crisis. In order to face these challenges they are adopting new principles to reduce costs and remove the waste in their organizations.

The traditional cost plus approach, in which the selling price of a product is established only after its development by adding the desired profit margin, may result in not being competitive in the market, thus not focusing on delivering value to their customers. The lean accounting approach, based on the principles of lean manufacturing, to deliver value to their customer, overcomes these weaknesses. By establishing a target cost of the product on the basis of what the market can bear, they will focus on how to design the product and its key characteristics to deliver value to the customer. Thus, the target cost is in line with the principles of lean. The focus of this thesis was lean accounting in aerospace, and on accurately predicting target costs.

In this thesis, several models to predict target costs for commodities are presented and applied at a major aerospace company, Bombardier Aerospace, the world's third largest civil aircraft manufacturer specializing in the manufacture and assembly of both commercial and business aircrafts.

In this thesis, three models are developed to estimate target cost, each of which is applied to the main landing gear at Bombardier. In order to develop the target cost, the pertinent cost drivers were obtained. This thesis shows the necessary steps and demonstrates the rigour in obtaining the right cost drivers.

The first methodology used to develop target cost models is linear regression. Two regression models are developed. The first model is based on a multiple linear regression model, and the second is based on a non-linear equation. A sub-sampling method, namely the jackknife technique is used to increase the accuracy of the models. Moreover, three data points are removed from the analysis, and are used to calculate the accuracy in predicting the costs.

Thereafter, two techniques are chosen to determine the number of factors to be kept in the final cost models. The two techniques both recommend keeping one cost driver, namely the maximum take-off weight, in the regression models. The results show that both models have comparable yet mediocre results. To complement the regression models, a complex non-linear model was developed. Its overall performance was superior to those of the regression models; however it did contain some high errors.

In order to overcome the shortcomings of these models, two artificial neural networks based on different training algorithms are developed. The first training mechanism is that of error back propagation, and the second is trained using the genetic algorithm. Three trials are conducted, and the both neural network models increase the accuracy of the prediction by at least a factor of 4. When compared to one another, the genetic algorithm outperforms that of back propagation. This research also questions the claims of other researchers' statements of not being able to derive meaningful results using limited data, like that presented in the case. Moreover, the sensitivity analysis of the number of neurons in the hidden layer showed a minimal impact on the final model, which is also contrary to previous research, indicating the high sensitivity of neurons in the hidden layer.

The final model developed is based on a modified version of the traditional data envelopment analysis model, to rank the programs in order of their efficiency, and thus, the target cost. With this model, the suppliers are ranked and target costs can be predicted.

The models were developed using the cost drivers. In this case, the cost drivers were height, maximum take-off weight, and weight for the main landing gear; the data of 13 programs is collected for the analysis. The commercial data was masked to protect proprietary information.

The cost models yielded accurate results, and thus the analysis was repeated for other commodities. The cost models for the other commodities (wings, engines, and the auxiliary power units) had reasonable estimates, with errors in the magnitude of 10%. From the finding of the analysis there are several practical applications, of which some were already implemented. The practical applications pertain to using the cost models to conduct trade-off studies, allocation of budget, negotiation tools and even extending the use of the models to determine the suppliers to be considered for future dealings.

While the analysis highlights the importance of obtaining the pertinent cost drivers, it also hints to the amount of time and effort required from many stakeholders across the organization. This may require the support from management to align the priorities across the domains to get the required support for these initiatives. Finally this thesis also highlights the challenges faced when proposing to implement the target cost models based upon artificial neural network models.

This research shows that regression models are very sensitive and a non-linear model may not necessarily outperform a linear model when estimating the cost. Furthermore, by using two different neural network models, it was shown the models trained by the genetic algorithm had more meaningful results. Research applied in other domains has also indicated NN trained with the GA has outperformed those using the BP training algorithm. The findings of this research coupled previous studies infers that models trained using the genetic algorithm will always outperform those models trained using back propagation. Finally an adapted version of the DEA model was developed. This model ranks suppliers, but it can also be used as a mechanism to predict the target cost.

Even though the models have promising results, there are limitations to the model. The model is only as good as its input data. This highlights the sensitivity and credibility of the model depending upon the right cost drivers. If the wrong cost drivers are selected, the results will be of no value. Moreover as the cost drivers differ from commodity to commodity they have to be identified each time and the neural network models may need to be tuned from one commodity to another. Furthermore, using parametric analysis, the predetermined relationship, such as linear, non-linear or exponential has to be specified. Thus other complex relationships exist; the regression models will have limited use. Finally, the underlying assumptions of the CERs are that the data and cost drivers selected in the final model will be representative of the cost of the future. It does not take into any design or technological changes that will potentially change the cost drivers, which will limit the use of the developed models. Moreover, the focus of the target cost models is for the recurring costs only. The non-recurring costs, such as the design and testing of the commodity are not taken into account in the cost models. The non-recurring costs are typically considered as stand-alone items in the business case, and are allocated at the aircraft level based upon the sales forecast. However, other models, as mentioned in the literature review, have been and can be further developed, to account for those costs.

Even though the NN models predicted the costs reasonably, they also have their limitations. Many parameters have to be set, in order to train the model. If the parameters are not set appropriately, the results can be skewed, and the NN models be trapped in the local minima, not being able to find a better solution. This can partially be overcome by a sensitivity analysis and by trial and error, as was done in this case, to partially overcome this limitation.

There can be several future applications of this thesis. Higher order parametric models can be developed to estimate the target cost. As the regression models did not take into complex relationships. The use of higher order model would allow to model complex relationships that may exist and are not accounted for in the regression-based models.

Moreover, there are other types of training algorithms such as simulated annealing, which can be used in the neural network models to develop the target cost. The models developed using various training mechanisms can be applied to see if they are able to predict the cost better than those presented in the case. Finally, as the neural network models presented in this thesis have a fixed mechanism to sequentially adjust the weights, an adaptive weight adjustment technique can be used to see the impact on the accuracy of the developed target cost models.

REFERENCES

P. Ahlstrom, C. Karlsson, Change processes towards lean production: the role of the management accounting system, International Journal of Production and Operations Management, vol. 16, no. 11, pp. 42-56, 1996

F. Ahmad, N. A. M. Isa, M. K. Osman, Z. Hussain, Performance comparison of gradient descent and genetic algorithm based artificial neural networks training, 10th International Conference on Intelligent Systems Design and Applications (ISDA), 2010.

AIAC, Aerospace Industries Association of Canada, 2002[www.aiac.ca/corporate-membershp/aiac-mebers. Latest access 04/06/12]

P. Andersen, N. C. Petersen, A procedure for ranking efficient units in data envelopment analysis, Management Science, vol. 39, no. 2, 1993.

C. Ax, J. Greve, U. Nilsson, The impact of competition and uncertainty on the adoption of target costing, International Journal of Production Economics, vol. 115 no. 1, pp. 92–103, 2008.

A. Bahadir, The role of management accounting systems in implementing lean business strategies, Master’s Thesis, Erasmus University, Rotterdam, 2011.

H. A. Bashir, V. Thomson, Estimating design effort for GE hydro projects, Computers & Industrial Engineering, vol. 46, no. 2, pp. 195-204, 2004.

Y. Beauregard, N. Bhuiyan, V. Thomson, Lean engineering in product development, Canadian Aeronautics and Space Journal, vol. 54, no. 2, pp. 19-30, 2008.

Y. Beauregard, A multi-criteria performance study of lean engineering, PhD thesis, Concordia University, Montreal, Canada, April, 2010.

S. J. Benjamin, S. Muthaiyah, M. S. Marathamuthu, An improved methodology for absorption costing: efficiency based absorption costing (EBAC), The Journal of Applied Business Research, vol. 25, no. 6, pp. 87-104, 2009.

V. S. Berg, Water utility benchmarking: measurement, methodologies, and performance incentives, International Water Association, 2010.

S. Berg, C. Lin, Consistency in performance rankings: the Peru water sector, Applied Economics, vol. 40, no. 6, pp. 793-805, 2008.

C. Bi, F. Wei, Civil aircraft maintenance target cost allocation based upon Value Engineering, Communication Software and Networks (ICCSN), IEEE 3rd International Conference on Communication Software and Networks, pp. 521 - 524, Xi'an, China, 2011.

C. Bishop, Neural networks for pattern recognition, Oxford Press, USA, 1996.

J. T. Black, D. T. Phillips, Introduction to lean engineering, Prentice Hall, 2012.

S. A. Butsher, A. Stephan, M. Laker, Market-driven product development, Marketing Management, vol. 9, no. 3, pp. 48-54, 2000.

L. P. F. Carmo, F. Cadovani, Advances and challenges for adoption of activity based costing (ABC) by public sector: a comparative study of Brazil, Colombia, Uruguay and United States, International Business Research, vol. 5, no. 2, pp. 150-158, 2012.

S. Cavalieri, P. Maccarrone, R. Pinto, Parametric vs. neural network models for the estimation of production costs: A case study in the automotive industry, International Journal of Production Economics, vol. 1, pp. 165–177, 2004.

A. C. Caputo, P. M. Pelagagge, Parametric and neural methods for cost estimation of process vessels, International Journal of Production Economics, vol. 112, pp. 934–954, 2008.

H. K. Chan, S. Yin, F.T.S. Chan, Implementing just-in-time philosophy to reverse logistics systems: a review, International Journal of Production Research, vol. 48, no. 21, pp. 6293–6313, 2010.

D. W. M. Chan, A. P. C. Chan, P. T. L. Lam, J. H. L. Chan, Exploring the key risks and risk mitigation measures for guaranteed maximum price and target cost contracts in construction, Construction Law Journal, vol. 26, no. 5, pp. 364-378, 2010.

A. Charnes, W. W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, European Journal of Operations Research, pp. 429-444, vol. 2, 1978.

J. Choe, The taxonomy of knowledge management strategies in manufacturing firms: Use of target costing and IT Infrastructure, African Journal of Business Management, vol. 15, no. 5, pp. 6597-6607, 2011.

J. S. Chou, Y. Tai, Generalized regression neural nets in estimating the high-tech equipment project cost, Computer Engineering and Applications (ICCEA), 2010 Second International Conference on Computer Engineering and Applications, pp. 281-284, Bali Island, 2010.

G. Cokins, S. Căpuşneanu, C-M. Barbu, Decisions based on synthesis documents information of the ABC (activity-based costing) method, International Journal of Accounting and Financial Reporting, vol. 1, no. 1, pp. 112-132, 2011.

Conference Board of Canada, Canadian Aerospace industry contends with slow rebound in demand and fierce global competition, News Release, pp. 12-67, 2011.

R. Cooper, B. H. Maskell, How to manage through worse-before-better, MIT Sloan management review, vol. 49, no. 4 , pp. 58-65, 2008.

N. S. Currey, Aircraft landing gear design: principles and practices, 1988.

H. Dawid, Adaptive learning by genetic algorithms: analytical results and applications to economic models, Springer, New York, 1996.

G. K. DeBusk, use lean accounting to add value to the organization, The Journal of Corporate Accounting & Finance, vol. 23, no. 3, pp. 35–41, 2012.

J. DeFilippo, Management accounting learns to adapt to Pratt & Whitney's manufacturing cells, The Learning Organization, vol.3, no.2, pp. 4-10, 1996.

B. Efron, R. Tibshirani, An Introduction to the bootstrap (Monographs on Statistics and Applied Probability), Chapman and Hall, Florida, 1993.

L. M. Ellram, The role of supply management in target costing, Center for Advanced Purchasing Studies, Tempe, Arizona, 1999.

L. M. Ellram, Purchasing and supply management's participation in the target costing process, Journal of Supply Chain Management, vol. 36, no. 2, pp. 39-51, 2000.

L. M. Ellram, The implementation of target costing in the United States: theory versus practice, The Journal of Supply Chain Management, vol. 42, no. 1, pp. 13-26, 2006.

A. Elragal, M. Haddara, The use of expert panels in ERP cost estimation research, Enterprise Information Systems: Communications in Computer and Information Science, vol. 110, no. 2, pp. 97-108, 2010.

R. B. Fritzch, Activity-based costing and the theory of constraints: using time horizons to resolve two alternate concepts of product cost, Journal of Applied Business Research, vol. 14, no. 1, pp.83-90, 2011.

T. P. Filomena, F. J. K. Neto, M. R. Duffey, Target costing operationalization during product development: model and application, International Journal of Production Economics, vol. 118, no. 2, pp. 398–409, 2009.

P. M. M. Foussier, From product description to cost: a practical approach. vol. 2: Building a Specific Model, Springer, Berlin, 2006.

N. Fragkakis, S. Lambropoulos, G. Tsiambaos, Parametric model for conceptual cost estimation of concrete bridge foundations, Journal of Infrastructure Systems, vol. 17, no. 2, pp. 66-74, 2012.

Z. M. Fu, G. M. Liu, Prediction for air-bending spring back radius of sheet metal using back propagation neural network and micro genetic algorithm, Advanced Materials Research, vol. 219-220, pp. 1174 - 1177, 2011.

S. Gamal, A suggested framework for the integration of activity-based costing (ABC) in a lean environment to enhance companies competitive position- A case study in Egypt, AAA 2012 Management Accounting Section (MAS), Meeting Paper, 2011.

E. M. Goldratt, Theory of constraints, North River Press, Massachusetts, 1999.

E. M. Goldratt, R. E. Fox, The goal: a process of ongoing improvement, North River Press, Massachusetts, 1996.

E. M. Goldratt, R. E. Fox, The race, North River Press, Massachusetts, 1992.

M. Hanid, L. Koskela, M. Siriwardena, Traditional cost management vs. lean cost management, Proceedings: 18th CIB World Building Congress, pp. 280-293, United Kingdom, 2010.

M. Hassoun, Fundamentals of artificial neural network, MIT Press, London, 1995.

J. H. Holland, adaption in natural and artificial systems, University of Michigan Press, Michigan, 1975.

U. Ibusuki, P. C. Kaminski, Product development process with focus on value engineering and target-costing: a case study in an automotive company. International Journal of Production Economics, vol. 105, no.2, pp. 459–474, 2007.

P. Ifandoudas, B. Gurd, Costing for decision-making in a theory of constraints environment, Journal of Applied Management Accounting Research, vol. 8, no. 10, pp. 43-58, 2010.

ISPA, International Society of Parametrics Analysis, Parametric estimating handbook, ISPA/SCEA Joint Office, Viginia, 2009.

H. Iranmanesh, V. Thomson, Competitive advantage by adjusting design characteristics to satisfy cost targets, International Journal of Production Economics, vol. 115, no. 1, pp. 64–71, 2008.

R. Jenson, J. Brackner, C. Skousen, Management accounting in support of manufacturing excellence, Institute of Management Accountants, Montvale, New Jersey, 1996.

H. T. Johnson, R. S. Kaplan, Relevance lost: The rise and fall of management accounting, Harvard business School Press, Boston, Massachusetts, 1987.

H. T. Johnson, Performance Measurement for competitive excellence in R.S Kaplan(Ed.), Measures for Manufacturing Excellence , Harvard business School Press, Boston, Massachusetts, 1990.

H. T. Johnson, Relevance regained: from top-down control to bottom-up empowerment, The Free Press, New York, 1992.

B. Ju, L. F. Xi, A product cost estimation for the early design of sedans using neural networks, International Journal of Automotive Technology and Management, vol. 8, no. 3, pp. 331 - 349, 2008.

B. Ju, L. Xi, and X. Zhou, New product design based target cost control with BP neural network and genetic Algorithm - A Case Study in Chinese Automobile Industry, Lecture Notes in Computer Science, vol. 5821, pp. 111-122, 2009.

C. Kao, Efficiency decomposition for parallel production systems, Journal of the Operational Research Society, vol. 63, pp. 64–71, 2012.

R. Kaplan, One Cost System isn't enough" Harvard Business Review, pp. 61-66, 1988.

R. S. Kaplan, Innovation action research: creating new management theory and practice, Journal of Management Accounting Research, vol. 10, pp. 89-118, 1998.

V. Kecman, Learning and soft computing, MIT Press, Michigan, 2001.

R. Kee, The sufficiency of target costing for evaluating production-related decisions, International Journal of Production Economics, vol. 126, no.2, pp. 204–211, 2010.

M. C. Kocakülâh, A. D. Austill, Product development and cost management using target costing: a discussion and case analysis, Journal of Business & Economics Research, vol. 4, no. 2, 2006.

M. H. Kutner, C. J. Nachtsheim, J. Neter, and W. Li, Applied linear statistical models, McGraw-Hill, New York, 2004

E. Lander, J. K. Liker, The Toyota production system and art: making highly customized and creative product the Toyota way, International journal of production research, vol.45, no.16, pp. 3681-3698, 2007.

A. Layer, E.T. Brine, H. F. Van, H. Kals, S. Haasis, Recent and future trends in cost estimation. International Journal of Computer Integrated Manufacturing, vol. 15, pp. 499-510, 2002.

C. C. Li, Path Analysis - a primar, Box Wood Press, 1975.

S. Looney, T. Gulledge Jr., Use of the correlation coefficient with normal probability pots, The American Statistician, vol. 39, pp. 75-79, Feb. 1985.

P. Lorino, Target costing practices and implementation, International Federation of Accountants: Articles of Merit, 1995.

B. Maskell, Lean accounting for lean manufacturers, Manufacturing Engineering, vol. 125, no.12, 2000.

B. Maskell, Making the numbers count, Productivity Press, Oregon, 1996.

B. Maskell, B. L. Baggaley, Lean management accounting, 2002 [www.maskell.com. Latest access 03/02/12]

B. Maskell, B. Baggaley, A proven system for measuring and managing the lean enterprise, Productivity Press, New York, 2004.

B. Maskell, B. L. Baggaley, Lean accounting: what's it all about?, Association for Manufacturing Excellence Target Magazine, vol. 22, no.1, pp. 35-43, 2002.

B. Maskell, S. Lilly, Life's little lean accounting instruction book, BMA Publishing, New Jersey, 2006.

D. F. X. Mathaisel, S. A. Hirsch, C. L. Comm, Transforming urban public transportation: A Lean Enterprise Approach, Journal of Business & Economics Research, vol. 6, no. 7, 2008.

Z. Miao, K. L. Xu, Modeling and simulation of lean supply chain with the consideration of delivery consolidation, Key Engineering Materials, vols. 467 - 469, pp. 853-858, 2011.

B. Modarressa, A. Ansari, D. L. Lockwood, Kaizen costing for lean manufacturing: a case study, International Journal of Production Research, vol. 43, no. 9, pp. 1751-1760, 2005.

Y. Monden, Cost reduction systems: target costing and kaizen costing, Productivity Press, Oregon, 1995.

Y. Monden, K. Hamada, Target costing and kaizen costing in Japanese automobile companies, Journal of Management Accounting Research Fall, pp. 16-34, 1991.

D. C. Montgomery, Introduction to Statistical Quality Control, John Wiley, Ney York, 2005.

K. Muralidhar, R. Parsa, R. Sarathy, A general additive data perturbation method for database security, Management Science, vol. 45, no. 10, pp. 1399-1415, 1999.

D. Nicolini, C. Tomkins, R. Holti, A. Oldman, M. Smalley, Can target costing and whole life costing be applied in the construction industry?, British Journal of Management, vol. 11, no. 4, pp. 303-324, 2000.

J. Oakland, M. Marosszeky, Total quality in the construction supply chain, Elsevier India Private Limited, India, 2007.

B. O. Odedairo, D. Bell, Framework for introducing and implementing value methods: a novel toolkit for small and medium scale industries in developing nations, International Journal of Basic & Applied Sciences, vol. 9, no. 10, pp. 130-146, 2009.

H. H. Orkhu, H. Ball, Comparing performances of back propagation and genetic algorithms in the data classification, Expert Systems with Applications, vol. 38, no. 4, pp. 3703-3709, 2011.

A. Palmer, Dimensional analysis and intelligent experimentation, World Scientific Publishing Company, 2008.

A. S. Pandya, R. B. Macy, Pattern recognition with neural networks in C++, CRC Press, IEEE Press, Florida, 1996.

A. Pennanen, G. Ballard, Y. Haahtela, Target costing and designing to targets in construction, Journal of Financial Management of Property and Construction, vol. 16, no. 1, pp.52-63, 2011.

PMI, Project Management Institute, A guide to the project management book of knowledge, Project Management Institute Standards Committee, 2000.

S. Provorovs, A. Borisov, Use of linear genetic programming and artificial neural network methods to solve classification task, Scientific Journal of Riga Technical University, vol. 45, pp. 133-138, 2011.

J. E. Quintela Varajão, M. M. Cruz-Cunha, G. D. Putnik & A. Trigo (Eds.), Enterprise information systems, vol. 110, pp. 97-108, Springer, Berlin Heidelberg, 2010.

S. Rahman, D. J. Vanier, Life cycle cost analysis as a decision support tool for managing municipal infrastructure, CIB 2004 Triennial Congress, Toronto, 2004.

E. Rhodes, J. P. Warren, R. Carter, Supply chains and total product systems, Wiley-Blackwell, 2006.

M. Rother, J. Shook, Learning to see: Value-stream mapping to create value and eliminate muda, Lean Enterprise Institute, Cambridge, MA, 1999.

A. Salam, N. Bhuiyan, G. J. Gouw, S. A. Raza, Measuring design effort in product development, VDM Verlag, Germany, 2008.

A. Salam, N. Bhuiyan, G. J. Gouw, S. A. Raza, Estimating design effort for the compressor design department: A case study at Pratt & Whitney Canada, Design Studies, vol. 30 no. 3, pp. 303-319, 2009.

A. R. Sayadi, A. Lashgari, J. Paraszczak, Hard-rock LHD cost estimation using single and multiple regressions based on principal component analysis, Tunneling and Underground Space Technology , vol. 27, pp. 133–141, 2012.

A. Schulze, T. Störmer, Lean product development enabling management factors for waste elimination, International Journal of Technology Management, vol. 57, no. 1, pp. 71-91, 2012.

M. Slater, Target costing as a strategic cost management tool in the South African motor industry, Thesis, Nelson Mandela Metropolitan University, January 2010.

A. E. Smith, A. K. Mason, Cost estimation predictive modeling: regression versus neural network, The Engineering Economist, vol. 42, no. 2, pp. 137-161, 1997.

J. A. Snyman, Practical mathematical optimization: an introduction to basic optimization theory and classical and new gradient-based algorithms, Springer, New York, 2005.

Statistics Canada, 2012 [www.statcan.gc.ca/start-debut-eng.html, Latest access 03/02/12]

J. Stenzel, Lean Accounting: best practices for sustainable integration, Wiley & Sons Inc., New Jersey, 2007.

T. Sueyoshia, M. Goto, DEA approach for unified efficiency measurement: Assessment of Japanese fossil fuel power generation, Energy Economics, vol. 33, no. 2, pp. 292-303, 2011.

J. Tu, Advantages and disadvantages of using artificial neural networks versus logistic regression for predicting medical outcomes, pp. 1225-1231, 1996.

J. Tu, Z. Fang, Supply chain integration of virtual organization , International Conference on Consumer Electronics, Communications and Networks , 2011.

P. B. B. Turney, Common Cents: The ABC performance breakthrough: How to succeed with activity based costing, Cost Technology, Hillsboro, Oregon, 1991.

K. T. Ulrich, S. D. Eppinger, Product design and development, 5th Edition, McGraw-Hill, New York, 2012.

Z. Wang, What shop floor management can contribute to strategic cost management, (working paper), Graduate School of Commerce and Management, Hitotsubashi University, April 2011.

Y. Ward, A. Graves, A new cost management & accounting approach for lean enterprises, (working paper), Irish Academy of Management Meeting Annual Conference, Trinity College Dublin, September 2004.

Y. Ward, A. Graves, Lean performance measurement for aerospace management, vol. 1, no.1, pp. 85-96, 2001.

S. Weisberg, Transformation: applied linear regression, Wiley-Interscience, Hoboken, New Jersey, 2005.

J. P. Womack, D.T. Jones, Lean thinking: banish waste and create wealth in your Corporation, Free Press, New York, 1996.

J. P. Womack, D.T. Jones, D. Roos, The machine that changed the world: based on the Massachusetts Institute of Technology 5-million dollar 5-year study on the future of the automobile, Rawson Associates, 1990.

S. Wright, The method of path coefficients, Annals of Math Stat, vol. 5, pp. 161-215, 1934.

H. Yazdifar, D. Askarany, A comparative study of the adoption and implementation of target costing in the UK, Australia and New Zealand, International Journal of Production Economics, vol.135,pp. 382-392, 2012.

M. Zangeneh, M. Omid, A. Akram, A comparative study between parametric and artificial neural networks approaches for economical assessment of potato production in Iran, Spanish Journal of Agricultural Research, vol. 9, no. 3, pp. 3061-3070, 2011.

I. J. Zbib, T. Rakotobe-Joel, R. Rigoli, Target costing: the key to supply chain excellence, International Business & Economics Research Journal, vol. 2, no. 11, pp. 27-34, 2011.

J. Zhang, T. Li, X. Chen, L. Gu, Z. H.Wang, H. X. Cui, Prediction for air-bending springback radius of sheet metal using back propagation neural network and micro genetic algorithm, Materials Science Forum, vol. 704-705, pp. 1223-1230, 2012.

2011 BA Annual Report, 2011 Bombardier Annual Report
[bombardier.com/maintenance/2011Q4/BombardierAnnualReport_Dec2011_en.pdf,
Latest access 03/03/12]

APPENDIX A

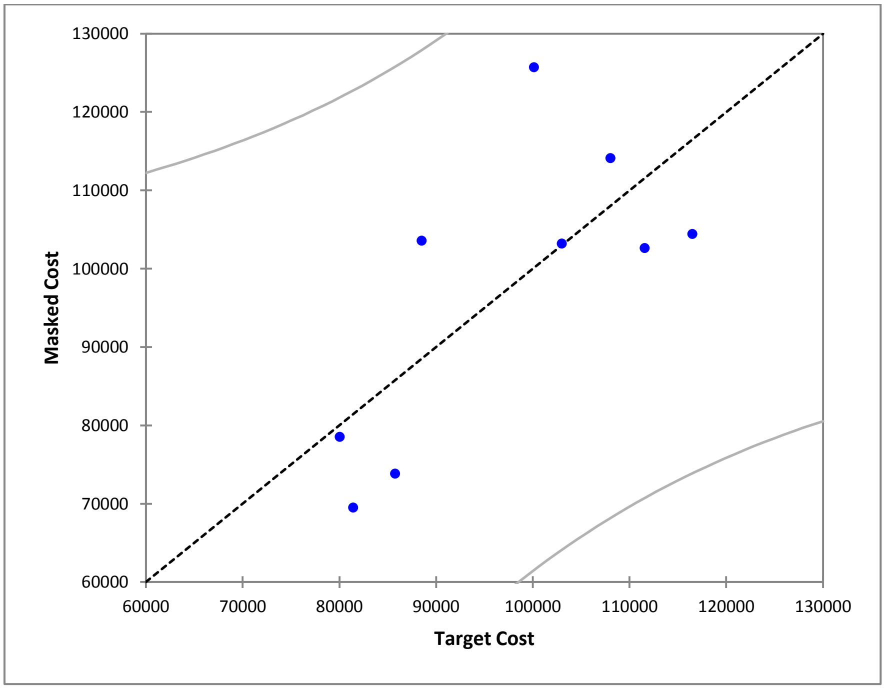


Figure A.1: SPC chart for LR, 2 factors, sample A

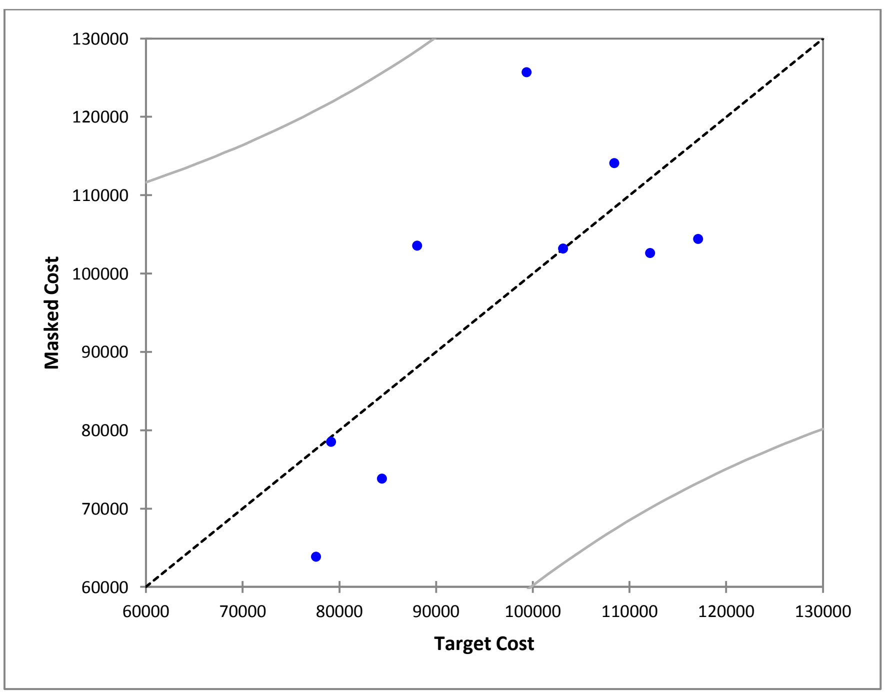


Figure A.2: SPC chart for LR, 2 factors, sample B

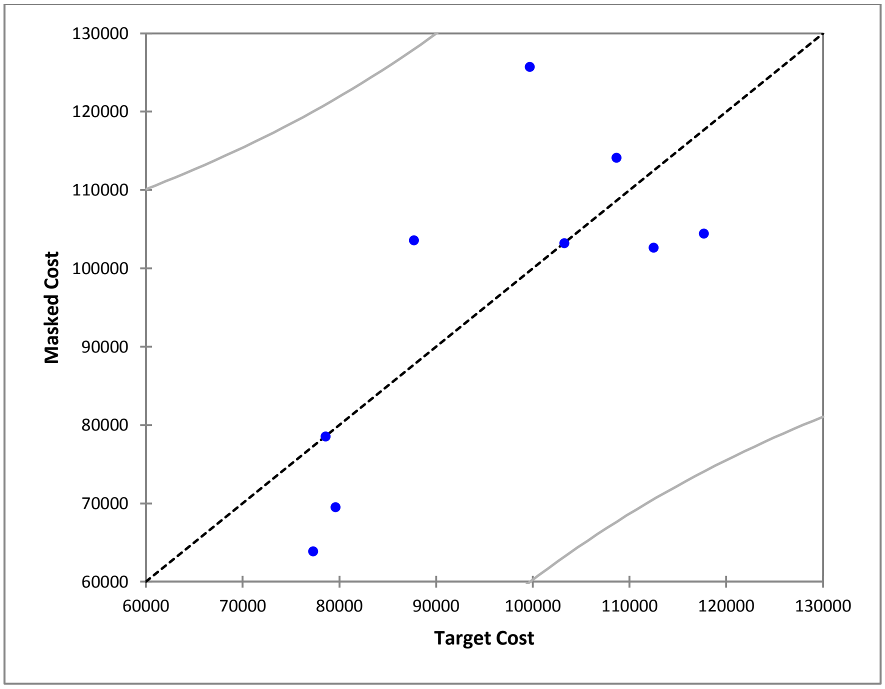


Figure A.3: SPC chart for LR, 2 factors, sample C

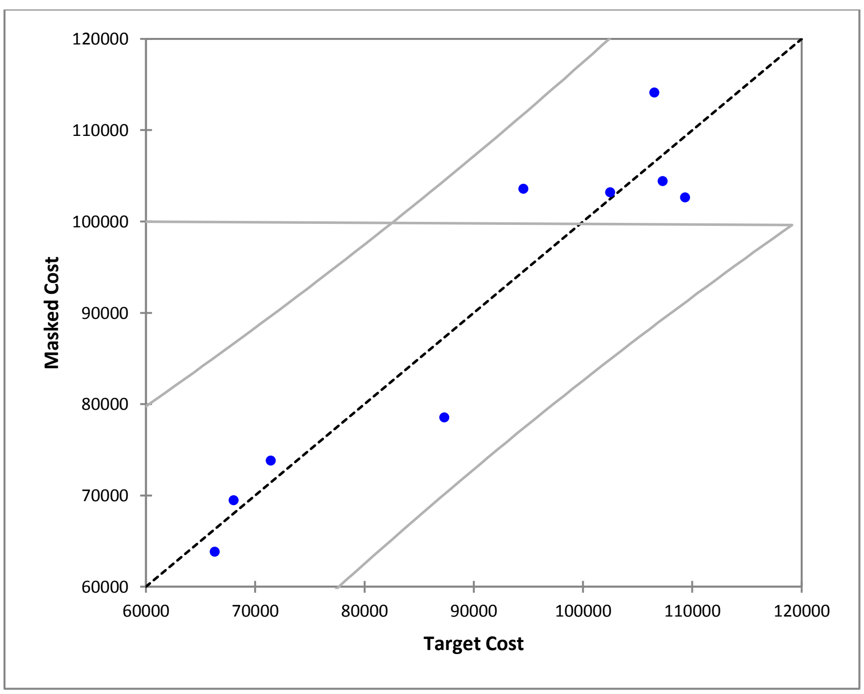


Figure A.4: SPC chart for LR, 2 factors, sample D

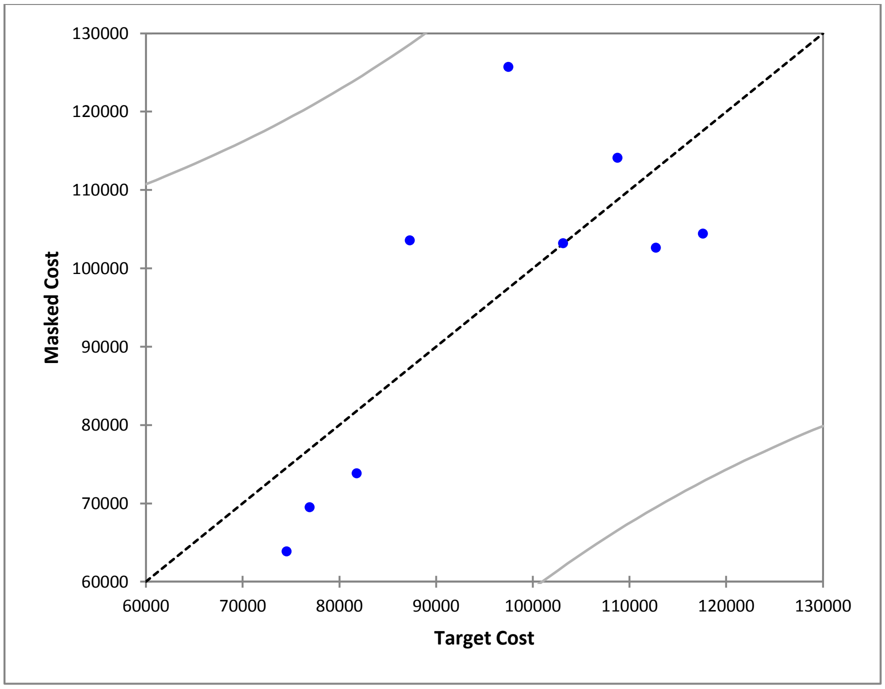


Figure A.5: SPC chart for LR, 2 factors, sample E

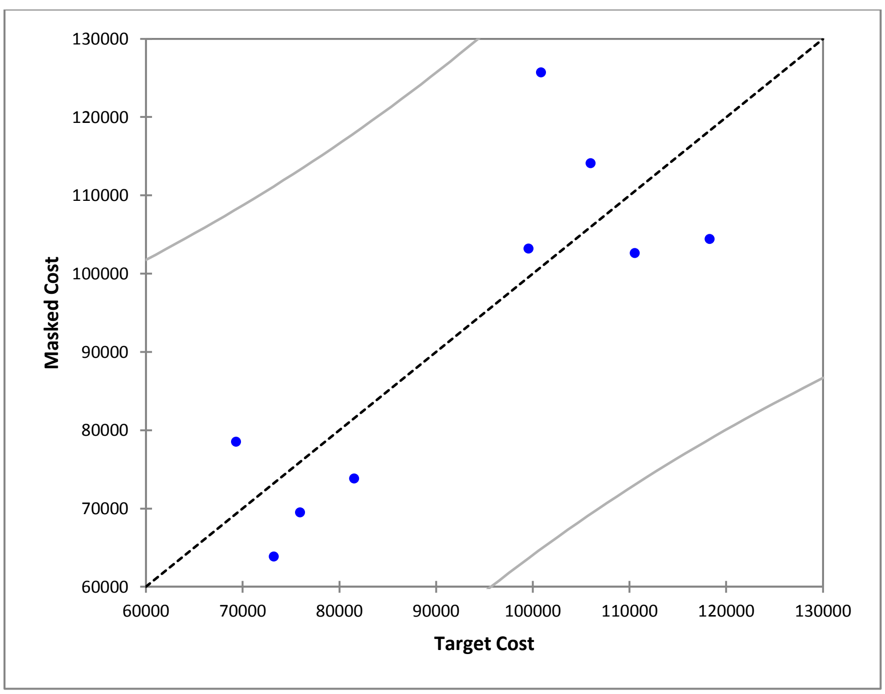


Figure A.6: SPC chart for LR, 2 factors, sample F

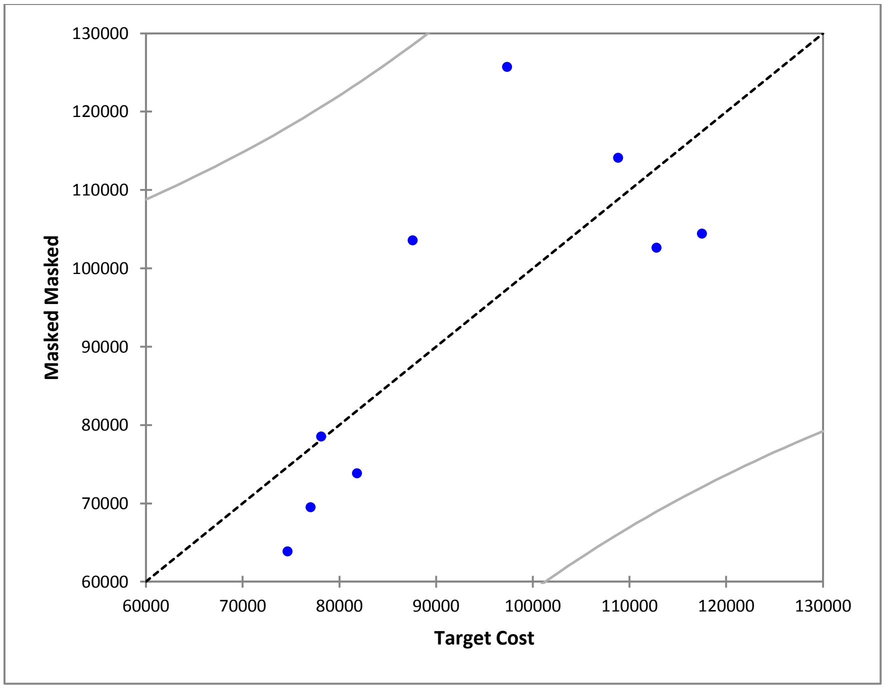


Figure A.7: SPC chart for LR, 2 factors, sample G

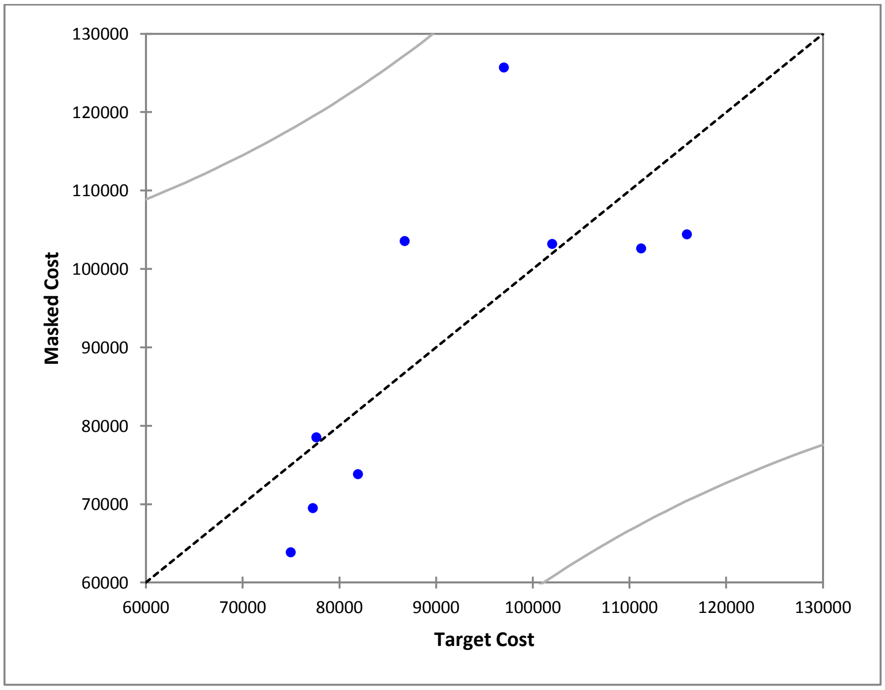


Figure A.8: SPC chart for LR, 2 factors, sample H

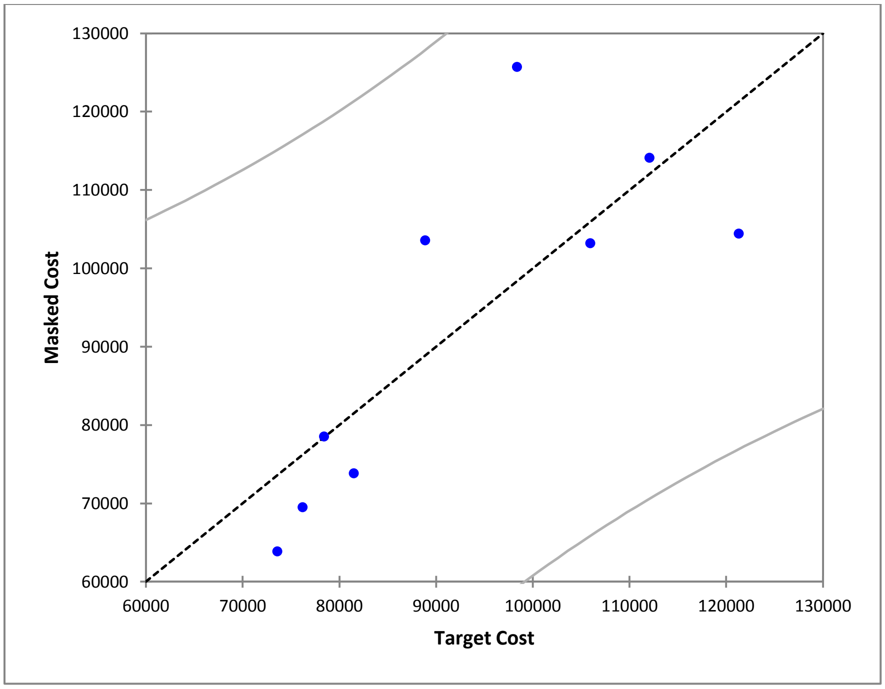


Figure A.9: SPC chart for LR, 2 factors, sample I

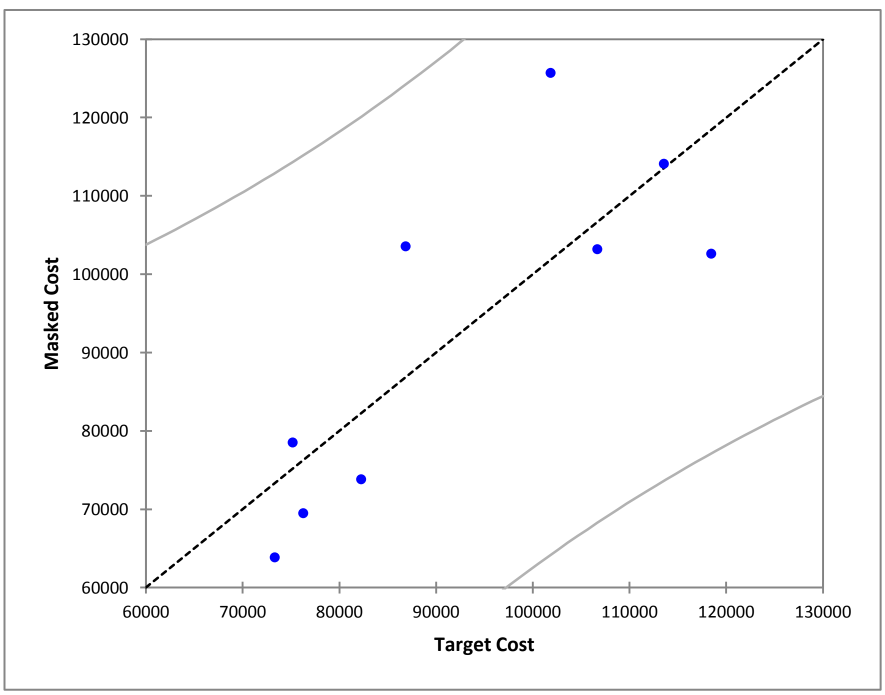


Figure A.10: SPC chart for LR, 2 factors, sample J

APPENDIX B

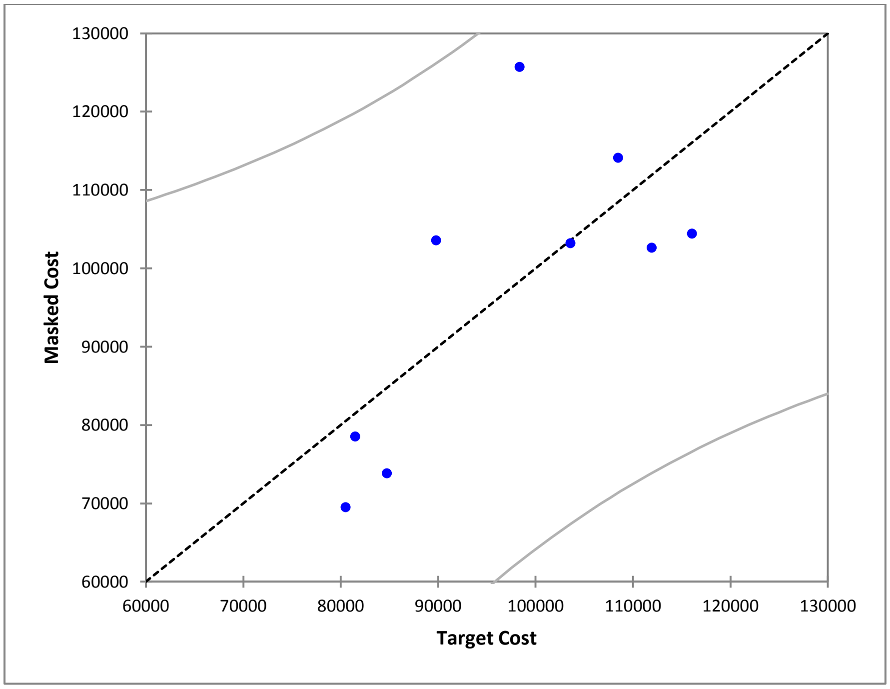


Figure B.1: SPC chart for LR, 1 factor, sample A

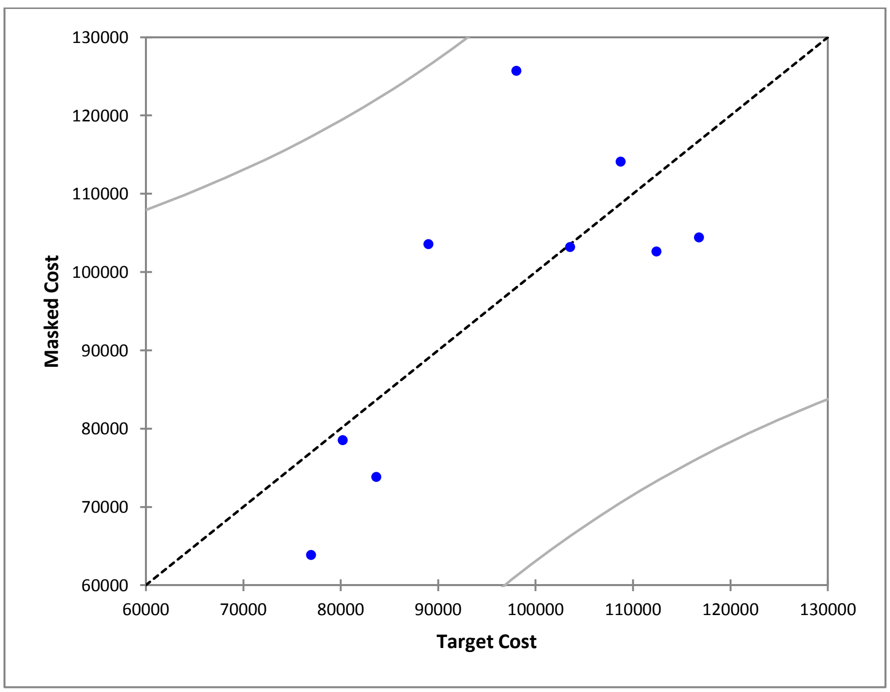


Figure B.2: SPC chart for LR, 1 factor, sample B

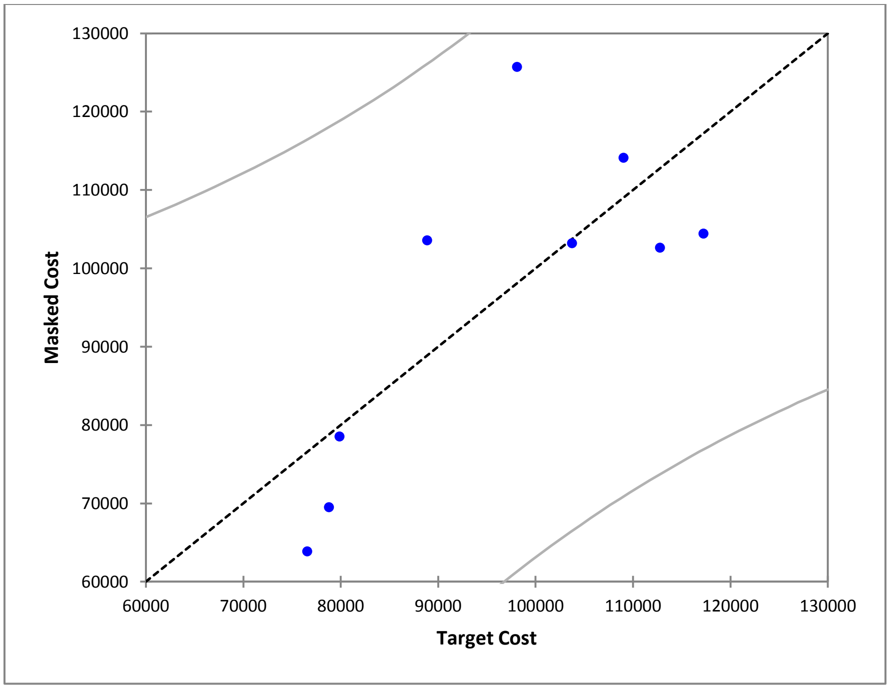


Figure B.3: SPC chart for LR, 1 factor, sample C

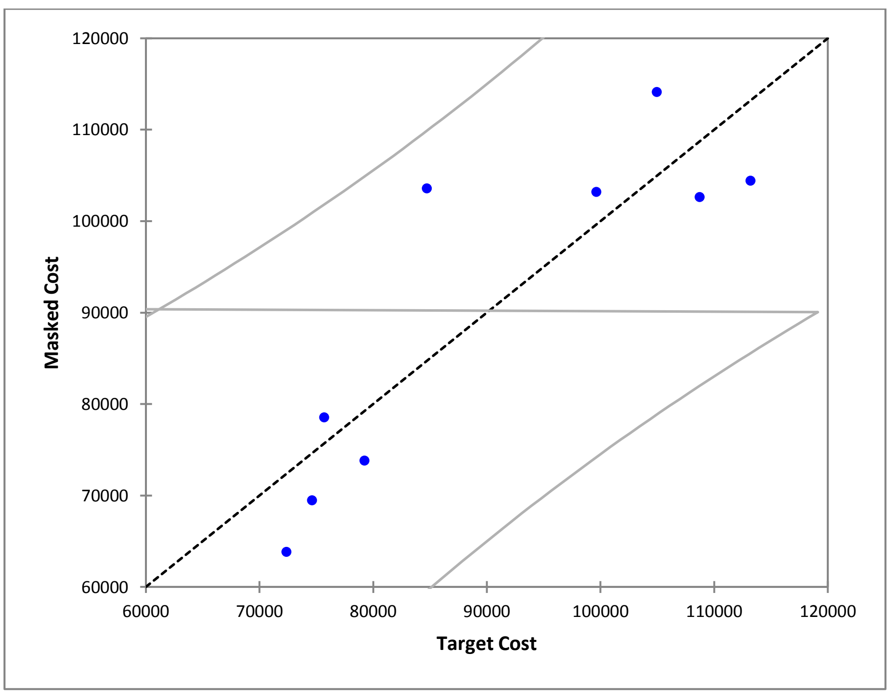


Figure B.4: SPC chart for LR, 1 factor, sample D

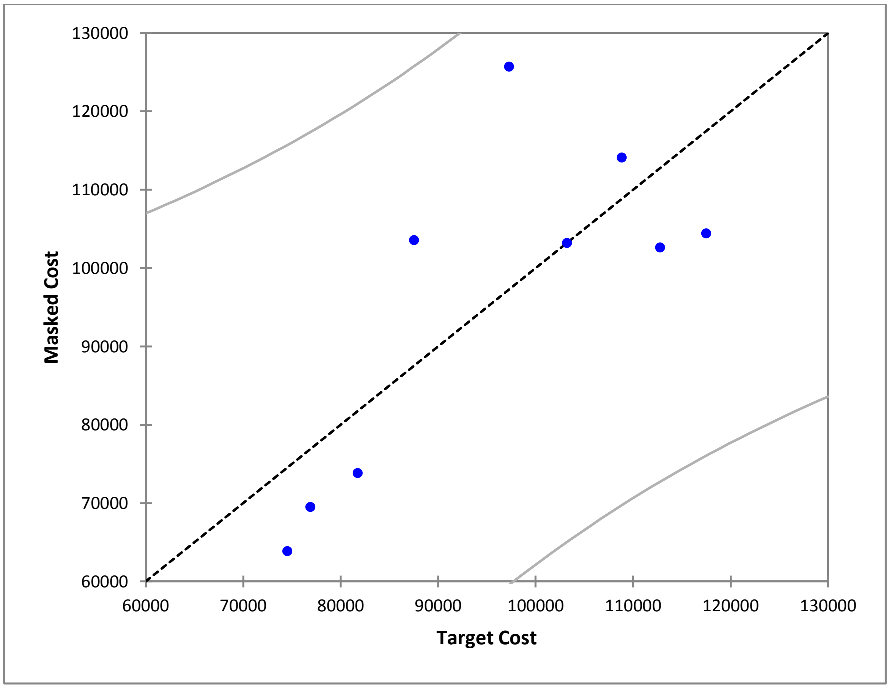


Figure B.5: SPC chart for LR, 1 factor, sample E

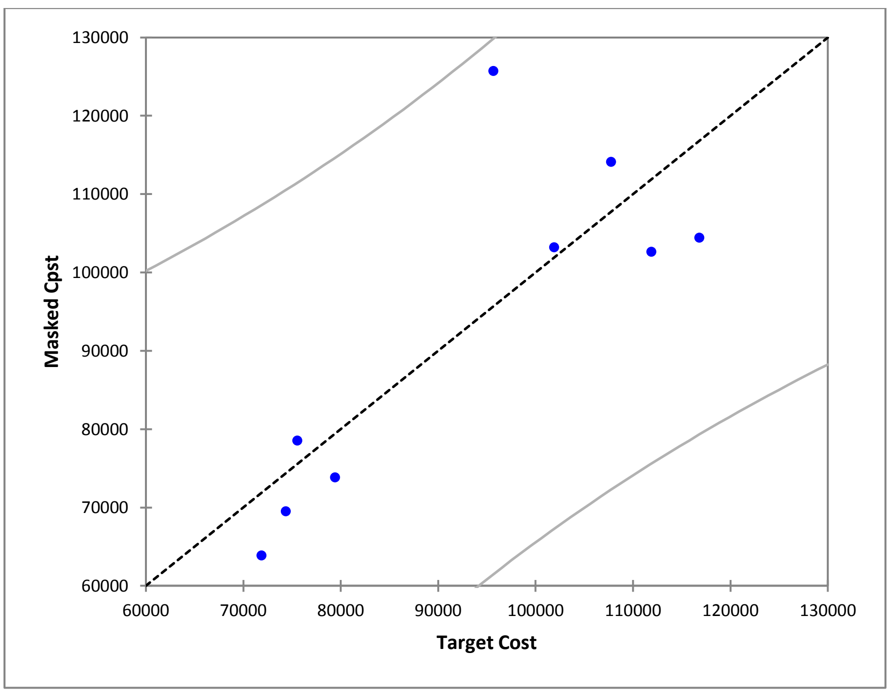


Figure B.6: SPC chart for LR, 1 factor, sample F

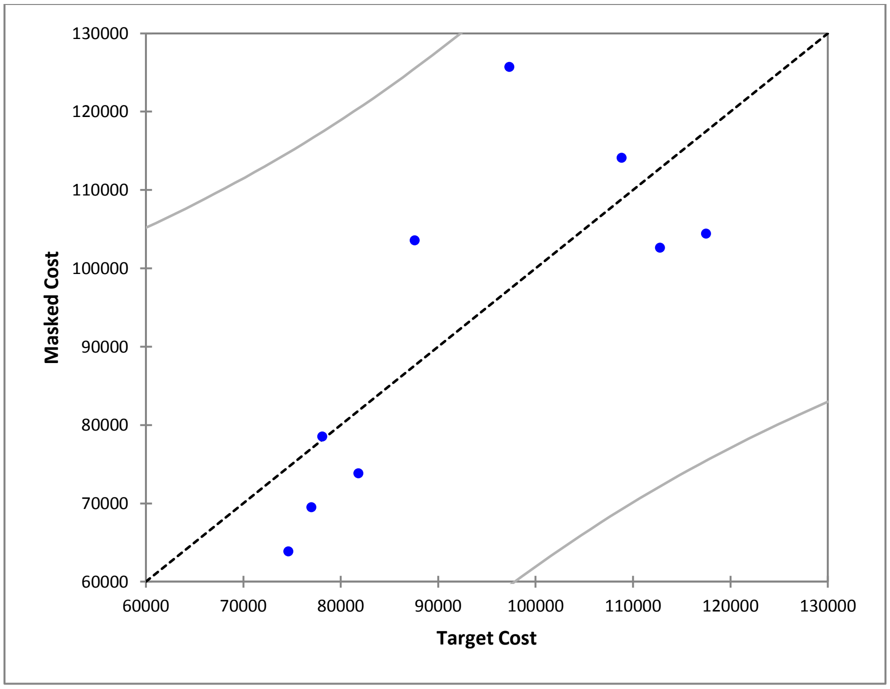


Figure B.7: SPC chart for LR, 1 factor, sample G

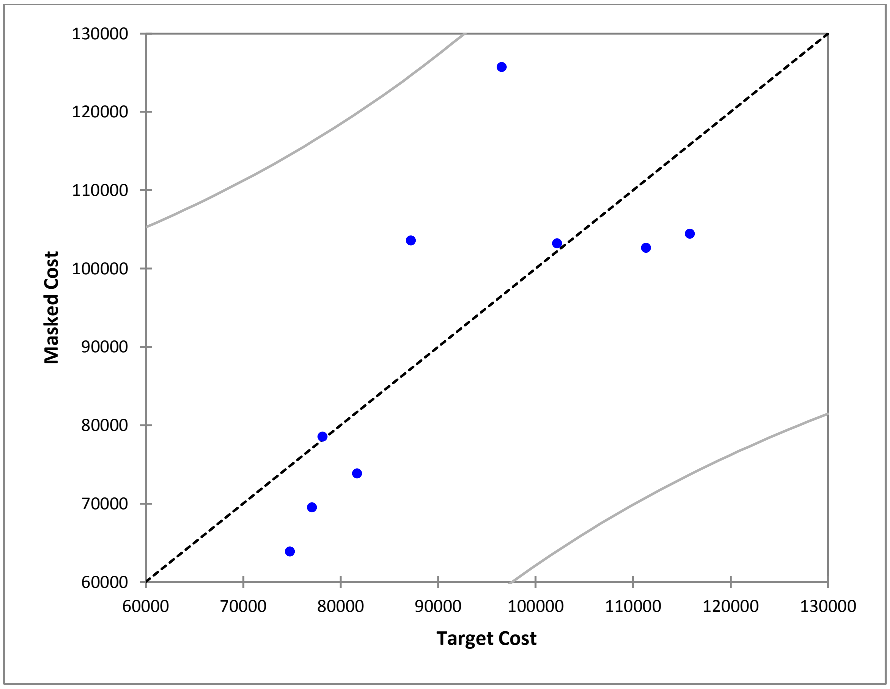


Figure B.8: SPC chart for LR, 1 factor, sample H

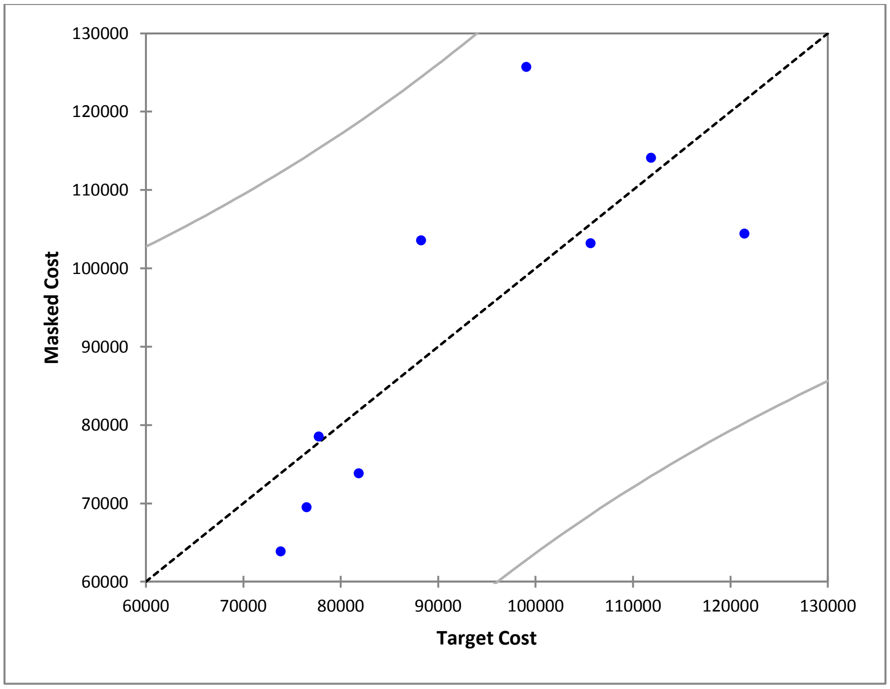


Figure B.9: SPC chart for LR, 1 factor, sample I

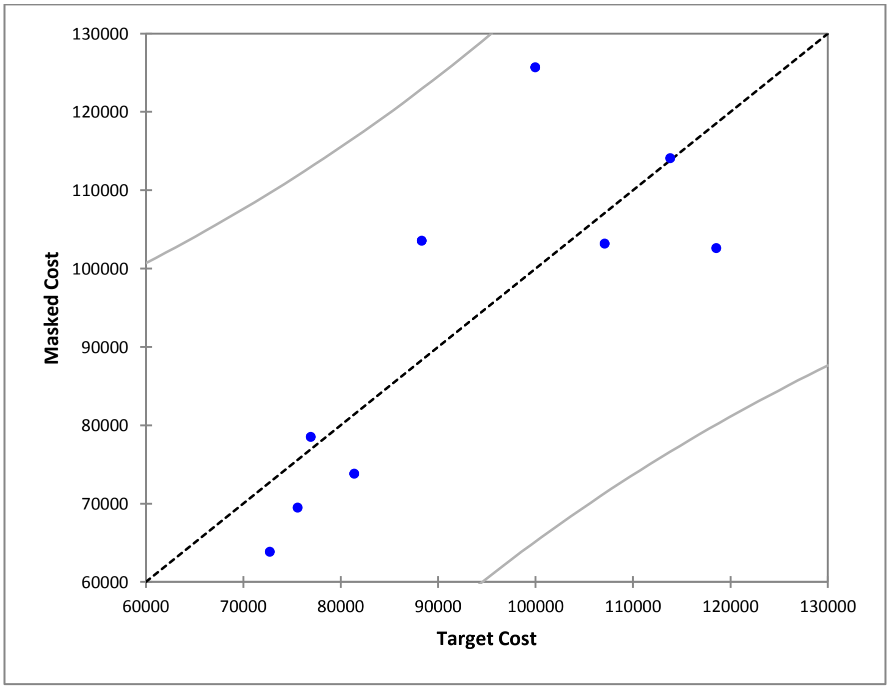


Figure B.10: SPC chart for LR, 1 factor, sample J

APPENDIX C

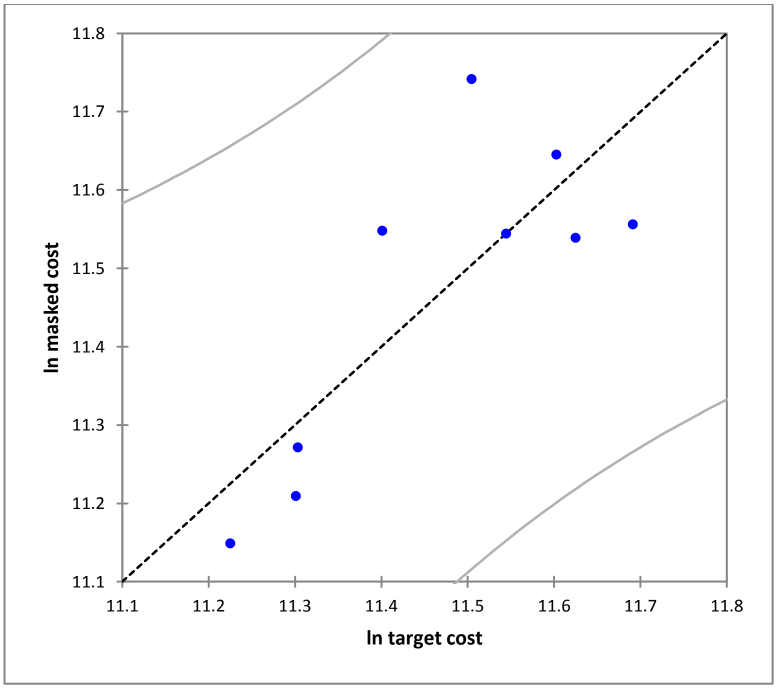


Figure C.1: SPC chart for NLM, 3 factors, sample A

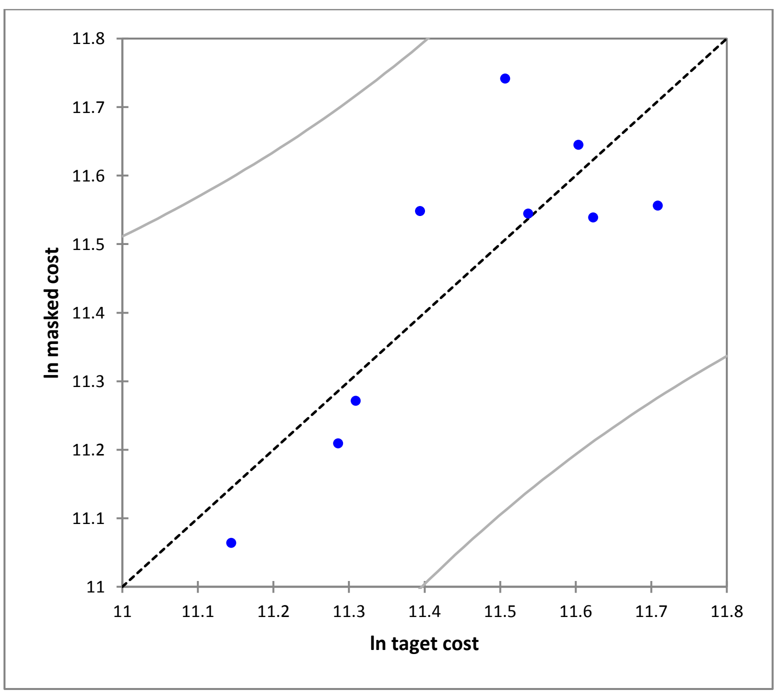


Figure C.2: SPC chart for NLM, 3 factors, sample B

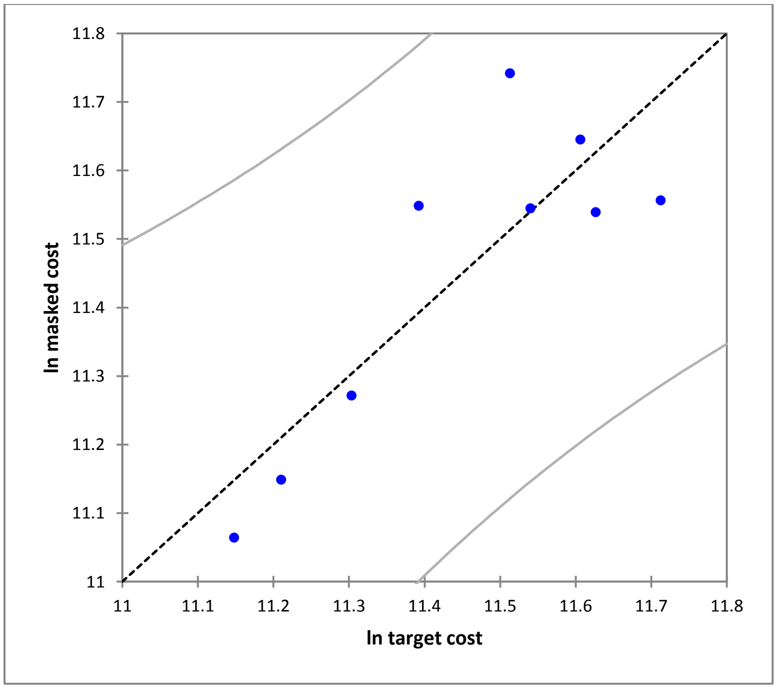


Figure C.3: SPC chart for NLM, 3 factors, sample C

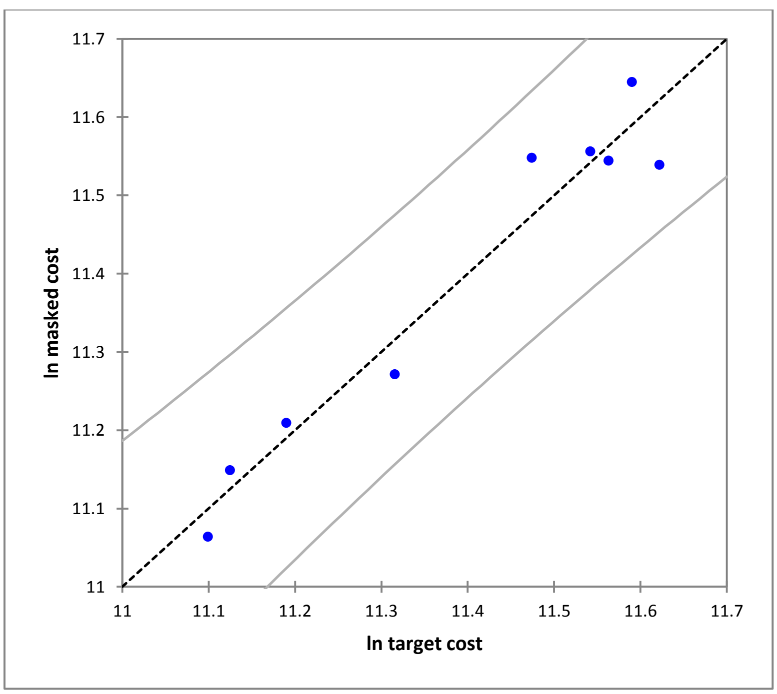


Figure C.4: SPC chart for NLM, 3 factors, sample D

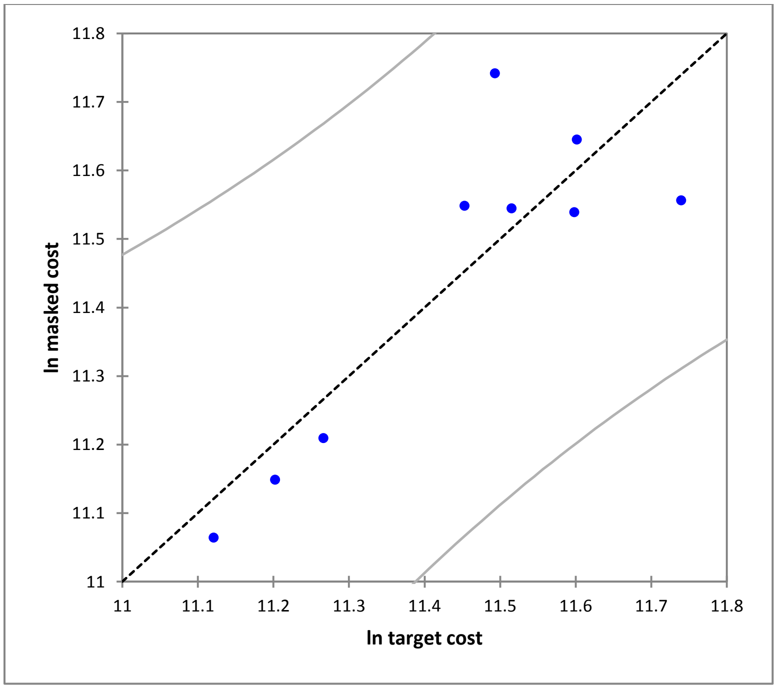


Figure C.5: SPC chart for NLM, 3 factors, sample E

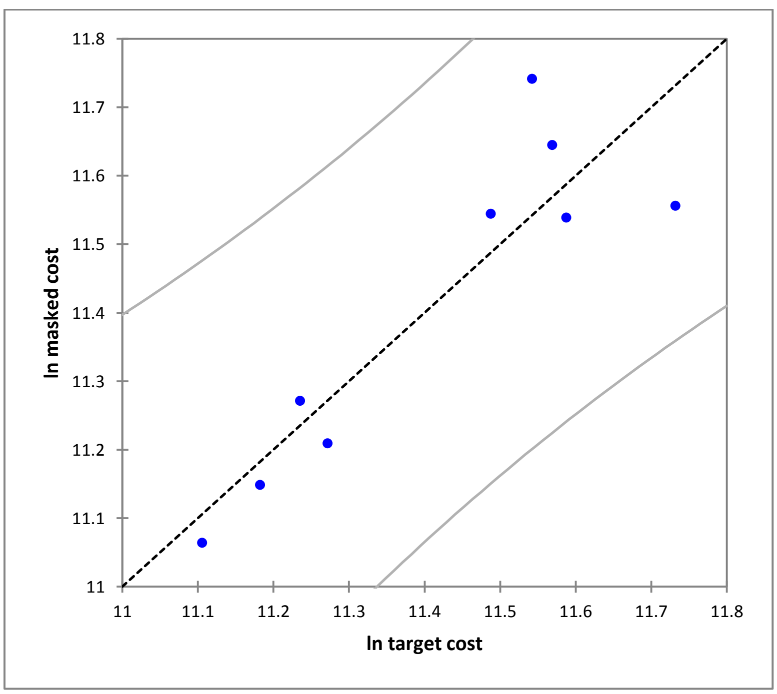


Figure C.6: SPC chart for NLM, 3 factors, sample F

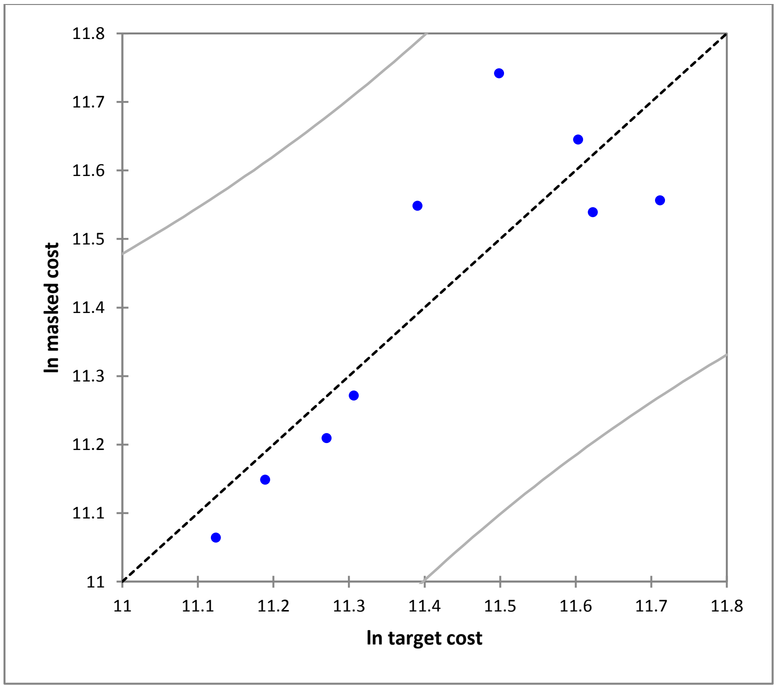


Figure C.7: SPC chart for NLM, 3 factors, sample G

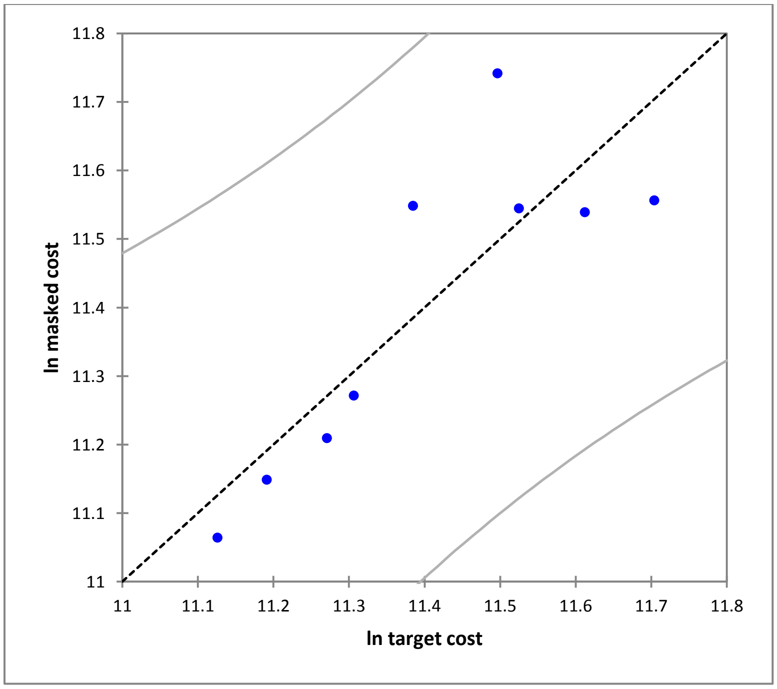


Figure C.8: SPC chart for NLM, 3 factors, sample H

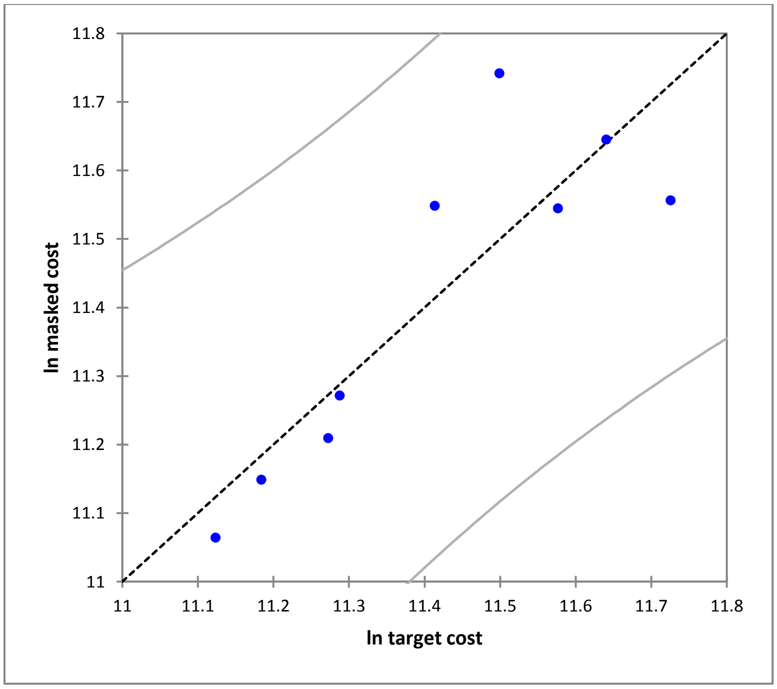


Figure C.9: SPC chart for NLM, 3 factors, sample I

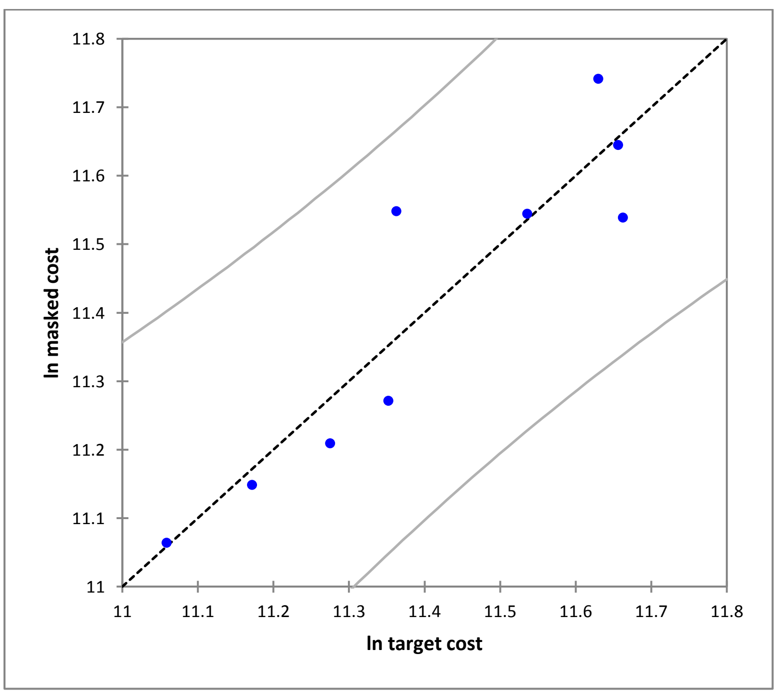


Figure C.10: SPC chart for NLM, 3 factors, sample J

APPENDIX D

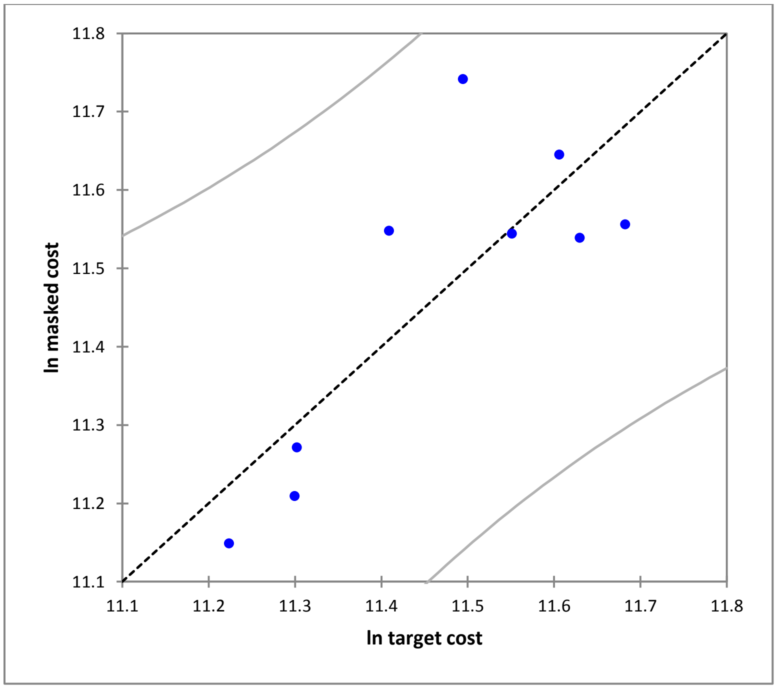


Figure D.1: SPC chart for NLM, 2 factors, sample A

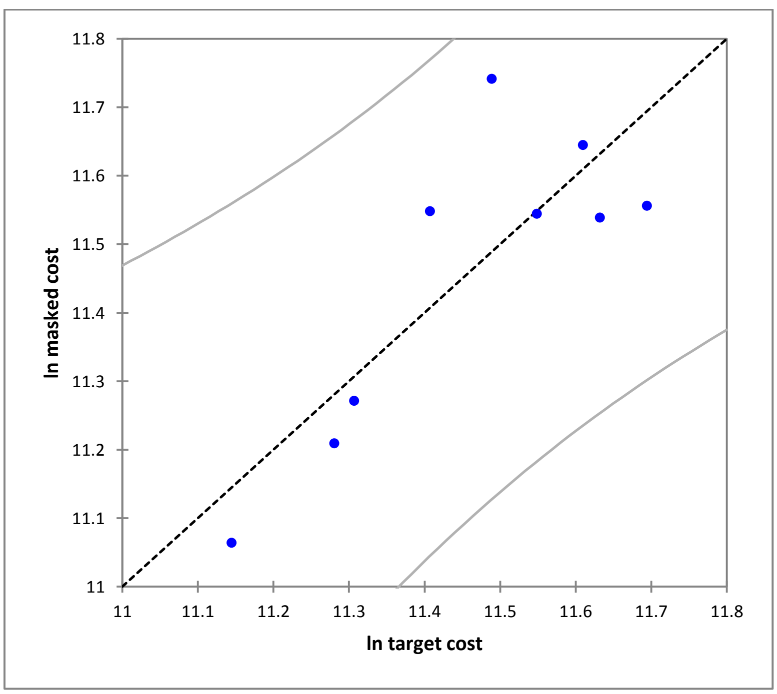


Figure D.2: SPC chart for NLM, 2 factors, sample B

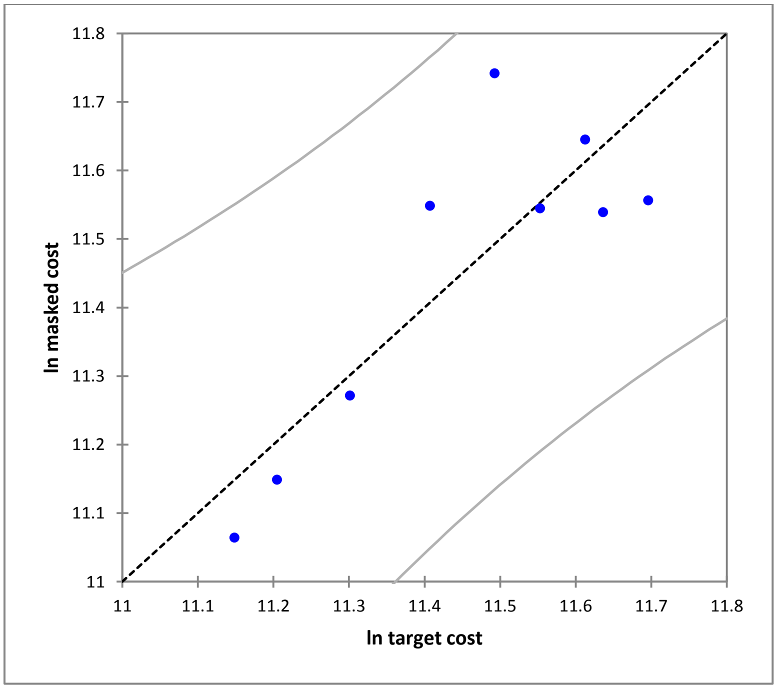


Figure D.3: SPC chart for NLM, 2 factors, sample C

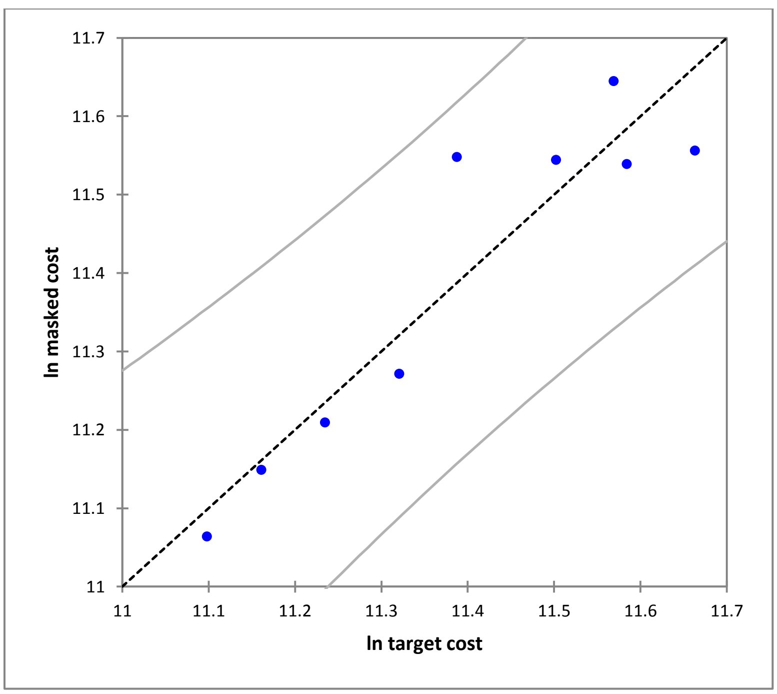


Figure D.4: SPC chart for NLM, 2 factors, sample D

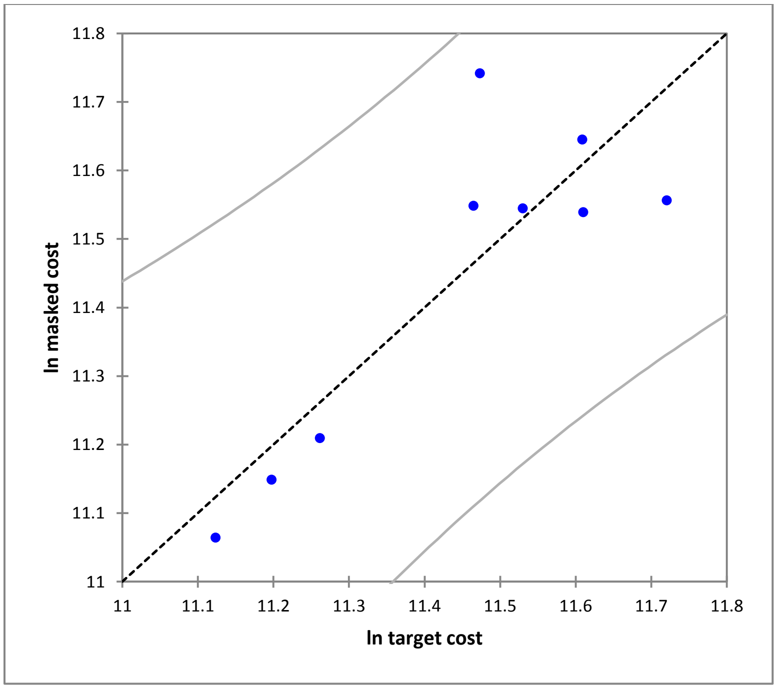


Figure D.5: SPC chart for NLM, 2 factors, sample E

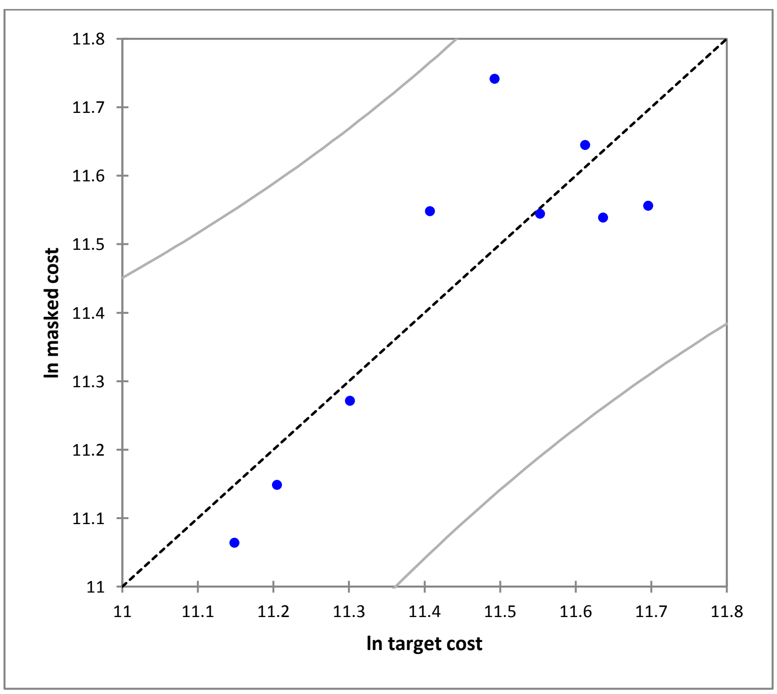


Figure D.6: SPC chart for NLM, 2 factors, sample F

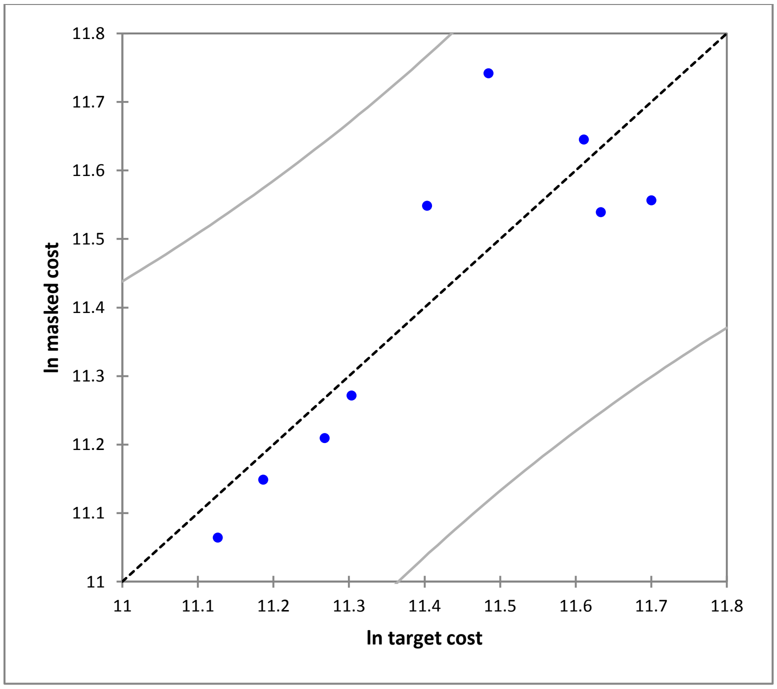


Figure D.7: SPC chart for NLM, 2 factors, sample G

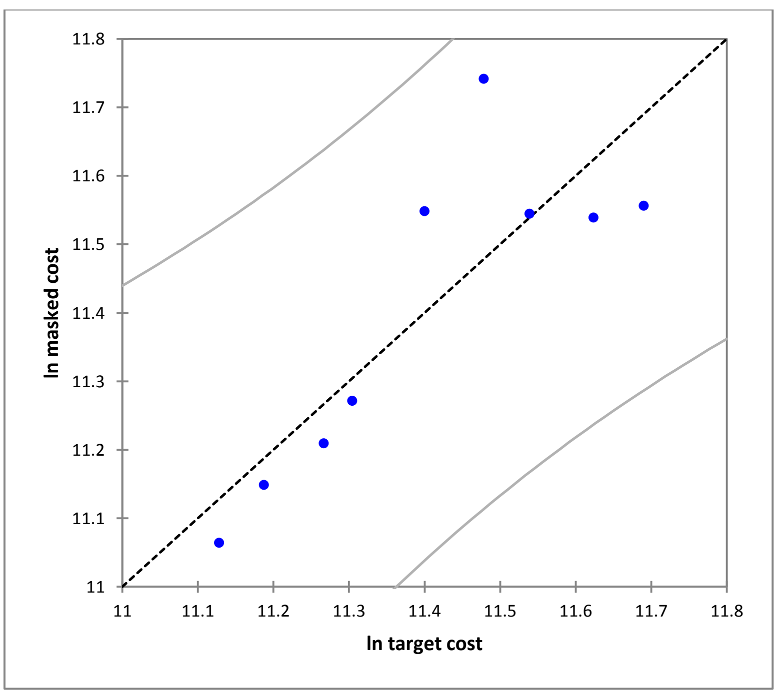


Figure D.8: SPC chart for NLM, 2 factors, sample H

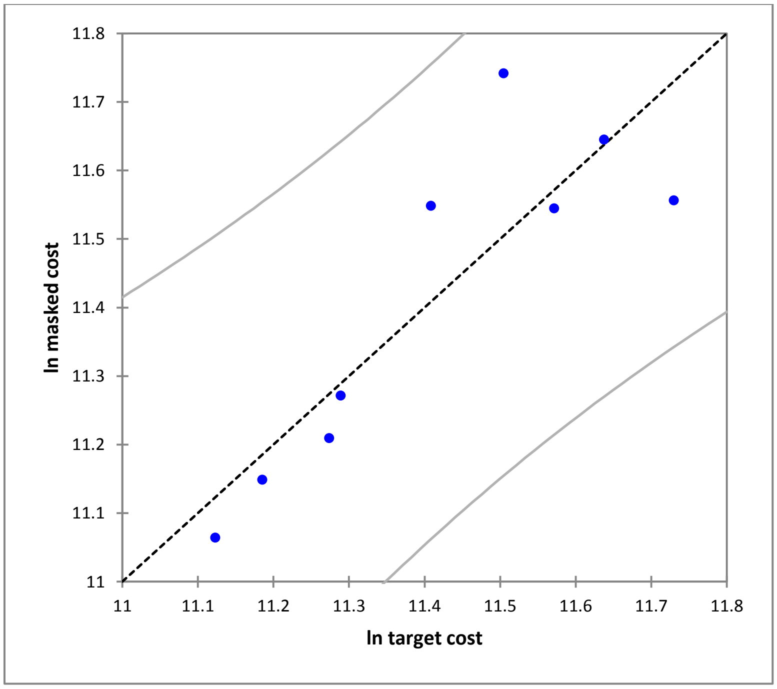


Figure D.9: SPC chart for NLM, 2 factors, sample I

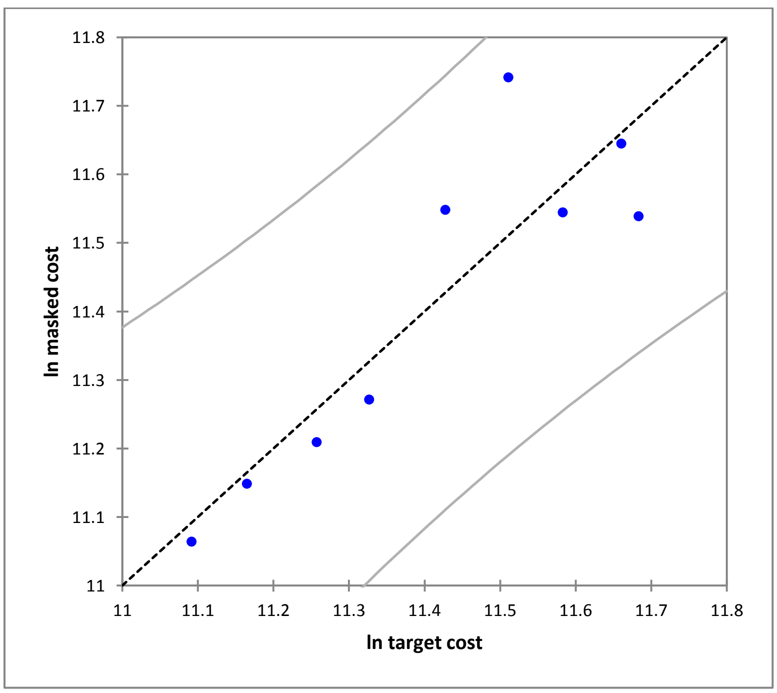


Figure D.10: SPC chart for NLM, 2 factors, sample J

APPENDIX E

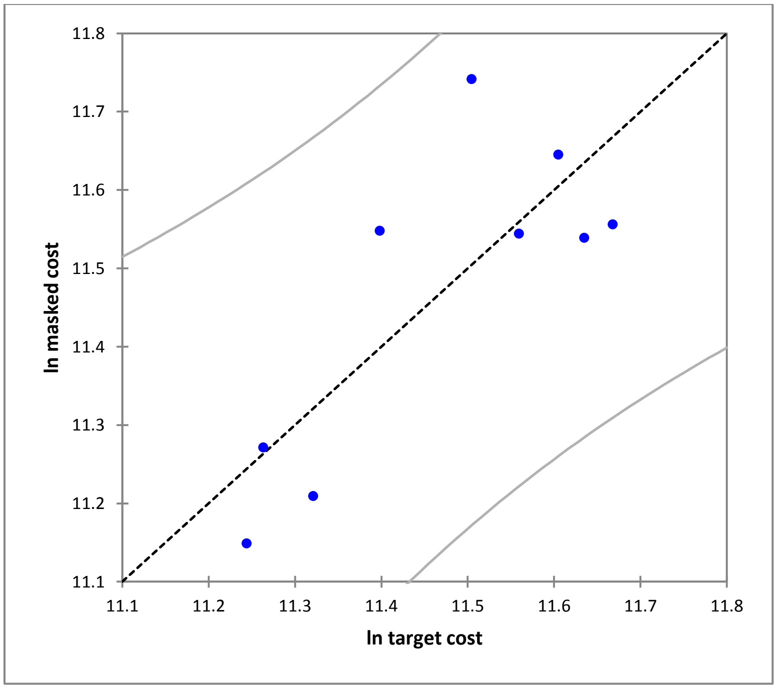


Figure E.1: SPC chart for NLM, 1 factor, sample A

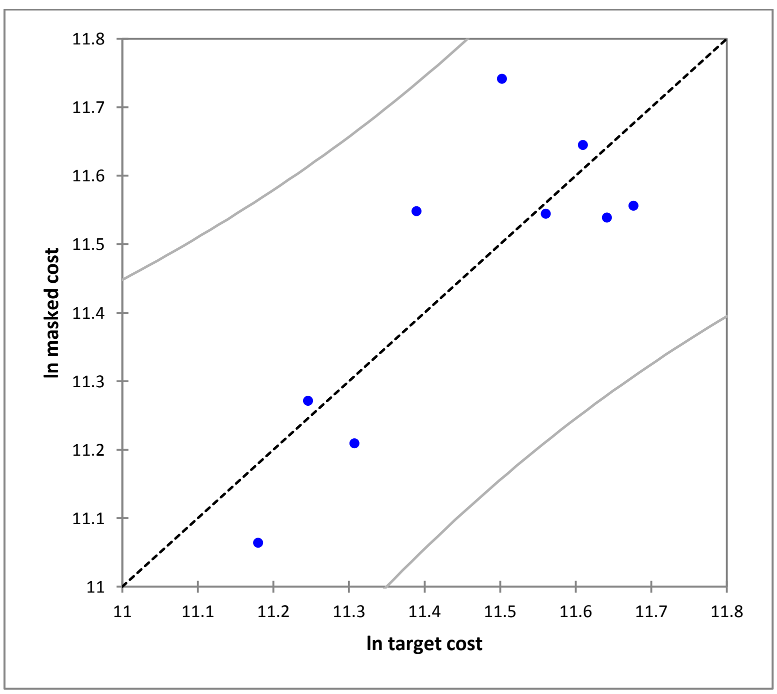


Figure E.2: SPC chart for NLM, 1 factor, sample B

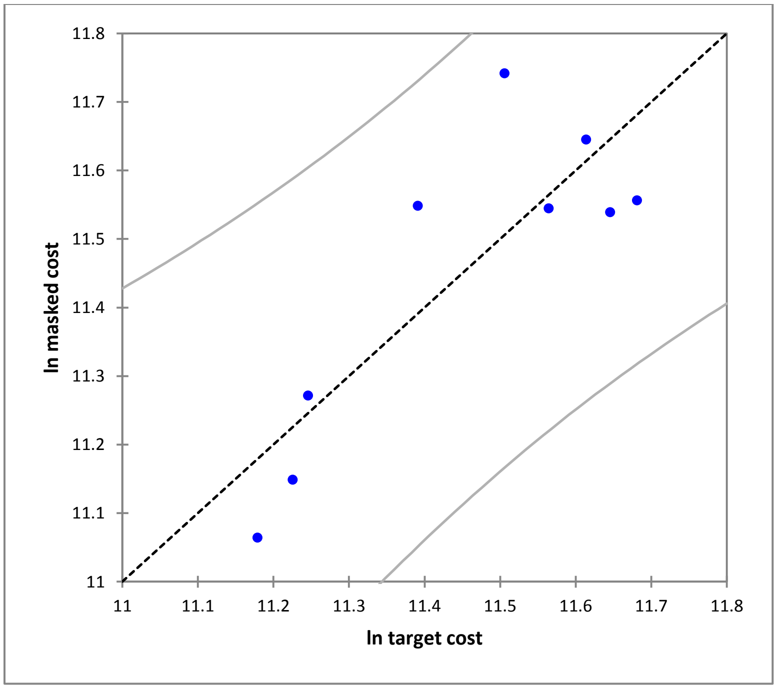


Figure E.3: SPC chart for NLM, 1 factor, sample C

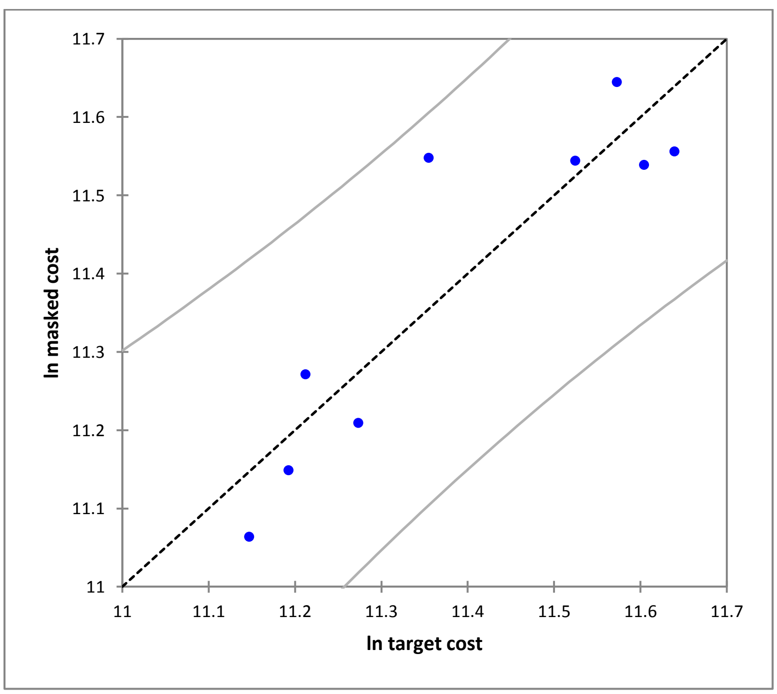


Figure E.4: SPC chart for NLM, 1 factor, sample D

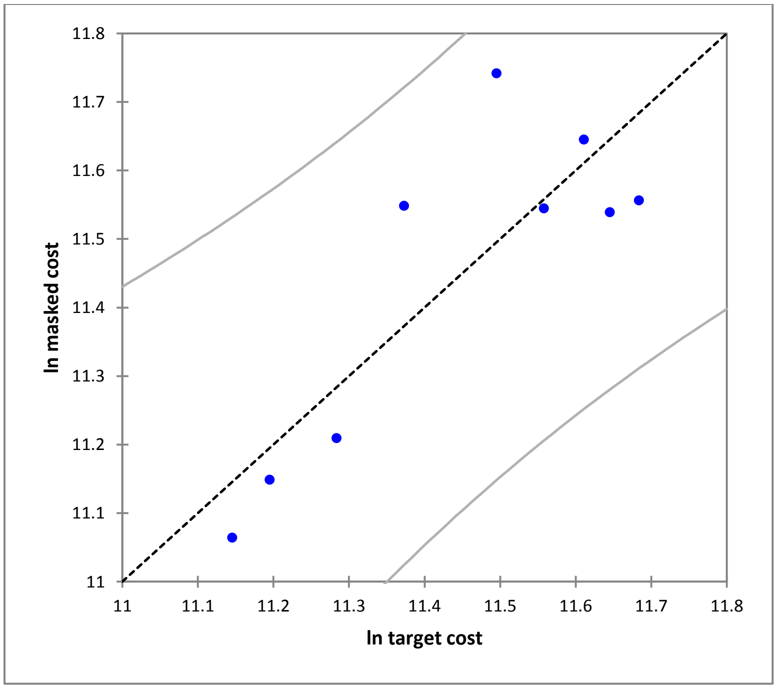


Figure E.5: SPC chart for NLM, 1 factor, sample E

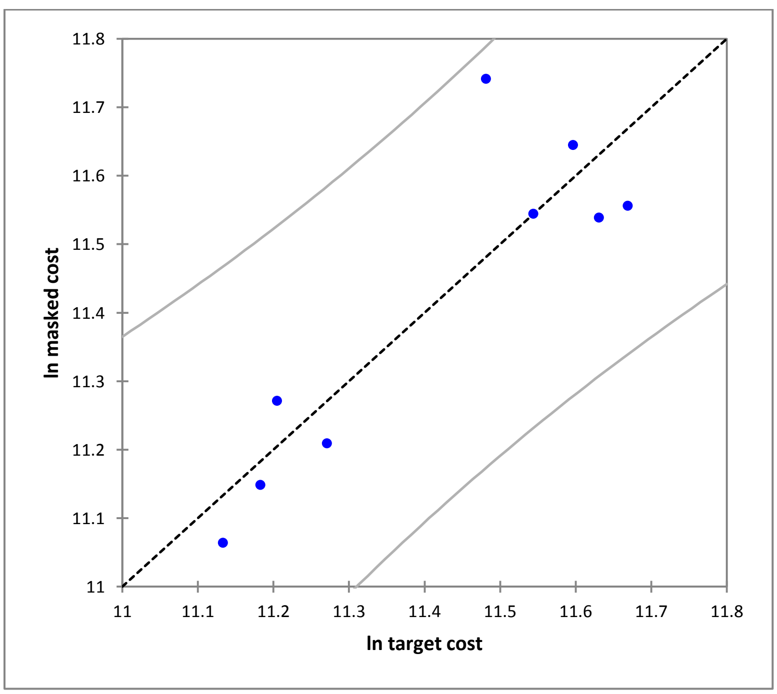


Figure E.6: SPC chart for NLM, 1 factor, sample F

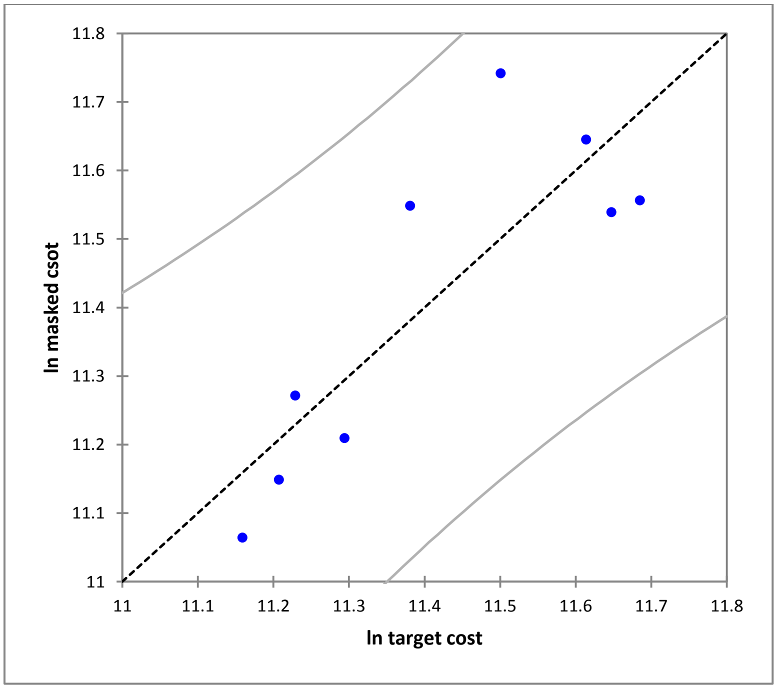


Figure E.7: SPC chart for NLM, 1 factor, sample G

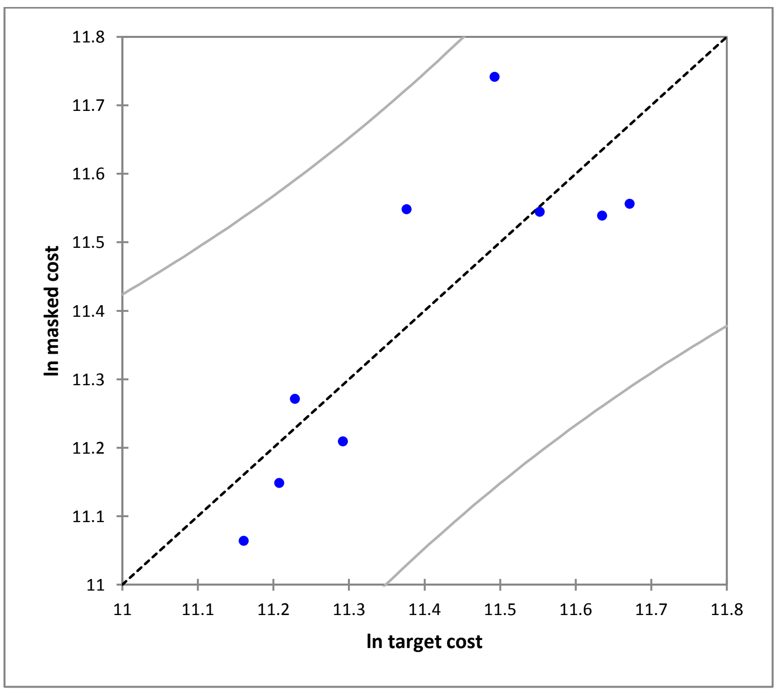


Figure E.8: SPC chart for NLM, 1 factor, sample H

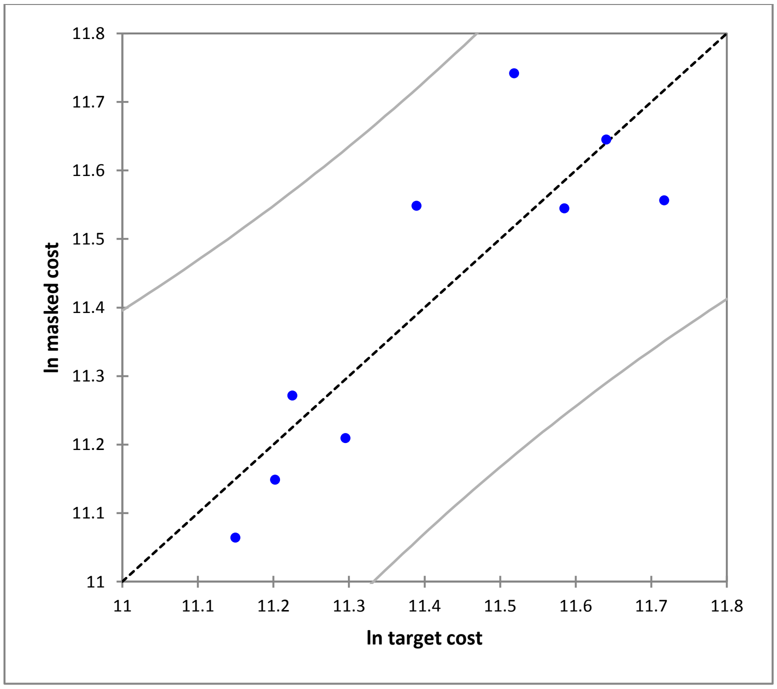


Figure E.9: SPC chart for NLM, 1 factor, sample I

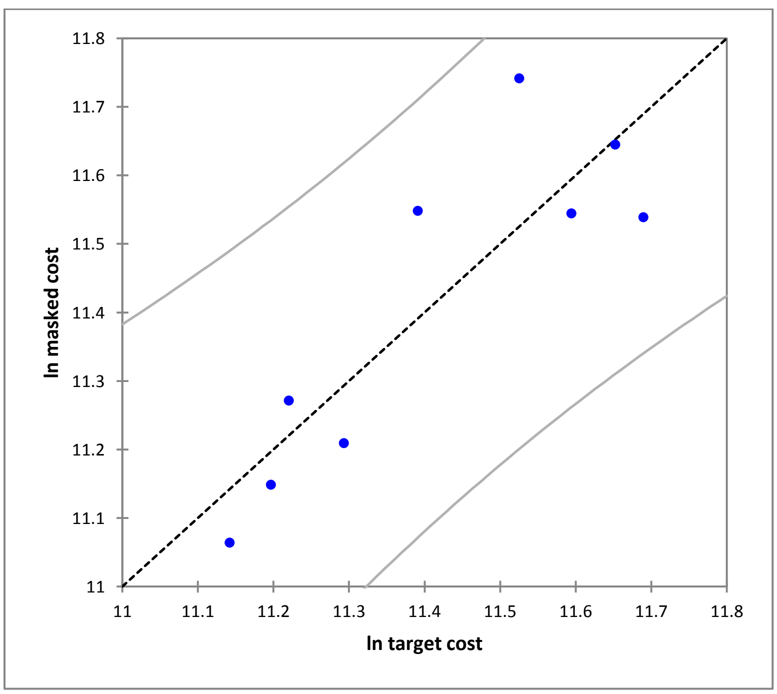


Figure E.10: SPC chart for NLM, 1 factor, sample J