HYBRID MODEL FOR COMMERCIAL MARGIN PREDICTION IN READY MIXED CONCRETE BUSINESS

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หัวข้อวิทยานิพนธ์	แบบจำลองผสมเพื่อการพยากรณ์ผลกำไรทางการค้าในธุรกิจคอนกรีตผสมเสร็จ
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บทคัดย่อ

แบบจำลองโดยทั่วไปมีความเหมาะสมสำหรับข้อมูลที่มีความสัมพันธ์เชิงเส้นตรง แต่ในขณะที่แบบจำลองบางประเภทเหมาะสมสำหรับข้อมูลที่ไม่มีความสัมพันธ์เชิงเส้นตรง เช่น แบบจำลองการถดถอยพหุคูณมีความเหมาะสมกับข้อมูลที่มีความสัมพันธ์เชิงเส้นตรง ขณะที่แบบจำลองโครงข่ายประสาทเทียม มีความเหมาะสมสำหรับข้อมูลที่ไม่มีความสัมพันธ์เชิงเส้นตรง ดังนั้น แบบจำลองผสมจึงมีความเหมาะสมเพื่อการพยากรณ์ทั้งข้อมูลที่มีความสัมพันธ์เชิงเส้นตรงและข้อมูลที่ไม่มีความสัมพันธ์เชิงเส้นตรง วิทยานิพนธ์นี้นำเสนอ (1) แบบจำลองผสมการถดถอยพหุคูณกับแบบจำลองโครงข่ายประสาทเทียม (hybrid multiple regression with neural network model) และ (2) แบบจำลองผสมการตัดสินใจด้วยวิธีวิเคราะห์เชิงลำดับชั้นกับการวิเคราะห์พื้นผิวตอบสนอง (hybrid analytical hierarchy process with response surface methodology) เพื่อการพยากรณ์ผลกำไรทางการค้าในธุรกิจคอนกรีตผสมเสร็จ โดยที่ประสิทธิภาพของการพยากรณ์จะนำมาเปรียบเทียบระหว่างสองแบบจำลองผสม โดยใช้ค่าเปอร์เซนต์คลาดเคลื่อนเฉลี่ยสัมบูรณ์ (MAPE) และค่ารากที่สองของค่าคลาดเคลื่อนกำลังสองเฉลี่ย (RMSE) เพื่อเปรียบเทียบผลความแม่นยำของค่าพยากรณ์ ผลการวิจัยพบว่า ค่า MAPE และค่า RMSE ของแบบจำลองผสมการถดถอยพหุคูณกับแบบจำลองโครงข่ายประสาทเทียมมีค่าน้อยกว่าแบบจำลองผสมการตัดสินใจด้วยวิธีวิเคราะห์เชิงลำดับชั้นกับการวิเคราะห์พื้นผิวตอบสนอง ดังนั้น จึงสามารถสรุปได้ว่า แบบจำลองผสมการถดถอยพหุคูณกับแบบจำลองโครงข่ายประสาทเทียมมีความเหมาะสมที่จะนำมาใช้สำหรับการพยากรณ์ผลกำไรทางการค้า ในธุรกิจคอนกรีตผสมเสร็จได้ดีกว่าแบบจำลองผสมการตัดสินใจด้วยวิธีวิเคราะห์เชิงลำดับชั้นกับการวิเคราะห์พื้นผิวตอบสนอง

คำสำคัญ : คอนกรีตผสมเสร็จ, แบบจำลองผสม, ผลกำไรทางการค้า

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ABSTRACT

The normal single model is either generally suited in prediction of linear relationship or normally fitted in prediction of non linear relationship e.g. multiple regression is suited for linear relationship whereas artificial neural network is fitted with non-linear relationship. The hybrid model is superior predicted method for both linear and non-linear relationship. This thesis proposes (1) hybrid multiple regression with neural network and (2) hybrid analytical hierarchy process with response surface methodology models for commercial margin prediction in ready mixed concrete business. The performance of prediction was compared between two hybrid models using mean absolute percentage error (MAPE) and root mean square error (RMSE) in order to evaluate the result performance. Based on experimental results, the MAPE and RMSE values of hybrid multiple regression with neural network model are lower than hybrid analytical hierarchy process with response surface methodology model. As the results, it can be claimed that hybrid multiple regression with neural network model is more suitable for commercial margin prediction in ready mixed concrete business than hybrid analytical hierarchy process with response surface methodology model.

Keywords: Ready mixed concrete, hybrid model, commercial margin

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LIST OF ABBREVIATIONS

MR	- Multiple regression
ANN	- Artificial neural network
AHP	- Analytical hierarchy process
RSM	- Response surface methodology
ARIMA	- Autoregressive integrated moving average
RMC	- Ready mixed concrete
CM	- Commercial margin or contribution margin
MAPE	- Mean absolute percentage error
RMSE	- Root mean square error
YOY	- Year over year
USD/bbl	- United States dollar/barrel

CHAPTER 1

INTRODUCTION

1.1 STATEMENT AND SIGNIFICANCE OF THE PROBLEMS

Ready mixed concrete industry in Thailand is facing cost increasing problem because of economic situation and government policy. The inflation rate and oil price are the major impact to ready mixed concrete raw material cost. The core inflation rate slightly increase compared with Y2011. Inflation rate in 2012 is still at a relatively high level due to related cost pressures. Headline inflation will be at 3.5-4.0% and core inflation, which excludes prices of fresh food and energy, will be about 2.5-3.0% (Siam Commercial Bank Economic Intelligence Center. 2012). The rise in domestic energy prices is due to the tight supply of crude oil and the situation in the Middle East which is still uncertainty. Table 1 shows the economic main forecasts. Pressures on costs come from high energy prices, inflation rate, and increased minimum wage.

Table 1.1 The economic main forecasts

	Actual 2011	2012 Q1	2012 Q2	2012 Q3*	2012 Q4*	2012*
Head line inflation (%YOY)	3.8	3.4	3.4	3.7	3.2	3.5 - 4.0
Core inflation (%YOY)	2.4	2.7	2.5	2.6	2.7	2.5 - 3.0
Oil price (USD/bbl)	111.1					119*
Source: Siam Commercial Bank Economic Intelligence Center (2012) *: forecast value						

The government policy to increase minimum wages nationwide will have an impact on costs for entrepreneurs, especially in businesses which use a large number of unskilled workers and wages constitute a high proportion of total costs. On average, the minimum wage policy will have an impact on the production cost by about 3.3% in 2012, while the actual impact will vary across industries by the proportion of unskilled workers employed and the ability to enhance production efficiency. Businesses which will be impacted most are construction, with costs increasing by about 4.6%. Figure 1.1 shows the effect of minimum wage rise on the cost of production by industry.

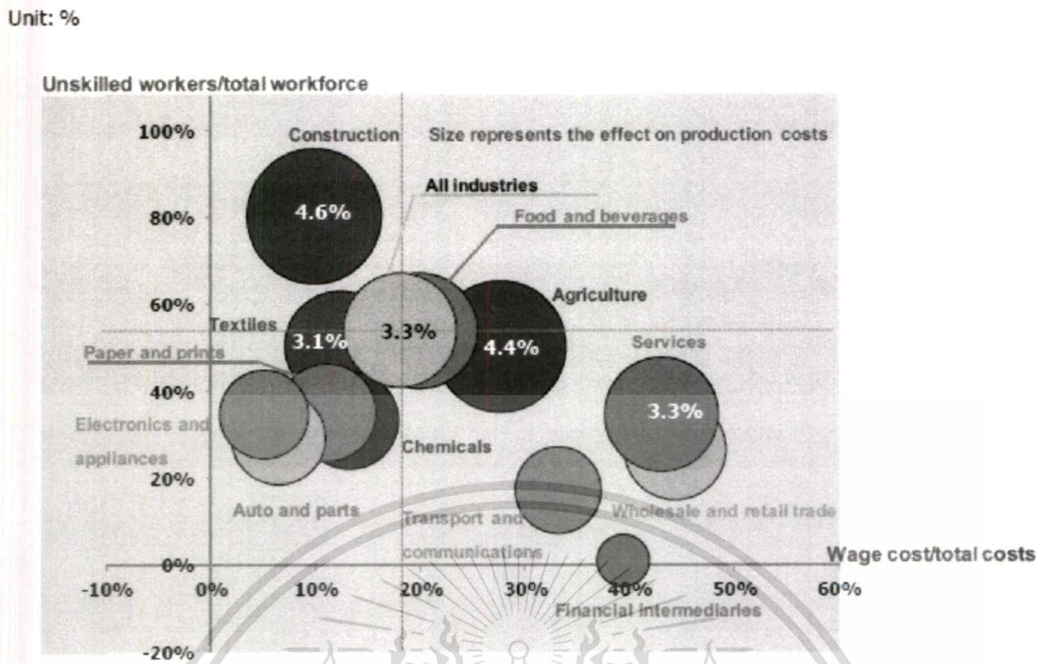

Figure 1.1 Effect minimum wage rise on the cost of production by industry

Source: Siam Commercial Bank (2012)

The jump in minimum wage to 300 baht will have an unavoidable impact on the costs of production for ready mixed concrete business. In the long term, entrepreneurs will have to introduce efficient machinery or technology into the production in order to increase productivity and compensate for the reduction in labor employment. Meanwhile, different industries have the ability to adjust differently both in terms of improving production efficiency and procuring replacement materials. As the results, the cost conscious concept will be able to monitor their business performance in accordance with the higher labor costs.

Currently, ready mixed concrete business is high competition in Thailand especially in large and mega project segments which is affected from market situation and global economic. All ready mixed concrete players try to maintain their market positions in order to secure sales volume. Contractors are quite demand low selling price, price holding throughout the project period, and long term credit condition. The demand is slow down as same as the selling price is competitively low, while the raw material cost are growing up because of fuel price and unforeseen situation. The other substitution products such as precast concrete, prefabrication concrete and asphalt are major threat for ready mixed concrete business. As such, ready mixed concrete business should closely monitor price and cost performance in order to gain more profitability. The way of survival business is to review internal transaction management. The transaction management provides price and cost information to calculate commercial margin that is the key financial goal for management to calculate profitability of business transaction.

1.2 OBJECTIVES OF THE RESEARCH

1.2.1 To propose 2 hybrid models i.e. (1) hybrid multiple regression with artificial neural network model and (2) hybrid analytical hierarchy process with response surface model for predicting commercial margin.

1.2.2 To compare the efficiency accuracy of 2 hybrid models using root mean square error (RMSE) and mean absolute percentage error (MAPE).

1.3 UTILIZATION OF THE RESEARCH

1.3.1 The performance evaluation of hybrid models in this research can be adopted to predict the commercial margin effectively and can support ready mixed business to predict the commercial margin accurately.

1.3.2 The commercial margin prediction from hybrid models can be applied for sales to calculate the reasonable margin and profit in the high competition environment.

1.3.3 The proposed hybrid model can be applied to other businesses.

1.4 SCOPE OF THE RESEARCH

1.4.1 Data is collected from one of the ready mixed concrete businesses in Thailand from January 2009 – December 2011.

1.4.2 Twelve explanatory variables affecting the commercial margin are selected to test the model.

1.4.3 All raw data are normalized to be normal distribution.

1.4.4 Two hybrid models are compared to predict commercial margin i.e. (1) hybrid multiple regression with artificial neural network model and (2) hybrid analytical hierarchy process with response surface methodology.

1.5 DIFFINITION OF TECHNICAL TERM

1.5.1 Ready mixed concrete is an essential material in contemporary construction and engineering projects. Ready mixed concrete is a mixture of four basic ingredients: sand, rock, cement, as well as chemical compounds known as admixtures, which is mixed with water at a plant and transported directly to a construction site.

1.5.2 Commercial margin or contribution margin refers to the value remaining after deduction of variable expenses from income, which the commercial margin expresses the difference between sales of merchandise and cost of merchandise sold.

1.5.3 Hybrid model is a method to merge two methods in order to improve the prediction accuracy, which can be also referred as combined models or ensemble models and often used synonymously. Hybrid model can be implemented in three different ways; linear models, nonlinear models, and both linear and nonlinear models.

CHAPTER 2

LITERATURE REVIEW

This chapter will introduce ready mixed concrete, commercial margin, methodologies, which are employed in this research i.e. multiple regression (MR), artificial neural network (ANN), analytical hierarchy process (AHP), response surface methodology (RSM), hybrid model, and related work.

2.1 READY MIXED CONCRETE

Ready mixed concrete is used as a building material because of two main advantages. The first one is cheaper than other materials such as steel, wood, and so on. The second is that ready mixed concrete allows great diversity in design and function, which can be poured into molds of any shape. Ready mixed concrete is a perishable product that needs delivery within 1.5 to 2.5 hours before it becomes too stiff to be workable.

Ready mixed concrete is consumed by the construction sector to build infrastructure, commercial and residential building, factories, and so on. Demand of ready mixed concrete is inelastic because it is small part of construction cost. Concrete cost is around 10 % of materials cost for any sector of construction. The other substitution products such as precast concrete, prefabrication concrete and asphalt are major threat for ready mixed concrete business. Therefore, the ready mixed concrete market substantially affects the volume of the construction activity.

Ready mixed concrete is produced by blending cement, aggregate, additives and water which is produced in a factory, and then delivered to construction site by truck mounted transit mixers. The ready mixed concrete business practice are described in Appendix A. Ready mixed concrete is also referred as the customized concrete products for commercial purpose and different specific applications. The process of ready mixed concrete production and delivery directly affects to total cost. In high competition market like Thailand, companies in the ready mixed concrete industry are facing the several problem e.g. peak period scheduling, long delivery distance, fluctuated demand, low selling price, high raw material cost and transportation cost, long credit term, high marketing cost, cost-effective manner, and so on. As a results, commercial margin or contribution margin is the key financial goal for management to monitor business survival in order to calculate profitability of business.

2.2 COMMERCIAL MARGIN OR CONTRIBUTION MARGIN

The contribution margin is the difference of revenues and variable expenses (Walther and Skousen. 2009). The contribution margin is a conceptual number reflecting the amount available from each sale, after deducting all variable costs associated with the unit sold. Some of these variable costs are product costs, and some are selling and administration in nature. The commercial margin is generally a number calculated for internal use and analysis.

The contribution margin is the difference between the sales price and the variable cost per unit (Lanen et al. 2011). Contribution margin refers to the value remaining after deduction of variable expenses from income, which the commercial margin expresses the difference between sales of merchandise and cost of merchandise sold. The contribution margin is important information for managers because it allows them to assess the profitability of products before factoring in fixed costs (which tends to be more difficult to change in the short run). The contribution margin income statement format is used more for internal decision-making and performance evaluation purposes.

Based on a literature survey and ready mixed concrete business practice, ready mixed concrete plant transforms raw material to concrete within the production facility and delivers concrete to different construction sites. The ready mixed concrete production and delivery are essentially effected to commercial margin or contribution margin, which is a transaction process for strategically managing the related information flows throughout the organization that the current and future profitability is maximized by cost effectiveness. It means that there are 12 factors that will effect contribution margin in ready mixed concrete business in practices. All 12 variables are divided into 3 groups such as selling condition, selling price, and variable cost. Selling condition consists of credit term, demand and distance. Selling price consist of product price list, extra charge, discount, and rebate. Variable costs consist of freight cost, carrying receivable cost, marketing cost, raw material cost, and other variable production cost. All 12 variables are described as below and shown in Table 2.1.

1. Credit term means the conditions, which company will be extended to a customer. Credit term is the negotiation term, which company offers to customer e.g. the maximum time allowed payment, the total credit amount, discount agreement, and the rate of late payment penalty. In this research, credit term is maximum payment allowed time in days under the specific discount and credit amount agreement condition. Normally practice of ready mixed concrete business, the large amount volume of ready mixed concrete and big contractors will receive the

credit term longer than the small volume due to the economics of scale and power of negotiation, which will effect with selling price.

2. Demand means the amount of ready mixed concrete volume in cubic meter, which customers place the order to business. The big project which has a huge ready mixed concrete volume should get high discount and long credit term that is affected commercial margin.

3. Distance means the delivery distance in kilometer from ready mixed concrete plant to the construction site. The longer delivery distance will be quoted the higher selling price or the lower discount, which directly affect to the variable cost.

4. Product price list is the standard price of each product, which the normal price is quoted to every customer in THB bath. Each of strength class of ready mixed concrete product will have the different product price list.

5. Extra charge is special price added on top of product price list in THB bath. It is a special agreement that customer request specific products or services which customer accept to pay extra to company.

6. Discount refers to the deduction to product or service price list in THB bath, which is offered by the seller. The big contractor and huge concrete volume should have the higher discount, that will be totally effected the selling price and income.

7. Rebate is an amount paid by way of reduction, return, or refund on what has already been paid or contributed. It is a type of sales promotion marketer use primarily as incentives or supplements to product sales. Rebates are offered to customer by many reason e.g. early payment, volume rebate, special rebate due to specific reason, and etc. All rebates are directly effect to selling price.

8. Freight cost is the incurred cost for delivery ready mixed concrete products from the plant or distributor to a customer or construction site. In some cases, the customer pays for freight cost as part of its bill. Some construction sites offer free delivery as part of promoting products. The freight cost will align with the delivery distance, which effect with selling price.

9. Carrying receivable cost is the allocated costs of average investments in accounts receivable; debts represent the currently unpaid element of sales and therefore receivables break the circle of cash flows inside the company and tie up company's financial resources. The financial need resulting from credit sale or bad debts expenses should be covered by other sources of finance (e.g. short term credit). Costs of carrying receivables are therefore closely related to costs of available sources of funds. Carrying receivable costs are calculated to simulate the

financial costs incurred for the outstanding account receivables per transaction. The calculation is done on the basis of the short-term interest rate.

10. Marketing cost can be either a fixed cost if company builds a marketing budget based on previous revenue or a variable cost if companies use conversions as your marketing budget base. Marketing can also fall under discretionary category for sponsorships, pubic relation, bonuses, charitable donations, and so on. In this research, market cost is the allocated sales and marketing cost due to specific product or service activities, which is a variable cost.

11. Raw material cost is the variable costs that refer to the costs associated directly with the number of units of product that are produced ready mixed concrete. In this research, raw material cost is including cement, aggregates, admixture, additive cost and so on.

12. Other variable production cost are the allocated production cost per cubic meter except raw material cost, that consider based on specific product e.g. fiber cement, cooling aggregate, liquid nitrogen, hot water, steam and so on.

Table 2.1 Explanatory variables

Variables	Meaning
Credit term (day)	Payment condition of transaction selling
Demand (cubic meter)	Concrete quantities that customer placed the order to business
Distance (kilometers)	Average distance that deliver concrete to customer
Product price list (Baht)	Selling price list that quote to customer
Extra charge (Baht)	Addition selling price that quote to customer
Discount (Baht)	Pricing discount for customer
Rebate (Baht)	Special discount for customer
Freight cost (Baht)	Delivering cost
Carrying receivable cost (Baht)	Allocated cost of customer's day sale outstanding (DSO)
Marketing cost (Baht)	Allocated sales and marketing cost
Raw material cost (Baht)	Total variable raw material production cost
Other variable production cost (Baht)	Allocated production cost except materials based on the need for the specific product

Therefore, in this research, the variables are 12 factors affecting commercial margin including credit term (day), demand (cubic meter), distance (kilometers), product price list (Baht), extra charge (Baht), discount (Baht), rebate (Baht), freight cost (Baht), carrying receivable cost (Baht), marketing cost (Baht), raw material cost (Baht) and other variable production cost (Baht). All variables can be categorized into 3 groups, which shown in Figure 2.1.

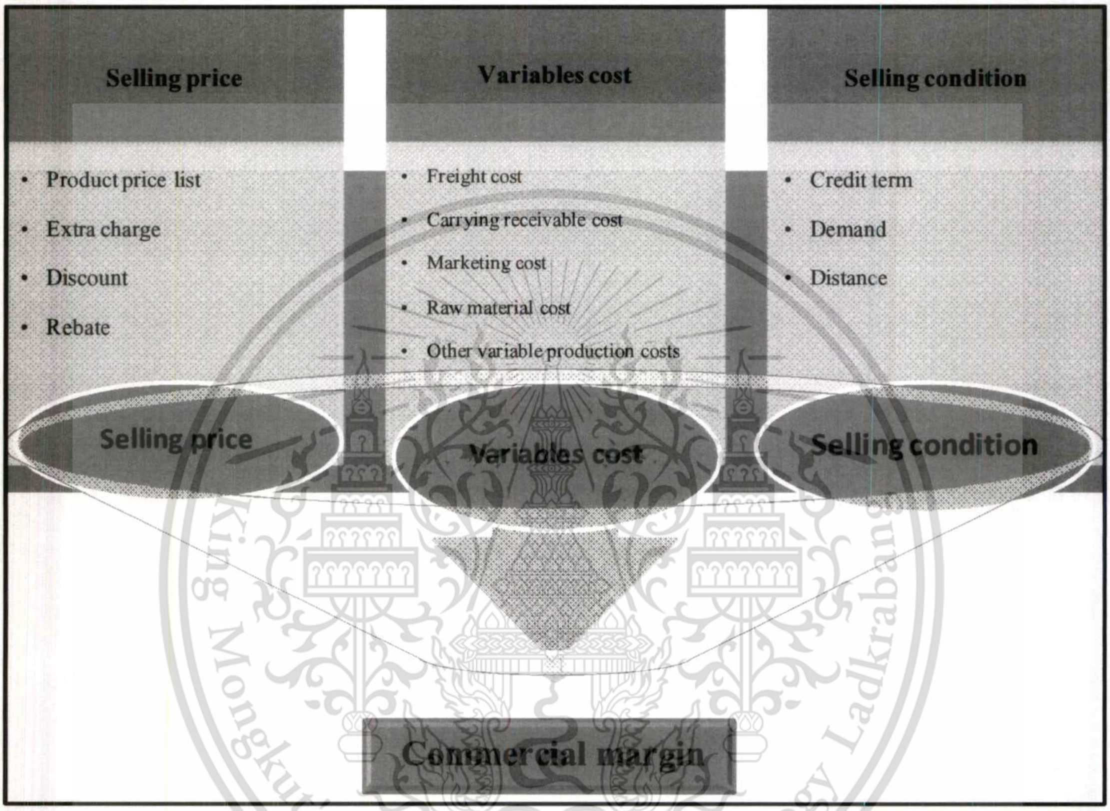

Figure 2.1 Variables affecting commercial margin

2.3 METHODOLOGIES

2.3.1 Multiple regression

The multiple regression (MR) approach is a statistical method to investigate the relationship between one dependent variable and one or more independent variables (Pindyk and Rubinfeld. 1991). MR is a method used to model the linear relationship between a dependent variable and one or more independent variables. The dependent variable is sometimes also called the predictand, and the independent variables are called the predictors. The MR model expresses the value of a predictand variable as a linear function of one or more predictor variables and an error term. The structure of MR model is showed in Figure 2.2.

$$y_i = \beta_0 + \beta_1 x_{i,1} + \beta_2 x_{i,2} + \ldots + \beta_k x_{i,k} + \varepsilon_i \qquad (2.1)$$

Where β_0 = regression constant

β_k = coefficient on the k^{th} predictor

k = total number of predictors

$x_{i,k}$ = value of the k^{th} predictor

Y_i = predictand

ε_i = error term

The model of equation *(2.1)* is estimated by least squares, which yields parameter estimates such that the sum of squares of errors is minimized. The resulting prediction equation is

$$\hat{y}_i = \hat{\beta}_0 + \hat{\beta}_1 x_{i,1} + \hat{\beta}_2 x_{i,2} + \ldots + \hat{\beta}_k x_{i,k} + \varepsilon_i \qquad (2.2)$$

Where "^" = estimated values

The error term in equation *(2.1)* is unknown because the true model is unknown. Once the model has been estimated, the regression residuals are defined as

$$\varepsilon_i = y_i - \hat{y}_i \qquad (2.3)$$

Where y_i = observed value of predictand in i

$\hat{y}_i$ = predicted value of predictand in i

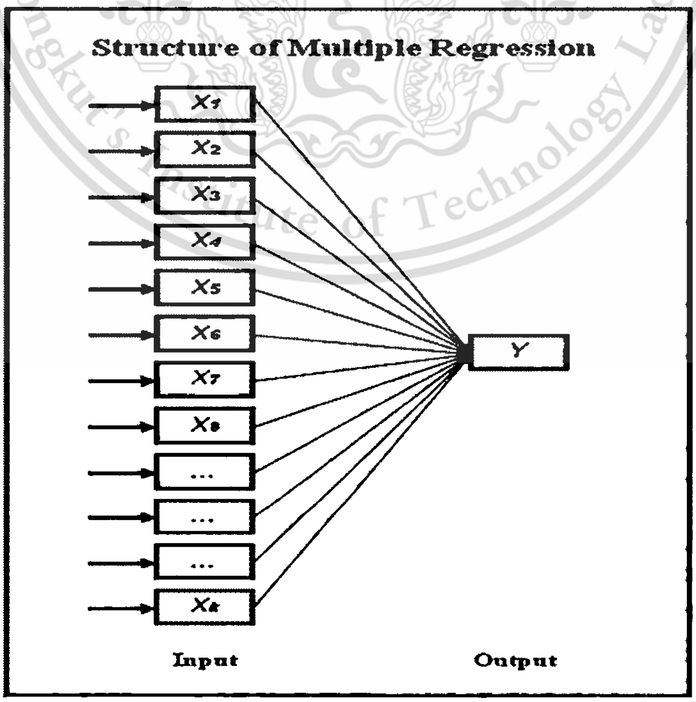

Figure 2.2 Structure of multiple regression

Source: Pindyk and Rubinfeld (1991)

The residuals measure the closeness of fit of the predicted values and actual predictand in the calibration period. The algorithm for estimating the regression equation (solution of the normal equations) guarantees that the residuals have a mean of zero for the calibration period. The variance of the residuals measures the "size" of the error, and is small if the model fits the data well.

Multiple regression is a flexible method of data analysis that may be appropriated whenever a quantitative variable (the dependent or criterion variable) is to be examined in relationship to any other factors (expressed as independent or predictor variables). Relationships may be nonlinear, independent variables may be quantitative or qualitative, and one can examine the effects of a single variable or multiple variables with or without the effects of other variables taken into account (Cohen et al. 2003).

Multiple regression analysis creates a mathematical description of the relationship between a dependent variable (y) and several independent variables (x). The dependent variable is called response while the independent variables are called regressors. The technique involves predicting (fitting) the response variable using a linear combination of the regressors (Jay. 2004). The linear model is described in two forms, the true model and the estimated model. The true model is a representation of the actual observed values. The estimated model represents the predicted or expected values. We enumerate the regressors as $x_1, x_2, \ldots, x_k$ where k represents the number of regressors ($n >= 2$). The model also includes parameters β and ε. The parameters β_0, $\beta_1, \ldots, \beta_k$ are coefficients that represent the amount the response variable changes when the corresponding regressor changes by one unit. The intercept, β_0, is a constant where the regression line intercepts the y-axis. Error in the true model is represented by ε. It is a difference between the actual value and its predicted value. In the estimated model, the difference is called a residual (Sall et al. 2005).

2.3.2 Artificial neural network

The artificial neural network (ANN) is a mathematical structure designed to mimic the information processing functions of a network of neurons in the brain. ANN that respond to inputs through modifiable weights, thresholds, and mathematical transfer functions that process information through many interconnected units are highly parallel systems. Each unit processes the pattern of activity it receives from other units, and then broadcasts its response to still other units. ANN is particularly well suited for problems in which large datasets contain complicated nonlinear relations among many different inputs (Minsky and Papert. 1988).

ANN is flexible nonlinear model capability that can approximate a large class of functions with a high degree of accuracy. The prediction of this experiment is used multi - layer perceptron. MLP consists of a large class of feed forward neural network with hidden nodes between the input and output nodes. All nodes in a layer are connected to all nodes in the adjacent layers through unidirectional links and all links are represented by connection weights. The ANN architecture encompasses three nodes, input, hidden, and output node, which shown in Figure 2.3.

The input - output elements are trained by using a back propagation learning algorithm. The data feed forward is the relationship between input and output presented as following;

$$y_i = f(\sum_{j=1}^{N_h}(\mu_{ij} f(\sum_{k=1}^{N_i} v_{jk} x_k + \theta_j) + \lambda_i)). \qquad (2.4)$$

Where y_i = the output of *i-th* node

x_k = the input of *k-th* node

μ_{ij} = the connective weight between hidden node and output node

v_{jk} = the connective weight between input node and hidden node

θ_j or λ_i = bias term, which is the threshold of the transfer function

N_i = the number of nodes in input

N_h = the number of nodes in hidden node

N_o = the number of nodes in output node

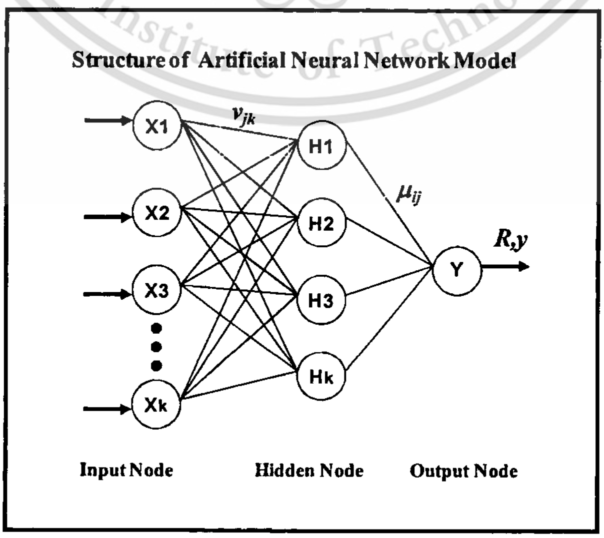

Figure 2.3 Structure of artificial neural network model

Source: Written and Frank (2005)

The hidden node transfer function f is selected as Sigmoid function as following:

$$f(x) = 1/[1+\exp(-x)] \tag{2.5}$$

The system has error back - propagation during trained network. To monitor the performance of the network, the system is used error function as following;

$$E(w) = \sum_{p=1}^{P}(\sum_{i=1}^{N_o}(y_i^p - o_i^p)^2 \tag{2.6}$$

Where $E\ (w)$ = the system error function

y_i^p = the actual value of output node i for training pattern p

o_i^p = the predicted value of output node i for training pattern p

P = the number of sample

The ANN model procedure starts from collecting the related data. The architecture and parameter are architecture, learning rate, momentum, and epoch. All weights are selected randomly to train. The minimum error is employed to predict the future outcome.

2.3.3 Response surface methodology

Response surface methodology (RSM) is a collection of statistical and mathematical techniques useful for developing, improving and optimizing processes (Raymond and Montgomery. 2002). The most extensive applications of RSM are in the particular situations where several input variables potentially influence some performance measures or quality characteristics of the process. Thus performance measure or quality characteristic is called the response. The input variables are sometimes called independent variables, and they are subject to the control of the scientist or engineer. The field of response surface methodology consists of the experimental strategy for exploring the space of the process or independent variables, empirical statistical modeling to develop an appropriate approximating relationship between the yield and the process variables and optimization methods for finding the values of the process variables that produce desirable values of the response. Statistical modeling to develop an appropriate approximating model between the response y, k independent variables $\xi_1, \xi_2, \ldots, \xi_k$ and error ε.

In general, the relationship is

$$y = f(\xi_1, \xi_2, \ldots, \xi_k) + \varepsilon \tag{2.7}$$

where the form of the true response function f is unknown and perhaps very complicated, and ε is a term that represents other sources of variability not accounted for in f. Usually ε includes effects such as measurement error on the response, background noise, the effect of other variables, and so on. Usually ε is treated as a statistical error, often assuming it to have a normal distribution with mean zero and variance σ^2. Then

$$E(y) = \eta = E\,[f(\xi_1,\ \xi_2,\ldots,\xi_k)] + E(\varepsilon) = f(\xi_1,\ \xi_2,\ldots,\xi_k) \qquad (2.8)$$

The variables $\xi_1, \xi_2, \ldots, \xi_k$ are usually called the natural variables, because they are expressed in the natural units of measurement, such as degrees Celsius, pounds per square inch, etc. In much RSM work it is convenient to transform the natural variables to code variables x_1, x_2, ...,x_k, which are usually defined to be dimensionless with mean zero and the same standard deviation. In terms of the coded variables, the response function $E(y)$ will be written as:

$$\eta = f(x_1, x_2, \ldots, x_k) \qquad (2.9)$$

Because the form of the true response function f is unknown, we must approximate it. In fact, successful use of RSM is critically dependent upon the experimenter's ability to develop a suitable approximation for f. Usually, a low-order polynomial in some relatively small region of the independent variable space is appropriate. In many cases, either a first-order or a second order model is used.

The first-order model is likely to be appropriate when the experimenter is interested in approximating the true response surface over a relatively small region of the independent variable space in a location where there is little curvature in f.

For the case of two independent variables, the first-order model in terms of the coded variables is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 \qquad (2.10)$$

The form of the first-order model in η is sometimes called a main effects model, because it includes only the main effects of the two variables x_1 and x_2. If there is an interaction between these variables, it can be added to the model easily as follows:

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + +\beta_{12} x_1 x_2 \qquad (2.11)$$

This is the first-order model with interaction. Adding the interaction term introduces curvature into the response function.

Often the curvature in the true response surface is strong enough that the first-order model (even with the interaction term included) is inadequate. A second-order model will likely be required in these situations. For the case of two variables, the second-order model is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{12} x_1 x_2 \qquad (2.12)$$

This model would likely be useful as an approximation to the true response surface in a relatively small region.

The second-order model is widely used in response surface methodology for several reasons:

1. The second-order model is very flexible. It can take on a wide variety of functional forms, so it will often work well as an approximation to the true response surface.

2. It is easy to estimate the parameters (β) in the second-order model by using the method of least squares.

3. There is considerable practical experience indicating that second-order models work well in solving real response surface problems.

In general, the first-order model is

$$\eta = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k \tag{2.13}$$

and the second-order model is

$$\eta = \beta_0 + \sum_{i=1}^{k} \beta_i x_i + \sum_{i=1}^{k} \beta_i x_i^2 + \sum \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \tag{2.14}$$

In some infrequent situations, approximating polynomials of order greater than two are used. The general motivation for a polynomial approximation for the true response function f is based on the Taylor series expansion around the point x_{10}, x_{20} ,..., x_{k0}.

Finally, there is a close connection between RSM and linear regression analysis. For example, consider the model

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots + \beta_k x_k + \varepsilon \tag{2.15}$$

The β's are a set of unknown parameters. To estimate the values of these parameters, we must collect data on the system we are studying. Because, in general, polynomial models are linear functions of the unknown β's, we refer to the technique as linear regression analysis.

In order to fit the models sequentially (first and second order polynomial models), the second order designs are used for choosing the proper experimental points. There are many designs available for fitting a second order model. The most popular one is the central composite design (CCD) which is introduced by Box and Wilson (1951). The CCD contains an imbedded factorial or fractional factorial design with centre points, in addition to axial points, which allow for curvature, cube points are also present. So, it consists of factorial points, central points, and axial points, which is shown in figure 2.4. If the distance from the centre of the design space to a factorial point is ±1 unit for each factor, the distance from the centre of the design space to an axial point is $\pm \alpha$. The precise value of α depends on certain properties desired for the design and on the number of factors involved.

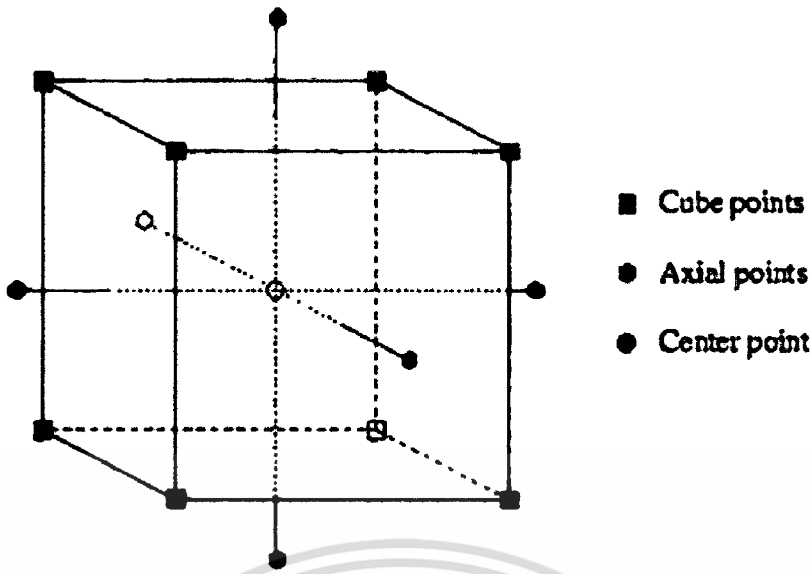

Figure 2.4 Central composite design

2.3.4 Analytical hierarchy process

Analytical hierarchy process (AHP) is a decision aiding method (Saaty. 1980, 1990). It aims at quantifying relative priorities for a given set of alternatives on a ratio scale, based on the judgment of the decision maker, and stresses the importance of the intuitive judgments of a decision maker as well as the consistency of the comparison of alternatives in the decision making process. Since a decision maker bases judgments on knowledge and experience, then makes decisions accordingly, the AHP approach agrees well with the behavior of a decision maker. The strength of this approach is that it organizes tangible and intangible factors in a systematic way and provides a structured yet relatively simple solution to the decision-making problems. In addition, by breaking a problem down in a logical fashion from the large, descending in gradual steps, to the smaller and smaller, one is able to connect, through simple paired comparison judgments, the small to the large. The analytic hierarchy process (AHP) allows for consistency because in making judgments people are more likely to be cardinally inconsistent than cardinally consistent because they cannot estimate precisely measurement values even from a known scale and worse when they deal with intangibles and ordinal intransitive. One reason for filling out an entire matrix is to improve the validity of the judgments in the real world. When deal with tangibles, a pairwise comparison judgment matrix may be perfectly consistent but irrelevant and far off the mark of the true values. The AHP also uses a principle of hierarchic composition to derive composite priorities of alternatives with respect to multiple criteria from their priorities with respect to each criterion. It consists of multiplying each priority of an alternative by the priority of its corresponding criterion and adding over all the criteria to obtain the overall priority of that alternative. To make comparisons, scales of numbers are needed that indicates how many times more important or dominant one element is over another element with respect to the criterion or property with respect to which they are compared. Table 2.2 demonstrates the fundamental scale of absolute numbers (Saaty. 1980).

Table 2.2 Fundamental scale of absolute numbers

Important	Definition	Explanation
1	Equal importance	Two activities contribute equal to the objective.
3	Moderate importance	Experience and favor slightly favor one activity over another.
5	Strong importance	Experience and favor strongly favor one activity over another.
7	Very strong or demonstrated importance	One activity is favored very strong over another, its dominance demonstrated.
9	Extreme importance	The evidence favoring one activity over another is of the highest possible order of affirmation.
2,4,6,8	Compromise between above value	Sometimes one need to interpolate a compromise judgment numerically because there is no adequate word to describe it.
Reciprocals of the above	If activities i has one of the above non zero numbers assigned to it when compared with activities j, then j has the reciprocal value compared with i	A comparison mandate by choosing the smallest element as the unit of element the larger one as a multiple of that unit.
Source: Saaty (1980)		

To make a decision in an organized way to generate priorities the decision is need into the following steps.

1) Define the problem and determine the kind of knowledge sought.

2) Structure the decision hierarchy from the top with the goal of the decision, then the objectives from a broad perspective, through the intermediate levels (criteria on which subsequent elements depend) to the lowest level (which usually is a set of the alternatives).

3) Construct a set of pairwise comparison matrices. Each element in an goal level is used to compare the elements in the criteria level with respect to it.

4) Use the priorities obtained from the comparisons to weigh the priorities in the sub criteria level. Then for each element in the sub criteria level add its weighed values and obtain its overall or global priority. Continue this process of weighing and adding until the final priorities of the alternatives in the bottom most level are obtained. Figure 2.5 shows the hierarchy structure.

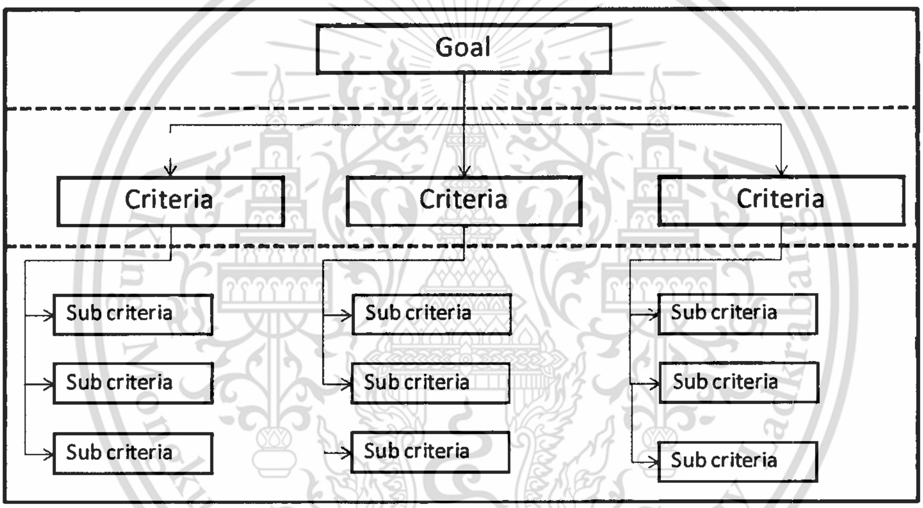

Figure 2.5 The hierarchy structure

Source: Saaty (1980)

Paired comparisons in the AHP are given in terms of consistent and near consistent matrices. The consistent setting up leads to computing the principal eigenvector of the following equation written out in slightly elaborated but familiar matrix form:

$$Aw = \begin{matrix} A_1 \\ \vdots \\ A_n \end{matrix} \overset{\begin{matrix} A_1 & \cdots & A_n \end{matrix}}{\begin{bmatrix} \frac{w_1}{w_1} & \cdots & \frac{w_1}{w_n} \\ \vdots & & \vdots \\ \frac{w_n}{w_1} & \cdots & \frac{w_n}{w_n} \end{bmatrix}} \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = n \begin{bmatrix} w_1 \\ \vdots \\ w_n \end{bmatrix} = nw. \qquad (2.16)$$

When written out as a system of equations we have

$$\sum_{j=1}^{n} a_{ij} w_j = \lambda_{\max} w_i \qquad (2.17)$$

$$a_{ji} = 1 / a_{ij} \ \ or \ \ a_{ij} a_{ji} = 1 \qquad (2.18)$$

$$a_{ij} a_{jk} = a_{ik}, i, j, k = 1, ..., n \qquad (2.19)$$

$$\sum_{i=1}^{n} w_i = 1 \qquad (2.20)$$

The criterion is basically grounded on the definition of a consistency index (CI) and consistency ratio (CR), which can be calculated by using formula as follows:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \qquad (2.21)$$

$$CR = \frac{CI}{RI} \qquad (2.22)$$

Where W_i = the eigenvalue of criterion i

λmax = the largest eigenvalue of the pairwise comparison matrix

CI = the consistency index

RI = the random index

CR = the consistency ratio

The test of consistency index result will be very useful in the AHP method. If the CR is smaller than 0.1, the data results are consistent, while the CR is more than 0.1, the acquired data is inconsistent. The random index (RI) is determined in Table 2.3 as follows;

Table 2.3 The random consistency index

N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
RI	0	0	.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49	1.51	1.48	1.56	1.57	1.59
Source: Saaty (1980)															

2.3.5 Hybrid model

Hybrid model has been introduced to overcome the deficiency of using a individual statistical methods e.g. MR, ANN, AHP, RSM and so on. Hybrid model merge two different methods in order to improve the prediction accuracy. Hybrid models approach can, therefore, combine the strength of both models. In this research, the hybrid models are the combination of two methods together in order to increase the efficiency and accuracy of the prediction i.e.

(1) Hybrid multiple regression with artificial neural network model and

(2) Hybrid analytical hierarchy process with response surface methodology

To sum up, this research differs from previous works in several aspects. Some of them do not identify the relationship between quantitative variables. Some of them consider only the past data via using time series approach such as ARIMA model. In the light of these gaps, in this research, are proposed two hybrid models. The first one is hybrid multiple regression with artificial neural network model, which is integrated the strength of MR and ANN together. The second one is hybrid analytical hierarchy process with response surface methodology model, which is integrated the strength of AHP and RSM together.

2.3.6 Stepwise analysis

As the evaluation of all possible regressions can be burdensome, various methods have been developed for evaluating only a small number of subset regression models by either adding or deleting variables one at a time. These methods are generally referred to as stepwise regression, which is a popular procedure. At each step, the best remaining variable is added, provided it passes the significant at 5% criterion. The process continues until no more variables are added or removed. Stepwise regression is a way of choosing predictors of a particular dependent variable on the basis of statistical criteria. Essentially the statistical procedure decides which independent variable is the best predictor, the second best predictor, etc. Stepwise is usually a good choice though one can enter all variables simultaneously as an alternative. Similarly, one can enter all of the variables simultaneously and gradually eliminate predictors one by one if elimination does little to change the overall prediction (Cohen et al. 2003).

2.3.7 Performance comparison

The performance of prediction is compared between two hybrid models by mean absolute percentage error (MAPE) and root mean square error (RMSE) in order to evaluate the results performance. The formulas are shown as following (Devore. 2004);

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| * 100 \qquad (2.23)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \qquad (2.24)$$

Where Y_t = the actual observation for time period t.

$\hat{Y}_t$ = the forecast value for time period t.

2.4 Related work

2.4.1 Ready mixed concrete

Cao et al. (2004) proposed a new approach for concrete plant operations optimization by combining a ready mixed concrete (RMC) production simulation tool (called HKCONSIM) with a genetic algorithm (GA) based optimization procedure. A revamped HKCONSIM computer system can be used to automate the simulation model construction, conduct simulation experiments on certain scenarios of site orders and resource provisions, and optimize the system performance measures under a stochastic simulation environment. HKCONSIM is suitable for assisting a RMC plant in its resource provision planning and concrete production scheduling in order to meet given demands at a number of sites for concrete over a working day, determine the least costly, most productive amount of truck mixer resources to improve the supply service level and the utilization level of the truck mixer resources available. The proposed model is mainly concerned with how to apply operations simulation modeling and GA optimization to resource planning and production planning of a RMC plant in order to achieve better plant-site coordination and meet the daily demand of sites for concrete. The emphasis of the simulation and optimization models are 1) the estimation of the number of truck mixers of certain volume capacity to be deployed, 2) the estimation of the inter arrival times of consecutive truck mixers on different sites, 3) the service levels in terms of timely delivery achieved on each site, and 4) the utilization levels of plant resources available (i.e. mainly the hatching bays and truck mixers). The simulation model allows the user to input nine variables that are suitable in the study as following;

1) The site demand
2) The site ID
3) The volume of concrete ordered
4) The plant to site traveling distance range
5) The method for placing concrete
6) The site requirement for truck mixer volume capacity
7) The first tuck mixer's arrival time
8) The estimated inter arrival time of consecutive truck mixers
9) The priority of a site

Combined simulation and genetic algorithms can be successfully applied to model and optimize the concrete plant operations in a practical one plant-multi site concrete production and supply setting. The genetic optimization is suitable for finding the near optimal solutions in a relatively short time. The two different optimization objectives (SSL and TOI) can be used in different situations to address different priorities. Taking the SSL objective can reduce the site idle time, improving the site service level. By contrast, selecting the TOI objective can increase the plant's resource utilization rates and the overall efficiency of the total system. The simulation optimization tool developed will help the users to analyze the performance of a complicated logistics system and evaluate various scenarios postulated.

Lu and Lam (2009) presented the power and capability of the simulation technology in tackling the concrete production systems subject to practical constraints. To confront the complexity, uncertainty and variability within a one plant-multisite RMC production system of practical size, they have developed a special purpose simulation tool for rapidly building a simulation model for a typical one-plant-multisite system of concrete production and delivery based on a simplified discrete event simulation approach. To automatically identify the optimum solution through simulation, evolutionary computing based optimization algorithms have been integrated to augment simulation's power in dealing with complex RMC operation planning. In this research, particular emphasis had been placed on validation and application of this simulation-optimization integrated solution in a practical setting, as illustrated by a case study describing one-day operations of a Hong Kong RMC plant. There were 7 variables in this simulation as following;

1) The grade or strength of concrete ordered

2) The quantity of concrete ordered

3) The site location

4) The particular requirement on the mixer truck type (namely, requesting the delivery service by small truck only, or big truck only, or no requirement)

5) The pour start time (i.e. the arrival time of the first mixer truck)

6) The estimated supply rate (approximated in terms of the interval time between consecutive truck arrivals, or the quantity of concrete delivered per hour m3/hr)

7) The distance from plat to job site.

The simulation model was validated first by comparing the simulation outputs against the actual records in light of the performance measure of the "Total Operations Inefficiency" and the scatter plot relating two site-specific ratios. Based on valid simulations, optimization analyses were carried out for three "what-if" scenarios postulated with practical implications. They have gained the following insights from the case study i.e. 1) the model can serve as a useful parallel to the actual system for enhancing its performance, 2) optimization of the inter arrival times for all sites helps draw up the best concrete production schedule, thereby significantly enhancing the performance of a concrete plant in utilizing the trucks available to meet demands from multiple site clients, 3) the truck resources are found to be oversupplied in the actual case, and reconfiguration of the truck fleet helps significantly cut the fleet size while maintaining the similar level of delivery service, and 4) the system can be further fine-tuned by a small margin by rearranging the pour start times on several large pours. Finally, the simulation system, powered by the optimization engine resulting from recent computing research, was ready to provide concrete plant managers with direct assistance in coping with the challenges of generating the best operation strategy in delivering concrete to multiple site clients.

Graham et al. (2006) presented a neural network methodology to model problem and outline the two main architectures employed: Feed-forward network and an Elman network. Many combinations of layers, training algorithms, number of neurons, activation functions and format of data were considered and the results were validated using an independent validation data set with five goodness-of-fit tests. There were eight variables in the collected data that were deemed suitable for use in this study as following;

1) Month of operation

2) Type of operation

3) Truck volume

4) Total operation volume

5) Average inter-arrival time

6) Number of loads in operation

7) Number of accepted loads

8) Number of rejected loads, which the output was productivity.

The results indicated that two and three layer feed forward networks provided the best estimates of concrete placing productivity and that the Elman network, not previously considered in this type of study, was less successful. The ready mixed concrete delivery system is a common construction process in a very wide range of construction projects. The ability of the planners and estimators of such projects to accurately determine the level of resources needed, and to estimate the output of an efficient and effective operation is highly important and thus modeling of the process can be useful.

2.4.2 Commercial margin

Groth and Byers (1996) considered the implications of combining variable cost in the concept of a product's contribution margin, which is a product's price minus its variable cost per unit, that is contribution margin = selling price - variable expense. The contribution margin provides a way to implement the idea that as each unit of product is sold, a set amount of income can be reserved to pay fixed costs. Some planners conduct their analyses in terms of the contribution margin as a way to assure that provisions to pay variable costs are automatically included. The concept of the contribution margin is critical in the creation of value. A particularly important point is the fact that a product's contribution margin represents the amount of money that can be used 1) to pay the firm's fixed costs and/or 2) as profits. The first priority must be used the contribution margins to pay for fixed costs because profits cannot be realized until all costs are paid. As products begin to be sold, therefore, all contribution margins are applied to fixed costs until they have been paid.

Li et al. (2009) proposed the maximization of contribution margin due to significant variable costs encountered in manufacturing. The term contribution margin thereby refers to the order specific difference between revenue and variable costs. Secondly, they assumed the demand for each product is a stochastic point process with an intensity that is a function of the vector of prices for the products and the time at which these prices are offered and the different demands arrive concurrently. In contrast, this research assumed the total demand for each product follows some kind of distribution and is price sensitive and high-margin demand comes after low-margin demand. This is very practical since business practitioners tend to conceptualize their businesses in terms of units of inventory sold. Lastly, their stochastic models were transformed into deterministic versions by replacing stochastic demands with their rates.

2.4.3 Multiple regression

Palia (2004) presented online sales forecasting with the multiple regression analysis data matrices package. The web-based multiple regression analysis data matrices package enables competing participant teams in the marketing simulation to apply their knowledge of multiple regression analysis in sales forecasting. Participants with web-access use this package to create nine data matrices (one data matrix for each strategic business unit) consisting of relevant predictor and response variables for each of the prior decision periods. Next, the data are screened for potential multicollinearity using correlation analysis. Then, the top two predictor variables that satisfy multiple regression analysis assumptions are used to build a linear unrestricted single-equation multiple regression models. The results were checked for potential heteroskedasticity.

Pavan et al. (2005) presented multiple regression based graphical modeling for images. Super resolution is one of the commonly referred inference problems in computer vision. In the case of images, this problem is generally addressed using a graphical model framework wherein each node represents a portion of the image and the edges between the nodes represent the statistical dependencies. However, the large dimensionality of images along with the large number of possible states for a node makes the inference problem computationally intractable. In this research, they proposed a representation wherein each node can be represented as a combination of multiple regression functions. The proposed approach achieves a tradeoff between the computational complexity and inference accuracy by varying the number of regression functions for a node.

2.4.4 Artificial neural network

Gao et al. (2005) proposed the neural network based fault detection with applications in ink jet printers. They explore the feasibility of using both feed forward and Elman neural network to detect assembly faults in ink jet printers. The method is an extension of the motor fault detection scheme recently proposed by the authors. Two types of cartridge faults are studied here: encoder belt misalignment and encoder strip error. These two faults are detected from the characteristics variants in the neural network based prediction of cartridge velocity signals. Simulation results demonstrate that neural network can be trained to effectively detect the inherent encoder faults.

Peters et al. (2006) proposed flood routing modeling with artificial neural network. For the modeling of the flood routing in the lower reaches of the Freiberger Mulde River and its tributaries the one-dimensional hydrodynamic modeling system had been applied. Furthermore, this model was used to generate a database to train multilayer feed forward networks. To guarantee numerical stability for the hydrodynamic modeling of some 60 kilometers of stream course an adequate resolution in space requires very small calculation time steps, which are some two orders of magnitude smaller than the input data resolution. This leads to quite high computation requirements seriously restricting the application especially when dealing with real time operations such as online flood forecasting. In order to solve this problem, the application of artificial neural network (ANN) was tested. The results showed the ability of adequately trained multilayer feed forward networks (MLFN) to reproduce the model performance.

Fernandes, and Teixeira (2008) presented the artificial neural network methodology for forecasting the tourism time series. This study developed models and apply them to sensitivity studies in order to predict the demand. It provided a deeper understanding of the tourism sector in Northern Portugal and contributes to already existing econometric studies by using the artificial neural networks methodology. This work's focus is on the treatment, analysis, and modeling of time series representing "Monthly Guest Nights in Hotels" in Northern Portugal recorded between January 1987 and December 2005. The model used 4 neurons in the hidden layer with the logistic activation function and was trained using the resilient back propagation algorithm. Each time series forecast depended on 12 preceding values. The analysis of the output forecast data of the selected ANN model showed a reasonably close result compared to the target data.

Pao (2008) proposed a comparison of neural network and multiple regression analysis in modeling capital structure. Empirical studies of the variation in debt ratios across firms have used statistical models singularly to analyze the important determinants of capital structure. Researchers, however, rarely employ non-linear models to examine the determinants and make little effort to identify a superior prediction model. This study adopted multiple linear regressions and artificial neural network (ANN) models with seven explanatory variables of corporation's feature and three external macro-economic control variables to analyze the important determinants of capital structures of the high-tech and traditional industries in Taiwan, respectively. Results of this study showed that the determinants of capital structure are different in both industries. The major different determinants are business-risk and growth opportunities. Based on the values of RMSE, the ANN models achieved a better fit and forecast than the regression models for debt ratio, and ANN models are able of catching sophisticated non-linear integrating effects in both industries.

Yordphet and Sanguansintukul (2010) presented the safety stock based on consumption forecast by artificial neural network. The safety stock based on consumption of components in the jewelry business was investigated using the forecasting capability of an artificial neural network (ANN). Generally, this business also has links with fashion; therefore, rapid change in the fashion industry makes the forecasting situation more complicated. The demand fluctuates with customer requirements and high competition in the marketplace. Factors such as late delivery and bad component quality can cause shortages of components. To prevent shortages, provide support to supply management and enhance customer satisfaction, an ANN is utilized for consumption forecast. The results of MAD and a tracking signal illustrated that the safety stock calculated from the network forecast are better than the company practice. It is implied that there are significant benefits from the inclusion of the consumption forecasting when determining the optimal safety stocks.

2.4.5 Response surface methodology

Noordin et al. (2004) proposed an application of response surface methodology in describing the performance of coated carbide tools when turning AISI 1045 steel. The performance of a multilayer tungsten carbide tool was described using response surface methodology (RSM) when turning AISI 1045 steel. Cutting tests were performed with constant depth of cut and under dry cutting conditions. The factors investigated were cutting speed, feed and the side cutting edge angle (SCEA) of the cutting edge. The main cutting force, i.e. the tangential force and surface roughness were the response variables investigated. The experimental plan was based on the face centered, central composite design (CCD). The experimental results indicated that the proposed mathematical models suggested could adequately describe the performance indicators within the limits of the factors that are being investigated. The feed is the most significant factor that influences the surface roughness and the tangential force. However, there are other factors that provide secondary contributions to the performance indicators. In the case of surface roughness, the SCEA2 and the interaction of feed and SCEA provides these contributions whilst for tangential force, the SCEA2, the interaction of feed and SCEA and the cutting speed provides the surface roughness.

Youn and Choi (2004) proposed a new response surface methodology for reliability-based design optimization. Deterministic optimum designs that are obtained without consideration of uncertainties could lead to unreliable designs, therefore calling for reliability-based design optimization (RBDO). However, it has been reported in literatures that when RBDO involves evaluation of probabilistic constraints it is prohibitively expensive or even diverges for many large-scale applications. Therefore, the hybrid mean value (HMV) method had been proposed by authors for highly efficient and stable RBDO by evaluating the probabilistic constraint effectively. However, even with the HMV method, the RBDO process could be still expensive for large-scale applications or applications where efficient design sensitivity analysis method is unavailable. To alleviate this difficulty, a new RBDO methodology developed integrating the HMV method with a proposed response surface method, which is specifically developed for reliability analysis and optimization. A large-scale example problem is employed to demonstrate the proposed RBDO method.

Lenth (2009) described the recent package RSM, which was designed to provide R software support for standard response surface methods. Functions are provided to generate central-composite and Box-Behnken designs. For analysis of the resulting data, the package provides for estimating the response surface, testing its lack of fit, displaying an ensemble of contour plots of the fitted surface, and doing follow-up analyses such as steepest ascent, canonical analysis, and ridge analysis. It also implements a coded-data structure to aid in this essential aspect of the methodology. The functions were designed in hopes of providing an intuitive and effective user interface.

Nicolai and Dekker (2009) proposed the automated response surface methodology for simulation optimization models with unknown variance. Response Surface Methodology (RSM) is a collection of mathematical and statistical techniques useful for developing, improving, and optimizing processes. Applications of RSM can be found in e.g. chemical, engineering and clinical sciences. Still, there did not seem to be an established code of practice for the automated application of RSM in the field of simulation optimization. This research aimed was to find the best settings for an automated RSM procedure when there was very little information about the objective function. Framework of the RSM procedures for finding optimal solutions and emphasize the use of both stopping rules and restart procedures were presented. Various versions of the RSM algorithms were compared on a number of test functions, including a simulation model for cancer screening. The results showed that considerable improvement is possible over the proposed settings in the existing literature.

Khuril and Mukhopadhyay (2010) provided a survey of the various stages in the development of response surface methodology (RSM). The coverage of these stages was organized in three parts that describe the evolution of RSM since its introduction in the early 1950s. Part I covers the period, 1951–1975, during which the so-called classical RSM was developed. This includes a review of basic experimental designs for fitting linear response surface models, in addition to a description of methods for the determination of optimum operating conditions. Part II, which covers the period, 1976–1999, discussed more recent modeling techniques in RSM, in addition to a coverage of Taguchi's robust parameter design and its response surface alternative approach. Part III provided coverage of further extensions and research directions in modern RSM. This includes discussions concerning response surface models with random effects, generalized linear models, and graphical techniques for comparing response surface designs.

2.4.6 Analytical hierarchy process

Kamal et al. (2001) presented analytical hierarchy process (AHP) as a potential decision making method for use in project management. The contractor prequalification problem was used as an example. A hierarchical structure was constructed for the prequalification criteria and the contractors wishing to prequalify for a project. By applying the AHP, the prequalification criteria were prioritized and descending-order lists of contractors were made in order to select the best contractors to perform the project. A sensitivity analysis was performed to check the sensitivity of the final decisions to minor changes in judgments. This research was presented group decision-making using the AHP. The AHP implementation steps were simplified by using the `Expert Choice' professional software that is available commercially and designed for implementing AHP.

Beynon (2002) proposed decision support (DS) and AHP, DS/AHP, method as a mathematical analysis, including an understanding of uncertainty. The AHP was developed to aid decision makers to rank or sort information based on a number of criteria. A recent advance is the DS/AHP method which incorporates the Dempster–Shafer theory of evidence with AHP. This method allows judgments on groups of decision alternatives (DA) to be made; it also offers a measure of uncertainty in the final results. A mathematical analysis of DS/AHP was included, constructing the functional form of the preference weightings given to groups of DA. These functions allowed an understanding of the appropriateness of the rating scale values used in the DS/AHP method, through evaluating the range of uncertainty able to be expressed by the decision maker.

Salem (2010) presented benchmarking criteria from the point of view of the actors who were involved in benchmarking processes within three Libyan Manufacturing Organizations (LMOs). It was described an application of the Analytic Hierarchy Process (AHP) that can help an organisation to determine its benchmarking criteria. It presented a structured hierarchy for assessing the key capabilities using the AHP. The hierarchy was illustrated using the four main criteria that manufacturing companies consider when carrying out benchmarking. AHP and benchmarking techniques make the implementation and analysis studies more effective, easy and applicable to companies. Further, AHP was used to calculate the relative weights of each criterion, sub criterion and specific sub criterion, to prioritize them, and finally to select the important benchmarking criterion within each of the three companies investigated.

Srdevic et al. (2011) proposed an approach for minimizing the risk of negligent, incompetent, or irresponsible group decision making by assigning weights to the decision makers (DMs) according to their demonstrated individual inconsistencies. A decision making framework was based on the analytic hierarchy process (AHP). The consistency ratio (CR) and total Euclidean distance (ED) were used to 'weight' involved decision makers. The approach was demonstrated in a practical example of ranking the agricultural producers who applied to the Provincial Fund for Agricultural Development of Vojvodina Province (Serbia) for loans for purchasing irrigation equipment.

2.4.7 Hybrid model

Tsenga et al. (2002) combined hybrid model with the seasonal time series ARIMA model and the neural network back propagation model in order to predict seasonal time series data. This model was used to forecast two seasonal time series data of total production value for Taiwan machinery industry and the soft drink time series. The hybrid model was also able to forecast certain significant turning points of the test time series.

Mishra et al. (2007) employed hybrid model, the combining of a linear stochastic model and a nonlinear ANN model, for drought forecasting. The proposed hybrid model could combine the advantages of both stochastic and ANN models. Using the Standardized Precipitation Index series, the hybrid model as well as the individual stochastic and ANN models was applied to forecast droughts in the Kansabati River basin in India, and their performances were compared. The results revealed that the hybrid model provided more accuracy in predicting droughts in the Kansabati River basin.

Flores et al. (2009) presented a hybrid approach by using evolutionary computation to produce a complete design of a neural network for modeling and forecasting time series. The hybrid models had proven to be better than the ARIMA models produced by a statistical analysis procedure and hand-made ANN.

Areekul et al. (2010) presented an approach for short-term price forecast based on combination of ARIMA and ANN. The linear ARIMA model and the nonlinear ANN model are used to analyze different forms of relationship in the time-series data. They verify the predictive ability of the proposed method by simulations three different cases price forecasting of ARIMA, ANN, and hybrid model approach. The results showed that hybrid model method could provide overall forecasting capability improvement of the price forecasting accuracy and gives better predictions than either ARIMA or ANN.

Merh et al. (2010) developed hybrid models ANN and ARIMA for forecasting the future index value and trend of Indian stock market. Simulation have been done using prices of daily open, high, low and close of SENSEX, BSE IT, BSE Oil & Gas, BSE 100 and S& P CNX Nifty. Simulation results of hybrid models were compared with results of ANN based models and ARIMA based models.

Zheng and Zhong (2010) proposed a hybrid methodology that combines both radial basis function (RBF) neural network and auto regression (AR) model based on binomial smoothing (BS) technique which is efficient in data processing. This method was examined by using the data of Canadian Lynx data. Empirical results indicated that the over-fitting problem can be eased to improve forecasting accuracy by using hybrid methodology.

Ján and Katarína (2010) conducted hybrid ARIMA - Neural Network model to predict aggregate water consumption. The hybrid model can complement each other in capturing patterns and internal dependencies of time series. The hybrid prediction method was used for prediction of water consumption based on time series collected and the hybrid ANN outperforms the individual forecasting model.

Delijaicov et al. (2010) synthesized a model for peen forming process planning. Statistical methods based on MR and ANN were applied to a data set generated by peen forming designed experiments with aluminum alloy plates, aiming to synthesize quantitative models relating the highest displacement of the plate with the respective variables of the process. The results showed that the estimated displacements from both models comply reasonably well with the experimental data, the obtained results exposed the superiority of the regressive model concerning accuracy.

Liu et al. (2010) proposed combinatorial predict model of enterprise profit based on stochastic partial elasticity theory and ANN. Nonlinear model was established to solve the combinatorial weighted coefficients by advance the predict accuracy to get a new predict value. Numerical simulation results showed that the new predict model of enterprise profit has strong generalization ability and could improve the predict accuracy effectively.

CHAPTER 3

RESEARCH METHODOLOGY

This chapter will introduce research methodologies used in this research, i.e. overview methodology, data preparation, identification explanatory variables, data analysis of 2 hybrid models and validation performance comparison.

3.1 OVERVIEW METHODOLOGY

In order to achieve the objectives of this research, the methodology adopted for the research consisted of five main stages. Table 3.1 illustrates the five stages of research design. The detail of each stage were explained as following;

Table 3.1 Summarize the five stages of research design

Stages	Activities
Stage 1	Review the commercial margin prediction in ready mixed concrete
Stage 2	Data preparation
Stage 3	Exploratory data analysis
Stage 4	Data analysis of 2 hybrid models
Stage 5	Validation performance comparison, discussion, and recommendation

Stage 1: The available literature review on ready mixed concrete, commercial margin, multiple regression, artificial neural network, analytical hierarchy process, response surface methodology, and hybrid model are comprehensively searched and proposed to identify the explanatory variables effecting contribution margin (chapter 2).

Stage 2: In this stage, all related actual variables data are collected to be the prepared data for commercial margin prediction in ready mixed concrete business (chapter 3).

Stage 3: All related variable data, which are identified in stage one, are used as a basis for commercial margin prediction. Since there was no research applications in the commercial margin prediction in ready mixed concrete business. The main objectives of exploratory data analysis stage are identified and explained. These exploratory data analysis are described in this chapter 3.

Stage 4: Data analysis is conducted two proposed hybrid models. The first one is hybrid multiple regression with artificial neural network model and the second is hybrid analytical hierarchy process with response surface methodology model (chapter 3 and 4).

Stage 5: The last step is to validate and apply performance comparison by 2 statistical methods i.e. root mean square error (RMSE) and mean absolute percentage error (MAPE). The discussion results and recommendation are provided.

3.2 DATA PREPARATION

The commercial margin in ready mixed concrete business depends on many factors, which are related with selling price, selling condition, and variable cost. In this research, the 983 observations daily transaction database from ready mixed concrete company in Thailand was collected during January 2009 – December 2011, which was prepared to be training data. The 30 observations during January - February 2012 were tested data. The raw data were collected, which are 12 factors affecting commercial margin and actual commercial margin as described in chapter 2 e.g. credit term (day), demand (cubic meter), distance (kilometers), product price list (Baht), extra charge (Baht), discount (Baht), rebate (Baht), freight cost (Baht), carrying receivable cost (Baht), marketing cost (Baht), raw material cost (Baht) and other variable production cost (Baht).

Raw data differ in the scales; therefore they should be normalized before proceeding with further statistical analysis. Normalization is the process of converting the actual score distribution of a data to a normal distribution, after which the mean and standard deviation can be conveniently used to indicate any score's position. So, all raw data are normalized to be normal distribution.

3.3 EXPLORATORY DATA ANLYSIS

Exploratory data analysis is a statistical technique used to identify and explain the variables (Devore. 2004). Furthermore, the method identifies the relationship between variables that may indirectly be connected. This technique can be adopted to understand the structure of a set of variables. The preliminary analysis is based on descriptive statistics, which is shown in

Table 3.2. This table is contained the descriptive statistics for the mean and standard deviation of each factors, which were normalized. This information reveals with the total number of observations, the minimum value, and the maximum value of each factor.

Table 3.2 Descriptive statistics of exploratory data analysis

Variables	N	Minimum	Maximum	Mean	SD
Credit Term	983	0.00072954	0.99999995	0.5032062015	0.27641324420
Demand	983	0.00030629	0.99999999	0.5110449051	0.27686126433
Distance	983	0.00022399	1.00000000	0.5133936521	0.26450209207
Product price	983	0.00034262	0.99999990	0.5104559348	0.27413424087
Extra charge	983	0.00006886	1.00000000	0.4722588595	0.25522938004
Discount	983	0.00024282	1.00000000	0.5132973757	0.26310871498
Rebate	983	0.34261384	1.00000000	0.4461399440	0.20164147094
Freight cost	983	0.00035617	0.99999961	0.5131351411	0.27847119253
Carrying receivables cost	983	0.00022726	1.00000000	0.5107698993	0.25651104901
Marketing cost	983	0.17761918	0.99999996	0.4594610641	0.25018741138
Raw material cost	983	0.00066517	0.99999765	0.5049086054	0.28126815854
Other production cost	983	0.00015176	0.99999990	0.5108512041	0.26306572088
Commercial margin	983	0.00000017	0.99999991	0.4926021906	0.28973127393

The commercial margin, Y, may depend on many independent variables. There are several criteria find a set of variables, X, that are the best variables to predict Y e.g. R^2, adjusted R^2, likelihood ratio test, forward selection, backward elimination, stepwise regression, etc (Cohen et al. 2003). In this research, stepwise regression is used for model selection for including or excluding variable X into the model. In order to analyze the stepwise regression of the variables data set, the availability of statistical packages using the Microsoft Excel tool is constructed.

Table 3.3 shows the results of stepwise regression analysis. As the results of the final model, the maximum value of R^2, and adjusted R^2 are 0.94 and 0.939 that are closely to 1.000. The value of significance of F change is 0.000. It means that there are 5 variables such as product price list, discount, raw material cost, extra charge, and marketing cost effecting to predict the commercial margin. Thus, all of 5 variables will be the input data of hybrid model. Other 7 variables will be eliminated from the hybrid model such as credit term, demand, distance, rebate, freight cost, carrying receivable cost, and other raw material cost.

Table 3.3 Stepwise regression model summary

Model Summary									
					Change Statistics				
Model	R	R^2	Adj. R^2	Std. Error	R2	F Change	df1	df2	Sig. F
1	.824a	0.68	0.678	0.16439568	0.678	2069.15	1	981	0.000
2	.903b	0.82	0.816	0.12441504	0.138	732.79	1	980	0.000
3	.950c	0.9	0.903	0.09038619	0.087	877.811	1	979	0.000
4	.964d	0.93	0.929	0.07707361	0.027	368.404	1	978	0.000
5	.969e	0.94	0.939	0.0716259	0.01	155.427	1	977	0.000
a. Predictors:Product price list									
b. Predictors:Product price list, Discount									
c. Predictors:Product price list, Discount, Raw material cost									
d. Predictors: Product price list, Discount, Raw material cost, Extra charge									
e. Predictors: Product price list, Discount, Raw material cost, Extra charge, Marketing cost									

3.4 DATA ANALYSIS USING 2 HYBRID MODELS

Two proposed approaches are conducted i.e. (1) hybrid multiple regression with artificial neural network, hybrid, which is called "MR with ANN", (2) hybrid analysis hierarchy process with response surface methodology, which is called "AHP with RSM", in order to predict commercial margin in ready mixed concrete business. In addition, the proposed hybrid approaches will combine the strength of MR with ANN and AHP with RSM techniques. Experimental framework of two hybrid models is illustrated in Figure 3.1.

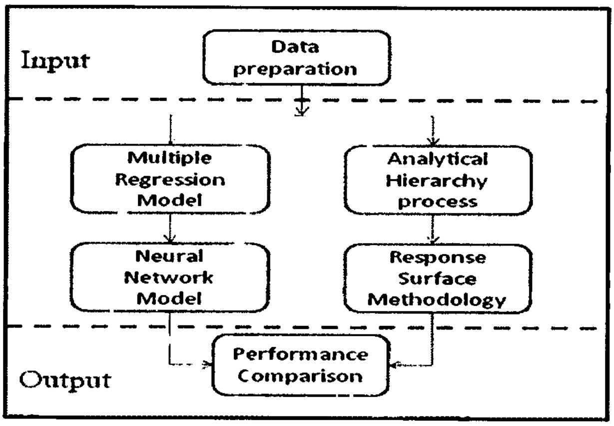

Figure 3.1 Experimental framework

3.4.1 Hybrid multiple regression with artificial neural network model

The normal single model is either generally suited in prediction of non-linear relationship or normally fitted in prediction of linear relationship. The hybrid model will be superior predicted method for both linear and non linear relationship. In this research, both multiple regression and artificial neural network have been conducted to predict commercial margin. Multiple regression model has achieved successes based on linear relationship. On the other hand, ANN model is more suitable for non-linear relationship. However, neither regression nor ANN is suitable for all circumstances. Hybrid model approach can, therefore, combine the strength of regression and ANN models to capture both linear and non-linear relationship. The hybrid model can be written as following:

$$Y_t = N_t + L_t \tag{3.1}$$

Where Y_t = the hybrid model at time t

N_t = the non-linear component at time t

L_t = the linear component at time t

The proposed hybrid multiple regression with artificial neural network model is displayed in Figure 3.2. In this research, the back propagation neural network learning algorithm is utilized to train the networks using WEKA software. The related parameters including learning rate, learning momentum, training epochs and hidden node are determined to obtain the optimum solution (Atthirawong and Chatchaipun. 2005). The experimental design presented in Table 3.4 was developed to generate ANN model. The parameters have been determined by trial and error in order to evaluate the optimal solution. There are totally 983 data, which are assigned to be training set.

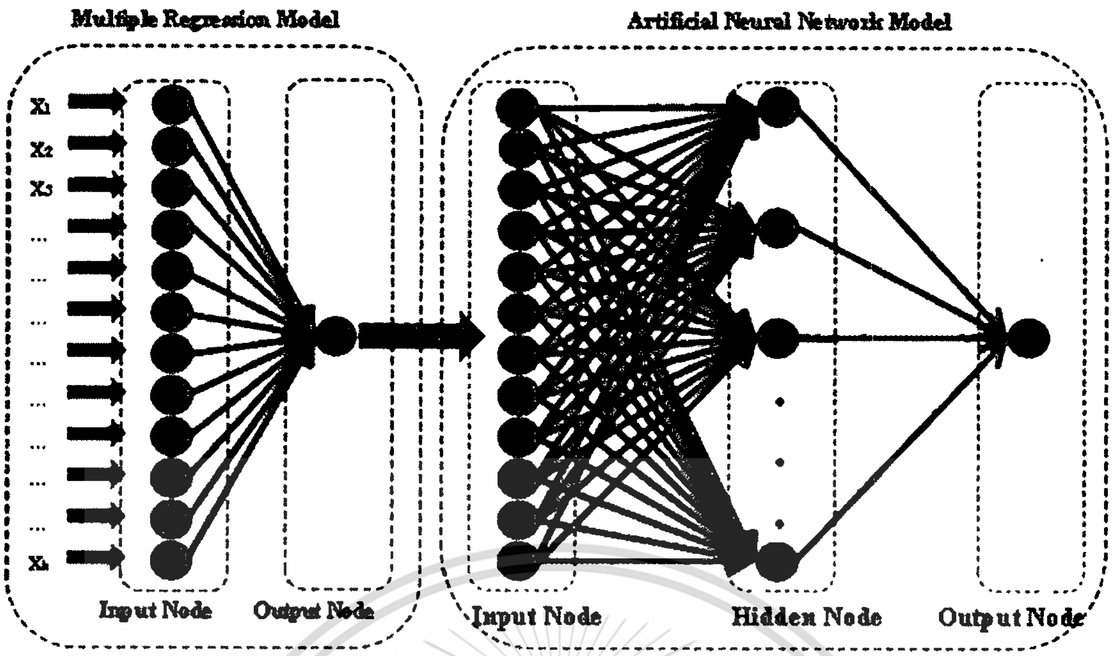

Figure 3.2 Hybrid multiple regression with artificial neural network model

Table 3.4 The experimental design for ANN model

Parameters	Experimental design
Number of layers	3 layers (Input: 1, Hidden: 1, Output 1)
Activation function	Sigmoid
Learning rate	0.1 - 0.9
Momentum	0.1 - 0.9
Number of iteration	500, 1000, 5,000, 10,000 and 50,000
Number of instance	983

The hybrid multiple regression with artificial neural network model is combined MR with ANN model. The MR method is used to predict the commercial margin while ANN method is used to analyze the residual of MR model. The residual will be the non-linear relationship and can be written as following;

$$e_t = Y_t - \hat{L}_t \tag{3.2}$$

Where e_t = residual at time t from liner model

$\hat{L}_t$ = predicted value at time t from the estimated linear relationship

The combined prediction can be written as following;

$$\hat{Y}_t = \hat{N}_t + \hat{L}_t \tag{3.3}$$

Where $\hat{Y}_t$ = the combined prediction at time t

$\hat{N}_t$ = predicted value at time t from the estimated non-linear relationship

The combined prediction can be calculated by equation *(3.3)*. The results from ANN method can be predicted the error terms for MR model. As the result, the hybrid MR with ANN model can increase overall performance.

The methodology of hybrid multiple regression with artificial neural networks model shown in Figure 3.3.

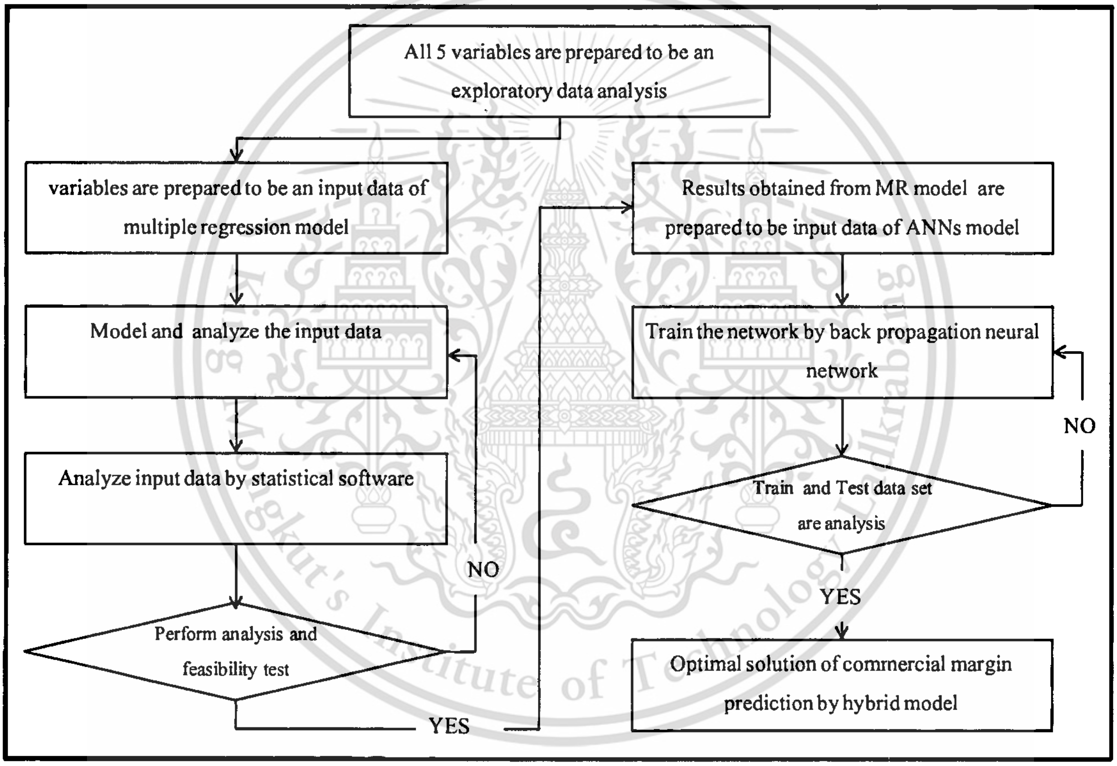

Figure 3.3 Hybrid MR with ANN model methodology

3.4.2 Hybrid analytical hierarchy process with response surface methodology model

The analytical hierarchy process (AHP) can be used to solve complex problems, which uses a multi - level hierarchy structure of objectives, criteria, sub criteria, and alternatives (Saaty. 2008) while response surface methodology (RSM) is to determine process variables for optimizing several responses simultaneously (Lenth. 2009). The hybrid model will be superior method to combine the strength of both AHP and RSM methods.

AHP is first employ in order to determine weight input for RSM. All relevant variables are structured into criteria and sub criteria as demonstrated in Figure 3.4. Pairwise comparison matrices are constructed. Five experts from RMC business are selected in order to assign priority followed methodology.

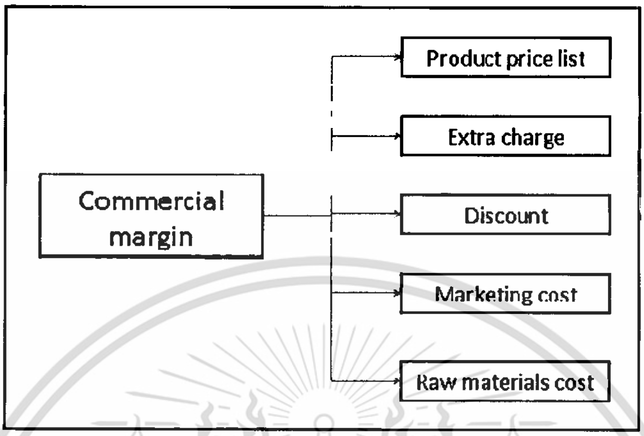

Figure 3.4 The hierarchy structure

The result of pairwise comparison matrix is needed to verify the consistency by equation *(2.21)* in chapter 2. The priority is accepted when the matrix is consistent. The consistency ratio should be less than 0.1, and then the priority can be used. Therefore, the decomposed weight of each sub criteria will be calculated by multiplying the main criteria weight by sub criteria weight. The decomposed weight is presented a generic weight for criteria and sub criteria. The results of AHP model will be then used as weight inputs into the response surface methodology model.

The sequential of the response surface methodology will start with generated the concerning factors which are the results from AHP model, that are likely to be important in response surface study. Usually this step is called a screening experiment. The functional relationship between result and the set of independent variables is needed to find the suitable approximation. The next step of RSM makes considerable the used of the first-order model and an optimization technique called the method of steepest ascent (descent) to determine the result that is near the optimum. The experiment must determine a set of adjustments that the result will move toward the optimum that is to estimate the maximum response. The last step is to do the response surface analysis in terms of the fitted surface when the process is near the optimum. The process wants a model that will accurately approximate the fitted response function within a relatively small region around the optimum. Once the approximating model has been obtained, this model may be analyzed to determine the optimum conditions for the process. This sequential experimental process is usually performed within some region of the independent variable space.

The methodology of hybrid analytical hierarchy process with response surface model is shown in Figure 3.5.

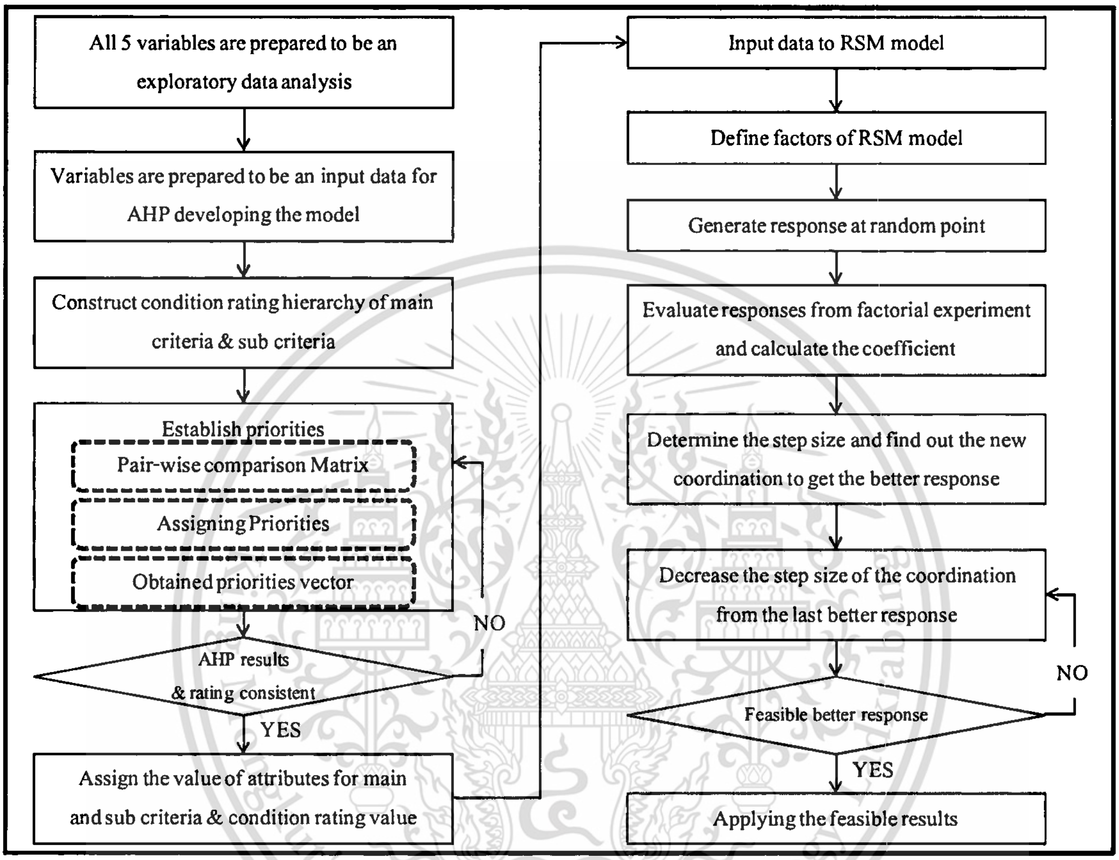

Figure 3.5 Hybrid AHP with RSM model methodology

3.5 PERFORMANCE COMPARISON OF 2 HYBRID MODELS

The results of both hybrid models are compared their performance accuracy. In this research, all residual of trained and tested data are prepared to measure performance in order to evaluate the efficiency of both hybrid models. The mean absolute percentage error (MAPE), and root mean squared error (RMSE) are widely employed to measure the error between actual and prediction value. The formulas are shown in eq. *(2.23)* and *(2.24)* respectively.

The value of MAPE and RMSE will be compared in order to evaluate the performance. The model, which has the lower MAPE and RMSE, will be superior and used in prediction commercial margin.

CHAPTER 4

RESULTS

This chapter presents the analysis of the empirical data to evaluate 2 hybrid models. In section 1 will be the evaluated of hybrid multiple regression with artificial neural network model while in section 2 will be the evaluation of hybrid analytical hierarchy process with response surface methodology model. The last section is related with the comparison the results of both hybrid models.

4.1 RESULTS OF HYBRID MR WITH ANN

The results of hybrid multiple regression with artificial neural network start with the regression model, which the result of multiple regression is used to input into artificial neural network model in order to find the best solutions.

The multiple regression method establishes a quantitative relationship between commercial and five variables. The first step results from multiple regression method are shown in Table 4.1 - 4.3. The multiple regression models can be written in eq. *(4.1)*.

The summary of regression statistics of normalized data in Table 4.1 are shown the value of R (0.969), R^2 (0.939196), Adjust R^2 (0.938885), Standard Error (0.071626) and Observations (983). The value of R^2 and Adjust R^2 are closely to 1.00. It means that the predicted values are closely to the actual value. So, the model can be used to evaluate the next step.

Table 4.1 Regression statistic summary

Regression statistic	
Multiple R	0.969000
R^2	0.939196
Adjusted R^2	0.938885
Standard Error	0.071626
Observations	983

The ANOVA output for the restricted model, Y = commercial margin, and 5 variables, in Table 4.2 are shown the degree of freedom of regression (5), residual (977), sum square error of regression (77.420941), sum square error of residual (5.012274), mean square error of regression (14.484188), mean square error of regression residual (0.005130), F-distribution value (3.018201), and significant F (0.000000). The result was performed significant confidence at 99 % level, which was concluded from significant F value (Sig. < 0.01). As the results, it can be claimed that it is accepted model. The coefficients of each variable are shown in Table 4.3. The constant value is 0.060649. The coefficient values of the 5 variables will be the regression model in eq.*(4.1)* in order to predict the commercial margin Y.

Table 4.2 ANOVA output for the restricted model

	df	SS	MS	F	Sig.
Regression	5	77.420941	14.484188	3.018201	0.000000
Residual	977	5.012274	0.005130		
Total	982	88.433215			

Table 4.3 The coefficients of each variable

	Coefficients	t	Sig.
Constant	0.060649	-8.421731	0.0000
Product price list : (Z_1)	3.367325	46.846372	0.0000
Extra charge : (Z_2)	0.153905	13.761965	0.0000
Discount : (Z_3)	-1.310494	-49.348557	0.0000
Marketing cost : (Z_4)	0.134217	12.467018	0.0000
Raw material cost : (Z_5)	-1.482635	-27.963763	0.0000

Therefore, the multiple regression model can be written as following:

$$\hat{Y} = 0.060649 + 3.367325 * Z_1 + 0.153905 * Z_2 - 1.310494 * Z_3 + 0.134217 * Z_4 - 1.482635 * Z_5 \quad (4.1)$$

The result of multiple regression model from eq. *(4.1)* will be the input data of artificial neural network method. Thus, all of the predicted value of commercial margin in eq. *(4.1)* is established for the artificial neural network model in order to reduce the error of the model. The combinations of different parameters of artificial neural network described in Table 4.4 are evaluated to find the optimal potential networks by trial and error. In this research, the back propagation neural network learning algorithm is utilized to train the networks. So, the optimal hybrid multiple regression with artificial neural network model is shown in Table 4.4.

Table 4.4 The optimal potential hybrid MR with ANN

Model	Architecture	Learning rate	Learning Momentum	Epoch
ANN	5-7-1	0.4	0.2	50,000

The results of hybrid MR with ANN model that used the optimal potential model from Table 4.4 in order to predict commercial margin, Y, are the best solution, which has the smallest error. The optimal results of the hybrid MR with ANN model from the WEKA software are shown in Table 4.5. The correlation coefficient value is closely to 1.00, which can be concluded that it is acceptable results

Table 4.5 The optimal results of hybrid MR with ANN

WEKA software results	Value
Correlation coefficient	0.9946
Mean absolute error	0.0233
Root mean squared error	0.0313
Relative absolute error	0.0913
Root relative squared error	0.108

The latest result of form Table 4.5 is the final results of hybrid multiple regression with artificial neural network model. The residual of the hybrid model will be the data set to calculate MAPE and RMSE in order to compare the performance as detail in Appendix B.

4.2 RESULTS OF HYBRID AHP WITH RSM

As the results of explanatory data analysis section, the AHP model was conducted in order to determine the priority weight of each criterion as shown in Figure 3.4. The questionnaire has to create for in-depth interview with sales managers from ready mixed concrete business. The final questionnaire is concentrated on the 5 criteria, which consist of product price list, extra charge, discount, rebate, fright cost, and raw material cost as shown detail in Appendix C.

The questionnaire is used to interview with sales manager from ready mixed concrete business. The in-depth interviews were conducted with 5 sales managers in ready mixed concrete business. The data was analyzed by using Microsoft Excel package. The consistency ratio and eigenvalue (λmax) results are shown in Table 4.6. The consistency ratios are 0.064, 0.044, 0.083, 0.065 and 0.076. All consistency ratios are lower than 0.1 which mean that it is acceptable to weigh the priorities. The consolidated pairwise comparisons are shown in Table 4.7 and the priority weight of variables results are shown in Table 4.8.

Table 4.6 The results of consistency ratio and eigenvalue

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5
λmax	5.285	5.194	5.373	5.291	5.339
Consistency ratio	0.064	0.044	0.083	0.065	0.076

Table 4.7 Consolidated pairwise comparison results

Pairwise Matrix	Product price list	Extra charge	Discount	Marketing cost	Raw material cost
Product price list	1	2.5	1.3	2.7	2.1
Extra charge	0.4	1	0.4	1.2	1.1
Discount	0.75	1.5	1	3.7	1.5
Marketing cost	0.375	0.714	0.25	1	0.7
Raw material Cost	0.43	0.95	0.44	1.38	1

Table 4.8 Results of priority weight of variables

Variables	Priority weight
Product price list	0.3330
Extra charge	0.1388
Discount	0.2567
Marketing cost	0.1013
Raw material cost	0.1701

The results of AHP method are prepared to be input data for response surface methodology. Then, the data analyze by Minitab software package. The design of experiment of the software package is conducted by using response surface design, which is an applied central composite design criterion in this research as detail in Figure 4.1. The criteria are applied to find the best solution by trial and error including linear, linear plus square, linear plus interaction and full quadratic models as detail in Table 4.9. As the results, the full quadratic model criteria is the best solution in this research, which has R^2 = 96.08 %, R^2 (predicted) = 95.72 %, R^2 (adjusted) = 96.00 %. The value of R^2 (predicted) and R^2 (adjusted) are closely to 1.00, which can be accepted the model results.

```
Central Composite Design

Factors:          5     Replicates:      1
Base runs:       54     Total runs:     54
Base blocks:      2     Total blocks:    2

Two-level factorial: Full factorial

Cube points:                  32
Center points in cube:         8
Axial points:                 10
Center points in axial:        4

Alpha: 2.366
```

Figure 4.1 Central Composite design criteria

Table 4.9 Results of hybrid AHP with RSM model

Model criteria	R^2	R^2 (pre)	R^2 (adj)
Linear	98.83%	98.36%	98.70%
Linear plus square	99.68%	99.37%	99.61%
Linear plus interactions	99.78%	99.11%	99.69%
Full quadratic	99.99%	99.99%	99.99%

The results of full quadratic criteria are the best solution which is used to evaluate the analysis of variance for commercial margin. The results of analysis of variance for commercial margin from full quadratic criteria are shown in Table 4.10.

Table 4.10 Results of analysis of variance from full quadratic criteria

Source	df	SS	Adj SS	Adj MS	F	Sig.
Regression	20	3.26010	3.260176	0.163009	47,275.72	0.000
- Linear	5	3.22201	0.493868	0.098774	28646.28	0.000
- Square	5	0.02799	0.007044	0.001409	404.57	0.000
- Interaction	10	0.01017	0.010169	0.001017	294.93	0.000
Residual error	33	0.00011	0.000114	0.000003		
Total	53	3.26029				

The results are performed significant confidence at 99 % level, which is concluded from significant F value (Sig. < 0.01). As the results, it can be concluded that it is accepted model. The significant F values of linear, square and interaction are also performed well and significant confidence at 99% level too. It means that linear, square and interaction are also including in the hybrid AHP with RSM model. So, the coefficients of each variable are shown in Table 4.11, which is the final model in order to predict the commercial margin.

Table 4.11 The coefficients of the response surface methodology model

Term	Coefficients
Constant	0.0242339
Product price list : (Z_1)	16.6626
Extra charge : (Z_2)	2.19008
Discount : (Z_3)	-7.01370
Marketing cost : (Z_4)	1.72696
Raw material cost : (Z_5)	-17.7198
Product price list * Product price list	52.8344
Extra charge * Extra charge	-17.8259
Discount * Discount	-5.38272
Marketing cost * Marketing cost	-14.1695
Raw material cost * Raw material cost	139.790
Product price list * Extra charge	-27.2409
Product price list * Discount	-30.4762
Product price list * Marketing cost	-23.5708
Product price list * Raw material cost	-179.961
Extra charge * Discount	14.3367
Extra charge * Marketing cost	12.7653
Extra charge * Raw material cost	40.4216
Discount * Marketing cost	17.2838
Discount * Raw material cost	68.6300
Marketing cost * Raw material cost	19.6325

The result of this model is the final results of hybrid AHP with RSM model, which the residual will be prepared to evaluate performance. So, the commercial margin is calculated by eq.*(4.2)*. Therefore, the final model can be written as following;

$$\begin{aligned}\hat{Y} &= 0.0242339 + 16.6626*Z_1 + 2.19008*Z_2 - 7.01370*Z_3 + 1.72696*Z_4 \\ &- 17.7198*Z_5 + 52.8344*Z_1*Z_1 - 17.8259*Z_2*Z_2 - 5.38272*Z_3*Z_3 \\ &- 14.1695*Z_4*Z_4 + 139.790*Z_5*Z_5 - 27.2409*Z_1*Z_2 - 30.4762*Z_1*Z_3 \\ &- 23.5708*Z_1*Z_4 - 179.961*Z_1*Z_5 + 14.3367*Z_2*Z_3 + 12.7653*Z_2*Z_4 \\ &+ 40.4216*Z_2*Z_5 + 17.2838*Z_3*Z_4 + 68.6300*Z_3*Z_5 + 19.6325*Z_4*Z_5\end{aligned} \qquad (4.2)$$

The residual plots for commercial margin is shown in Figure 4.2 and the residual value of the hybrid AHP with RSM model are shown in Appendix D.

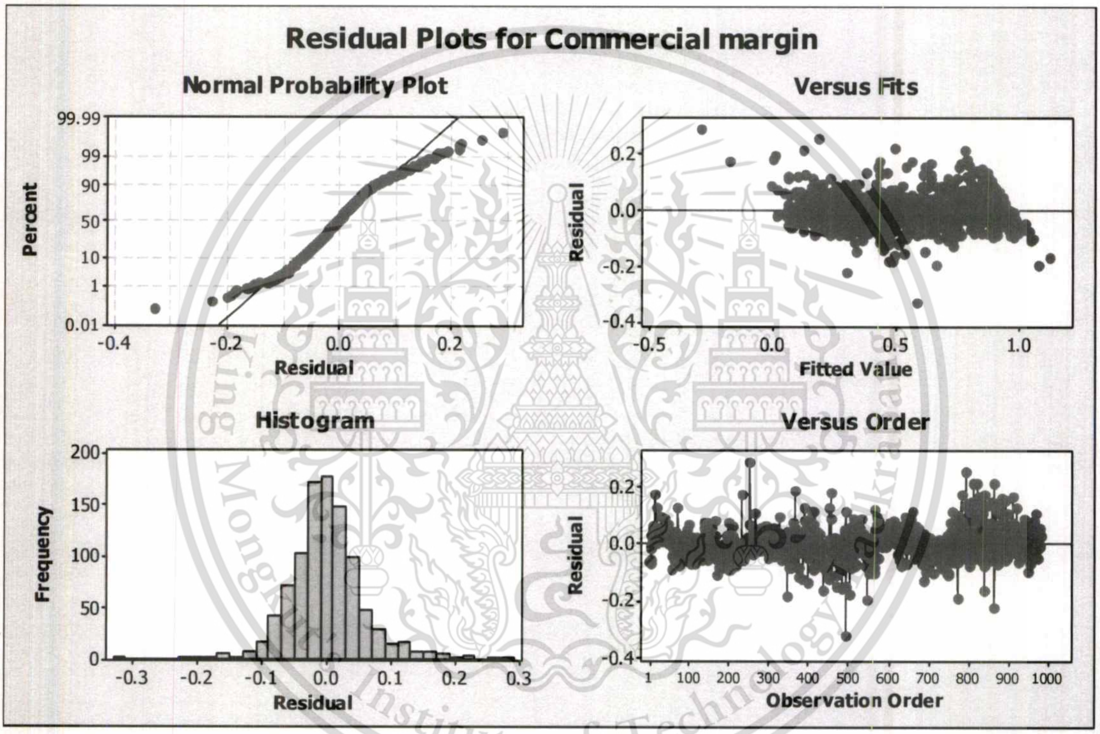

Figure 4.2 The residual plots of hybrid AHP with RSM model

Surface plot and contour plot of commercial margin between a pair of variables are presented in Appendix E. All graphs are shown the relationship between commercial margin and a pair of variables.

4.3 CAMPARISON RESULTS OF 2 HYBRID MODELS

The R^2 and adjust R^2 values of hybrid multiple regression with artificial neural network model and hybrid analytical hierarchy process with response surface methodology model are closely to 1.00 which indicate that the predicted values are closely the actual values. It can be implied that both models are acceptable to predict commercial margin in ready mixed concrete business.

The residual values of hybrid multiple regression with artificial neural network model and hybrid analytical hierarchy process with response surface methodology model are employed to evaluate the performance. The final model of hybrid multiple regression with artificial neural network model and hybrid analytical hierarchy process with response surface methodology model are testing with 30 days data set during January to February 2012 in order to measure performance. The test results of both hybrid models are shown in Figure 4.3 and 4.4 respectively.

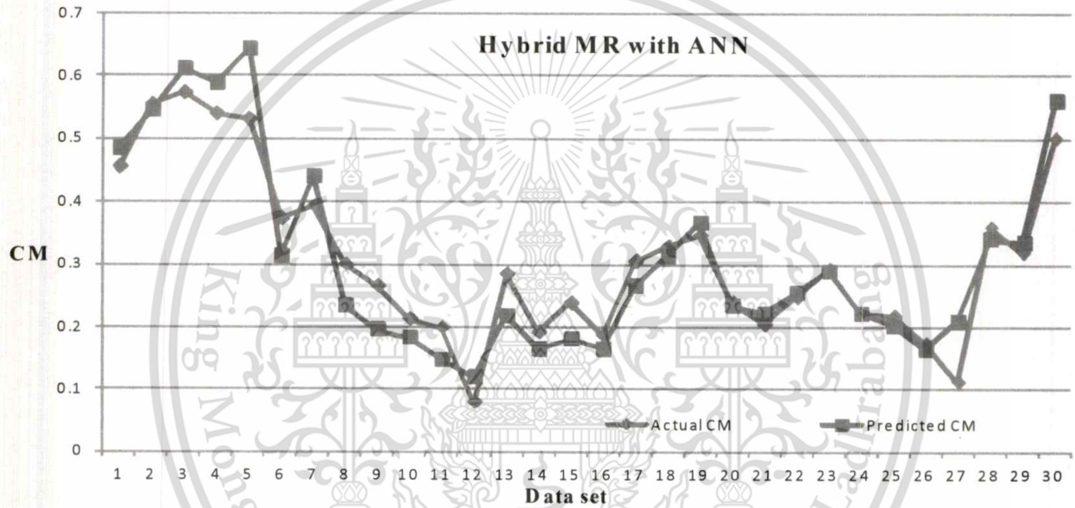

Figure 4.3 The test results of hybrid MR with ANN

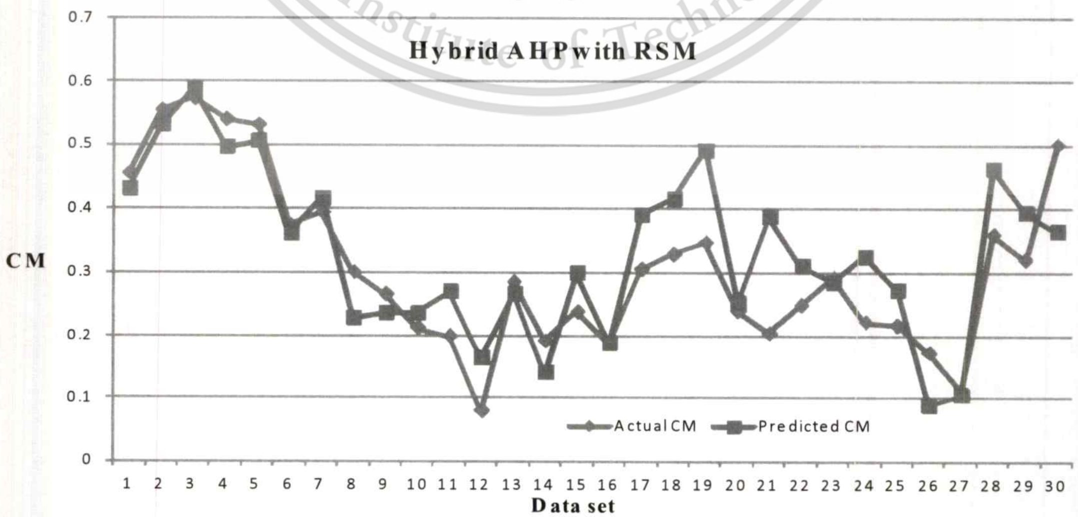

Figure 4.4 The test results of hybrid AHP with RSM

In this research, the performance of both hybrid models are measured using MAPE and RMSE by eq. *(2.24)* and eq. *(2.24)* in order to compare the results. Both MAPE and RMSE value of hybrid multiple regression with artificial neural network model are slightly smaller than hybrid analytical hierarchy process with response surface methodology model. The performances of both trained and tested data set are shown in Table 4.12.

Table 4.12 The performance comparison of 2 hybrid models

Hybrid Model	**MAPE**	**MAPE (test)**	**RMSE**	**RMSE (test)**
MR with ANN	8.993342	14.878000	0.031286	0.045800
AHP with RSM	12.994200	23.674000	0.043900	0.072800

Therefore, it can be concluded that hybrid multiple regression with artificial neural network model is better performance than hybrid analytical hierarchy process with response surface methodology model in order to predict commercial margin in ready mixed concrete business.

CHAPTER 5

CONCLUSION AND RECOMMENDATION

This chapter will be divided into 2 sections. The first section is conclusion and the last section is recommendation.

5.1 CONCLUSSION

The thesis entitled "Hybrid model for commercial margin prediction in ready mixed concrete business" is proposed hybrid multiple regression with artificial neural network and hybrid analytical hierarchy process with response surface methodology models for predicting commercial margin. All raw data are normalized to be normal distribution before proceeding with further statistical analysis. The results of both hybrid models are compared the performance accuracy by using mean absolute percentage error (MAPE) and root mean square error (RMSE).

5.1.1 The result of hybrid multiple regression with artificial neural network has correlation coefficient value 0.9949. The multiple regression model can be written as below.

$$\hat{Y} = 0.060649 + 3.367325 *Z_1 + 0.153905* Z_2 - 1.310494* Z_3 + 0.134217* Z_4 - 1.482635* Z_5 \quad (4.1)$$

The optimal artificial neural network model has 7 hidden node, leaning rate equal to 0.4, momentum equal to 0.2 and epoc equal to 50,000.

5.1.2 The result of hybrid analytical hierarchy process with response surface has value R^2 = 99.99 %, and R^2 (adjusted) = 99.99 %. The weight priority of analytical hierarchy process for product price, extra charge, discount, marketing cost and raw material cost are 0.333, 0.1338, 0.2567, 0.1013 and 0.1701 respectively. The full quadratic criterion is best fitted of response surface methodology which can be written the model as following;

$$\begin{aligned}\hat{Y} &= 0.0242339 + 16.6626*Z_1 + 2.19008*Z_2 - 7.01370*Z_3 + 1.72696*Z_4 \\ &- 17.7198*Z_5 + 52.8344*Z_1*Z_1 - 17.8259*Z_2*Z_2 - 5.38272*Z_3*Z_3 \\ &- 14.1695*Z_4*Z_4 + 139.790*Z_5*Z_5 - 27.2409*Z_1*Z_2 - 30.4762*Z_1*Z_3 \quad (4.2) \\ &- 23.5708*Z_1*Z_4 - 179.961*Z_1*Z_5 + 14.3367*Z_2*Z_3 + 12.7653*Z_2*Z_4 \\ &+ 40.4216*Z_2*Z_5 + 17.2838*Z_3*Z_4 + 68.6300*Z_3*Z_5 + 19.6325*Z_4*Z_5\end{aligned}$$

5.1.3 The results of hybrid multiple regression with artificial neural network and hybrid analytical hierarchy process with response surface are compared by using MAPE and RSME. The performance of hybrid multiple regression with artificial neural network model is better than hybrid analytical hierarchy process with response surface model which are indicated slightly lower value of MAPE and RMSE.

5.2 RECOMMENDATION

5.2.1 Hybrid models in this research can be applied to predict the commercial margin effectively and can be supported ready mixed business to predict the commercial margin accurately. In addition, commercial margin prediction from hybrid models can be applied for sales to calculate the reasonable margin and profit during the high competition environment. On the other hand, it is expected that the proposed hybrid models can be adopted in other businesses.

5.2.2 Other hybrid model such as hybrid multiple regression with response surface methodology, analytical hierarchy process with neural network, ARIMA with response surface methodology, may be conducted to compare the performance.

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APPENDIX A

Ready mixed concrete is a product, as well as a service, and delivery techniques have developed along with the production side (Dewar and Anderson. 1992). The ready-mixed concrete business has tended to outpace the construction industry in its willingness to innovate. Not all new ideas survived commercial pressures, mainly because purchasers were not always willing to pay a premium for an improvement in quality or service. The cost to the business of providing ever increasing levels of quality assurance has been considerable, while the complexity of mixes being specified has increased further the costs of quality control. The fact that most concrete suppliers are now supplied ready-mixed is a measure of how successful the business has been in terms of demands for quality, service, and price.

Ready-mixed concrete is a composite material which, like all well-designed composites, has resultant properties that combine the best qualities of the component materials. As the number of components is increased, so the range of properties and uses are increased, with greater than opportunity for optimization and economic benefit. Typical concrete consists of only 4 main components as describe in Figure A1.

1. Portland cement
2. Sand
3. Course aggregate (one, two or three fractions)
4. Water

The options and number of components can be increased by adopting various combinations of the following.

1. Different types of Portland cement
2. Chemical admixture e.g. accelerator, retarder, water reducer, etc.
3. Addition material e.g. PFA, GGBS. etc.
4. Natural sand, crushed rock fines or fine lightweight or heavyweight aggregate
5. Different maximum sizes of natural gravel, crushed rock or blast furnace
6. Slag as coarse aggregates
7. Light or heavyweight coarse aggregates.

The opportunities for optimization do not end with the choice of materials. There is also considerable scope for selection of proportions appropriate to specification requirements and the intended uses of the concrete.

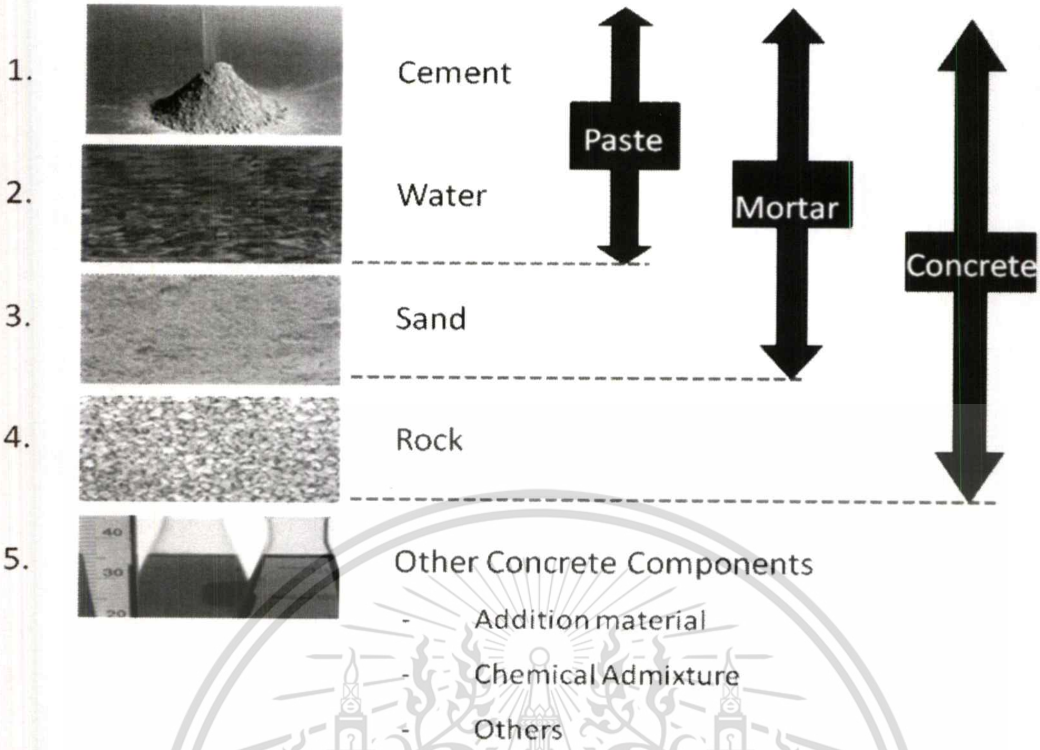

Figure A1 Concrete component

1. READY MIXED CONCRETE PRODUCTION METHOD

Ready mixed concrete plant, also known as a batch plant, is a machine that combines various ingredients to form concrete. Some of these inputs include sand, water, aggregate (rocks, gravel, etc.), addition component, potash, and cement as detail in Figure A2.

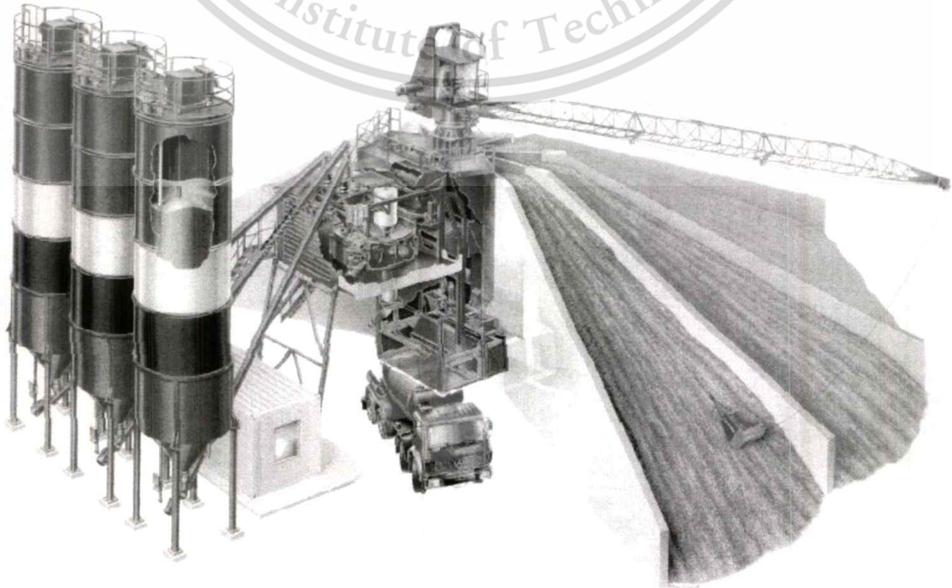

Figure A2 Ready mixed concrete plant

Currently, ready mixed concrete is very popular for contractor. The ready mixed concrete process is described in Figure A3. Ready-mixed concrete is produced using many different combinations of each of the elements of the process as following;

1. Handling the incoming materials
2. Batching the constituents
3. Mixing the concrete
4. Loading the delivery vehicles

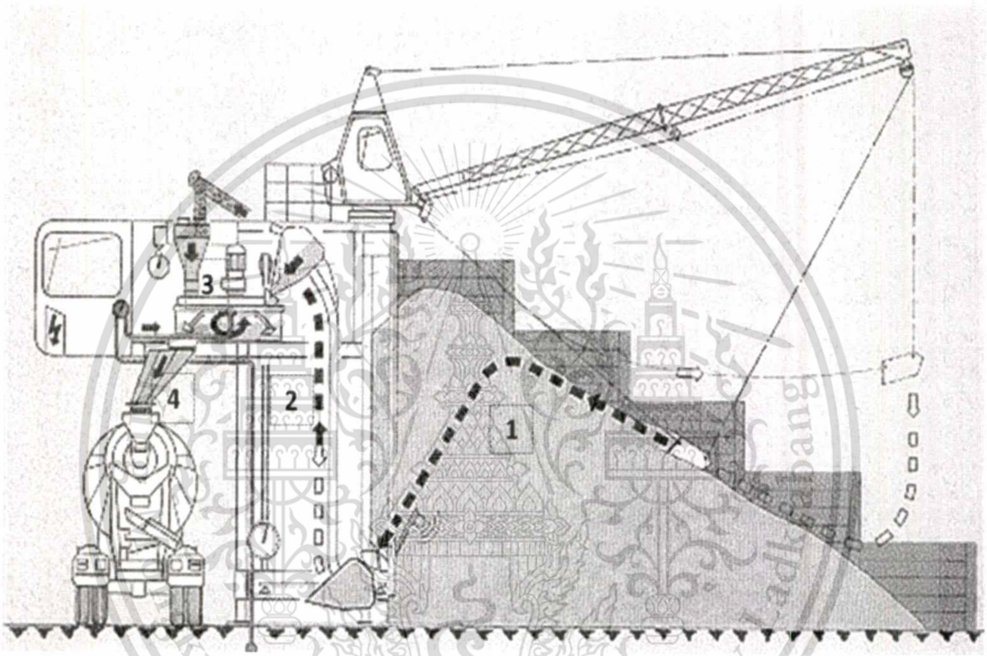

Figure A3 Ready mixed concrete process

The business has not settled on a 'best way', and choice has been based on economics related to perceived markets for each particular plant. As the shelf life of the product is so short, the production units (the plants) have had to be located convenient to potential markets. To produce ready-mixed concrete necessitates having realistic assessment of the likely size of the market and the types of concrete used locally, as well as:

1. Types of materials
2. Storage capacity
3. Processing sequences
4. Truck mixer capacity and throughput

5. Quality control requirements

6. Regulatory requirements

7. Duration of operation

The Material types are important to consider for ready mixed concrete production. The different types of cements for which provision has to be made will depend upon the types of concrete likely to be required in the market area, whereas the types of aggregates will be related to what is readily available: gravel, land-borne or marine; limestone; granite; sand; crushed rock fines.

The storage capacity is another key consideration. Handling incoming materials in bulk is fundamental to the economic production of ready-mixed concrete. The current legal weight limit on vehicles is a major factor influencing the delivery costs of cements and aggregates. When concrete production demand rises, the ready-mixed concrete producer relies on the cement maker's tanker fleet to keep the silos stocked, although changes in cement pricing have meant that it can be advantageous for the ready-mixed concrete company to collect the cement ex-works. The storage elements, cement silos and aggregate storage bins is obviously influenced by the bulk delivery vehicle capacity. Where plants are situated next to sources of aggregate supply, such as quarries, gravel pits, railheads or wharves, then storage facilities for the aggregates at the ready-mixed concrete plants do not need to be so large. Stabilizing the moisture content of the aggregate, particularly the sand, can be an important factor in determining the aggregate storage capacity and layout. The raw material storage is shown in Figure A4.

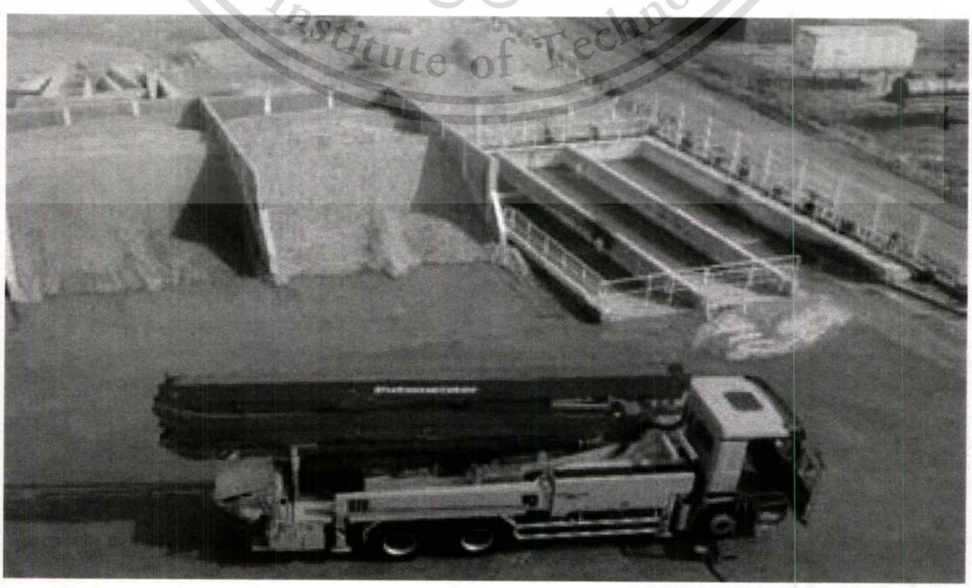

Figure A4 Raw material storage of ready mixed concrete plant

The processing sequence is important technique of ready mixed concrete business. The maximum batch size is a major factor in determining the rate of production of a plant. The accurate weighing of solid constituent materials has been a fundamental requirement for producing quality concrete for many years, but the degree of automation built into the batching process has only in recent years shown a marked increase. The reliability of automatic controls has improved and computerization has enabled more sophisticated adjustments to be incorporated. The commonest weighing equipment continues to be the balanced mechanical lever system, although load cell weighing is used. Controlling the discharge from storage and weigh hopper is in the main through gates operated by compressed air cylinders. The use of flow meters for water measurements is almost universal, although in some plants the water is weighted. The use of dispensers to measure admixtures is almost universal. Because modern truck mixers are able to thoroughly mix a wide range of concrete mixes, the justification for including a mixer in the processing sequence is often influenced by the local market demand for lean mix concretes. In general, plants in which all the concrete has to be processed through the mixer are only situated in urban locations. A compromise is to have two production streams: 1) dry-mixed going straight into the truck mixer and 2) wet-mixed going through a mixer. As well as adding to the capital costs a mixer will certainly increase the energy requirements of a plant and the maintenance costs, so the decision whether or not to include or omit a mixer in the production process can be a vital one in determining its commercial viability.

Truck mixer capacity is needed for consideration. The number of truck mixers operating from a plant is usually the critical factor in determining the throughput, and has to take into account both truck mixer capacity and radius of operations. The average number of truck mixers operating from plants in the Thailand is depending on the market demand and the average radius of operations is 10 - 20 km. When the demand for concrete is high, the number of truck mixers is increased, and when demand is low, sales are sought further away from the plant. Truck mixer is shown in Figure A5.

Quality control requirement is needed for ready mixed concrete business. The requirements for sampling, making cube specimens, curing and testing them under standard conditions involves the setting up of a laboratory where the test data can be collated and new mixes designed. The cost of quality control facilities has encouraged the grouping of plants within a company into areas, with the quality control being managed from one technical centre. The laboratory and mobile sampling and testing facilities and staffing, needed to monitor the constituent materials and to ensure that mixes supplied comply with the orders received, form a key part of any company's quality system, and the cost of setting up a laboratory and control system is a major item. The concrete laboratory is shown in Figure A6.

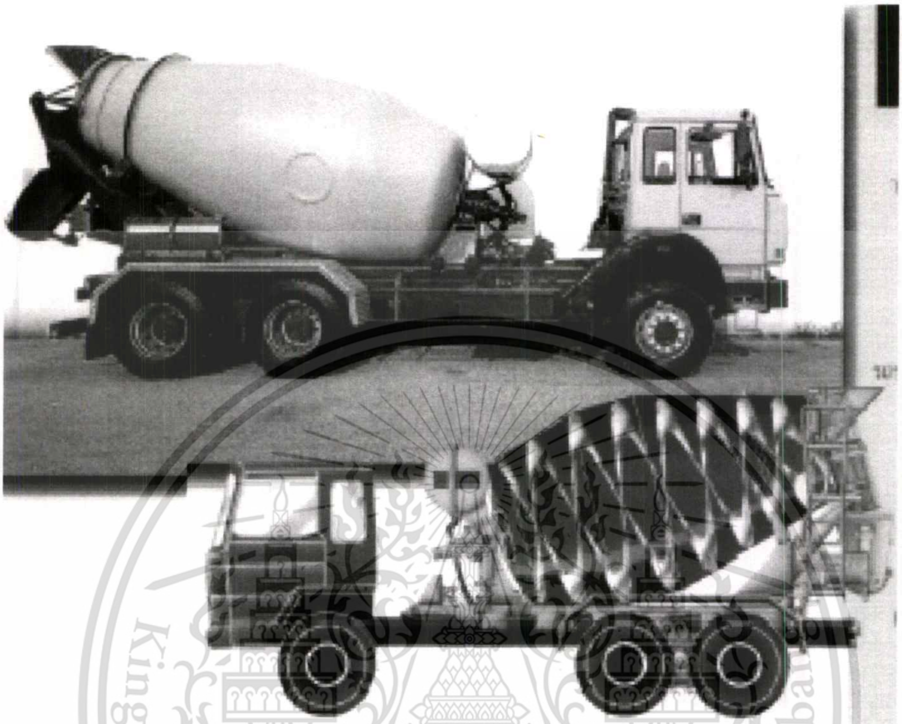

Figure A5 Truck mixer

Figure A6 Concrete laboratory

Regulatory requirements are based on Thailand Industrial Standard (TIS). The standard for ready mixed concrete is based on TIS 213 - 2552 (มอก. 213 - 2552). The others standard normally apply in ready mixed business are ASTM and BS standard.

Duration of operations is highly concentrated. The estimated time a plant is to be in operation is a critical factor in determining the type of plant to be installed. Few plants are truly mobile, but transportable plants are quite common, and many ready-mixed concrete producers now set up plants on major construction sites for the duration of the job. Whatever the period of time for which the plant is to be used, considerable expenditure on foundations, services, erection and dismantling, access roads and paved areas, wash-downs and effluent disposal will be required. No matter how relatively short the time a plant is to be in operation, the product has to be of the correct quality, so the standards of good practice remain the same.

2. ORGANIZING PRODUCTION AND DELIVERY

Organization within companies, for operating and controlling production and scheduling deliveries to sites, varies from company to company. Some companies' operations are controlled at depot or plant level, whereas a number of the larger and medium sized companies have centralized dispatching offices covering particular markets. Whilst the requirements lend themselves to computerization, the economics are influenced by geography and market conditions. Part of any company's organization is a very strict credit control system, made necessary by the short period between enquiry/order and delivery, and the inability to reclaim the delivered products.

Management systems have been developed using computers to improve productivity levels. The extent of computerization has varied between companies, from virtually complete computerization of every function, to the use of small personal computers for individual element. Currently, complete software and hardware packages are available covering accepting orders from customers, executing deliveries to customers including batch/mix control, scheduling constituent materials to plants, administration and invoicing, and GPS. The ready mixed concrete computerization system is shown in Figure A7.

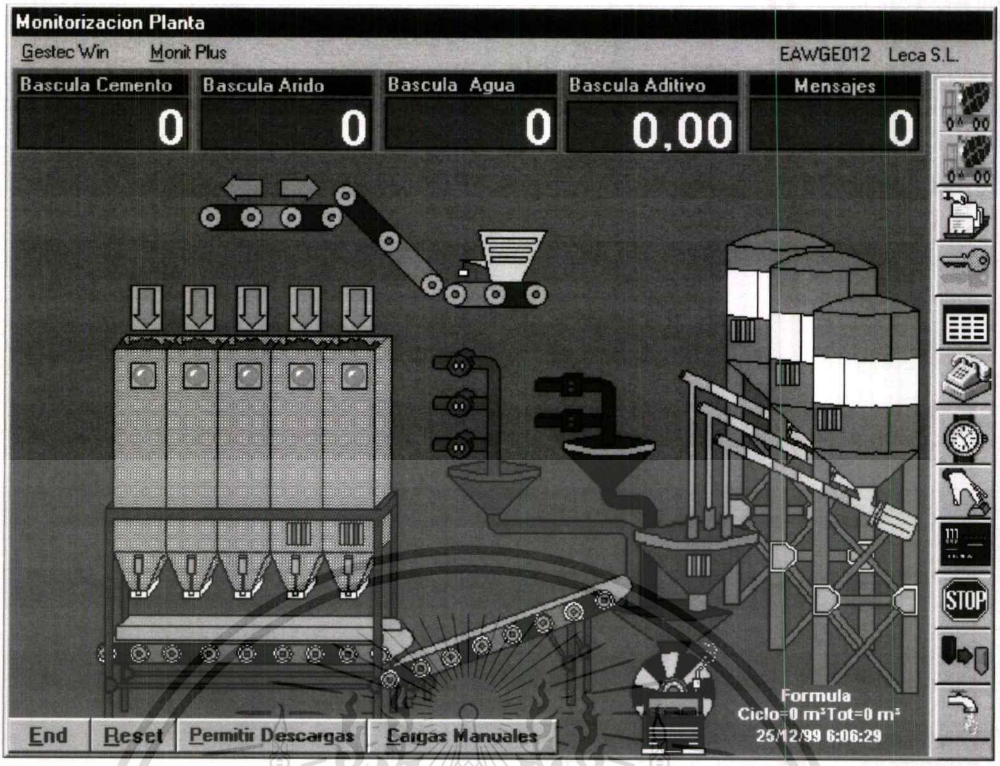

Figure A7 Computerization system of ready mixed concrete plant

3. DILIVERING

Truck mixer is a tool to deliver concrete to customers job site. Ready mixed concrete is not only a product, it is a service. The truck mixer has developed from a mobile site mixer into a specialized vehicle capable of mixing, delivering and distributing concrete in a very economic manner. Indeed, in the viability of ready-mixed concrete depends on the efficient utilization of the specialized truck mixer fleet.

The truck mixer can function in the production process in three basic ways. The first one is a mixer at a ready-mixed concrete plant. The truck mixer is loaded with the dry batched materials together with water and mixing is completed at the plant. During transit, the drum can be revolved slowly to keep the mix agitated. On arrival at site, the drum is rotated at mixing speed for a few minutes to ensure complete remixing, before discharge. The second is a mixer at the site. The truck mixer is loaded with the dry batched materials at the plant, which are then transported to the site. On arrival, mixing water is added and the mixing completed before discharge. The third is an agitator. The truck mixer is loaded with mixed concrete from a mixer at the plant. During transit the drum can be revolved slowly to keep the mix agitated and at site the drum is revolved at mixing speed to ensure complete remixing before discharge.

Although truck mixer vehicles available in the Thailand range from 1 to 9 cubic meters capacity, the majority in use have a load capacity of 5cubic meters of concrete because of law and regulation. With a 'shelf life' of only a few hours, ready-mixed concrete is very much a 'local delivery' service, the average distance from the depot or plant to point of delivery being about 10 - 20 km, varying between town and country. Long deliveries are possible, but the economics need careful scrutiny.

On arrival at the site, the standard truck mixer can: (1) mix the concrete and, with measured water addition, adjust the characteristics of the plastic concrete, (2) using a fitted chute and extensions, discharge the concrete direct, and (3) control the rate of discharge to suit the placing requirements on site.

The average number of truck mixers operating is depended on market demand. However, trucks can easily be moved from one depot or plant to another to meet peak demands. Business has a group of depots or plant in an area, rather than allow each individual depot or plant to control its vehicles. Central dispatching has been found to lead to higher utilization of the trucks. Figure A8 is shown the central dispatching of ready mixed concrete plant. Various sizes of truck mixers in a fleet can assist in economic scheduling of deliveries but in the main it is usual to standardize on one size.

Figure A8 Central dispatching system of ready mixed concrete plant

4. QUALITY ASSURANCE

The ready mixed concrete is necessary for business survival. The quality of concrete requires having assurance main 3 criteria. Firstly, the qualities required of the fresh and hardened concrete are objectively defined. Secondly, the production delivery and site processes are carried out under controlled conditions which allow the whole process to be able to be traced from the constituent materials right through to the cured concrete. Lastly, all testing carried out in the control and compliance testing is valid. Ready-mixed concrete production and delivery is only part of the QA process, but if the concrete is produced under conditions complying with TIS 213 - 2552. The other ASTM and BS standard are normally accepted in Thailand.

The ready-mixed concrete producer can only supply what is ordered, because the contract to supply only exists between the purchaser and supplier, so that the ready-mixed concrete producer is dependent upon the interpretation of the specification by the person who eventually orders the concrete. The concrete producer completes his part of the contract having produced the concrete and delivered it down the discharge chute. The producer has no control over how the concrete is placed, compacted, finished, cured or protected. Production control testing by the ready-mixed concrete producer is required to be in accordance with the agreed standards. Unless the compliance testing carried out by the purchaser is in accordance with the same agreed standards. Quality assurance covers the whole process, not just the production, but having assurance on the quality of the production process is a major element.

APPENDIX B

Table B1 The residual of hybrid MR with ANN model

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
1	0.033	27	0.005	53	0.026	79	0.016
2	0.04	28	-0.049	54	0.009	80	0.008
3	0.017	29	-0.065	55	0.028	81	0.019
4	-0.021	30	-0.055	56	0.017	82	0.008
5	-0.041	31	-0.02	57	-0.006	83	0.004
6	-0.022	32	0.002	58	-0.006	84	-0.005
7	-0.024	33	-0.011	59	0.007	85	0.002
8	-0.044	34	-0.01	60	0.023	86	0.019
9	-0.031	35	-0.009	61	0.014	87	-0.016
10	-0.048	36	-0.021	62	0.001	88	0.006
11	-0.041	37	-0.017	63	0.028	89	-0.067
12	-0.025	38	0	64	-0.018	90	-0.018
13	-0.006	39	-0.011	65	0.009	91	-0.036
14	-0.034	40	-0.019	66	-0.032	92	-0.036
15	-0.045	41	0.041	67	0.014	93	-0.01
16	-0.033	42	-0.005	68	-0.001	94	0
17	0.01	43	-0.005	69	0.009	95	-0.027
18	-0.06	44	-0.025	70	0.017	96	-0.064
19	-0.073	45	0.024	71	0.019	97	-0.019
20	-0.014	46	0.01	72	0.026	98	-0.073
21	-0.009	47	-0.008	73	0.009	99	0.018
22	-0.027	48	-0.003	74	0.007	100	0.002
23	-0.032	49	-0.002	75	-0.018	101	0.031
24	0.017	50	-0.009	76	0.022	102	0.01
25	-0.009	51	-0.009	77	0.053	103	0.035
26	-0.004	52	-0.013	78	-0.003	104	-0.042

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
105	-0.035	135	-0.011	165	0.013	195	0
106	0.007	136	-0.044	166	-0.027	196	-0.019
107	-0.008	137	-0.023	167	-0.006	197	0.023
108	-0.008	138	-0.062	168	-0.002	198	0.012
109	-0.032	139	-0.046	169	0.001	199	0.019
110	-0.019	140	-0.037	170	0.004	200	0
111	0.018	141	-0.016	171	0.058	201	-0.011
112	-0.025	142	-0.026	172	0.028	202	-0.01
113	0.005	143	-0.001	173	-0.006	203	0.008
114	0.019	144	-0.04	174	0.013	204	-0.003
115	0.047	145	-0.02	175	0.056	205	-0.001
116	0.017	146	-0.006	176	-0.004	206	0.004
117	-0.022	147	-0.008	177	0.019	207	-0.001
118	-0.029	148	0.014	178	0.006	208	0.003
119	0.004	149	-0.016	179	0.019	209	0.006
120	-0.029	150	0.009	180	0.035	210	0.01
121	-0.011	151	0.002	181	-0.03	211	0.004
122	-0.031	152	-0.004	182	0.03	212	0.028
123	0.026	153	0.016	183	0.005	213	-0.001
124	-0.043	154	0.005	184	-0.008	214	0.002
125	0.015	155	-0.059	185	-0.012	215	0.007
126	-0.014	156	-0.023	186	0.033	216	-0.002
127	-0.005	157	-0.004	187	0	217	0.011
128	-0.02	158	-0.033	188	-0.004	218	-0.012
129	0.015	159	-0.035	189	-0.019	219	0.024
130	0.017	160	0.015	190	0.019	220	0.004
131	0.023	161	0.017	191	0	221	-0.007
132	-0.029	162	0.007	192	-0.001	222	0.002
133	-0.005	163	0.021	193	-0.012	223	0.019
134	-0.003	164	-0.018	194	-0.002	224	0.021

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
225	0.027	255	-0.025	285	-0.033	315	-0.018
226	0.035	256	-0.038	286	-0.005	316	0.006
227	0.01	257	-0.014	287	-0.008	317	0.003
228	-0.002	258	-0.002	288	0.002	318	-0.005
229	0.002	259	-0.041	289	0.005	319	-0.015
230	0.019	260	0.01	290	-0.034	320	0.02
231	0.033	261	-0.049	291	-0.011	321	-0.005
232	0.016	262	-0.048	292	-0.036	322	0.007
233	-0.004	263	0.021	293	-0.034	323	0.013
234	-0.047	264	-0.035	294	0.005	324	-0.015
235	0.023	265	-0.022	295	-0.024	325	-0.005
236	0.011	266	-0.025	296	-0.027	326	-0.083
237	0.006	267	0.01	297	-0.004	327	-0.028
238	-0.01	268	-0.036	298	-0.015	328	-0.014
239	0.009	269	-0.001	299	-0.039	329	-0.022
240	0.027	270	0.025	300	-0.006	330	0.006
241	-0.021	271	-0.047	301	-0.002	331	0.008
242	0.018	272	-0.005	302	-0.013	332	0.052
243	-0.026	273	0.021	303	-0.018	333	0.001
244	0.017	274	-0.023	304	-0.014	334	0.002
245	0.021	275	-0.007	305	0.005	335	0.021
246	-0.032	276	0.004	306	-0.011	336	0.035
247	-0.03	277	-0.022	307	0.007	337	-0.009
248	-0.029	278	-0.053	308	0.025	338	0.014
249	-0.016	279	-0.023	309	-0.007	339	-0.007
250	-0.011	280	0.042	310	-0.003	340	0.009
251	-0.017	281	0.018	311	0.008	341	-0.017
252	-0.025	282	-0.009	312	0	342	0.002
253	-0.016	283	-0.05	313	0	343	-0.014
254	-0.064	284	0.008	314	-0.013	344	0.023

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
345	0.002	375	-0.032	405	-0.036	435	-0.059
346	0.022	376	0.073	406	0.029	436	-0.087
347	0.002	377	-0.028	407	-0.06	437	-0.075
348	0.008	378	0.015	408	-0.032	438	0.069
349	-0.002	379	-0.008	409	-0.04	439	-0.034
350	0.005	380	-0.009	410	-0.036	440	-0.036
351	0.007	381	-0.014	411	-0.063	441	0.007
352	0.031	382	-0.026	412	-0.036	442	-0.005
353	-0.073	383	-0.043	413	-0.017	443	-0.08
354	0.028	384	-0.004	414	0.102	444	-0.063
355	0.023	385	-0.018	415	-0.02	445	-0.018
356	0.015	386	-0.031	416	-0.113	446	0.033
357	0.013	387	-0.054	417	-0.046	447	0.038
358	-0.017	388	-0.049	418	-0.102	448	0.029
359	0.006	389	-0.016	419	-0.031	449	0.016
360	0.006	390	-0.014	420	-0.07	450	-0.05
361	-0.029	391	-0.031	421	-0.102	451	0.047
362	0.002	392	-0.015	422	-0.036	452	-0.066
363	-0.02	393	-0.092	423	-0.001	453	-0.018
364	-0.026	394	-0.02	424	-0.048	454	0.004
365	-0.024	395	-0.049	425	-0.083	455	-0.053
366	-0.034	396	-0.004	426	-0.01	456	0.032
367	-0.003	397	-0.009	427	-0.05	457	-0.006
368	-0.028	398	-0.018	428	-0.054	458	0.002
369	-0.025	399	-0.034	429	-0.02	459	0.007
370	-0.037	400	-0.033	430	-0.017	460	-0.01
371	-0.055	401	-0.012	431	0.017	461	0.002
372	-0.028	402	-0.035	432	-0.034	462	-0.025
373	-0.011	403	-0.014	433	-0.054	463	0.035
374	-0.004	404	0.006	434	-0.051	464	0.01

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
465	0.028	495	-0.084	525	0.03	555	-0.065
466	0.016	496	0.046	526	-0.028	556	-0.03
467	0.038	497	-0.011	527	-0.012	557	-0.008
468	-0.007	498	0.014	528	-0.035	558	-0.011
469	0.071	499	-0.004	529	-0.052	559	-0.041
470	0.008	500	-0.013	530	-0.043	560	-0.035
471	0.03	501	-0.006	531	0.001	561	0.017
472	0.092	502	-0.025	532	-0.001	562	0.018
473	0.055	503	0.048	533	0.014	563	-0.038
474	0.004	504	-0.004	534	-0.095	564	-0.025
475	-0.006	505	0.05	535	-0.023	565	-0.047
476	0	506	-0.001	536	-0.048	566	-0.024
477	0.026	507	0.035	537	0.006	567	-0.054
478	-0.012	508	0.012	538	0.023	568	-0.065
479	0.021	509	-0.018	539	0.003	569	-0.013
480	0.023	510	-0.014	540	0.017	570	-0.07
481	0.007	511	-0.019	541	0.013	571	-0.069
482	0.005	512	-0.009	542	0.021	572	-0.017
483	-0.019	513	-0.004	543	0.029	573	0.012
484	0.038	514	0.002	544	0.037	574	0.01
485	0.072	515	-0.023	545	0.017	575	-0.041
486	-0.009	516	-0.072	546	0.029	576	-0.052
487	-0.027	517	-0.003	547	0.008	577	0.011
488	-0.044	518	-0.008	548	0.012	578	-0.054
489	-0.024	519	0.061	549	-0.008	579	0.008
490	0.012	520	-0.028	550	-0.064	580	-0.028
491	0.008	521	0.004	551	-0.039	581	-0.027
492	0.004	522	-0.037	552	-0.011	582	-0.023
493	0.025	523	-0.028	553	-0.03	583	-0.004
494	-0.007	524	-0.05	554	0.003	584	-0.022

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
585	-0.012	615	-0.005	645	0.079	675	0.003
586	-0.025	616	-0.009	646	-0.027	676	0.014
587	0.019	617	-0.045	647	0.011	677	-0.02
588	-0.024	618	-0.011	648	-0.004	678	0.04
589	-0.035	619	0.007	649	-0.008	679	-0.002
590	-0.048	620	-0.01	650	-0.026	680	-0.037
591	-0.036	621	0.007	651	-0.038	681	-0.007
592	-0.019	622	0.028	652	-0.007	682	-0.03
593	0.046	623	-0.024	653	-0.017	683	-0.026
594	0.016	624	0.012	654	0.022	684	0.037
595	-0.04	625	0.024	655	-0.012	685	-0.027
596	-0.046	626	0.054	656	-0.008	686	-0.025
597	-0.003	627	-0.025	657	0.007	687	0.003
598	-0.042	628	0.02	658	-0.018	688	0.011
599	-0.031	629	0.019	659	0.013	689	-0.013
600	-0.009	630	0.013	660	0.016	690	0.008
601	-0.022	631	0.021	661	-0.032	691	-0.003
602	-0.011	632	0.012	662	0.003	692	0.026
603	-0.002	633	0.001	663	-0.048	693	-0.008
604	-0.003	634	0.03	664	0.044	694	0.031
605	-0.018	635	0.046	665	0.013	695	0.04
606	-0.016	636	0.037	666	0.002	696	0.018
607	0.011	637	0.016	667	0.037	697	0.054
608	0.019	638	-0.013	668	-0.021	698	0
609	-0.034	639	0.019	669	0.001	699	-0.016
610	-0.062	640	-0.041	670	0.004	700	0.028
611	-0.037	641	-0.013	671	-0.032	701	0.005
612	-0.033	642	-0.068	672	0.001	702	-0.002
613	-0.053	643	-0.024	673	-0.022	703	-0.011
614	-0.023	644	0.007	674	-0.012	704	0.001

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
705	0.034	735	0.038	765	-0.019	795	-0.006
706	-0.008	736	0.048	766	-0.004	796	-0.006
707	-0.008	737	0.007	767	0.037	797	-0.206
708	0.015	738	0.023	768	0.028	798	-0.009
709	-0.017	739	-0.002	769	-0.041	799	0.015
710	0.002	740	-0.001	770	-0.006	800	-0.006
711	0.049	741	0.043	771	-0.009	801	-0.004
712	0.005	742	0.018	772	-0.003	802	-0.007
713	-0.027	743	0.019	773	-0.066	803	-0.005
714	0.028	744	0.031	774	0.03	804	0.054
715	0.045	745	0.016	775	0.009	805	0.047
716	-0.026	746	-0.02	776	0.043	806	0.046
717	0.007	747	-0.018	777	0.03	807	0.034
718	0.01	748	-0.029	778	-0.005	808	-0.031
719	0.011	749	-0.023	779	-0.051	809	-0.003
720	0.005	750	-0.016	780	-0.018	810	0
721	0.039	751	0.005	781	-0.005	811	-0.009
722	0.031	752	-0.013	782	-0.021	812	-0.011
723	0.027	753	-0.016	783	-0.058	813	0.001
724	0.071	754	-0.018	784	-0.011	814	-0.077
725	-0.012	755	-0.016	785	-0.002	815	-0.001
726	-0.014	756	-0.016	786	0.003	816	-0.019
727	0.012	757	-0.029	787	-0.042	817	0.017
728	-0.013	758	-0.007	788	-0.009	818	-0.027
729	0.022	759	0.007	789	0.012	819	-0.064
730	-0.014	760	-0.032	790	-0.019	820	-0.006
731	0.018	761	0.008	791	-0.031	821	-0.054
732	0.043	762	0.031	792	-0.009	822	0.009
733	0.002	763	0.015	793	-0.015	823	-0.031
734	0.049	764	0.028	794	0.021	824	-0.011

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
825	-0.191	855	-0.017	885	0.01	915	-0.063
826	-0.001	856	-0.007	886	-0.018	916	-0.029
827	-0.004	857	0.029	887	-0.071	917	-0.011
828	0.021	858	-0.007	888	-0.034	918	-0.026
829	-0.005	859	0.02	889	-0.071	919	-0.015
830	-0.135	860	-0.047	890	-0.006	920	-0.005
831	0.018	861	0.043	891	-0.017	921	-0.019
832	-0.052	862	0	892	-0.014	922	-0.009
833	0	863	-0.057	893	-0.014	923	-0.067
834	-0.002	864	-0.026	894	0.005	924	-0.041
835	-0.007	865	-0.023	895	-0.091	925	-0.017
836	-0.017	866	-0.004	896	-0.021	926	-0.019
837	-0.016	867	-0.106	897	-0.01	927	-0.013
838	-0.024	868	0.063	898	-0.01	928	-0.028
839	-0.017	869	-0.053	899	0.046	929	-0.027
840	-0.008	870	-0.007	900	-0.027	930	-0.022
841	-0.008	871	-0.028	901	-0.029	931	0.009
842	-0.013	872	-0.035	902	-0.02	932	-0.038
843	-0.021	873	0.003	903	-0.006	933	-0.02
844	-0.06	874	-0.028	904	-0.041	934	0.027
845	-0.039	875	-0.001	905	-0.012	935	0.028
846	-0.021	876	-0.025	906	0.024	936	-0.003
847	0	877	-0.065	907	0.013	937	-0.003
848	-0.032	878	-0.007	908	0.034	938	-0.04
849	-0.004	879	0.005	909	-0.031	939	-0.024
850	-0.001	880	-0.052	910	-0.02	940	-0.013
851	-0.024	881	-0.004	911	-0.032	941	-0.015
852	-0.011	882	-0.027	912	-0.024	942	0.025
853	-0.014	883	0.026	913	-0.025	943	0.02
854	0.014	884	-0.069	914	-0.029	944	-0.022

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
945	-0.001	955	-0.04	965	-0.029	975	-0.022
946	-0.048	956	-0.049	966	-0.037	976	-0.037
947	-0.024	957	-0.013	967	-0.002	977	-0.022
948	-0.028	958	-0.038	968	-0.054	978	-0.015
949	-0.022	959	-0.032	969	-0.035	979	-0.033
950	-0.003	960	-0.024	970	-0.012	980	-0.038
951	0.01	961	-0.041	971	-0.037	981	-0.047
952	0.014	962	-0.031	972	0	982	-0.03
953	0.005	963	-0.037	973	-0.034	983	-0.044
954	-0.037	964	-0.024	974	0.004		

APPENDIX C

Table C1 The questionnaire of AHP technique

		A is more important than B				OR	B is more important than A			
Factor A	Factor B	Extreme	Very strong	Stong	Moderate	Equal	Moderate	Stong	Very strong	Extreme
Product price list	Extra charge	9	7	5	3	1	3	5	7	9
	Discount	9	7	5	3	1	3	5	7	9
	marketing cost	9	7	5	3	1	3	5	7	9
	Raw material cost	9	7	5	3	1	3	5	7	9

		A is more important than B				OR	B is more important than A			
Factor A	Factor B	Extreme	Very strong	Stong	Moderate	Equal	Moderate	Stong	Very strong	Extreme
Extra charge	Discount	9	7	5	3	1	3	5	7	9
	Marketing cost	9	7	5	3	1	3	5	7	9
	Raw material cost	9	7	5	3	1	3	5	7	9

		A is more important than B				OR	B is more important than A			
Factor A	Factor B	Extreme	Very strong	Stong	Moderate	Equal	Moderate	Stong	Very strong	Extreme
Discount	Marketing cost	9	7	5	3	1	3	5	7	9
	Raw material cost	9	7	5	3	1	3	5	7	9

		A is more important than B				OR	B is more important than A			
Factor A	Factor B	Extreme	Very strong	Stong	Moderate	Equal	Moderate	Stong	Very strong	Extreme
Marketing cost	Fright cost	9	7	5	3	1	3	5	7	9

APPENDIX D

Table D1 The residual of hybrid AHP with RSM model

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
1	-0.063	27	0.044	53	-0.002	79	0.009
2	-0.063	28	0.05	54	0.009	80	-0.032
3	-0.073	29	0.027	55	-0.043	81	-0.052
4	-0.007	30	0.092	56	0.009	82	-0.013
5	0.024	31	0.043	57	-0.091	83	-0.025
6	-0.019	32	0.034	58	-0.011	84	-0.021
7	0.031	33	0.041	59	0	85	-0.013
8	0.06	34	0.007	60	0.025	86	-0.014
9	0.052	35	0.023	61	-0.056	87	0.022
10	0.043	36	0.013	62	-0.028	88	0.003
11	0.038	37	0.045	63	-0.045	89	0.026
12	0.052	38	0.089	64	0.019	90	-0.005
13	0.043	39	0.022	65	0.043	91	-0.001
14	0.019	40	0.06	66	0.041	92	0.01
15	0.171	41	0.007	67	-0.013	93	-0.02
16	0.023	42	0.014	68	-0.012	94	0.022
17	0.002	43	0.037	69	-0.003	95	0
18	0.025	44	0.022	70	-0.028	96	0.046
19	0.129	45	0.009	71	-0.058	97	-0.019
20	0.054	46	0.042	72	-0.059	98	0.066
21	0.045	47	0.07	73	0.129	99	-0.04
22	0.04	48	0.007	74	-0.018	100	-0.058
23	0.042	49	0.001	75	-0.019	101	-0.066
24	0.004	50	0.036	76	-0.055	102	-0.023
25	0.029	51	0.013	77	-0.078	103	-0.076
26	0.011	52	0.014	78	-0.015	104	0.01

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
105	0.012	135	-0.013	165	-0.044	195	0.025
106	-0.044	136	0.025	166	0.078	196	-0.005
107	-0.021	137	-0.01	167	0.025	197	0.073
108	-0.014	138	0.072	168	-0.033	198	-0.078
109	0.019	139	0.055	169	-0.042	199	-0.087
110	-0.004	140	0	170	-0.038	200	-0.059
111	-0.029	141	0.009	171	-0.115	201	-0.091
112	0.007	142	0.004	172	-0.062	202	-0.033
113	0.007	143	-0.013	173	-0.061	203	-0.078
114	-0.047	144	0.024	174	-0.018	204	-0.091
115	-0.072	145	0.003	175	-0.087	205	-0.047
116	-0.057	146	0.074	176	-0.025	206	0.006
117	-0.016	147	-0.007	177	-0.061	207	-0.007
118	-0.011	148	-0.059	178	-0.028	208	0.026
119	-0.054	149	0.017	179	-0.065	209	-0.01
120	0.018	150	0.016	180	-0.065	210	0.057
121	-0.031	151	-0.028	181	-0.008	211	-0.032
122	-0.023	152	0	182	-0.077	212	-0.042
123	-0.033	153	0.016	183	-0.041	213	0.01
124	-0.022	154	-0.021	184	-0.004	214	-0.025
125	-0.018	155	0.057	185	-0.011	215	-0.07
126	-0.023	156	0.014	186	-0.064	216	0.015
127	-0.024	157	-0.017	187	-0.084	217	-0.044
128	-0.013	158	-0.036	188	-0.013	218	-0.079
129	-0.05	159	0.012	189	0.004	219	-0.059
130	-0.046	160	-0.024	190	-0.081	220	-0.021
131	-0.059	161	-0.048	191	-0.007	221	-0.028
132	0.015	162	0.008	192	-0.031	222	-0.036
133	-0.029	163	-0.043	193	-0.007	223	-0.029
134	-0.009	164	-0.043	194	-0.012	224	-0.02

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
225	-0.063	255	0.008	285	0.008	315	0.025
226	-0.044	256	-0.017	286	0.036	316	-0.011
227	-0.043	257	0.001	287	-0.015	317	-0.018
228	-0.009	258	-0.012	288	-0.011	318	0.004
229	-0.019	259	0.003	289	-0.009	319	-0.01
230	-0.019	260	-0.024	290	0.063	320	-0.027
231	-0.033	261	0.036	291	-0.003	321	0.038
232	-0.036	262	0.026	292	0.045	322	-0.007
233	-0.021	263	-0.04	293	0.061	323	0.033
234	0.172	264	-0.005	294	-0.02	324	-0.045
235	-0.039	265	0.005	295	0.041	325	-0.041
236	-0.057	266	-0.001	296	0.04	326	0.094
237	-0.01	267	-0.027	297	0.003	327	-0.046
238	-0.017	268	0.109	298	-0.009	328	0.02
239	0.002	269	-0.026	299	-0.05	329	-0.003
240	-0.023	270	-0.008	300	0.002	330	0.012
241	-0.03	271	0.018	301	0.001	331	-0.022
242	-0.047	272	0.002	302	0.016	332	-0.041
243	-0.02	273	-0.019	303	-0.009	333	-0.049
244	-0.023	274	0.04	304	-0.038	334	-0.057
245	-0.027	275	0.015	305	-0.007	335	-0.02
246	0.014	276	-0.021	306	0.001	336	-0.021
247	-0.011	277	-0.023	307	0.011	337	0.014
248	-0.033	278	0.03	308	-0.031	338	-0.016
249	0.023	279	0.008	309	-0.005	339	0.002
250	-0.025	280	0.052	310	0.013	340	-0.025
251	0.064	281	-0.026	311	0.016	341	0.003
252	0.003	282	0.005	312	-0.003	342	0.022
253	-0.027	283	-0.022	313	-0.044	343	0.004
254	0.29	284	-0.011	314	0.056	344	-0.011

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
345	0.038	375	-0.083	405	0.029	435	0.002
346	-0.006	376	-0.12	406	0.087	436	-0.024
347	-0.019	377	0.001	407	0.043	437	-0.007
348	-0.185	378	-0.032	408	0.111	438	-0.163
349	-0.015	379	0.006	409	0.055	439	-0.074
350	0.018	380	0.038	410	0.005	440	-0.046
351	-0.021	381	0.035	411	-0.015	441	-0.076
352	-0.051	382	0	412	0.111	442	-0.093
353	-0.021	383	0.017	413	-0.084	443	-0.089
354	-0.083	384	-0.023	414	-0.092	444	0
355	-0.083	385	-0.01	415	0.067	445	-0.019
356	0.03	386	0.01	416	0.015	446	-0.053
357	0.037	387	-0.123	417	0.01	447	-0.077
358	0.037	388	0.127	418	0.033	448	-0.099
359	-0.054	389	-0.002	419	0.009	449	-0.04
360	-0.051	390	-0.018	420	-0.007	450	0.002
361	0.016	391	0.022	421	0.041	451	-0.124
362	-0.018	392	0.079	422	0.001	452	0.125
363	0.073	393	-0.003	423	-0.078	453	-0.021
364	0.048	394	0.05	424	-0.009	454	0.011
365	0.023	395	0.06	425	0.003	455	0.086
366	0.19	396	0.003	426	-0.078	456	-0.051
367	0.016	397	-0.035	427	-0.036	457	0.181
368	0.055	398	0.016	428	0.032	458	-0.058
369	0.025	399	-0.141	429	-0.01	459	-0.062
370	0.008	400	-0.051	430	-0.058	460	-0.039
371	0.036	401	0.051	431	-0.022	461	-0.047
372	0.027	402	-0.031	432	-0.043	462	0.006
373	0.029	403	-0.043	433	-0.009	463	-0.004
374	-0.005	404	-0.004	434	-0.018	464	0.018

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
465	0.002	495	-0.046	525	-0.033	555	-0.027
466	0.005	496	-0.328	526	0.046	556	0.004
467	-0.048	497	-0.006	527	-0.009	557	-0.066
468	-0.012	498	-0.028	528	0.013	558	-0.038
469	-0.112	499	-0.011	529	0.052	559	0.019
470	-0.022	500	-0.006	530	-0.005	560	0.005
471	-0.026	501	-0.013	531	0.003	561	-0.048
472	-0.153	502	0.012	532	-0.026	562	-0.104
473	-0.114	503	-0.06	533	0.021	563	-0.05
474	-0.056	504	-0.182	534	0.086	564	-0.087
475	0.004	505	-0.018	535	0.019	565	-0.105
476	0.008	506	0.017	536	0.002	566	0.021
477	-0.074	507	-0.045	537	-0.02	567	0.121
478	-0.002	508	-0.085	538	-0.016	568	0.047
479	-0.014	509	0.039	539	0.037	569	-0.01
480	-0.048	510	0.058	540	-0.043	570	0.093
481	-0.047	511	0.028	541	-0.004	571	0.067
482	-0.013	512	0.037	542	-0.03	572	0.005
483	-0.093	513	0.012	543	-0.024	573	0.012
484	-0.078	514	-0.02	544	-0.078	574	0.013
485	-0.156	515	0.002	545	-0.018	575	0.002
486	-0.013	516	0.087	546	-0.198	576	0.066
487	-0.026	517	0.009	547	-0.051	577	-0.052
488	0.039	518	-0.072	548	-0.043	578	0.083
489	0.048	519	-0.077	549	-0.039	579	0.002
490	0.042	520	-0.015	550	-0.063	580	0.04
491	-0.055	521	-0.013	551	-0.027	581	0.025
492	-0.046	522	-0.016	552	0.019	582	0.046
493	0.116	523	0.034	553	0.014	583	0.007
494	-0.151	524	0.033	554	-0.109	584	0.02

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
585	0.009	615	0.036	645	-0.074	675	0.005
586	0.002	616	0.055	646	0.061	676	0.037
587	-0.013	617	0.033	647	0.031	677	0.054
588	0.051	618	0.038	648	-0.013	678	-0.031
589	0.008	619	0.005	649	0.037	679	-0.013
590	0.052	620	0.003	650	0.024	680	-0.052
591	0.043	621	0.013	651	0.022	681	-0.005
592	0.01	622	-0.042	652	0.013	682	0.012
593	-0.006	623	0.039	653	0.031	683	-0.001
594	-0.011	624	-0.037	654	-0.02	684	-0.07
595	0.026	625	0.008	655	0.025	685	-0.02
596	0.05	626	-0.06	656	0.087	686	-0.039
597	0.017	627	0.028	657	-0.004	687	-0.069
598	0.057	628	-0.004	658	0.004	688	-0.13
599	0.044	629	0.001	659	0.049	689	0.019
600	0.014	630	0.061	660	0.024	690	0.003
601	0.037	631	-0.002	661	0.068	691	0.032
602	0.071	632	0.005	662	0.037	692	-0.05
603	0.025	633	0.015	663	0.116	693	-0.035
604	0.013	634	-0.013	664	-0.053	694	-0.099
605	0.022	635	-0.079	665	0.016	695	-0.055
606	0.065	636	-0.016	666	0.011	696	-0.022
607	0.03	637	0.022	667	-0.035	697	-0.094
608	0.011	638	0.011	668	0.038	698	-0.016
609	0.027	639	-0.02	669	0.036	699	-0.008
610	0.063	640	0.04	670	0.017	700	-0.091
611	0.044	641	0.064	671	0.021	701	0.014
612	0.046	642	0.091	672	0.039	702	0.009
613	0.041	643	0.035	673	0.063	703	0.018
614	0.082	644	-0.018	674	0.027	704	0.006

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
705	-0.051	735	-0.088	765	0.036	795	0.029
706	-0.057	736	-0.082	766	0.039	796	0.006
707	-0.028	737	-0.025	767	0.024	797	0.252
708	0.011	738	-0.081	768	-0.064	798	-0.017
709	0.015	739	-0.019	769	0.097	799	0.008
710	0.003	740	-0.008	770	0.002	800	0.142
711	0.01	741	-0.084	771	0.002	801	-0.037
712	-0.007	742	-0.019	772	0.021	802	-0.071
713	0.003	743	-0.065	773	0.096	803	-0.023
714	-0.043	744	-0.07	774	-0.194	804	0.111
715	-0.106	745	-0.082	775	0.099	805	0.044
716	0.003	746	0.02	776	-0.054	806	-0.078
717	-0.058	747	0.025	777	0.092	807	0.044
718	-0.057	748	-0.103	778	-0.064	808	0.04
719	-0.046	749	-0.039	779	0.083	809	0.013
720	-0.025	750	-0.112	780	0.024	810	0.044
721	-0.023	751	-0.064	781	-0.015	811	0.145
722	0.004	752	-0.008	782	0.071	812	0.145
723	-0.03	753	-0.03	783	0.176	813	0.14
724	-0.03	754	-0.105	784	-0.055	814	0.213
725	0.001	755	0.035	785	-0.021	815	0.031
726	-0.015	756	-0.024	786	-0.014	816	-0.005
727	-0.042	757	0.023	787	0.083	817	-0.051
728	-0.057	758	0.075	788	-0.002	818	0.004
729	-0.012	759	0.039	789	0.018	819	0.081
730	0.014	760	0.113	790	0.048	820	0.075
731	-0.038	761	-0.029	791	0.009	821	0.129
732	-0.036	762	0.022	792	0.057	822	0
733	-0.035	763	-0.036	793	0.131	823	0.089
734	-0.031	764	-0.004	794	-0.022	824	0.115

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
825	0.212	855	-0.047	885	-0.039	915	0.167
826	-0.014	856	0.074	886	0.102	916	0.057
827	-0.053	857	-0.023	887	0.11	917	-0.017
828	-0.049	858	-0.058	888	0.026	918	-0.004
829	0.015	859	-0.025	889	0.153	919	-0.023
830	0.168	860	0.045	890	0.048	920	-0.031
831	-0.054	861	-0.024	891	0.016	921	-0.031
832	0.152	862	0.017	892	0.077	922	0.016
833	-0.034	863	0.15	893	0.024	923	0.129
834	-0.062	864	0.069	894	-0.057	924	-0.009
835	-0.006	865	0.008	895	0.153	925	0.023
836	0.02	866	0.029	896	0.036	926	-0.023
837	-0.059	867	0.217	897	0.013	927	0.048
838	0.11	868	-0.225	898	-0.003	928	0.03
839	-0.009	869	0.138	899	0.105	929	-0.031
840	-0.003	870	0.07	900	-0.055	930	-0.063
841	-0.068	871	0.123	901	0.034	931	-0.002
842	-0.081	872	-0.059	902	0.02	932	0.058
843	-0.167	873	0.014	903	0.043	933	-0.017
844	0.173	874	-0.07	904	0.005	934	-0.05
845	0.131	875	0.025	905	-0.043	935	-0.044
846	0.04	876	-0.016	906	0.039	936	-0.04
847	0.076	877	0.007	907	-0.004	937	0.012
848	-0.002	878	-0.03	908	0.012	938	-0.006
849	-0.036	879	0	909	0.027	939	-0.021
850	-0.028	880	0.14	910	0.04	940	-0.019
851	0.048	881	0.107	911	0.039	941	-0.013
852	0.03	882	0.112	912	0.029	942	0.085
853	-0.017	883	-0.048	913	0.073	943	-0.042
854	0.007	884	0.158	914	-0.02	944	-0.02

Instances	Residuals	Instances	Residuals	Instances	Residuals	Instances	Residuals
945	-0.039	955	0.008	965	0.024	975	-0.012
946	0.056	956	0.029	966	-0.003	976	-0.02
947	-0.031	957	-0.006	967	0.066	977	-0.052
948	-0.045	958	-0.073	968	0.08	978	0.003
949	0.027	959	0.002	969	0.017	979	-0.015
950	-0.048	960	-0.022	970	0.044	980	-0.008
951	-0.097	961	0.025	971	0.012	981	0.056
952	-0.049	962	-0.009	972	0.11	982	0.037
953	0.068	963	0.074	973	0.043	983	0.026
954	-0.027	964	0.006	974	0.053		

APPENDIX E

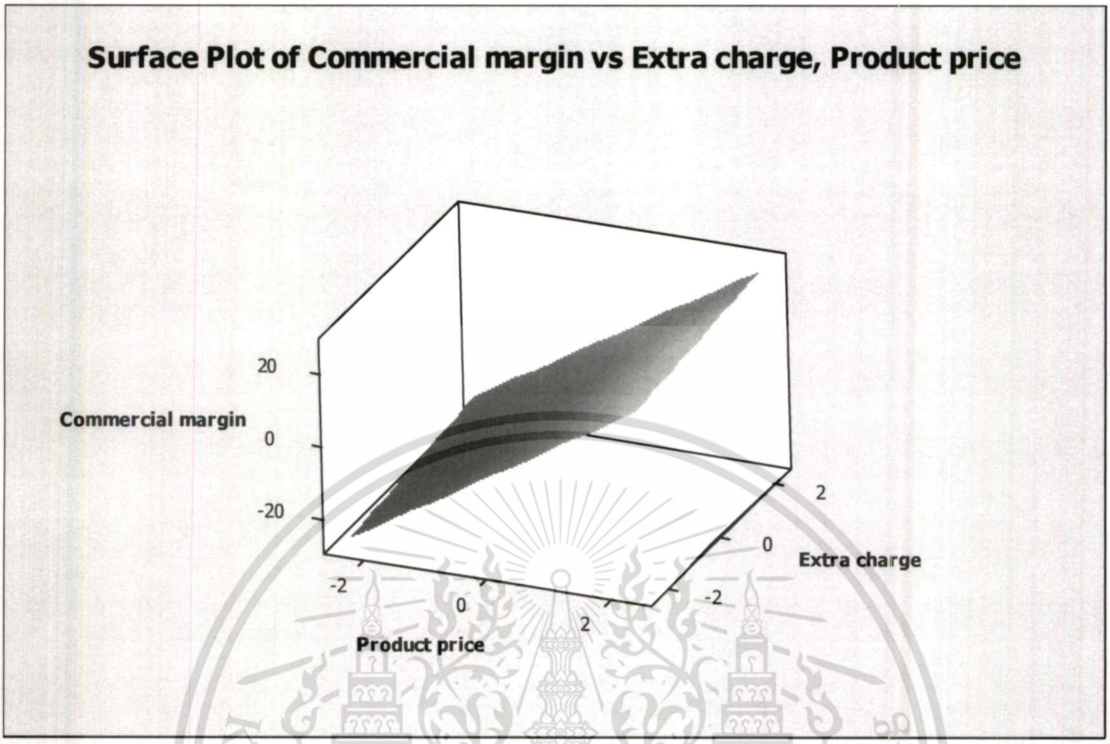

Figure E1 Surface plot of CM & extra charge, product price

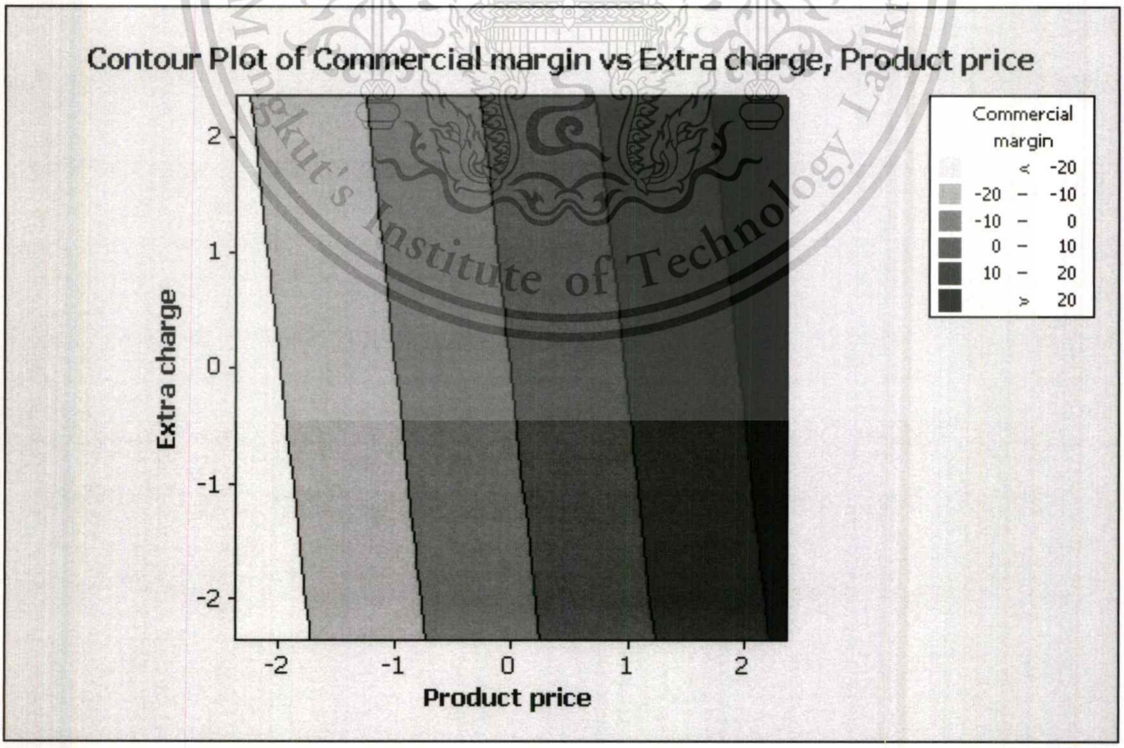

Figure E2 Contour plot of CM & extra charge, product price

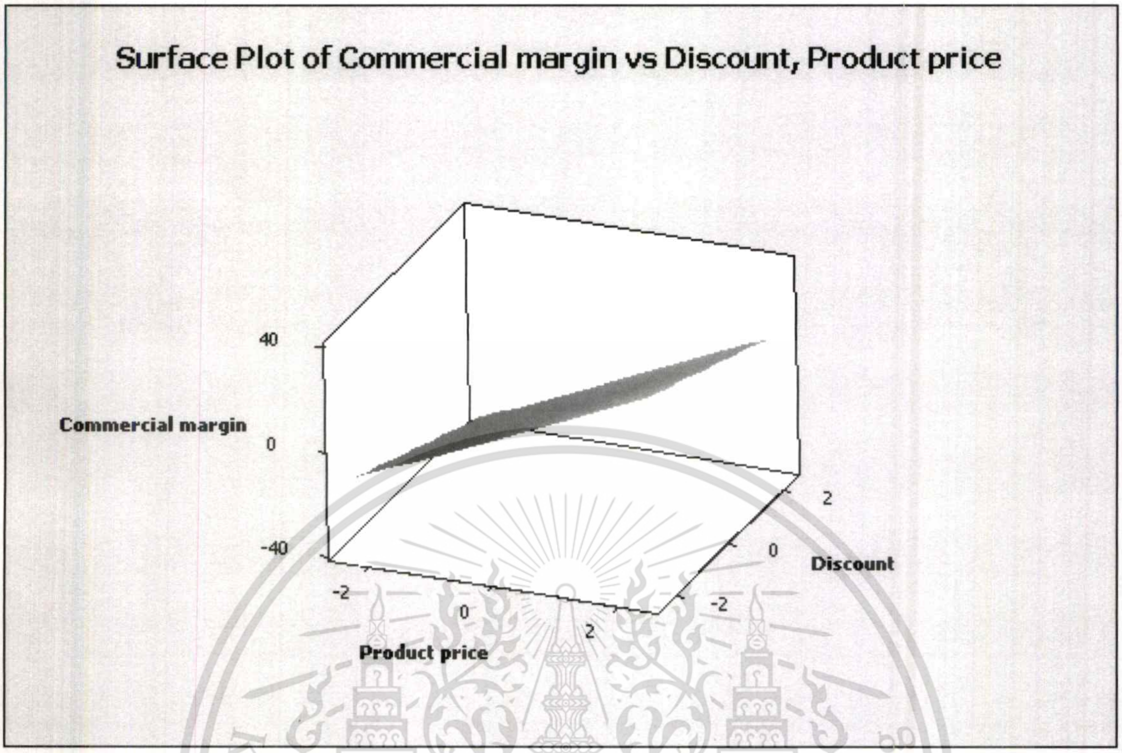

Figure E3 Surface plot of CM & discount, product price

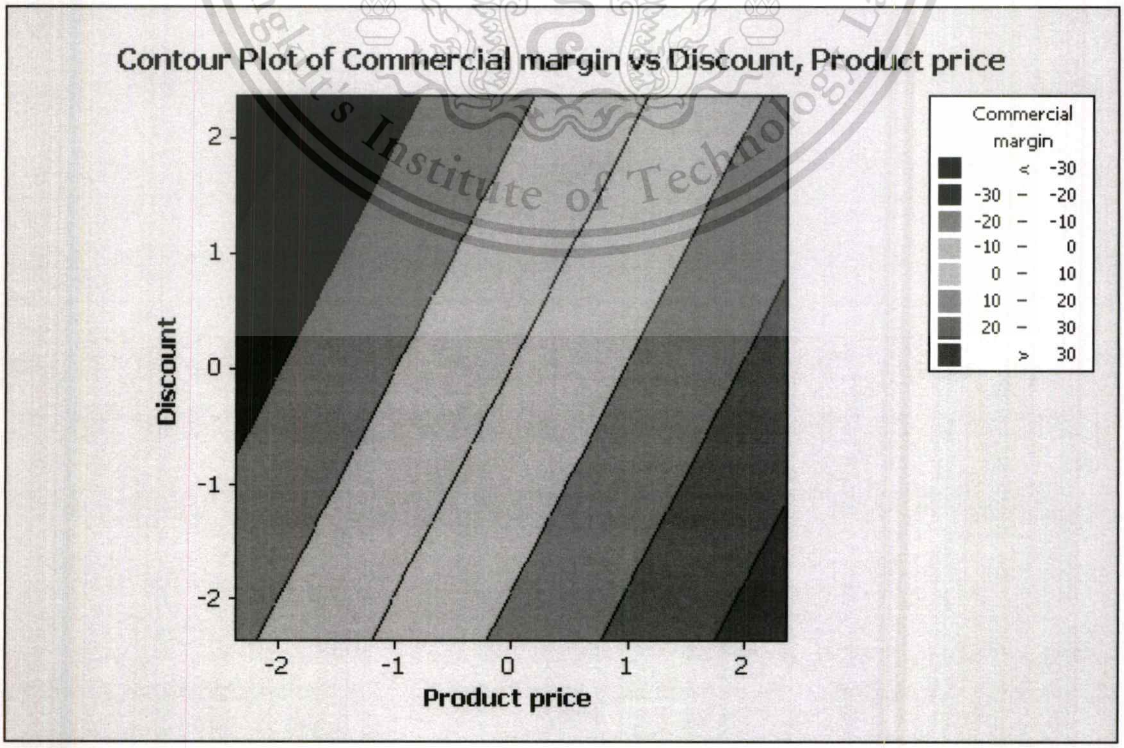

Figure E4 Contour plot of CM & discount, product price

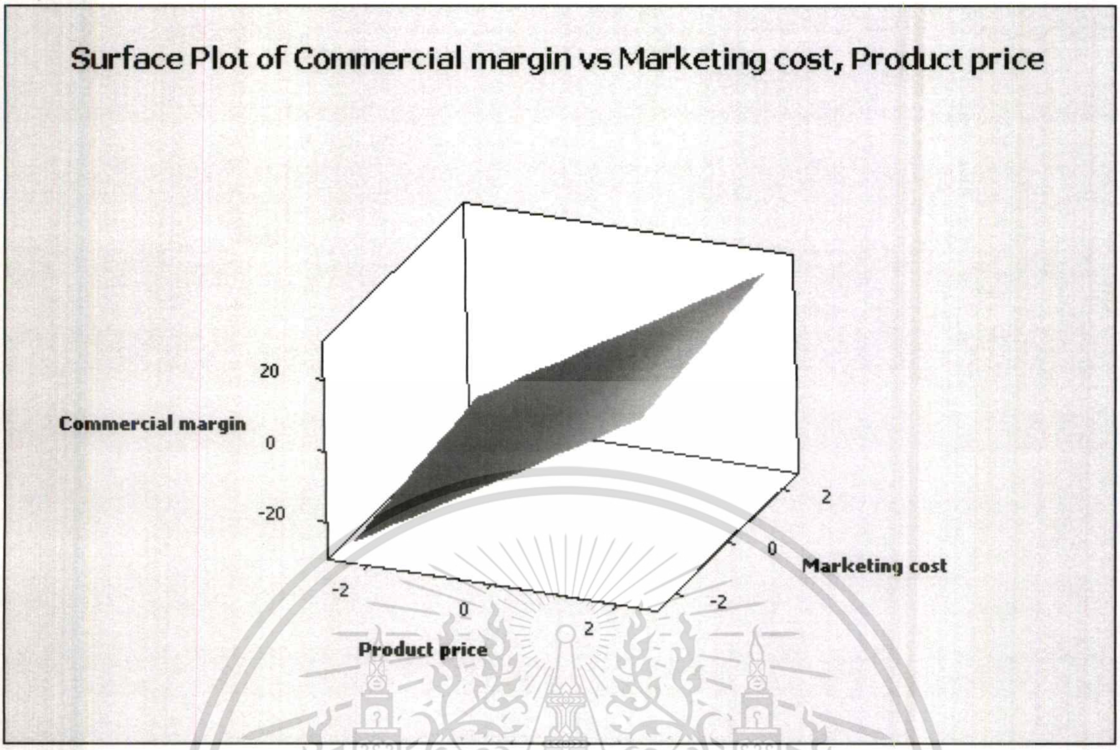

Figure E5 Surface plot of CM & marketing cost, product price

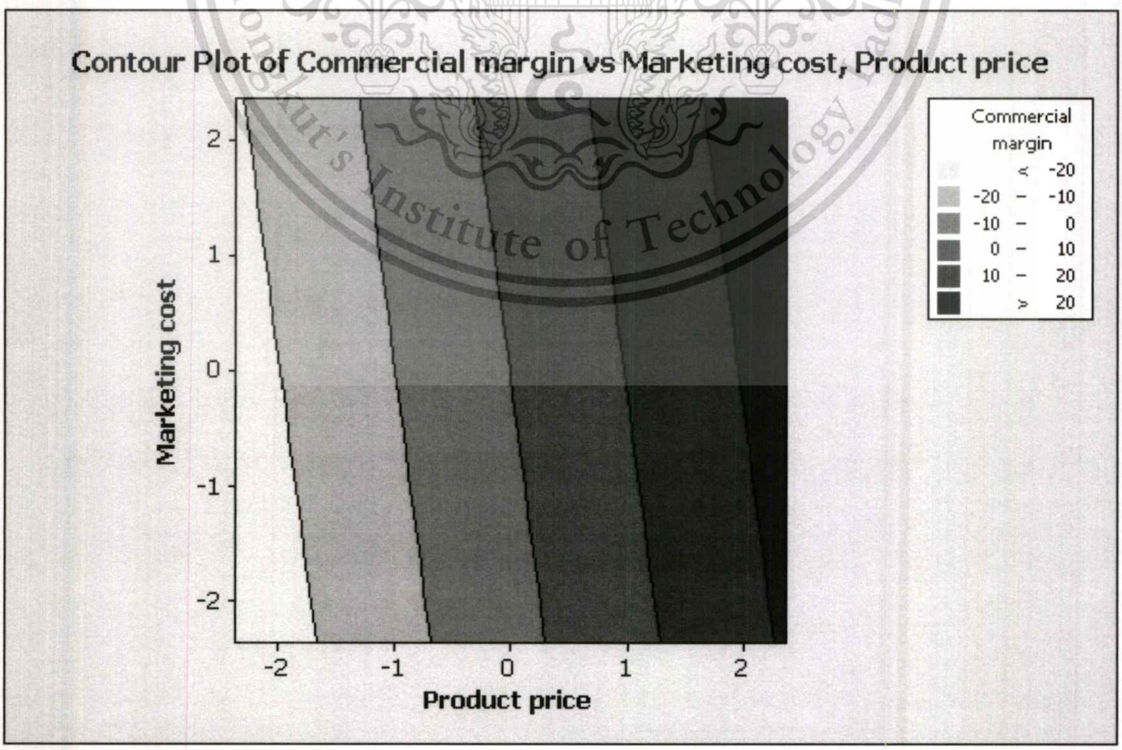

Figure E6 Contour plot of CM & marketing cost, product price

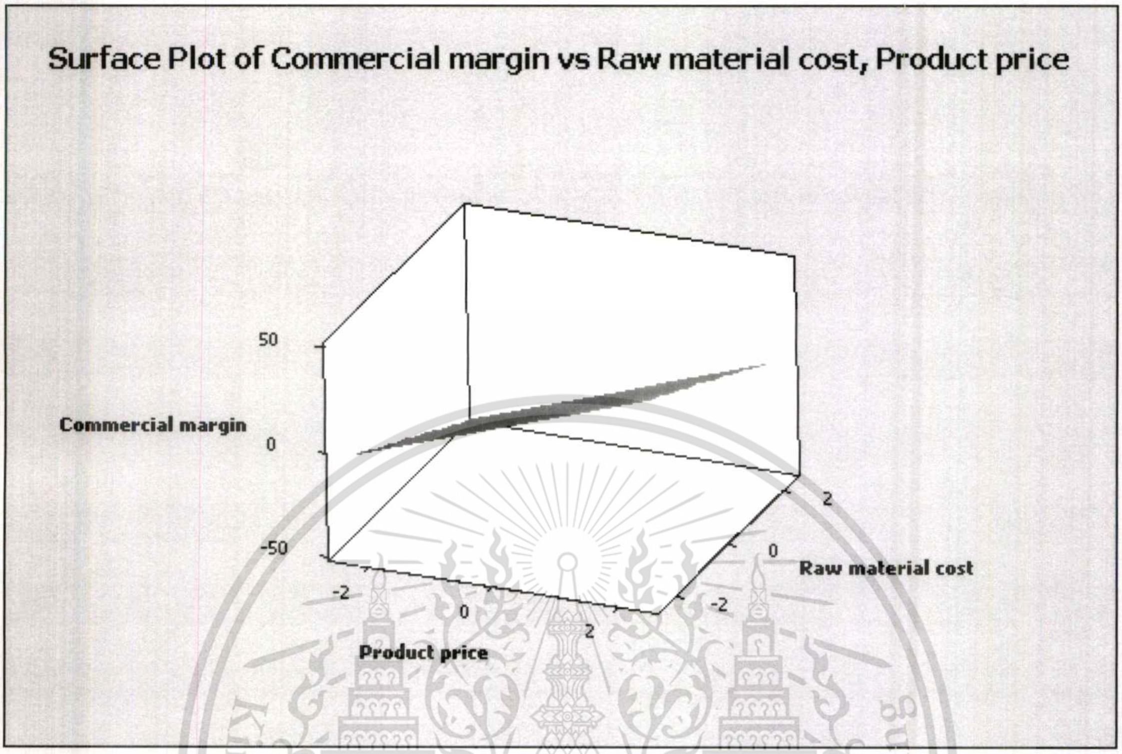

Figure E7 Surface plot of CM & raw material cost, product price

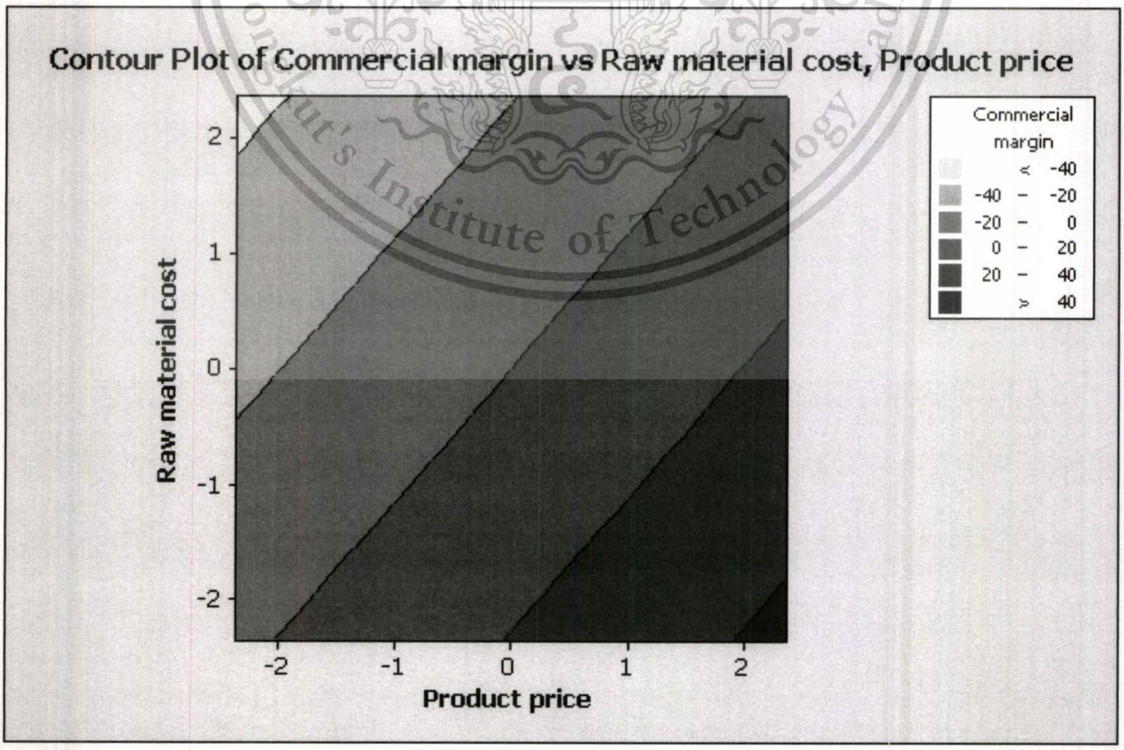

Figure E8 Contour plot of CM & & raw material cost, product price list

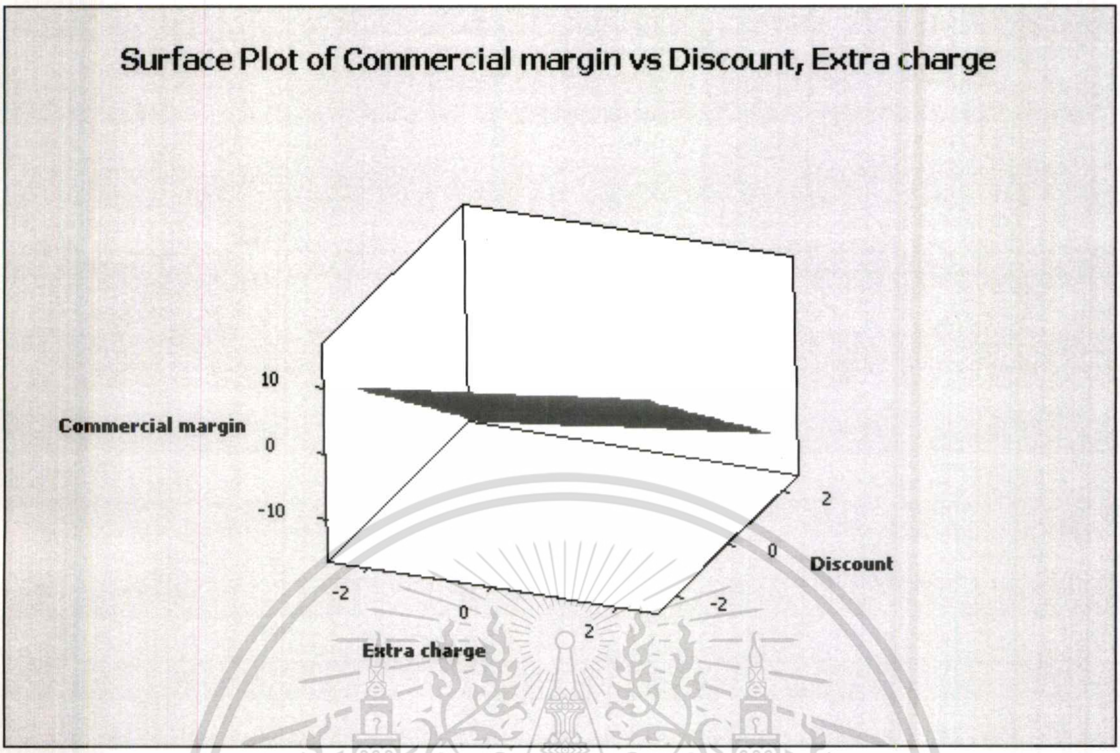

Figure E9 Surface plot of CM & discount, extra charge

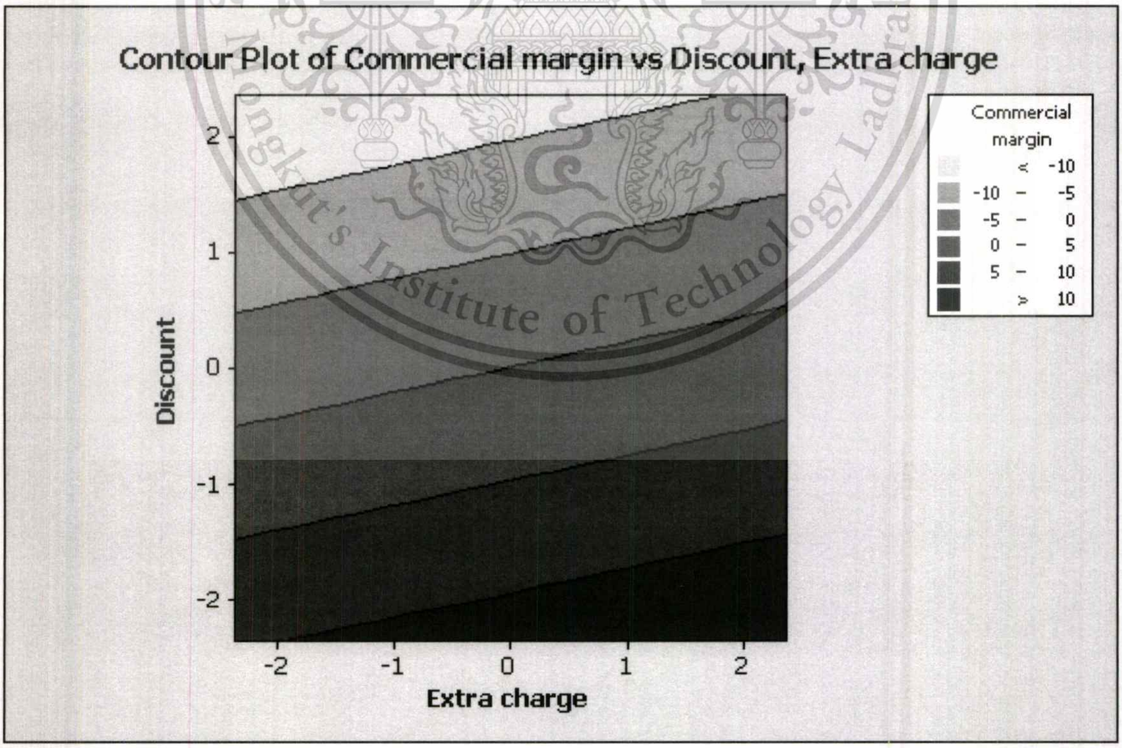

Figure E10 Contour plot of CM& discount, extra charge

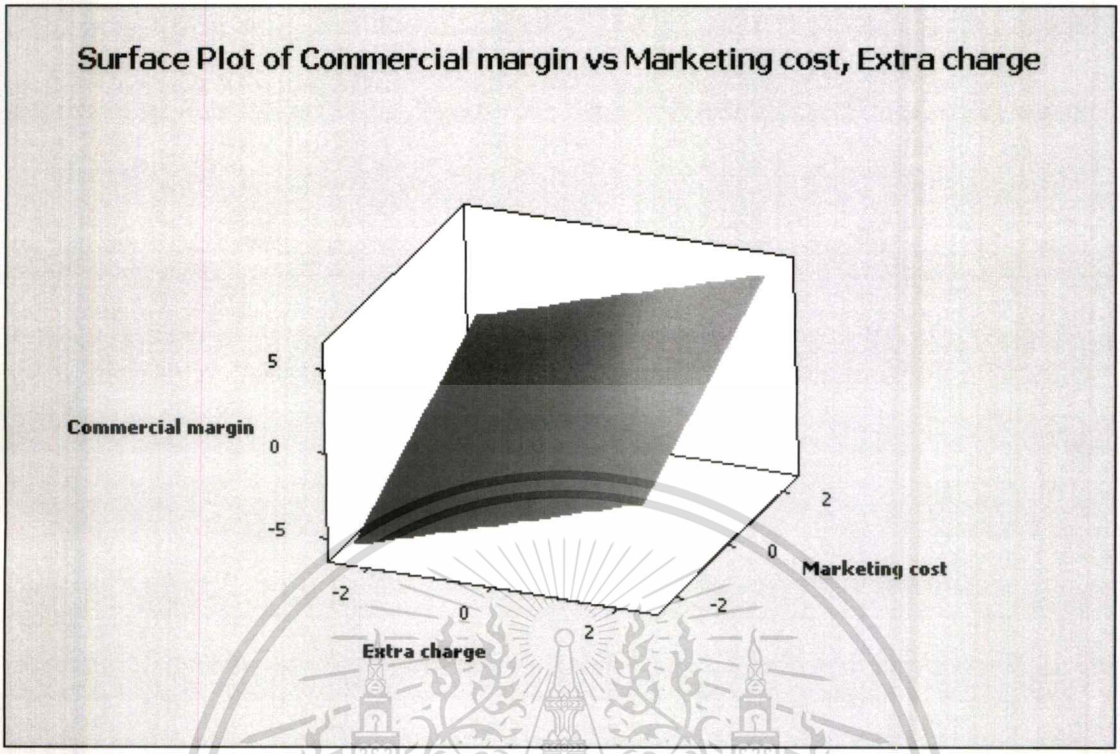

Figure E11 Surface plot of CM & marketing cost, extra charge

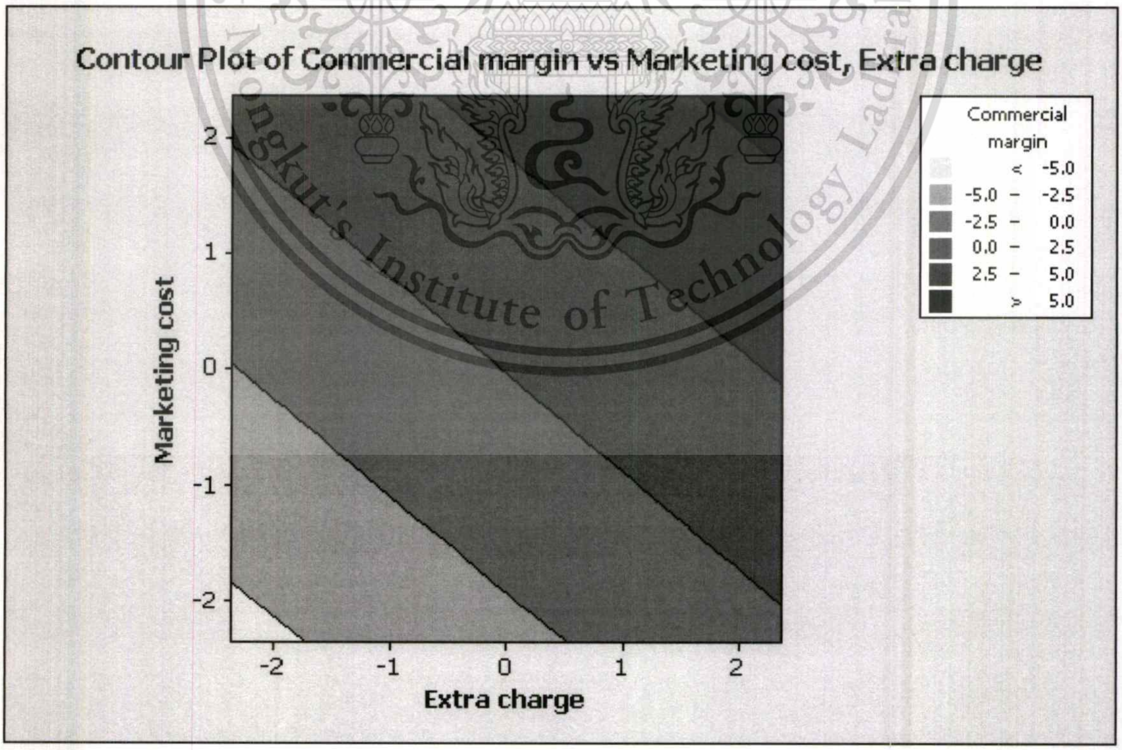

Figure E12 Contour plot of CM & marketing cost, extra charge

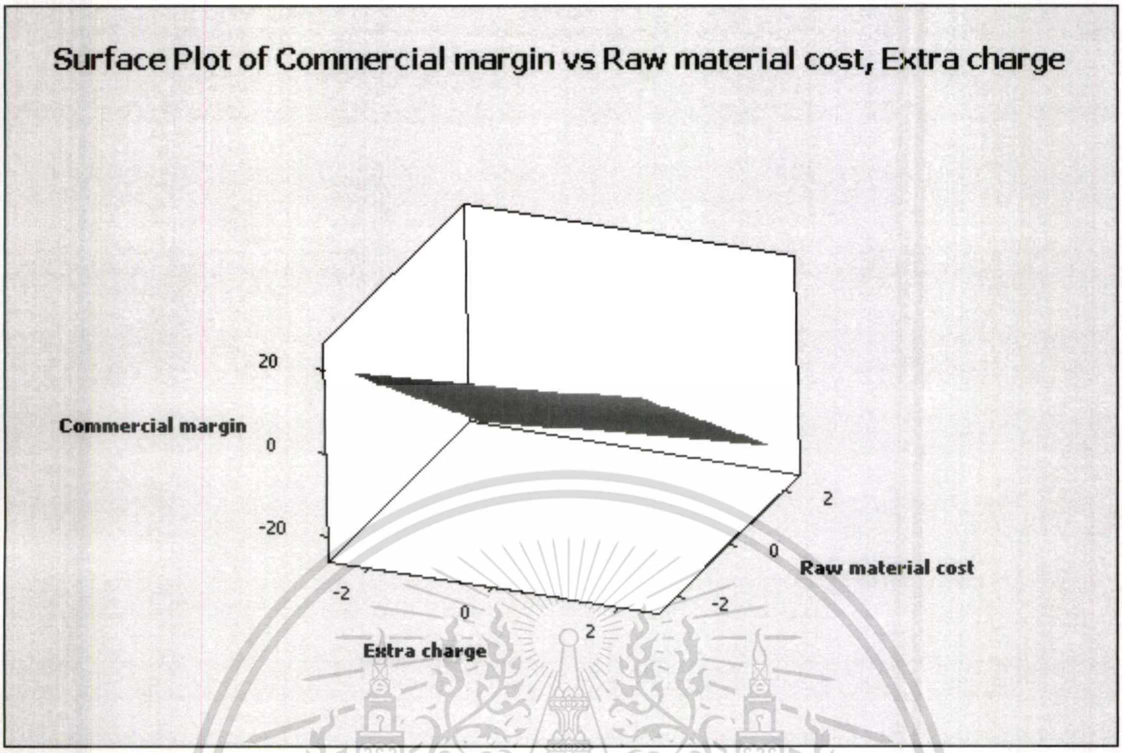

Figure E13 Surface plot of CM & raw material cost, extra charge

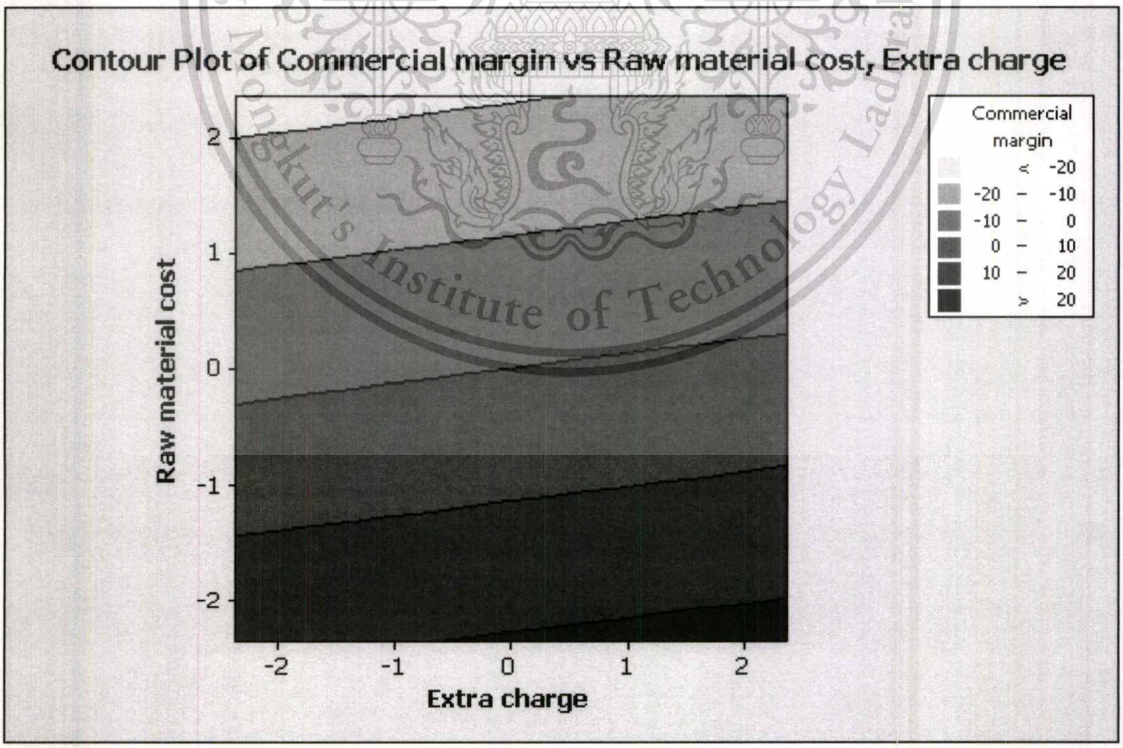

Figure E14 Contour plot of CM & raw material cost, extra charge

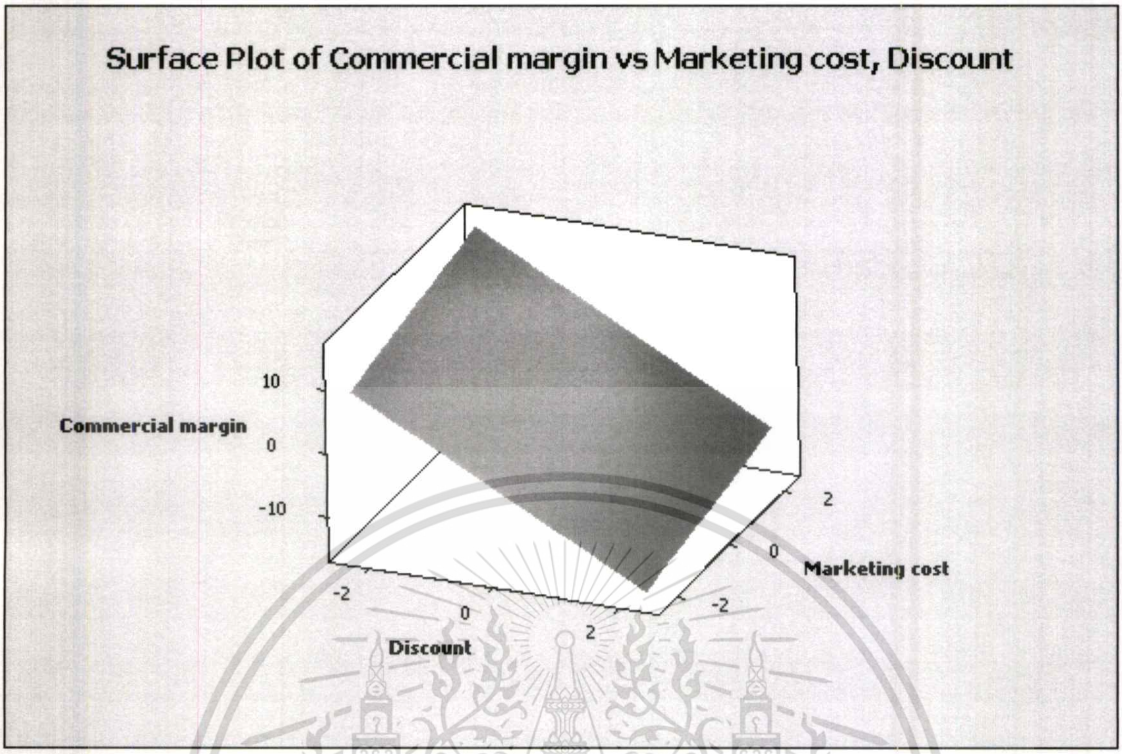

Figure E15 Surface plot of CM & marketing cost, discount

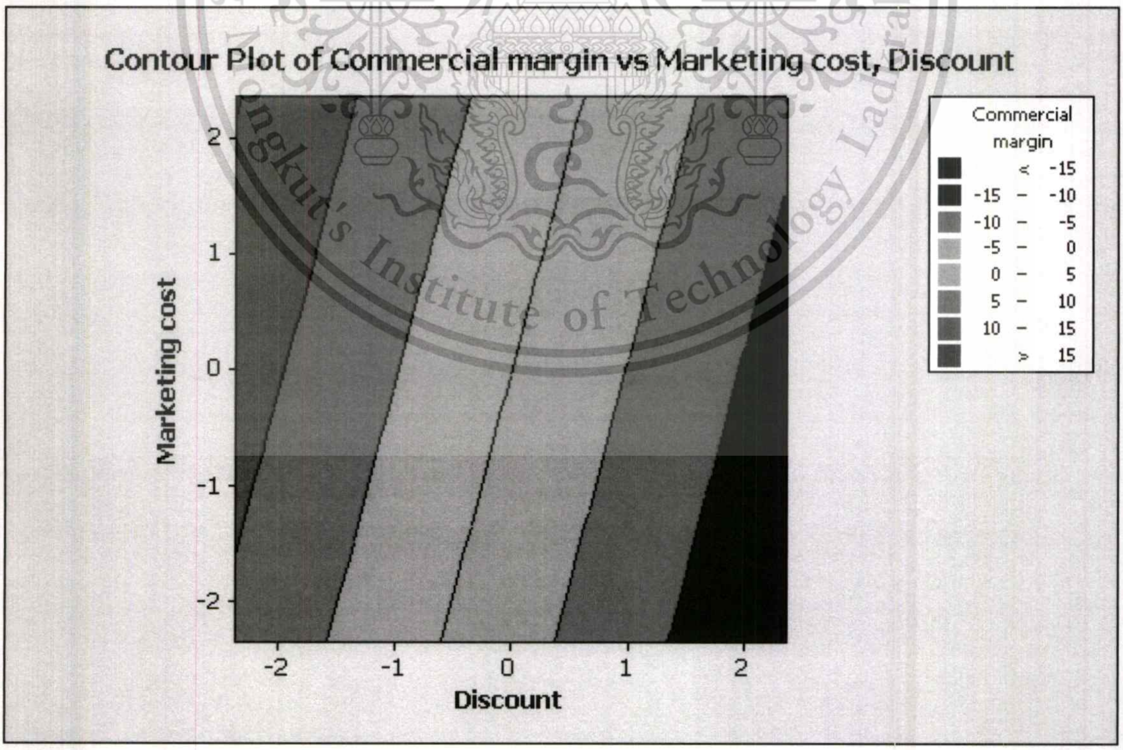

Figure E16 Contour plot of CM & marketing cost, discount

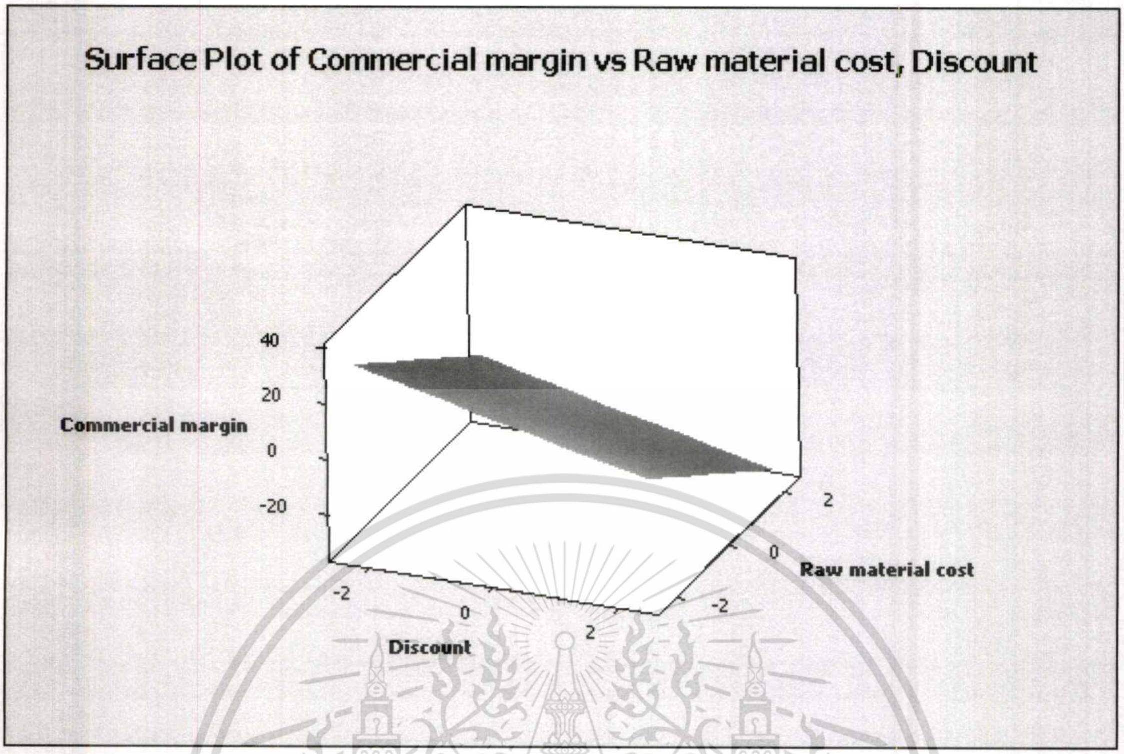

Figure E17 Surface plot of CM & raw material cost, discount

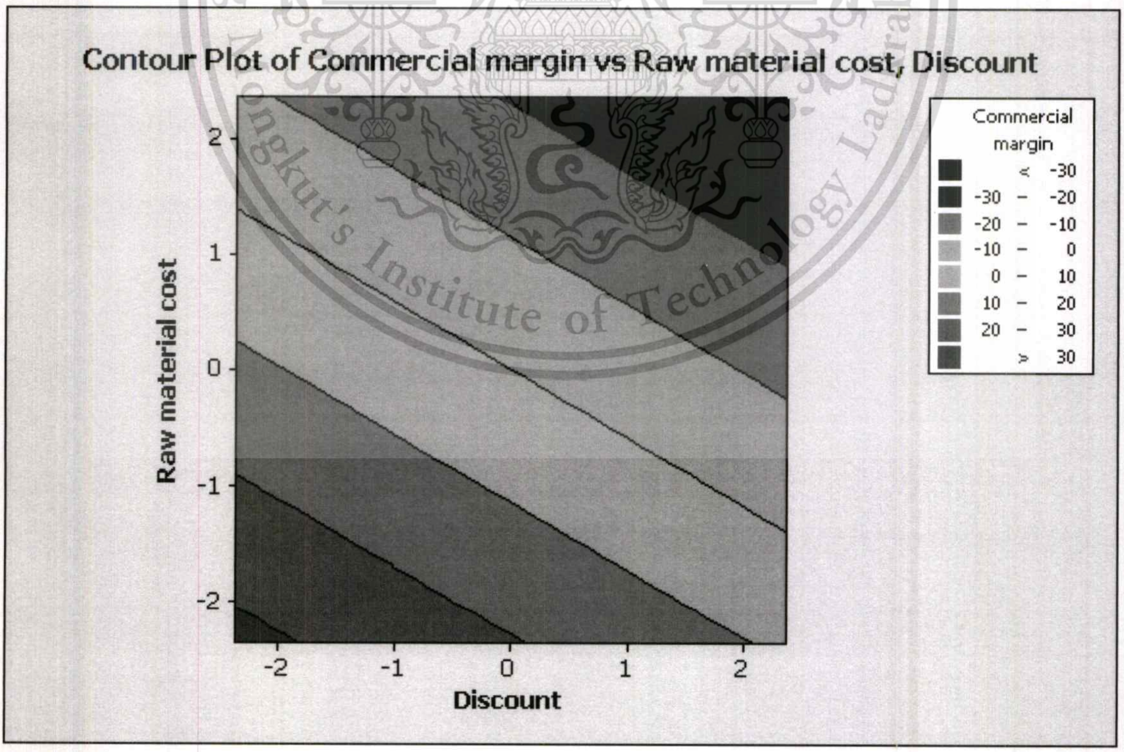

Figure E18 Contour plot of CM & raw material cost, discount

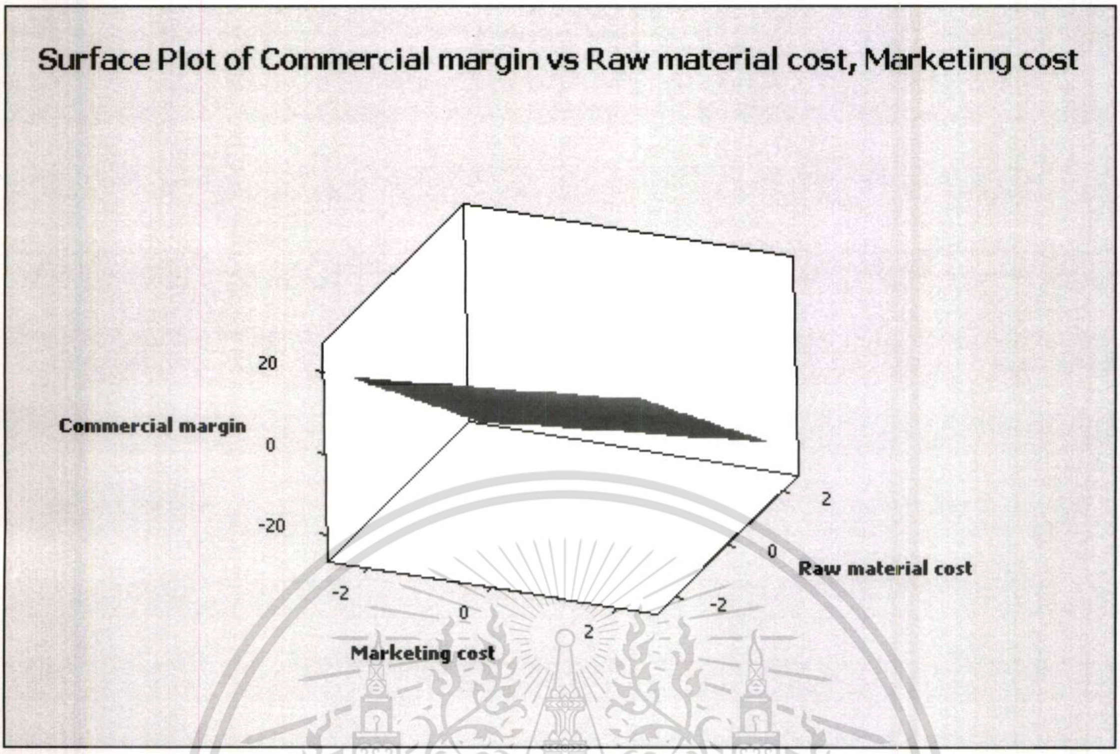

Figure E19 Surface plot of CM & raw material cost, marketing cost

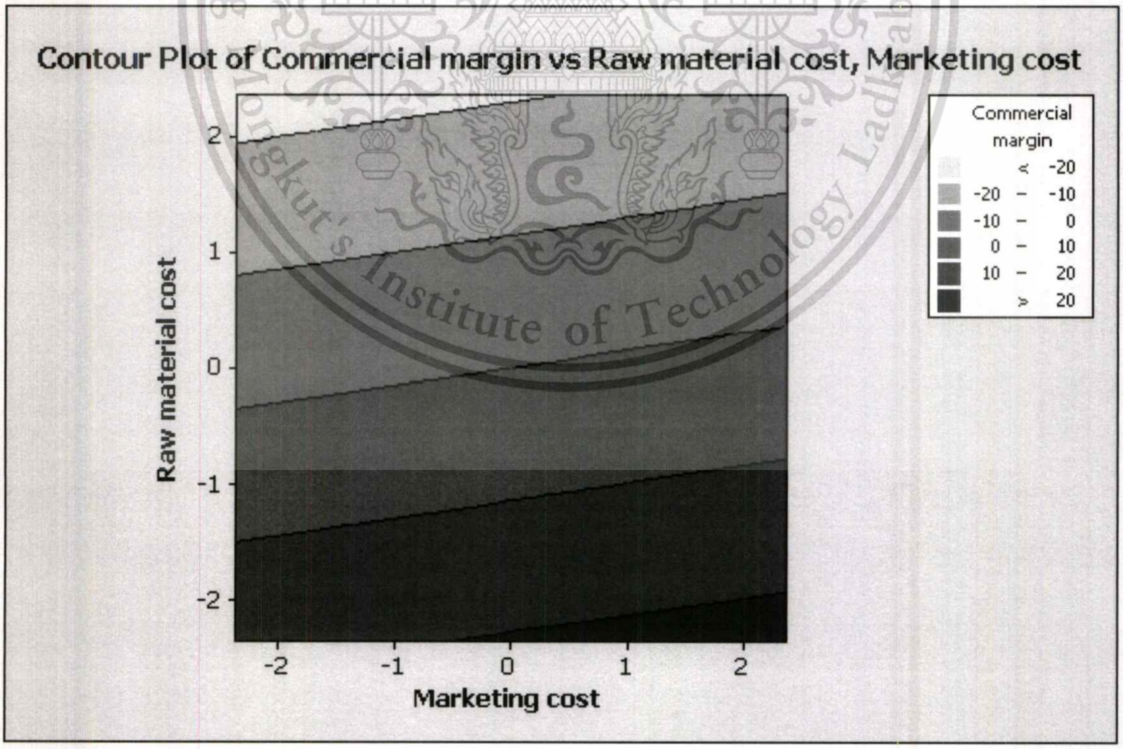

Figure E20 Contour plot of CM & raw material cost, marketing cost

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