Chapter 3

Research Design and Methods

The pockets of anecdotes and theories are indicative but inadequate in integrating the concept of lean for applying in stochastic environments. The research study aims to extend the understanding in the roles of lean concept on a case study. From the questions in this research, this Chapter explains a detail of research.

This research is called a lean enterprise transformation project by employing several tools comprise IDEF0, MCDM, VNM, Cobacabana, simulation, hybrid algorithm (Wanitwattanakosol and Sopadang, 2012). Chapters 4 to 6 of this thesis are based on individual research papers which have been published or submitted for publication in various scholarly journals and the proceeding conferences. They are introduced and concluded in such a way that they can also be read and understood independently of each other.

3.1 A Lean Roadmap

Chapter 4, based on the paper "*A performance improvement tool for Thai MTO manufacturing*" (Wanitwattanakosol et al., 2012), was a starting point to apply lean tools. In-depth interview with experts and practitioners of the case study was provided useful information. IDEF0 was exploited to explore activities and relate of components in business process. The empirical study was evaluated to suit for using the finalized SHEN (This name is used parts of the pioneers' name: SHaladdin and HEndry) model as a performance improvement benchmark.

First of all in-depth interview was done with selected persons to establish a process modeling, IDEF0. This method was very useful to capture activities and explore the relationship between components. The validity of the model was endorsed by a manager of the case study. Next, the final version of SHEN model was formed as a questionnaire for collecting data from the case study (see Appendix A). Almost principles were selected, except principle no.12 (Promote/market/sell every improvement) because qualified persons did not stay in touch about the field of sales and marketing. This research used a five-point Likert item which is a popular format of questionnaires (Burns and Bush, 2007). A typical five-level format is strongly disagree (1), disagree (2), neither agree or disagree (3), agree (4) and strongly agree (5), respectively, as depicted in Figure 3.1.

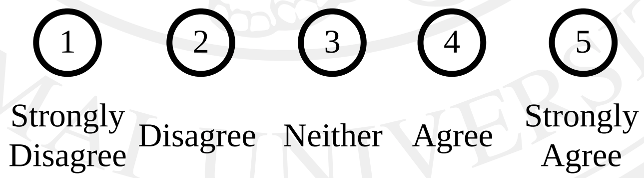

Figure 3.1 Scale used in Likert scale questions

A structure equation model (SEM) was set to imply a structure for the covariance between latent variables (factors). It is still practical to start the SEM analysis by drawing a path diagram. The path diagram comprised boxes and circles that are connected them by arrows. Observed variables are exhibited by a rectangular or square box and latent factors by a circle or ellipse. Single headed arrows are employed to identify causal relationship with the variable at the tail of the arrow causing the variable at the point in the model. Double headed arrows denote covariance or correlation without a causal interpretation. The SEM is a convenient framework for statistical analysis that includes several traditional multivariate procedures. It can combine factor analysis and regression analysis (Hox and Bechger, 1998).

Factor analysis is a statistical tool for grouping the variables by using covariance between a set of variables that cause variation and covariation among observed variables. It has two types: exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA attempts to discern a nature of the constructs influencing a set of responses. The primary objectives are to determine a number of common factors influencing a set of measures. In addition, strength of the relationship between each factor and each observed measure. While CFA examines whether a specified set of constructs is influencing responses in a predicted way. The primary objective of a CFA is to determine an ability of a predefined factor model to fit an observed set of data. Table 3.1 provides differences between EFA and CFA.

Table 3.1 Exploratory factor analysis versus confirmatory factor analysis

Exploratory factor analysis	**Confirmatory factor analysis**
Heuristic-weak literature base	Strong theory and/or strong empirical base
Determine the number of factor	Number of factors fixed a priori
Determine whether the factors are correlated or uncorrelated	Factors fixed a priori as correlated or uncorrelated
Variables free to load on all factors	Variables fixed to load on a specific factor(s)

Source: Adapted from (Stevens, 1996)

The scores from questionnaire in this research were analyzed from CFA that was conducted to clearly identify a structure of the SHEN model. Validity and reliability were two concepts in the testing method. They are fundamental measure between different variables that force to correlation. Validity is defined as an ability of the test to produce results consistent with other measures of the same characteristic. It is a study instrument to measure the systematic error inherent. Validity measures the correlation of the test. Validity assessment of questionnaires is a previously tool which requires definition of the scope carefully (Karras, 1997a). There are four concepts of validity, namely, face validity, content validity, criterion validity and construct validity (Burton and Mazerolle, 2011). Table 3.2 summarizes the meanings and aim of the terms for all concepts.

Table 3.2 Definition and aim of validity

Validity type	Definition	Aim
Face	Evaluates an instrument's appearance by a group of experts and/or potential participants.	Establishes an instrument's ease of use, clarity and readability.
Content	Evaluates an instrument's representativeness of the topic to be studied by a group of experts.	Establishes an instrument's credibility, accuracy, relevance and breadth of knowledge regarding the domain.
Criterion	Evaluates an instrument's correlation to another which is deemed unquestionable or identified as the gold standard.	Establishes an instrument's selection over another or establishing the predictability of the measure for a future criterion.
Construct	Evaluates an instrument's ability to relate to other variables or the degree to which it follows a pattern predicted by a theory.	Establishes an instrument's ability to evaluate the construct it was developed to measure.

Reliability is also known precision of a test and refers to an indicator of the amount of variability (Karras, 1997b). Reliability assessment has several methods to measure. They have some unique strength and weakness for each method that should be considered before applying. Summary of each method for assessing reliability is shown in Table 3.3 (O'Leary-Kelly and Vokurka, 1998). Validity and reliability were analyzed of each factor by using factor loading and Cronbach's alpha.

Table 3.3 Summary of each method for assessing reliability

Reliability method	**Feature**	**Advantage**	**Disadvantage**
Test–retest	It concern measuring at two different points in time (e.g., t and t+1) which using the same of scale and sample group.	Straightforward, intuitively appealing and measure with single indicators.	Variables are not stable over time. Effects of memory, learning and reactivity confound in assessing reliability.
Alternative forms	It is technique for reliability estimation. It involves two different measures at time t and another time at time t+1.	Minimizes effect of memory and measure with single indicators.	Variables are not stable over time. Effect of learning and reactivity confound in assessing reliability. Require to develop two unique measures.
Cronbach's coefficient	It is one of the popular methods to reliability assessment. It is base on correlation of indicators which range from 0 to 1.	Multiple indicators, increasing the number of indicators may be improve measure of reliability.	Measurement requires multiple indicators.
WLJ composite reliability	It employs CFA to derive a composite reliability index. It base on proportion of variance attributable to only the latent variable which range from 0 to 1.	Congeneric measures are the least limiting. Multiple indicators are straight of test assumption of congeneric measures by provide capability.	Reliability of measures is underestimates that are not congeneric. Measurement requires multiple indicators.

The statistical part was calculated by utilizing a computer commercial software package MINITAB® 15. Nevertheless, it is useful to understand a basic concept of factor loading and Cronbach's alpha, respectively. CFA has used many notations to compute factor loading as follows. ξ_i represents latent variables or common factors and x_i represents observed variables. A factor can locate to more than one observed variables. The two ξ_i are expected to covary, as signified by ϕ_{ij} on a double headed arrow. δ_i represent unique factors because they affect only a single observed variable. δ_i incorporate all the variance in each x_i such as measurement error. Finally, factor loadings are represented by λ_{ij} and a square factor loading is referred to a communality representing the proportion of variance in the i^{th} observed variable that is explained by the j^{th} latent variable (Brown, 2006). All notations are summarized in Table 3.4.

Table 3.4 Confirmatory factor analysis notations

Symbol	**Matrix form**	**Explanation**
ξ		Latent variable
x	X	Observed variable
λ	Λ	Factor loading
ϕ	Φ	Factor variance and covariance
δ	Θ_δ	Error variance and covariance

Source: Adapted from (Albright and Park, 2009)

When observed and latent variables are mean centered to have derivations from their mean, a CFA equation can be displayed by

$$X = \Lambda\xi + \delta \tag{3.1}$$

It is supposed that the error terms have a mean of zero, E(ξ) = 0 and that the common and unique factors are uncorrelated, E($\xi\delta'$) = 0.

When the x variables are measured as deviations from their means, it is easy to demonstrate that the sample covariance matrix for x can be decomposed as

$$\Sigma = \Lambda\Phi\Lambda' + \Theta \tag{3.2}$$

Where Φ represents the covariance matrix of the ξ factors and Θ represents the covariance matrix of the unique factors δ (Bollen, 1989). Estimation proceeds by finding the parameters $\hat{\Lambda}$, $\hat{\Phi}$ and $\hat{\Theta}$ so that predicted x covariance matrix Σ is as close to the sample covariance matrix as possible. The value of factor loading of each observed variable should be positive or negative (close to +1 or -1). It should be more than 0.300 to accept internal validity (Carr and Smeltzer, 1999).

Cronbach's alpha is reliability coefficient which is commonly used as a measure of internal consistency or reliability of a test score for a sample of examinees in the social sciences, business, nursing and other fields (Revelle and Zinbarg, 2009). It is defined as

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K}\sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{3.3}$$

where K is the number of components, σ_X^2 is the variance of the observed total test scores and $\sigma_{Y_j}^2$ represents the variance of component i for the current sample of persons. Its reliability value of each observed component might be more than 0.700 to accept internal validity which is measured from reliability Cronbach's alpha. If reliability Cronbach's alpha value more than 0.700, the internal factors have strong relationship to each other. Anyway, if reliability Cronbach's alpha value between

0.400 – 0.700, the internal factors have moderate relationship (Humphreys et al., 2004).

Finally, a scree test was used to classify the optimum number of factors satisfactory. It could be extracted prior the amount of unique variance begins to dominate the common variance structure. This test was derived by plotting the latent roots against the number of factors in their order of extraction and the shape of the resulting curve was used to evaluate the cutoff point (Hair et al., 2005).

3.2 Supplier Selection

Chapter 5, based on the paper "*Fuzzy stochastic analytical hierarchy process for selecting a material supplier in small and medium enterprises paradigm*" (Wanitwattanakosol and Sopadang, 2010) and "*Selection of material supplier in job shop environments: The extent analysis on fuzzy stochastic AHP*" (Wanitwattanakosol and Sopadang, 2010), related to the two tools mentioned above. Once the supplier becomes part of a well-managed, an effective and efficient system to select the suitable supplier plays a vital role in the business success. However, the selection of a suitable partner is not an easy decision and is associated with uncertainty and complexity. Material supplier was selected as a case-based approach. Two types of fuzzy stochastic AHP were compared and evaluated results through an illustrative example. The proposed methodology allowed for the selection of alternative suppliers in six steps as shown in Figure 3.2.

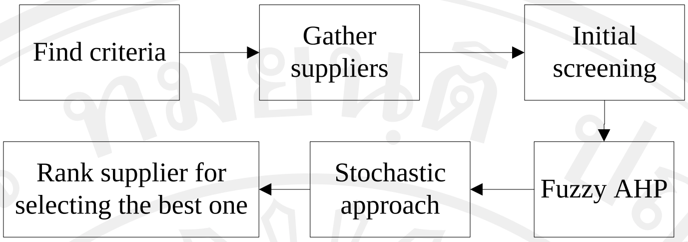

Figure 3.2 Procedure diagram of fuzzy stochastic AHP

A first step was to find relevant criteria, which had been widely discussed in the literature, especially for selection of material suppliers. In step two, the company identified the potential suppliers who should be harmonized of the business strategy of the company and its vision for future cooperation. Usually eight to ten providers might be considered for the initial appraisal.

An initial screening of the supplier was used in the next step. A noncompensatory technique was exploited to directly screen from the criteria. The noncompensatory technique is the stepwise reduction of the set of alternatives without trading off their deficiencies along some evaluation criteria for their strengths along other criteria (Jankowski, 1995). The conjunctive constraint method, is classified as the noncompensatory technique, was applied in this step where,

The conjunctive constraint method: every criterion has a minimum cut-off value specified by the DM. Those alternatives that failed a cut-off value on any of the evaluation criteria were eliminated**.** Choice sets formed by a conjunctive decision rule required that an alternative be acceptable on all relevant criteria for it to be included, thus

$$\text{Conjunctive Rule: } \prod_m I\left(x_{jm} > y_m\right) = 1 \qquad (3.4)$$

where x_{jm} is the level of criteria m for choice alternative j. The cut-off value, y_m, is the smallest level of the attribute that needs to be present for the DM. I equals one if the decision rule is satisfied and equals zero otherwise.

In step four, two types of defuzzification AHP approaches were employed which comprised a normalized method and an extent analysis method. Both method started from a hierarchy construction. Then, a fuzzy judgment matrix $\tilde{A}$ was built with all fuzzy judgment vectors. A weight vector $\tilde{W}$ was used to represent the DM's opinion on the relative importance of each criterion during the decision process. Fuzzy numbers ultimately needed to be interpreted for the criteria and alternatives. A defuzzification or ranking process had to be applied. A fuzzy number was defined by three parameters of the symmetric triangular fuzzy number $a_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ as previous explained in section 2.3. This research used linguistic important weight and rating as depicted in Table 3.5. Thus, a comparison $\tilde{A}$ where a_{ij} is a relative estimation of $\tilde{W}_i / \tilde{W}_j$

Table 3.5 TFNs of linguistic terms for the importance weights and ratings

Importance weights	Rated of suppliers	TFNs
Equally important (EI)	Very poor (VP)	(1/2, 1, 3/2)
Weakly more important (WMI)	Poor (P)	(1, 3/2, 2)
Strongly more important (SMI)	Fair (F)	(3/2, 2, 5/2)
Very strongly more important (VSMI)	Good (G)	(2, 5/2, 3)
Absolutely more important (AMI)	Very good (VG)	(5/2, 3, 7/2)

$$\tilde{A} = \begin{bmatrix} \tilde{W}_1/\tilde{W}_2 & \dots & \tilde{W}_n/\tilde{W}_1 \\ \tilde{W}_1/\tilde{W}_2 & \dots & \tilde{W}_n/\tilde{W}_2 \\ \tilde{W}_n/\tilde{W}_1 & \dots & \tilde{W}_n/\tilde{W}_n \end{bmatrix} \tag{3.5}$$

which $a_{ij} = \frac{1}{a_{ij}}$ and $\tilde{A}$ is a reciprocal matrix

On the one hand, the classical method was applied to calculate the relative importance of each pair of factors in the same hierarchy. An Equation 3.6 was used to estimate a fuzzy eigen vector from $\tilde{A}$

$$V_i = \left[\sum_{j=1}^{m} \left[\tilde{A}_i^j \otimes \left[\sum_{i=1}^{n} \tilde{A}_i^j \right]^{-1} \right] \right] / m \qquad (3.6)$$

or

$$V_i = \left[\sum_{j=1}^{m} \left[\left(l_j, m_j, u_j \right) \otimes \left[\sum_{i=1}^{n} \left(l_j, m_j, u_j \right) \right]^{-1} \right] \right] / m \qquad (3.7)$$

As the classical AHP methodology, eigenvector was to be normalized by

$$W_i = \left(\frac{V_u + V_{mi} + V_{ui}}{3} \right) \Big/ \sum_{i=1}^{m} W_i \qquad (3.8)$$

The $\lambda_{\max}$ value was used as a reference index to screen information for a consistency ratio (CR) calculation of the estimated vector. The acceptable CR range differed according to the matrix size such as 0.05 for a 3x3 matrix, 0.08 for a 4x4 matrix and 0.1 for all larger matrices. If the CR is equal or less than that value, it means that the assessment within the matrix is acceptable (Noorul Haq and Kannan, 2006). The consistency ratio was calculated by the following equation

$$CR = \frac{Concistency\ Index}{Random\ Concistency\ Index} \qquad (3.9)$$

The consistency index (CI) was expressed by

$$CI = \frac{\lambda_{\max - n}}{n-1} \qquad (3.10)$$

where

$$\lambda_{\max} = \frac{Z_{ii} + Z_{mi} + Z_{ui}}{3} \qquad (3.11)$$

which $$Z_i = \left(\sum_{i=1}^{n} \frac{T_i}{W_i} \right) / n \quad (3.12)$$

and $$T_i = \sum_{j=1}^{m} W_i^T \otimes \tilde{A}_i^j \quad (3.13)$$

Random consistency index (RI) was elaborated by Saaty which is stated in Table 3.6.

Table 3.6 Random consistency index based on matrix size

N	1	2	3	4	5	6	7	8	9	10
RCI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

On the other hand, the extent analysis method on fuzzy AHP was also used. The extent analysis method on fuzzy AHP was presented by Chang (1996). This method can describe as below.

Let $X = \{x_{1,} x_2, ..., x_n\}$ be an object set and $U = \{u_1, u_2, ..., u_n\}$ be a goal set. Therefore, m extent analysis values for each object could be obtained, with the following signs

$$M_i^1, M_i^2, ..., M_i^m, \qquad i = 1, 2, ..., n \quad (3.14)$$

where all the $M_i^j \left(j = 1, 2, ..., m \right)$ are triangular fuzzy numbers. The value of fuzzy synthetic extent with respect to the ith object is defined as

$$S_i = \sum_{j=1}^{m} M_i^j \otimes \left[\sum_{i=1}^{n} \sum_{j=1}^{m} M_i^j \right]^{-1} \quad (3.15)$$

where $$\sum_{j=1}^{m} M_i^j = \left(\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right) \quad (3.16)$$

and
$$\left[\sum_{i=1}^{n}\sum_{j=1}^{m}M_i^j\right]^{-1} = \left(\frac{1}{\sum_{i=1}^{n}u_j}, \frac{1}{\sum_{i=1}^{n}m_j}, \frac{1}{\sum_{i=1}^{n}l_j}\right) \tag{3.17}$$

The degree of possibility of $M_1 \geq M_2$ is defined as:

$$V\left(M_1 \geq M_2\right) = \sup_{x \geq y}\left[\min\left(\mu_{M_1}(x), \mu_{M_2}(y)\right)\right] \tag{3.18}$$

When a pair (x, y) exists such that $x \geq y$ and $\mu_{M_1}(x) = \mu_{M_2}(y) = 1$, hence $V\left(M_1 \geq M_2\right) = 1$ Since both M_1 and M_2 are convex fuzzy numbers,

$$V\left(M_1 \geq M_2\right) = 1 \qquad \text{iff} \qquad m_1 \geq m_2,$$

$$V\left(M_2 \geq M_1\right) = hgt\left(M_1 \cap M_2\right) = \mu_{M_1}(d) \tag{3.19}$$

where d is an ordinate of the highest intersection point D between μ_{M_1} and μ_{M_2} (see Figure 3.3).

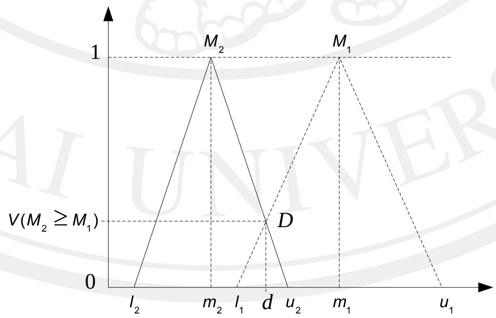

Figure 3.3 An intersection between M_1 and M_2

When $M_1 = (l_1, m_1, n_1)$ and $M_2 = (l_2, m_2, n_2)$, the ordinate of D is given by

$$V\left(M_2 \geq M_1\right) = hgt\left(M_1 \cap M_2\right) = \frac{l_1 - u_2}{(m_2 - u_2) - (m_1 - l_1)} \tag{3.20}$$

It should be note that the values of $V\left(M_1 \geq M_2\right)$ and $V\left(M_2 \geq M_1\right)$ are needed to compare M_1 and M_2.

The degree possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $M_i\left(i=1,2,\ldots,k\right)$ can be assigned by

$$V\left(M \geq M_1, M_2, \ldots, M_k\right) = V\left[\left(M \geq M_1\right) and \left(M \geq M_2\right) and \ldots and \left(M \geq M_k\right)\right]$$

$$= \min V\left(M \geq M_i\right), \qquad i = 1,2,\ldots,k. \tag{3.21}$$

Assume that

$$d'\left(A_i\right) = \min V\left(S_i \geq S_k\right) \tag{3.22}$$

for $k = 1,2,\ldots,n; k \neq i$ Then the weight vector is given by

$$W' = \left(d\left(A_1\right), d\left(A_2\right), \ldots, d\left(A_n\right)\right)^T \tag{3.23}$$

where $A_i\left(i=1,2,\ldots,n\right)$ are n elements.

Via normalization, the normalized weight vectors are

$$W = \left(d\left(A_1\right), d\left(A_2\right), \ldots, d\left(A_n\right)\right)^T \tag{3.24}$$

where W is a nonfuzzy number.

Each pairwise comparison judgment was then translated into the corresponding largest eigenvalue problem and was solved to find the normalized and unique priority weights. Figure 3.4 illustrates a schematic diagram for step 4.

Figure 3.4 Overview of fuzzy AHP treatment

A procedure of step five and six is depicted in Figure 3.5. A fuzzy stochastic AHP calculated local relative weights variances accounting for judgmental errors resulting from inconsistent pairwise comparisons (see section 2.3).

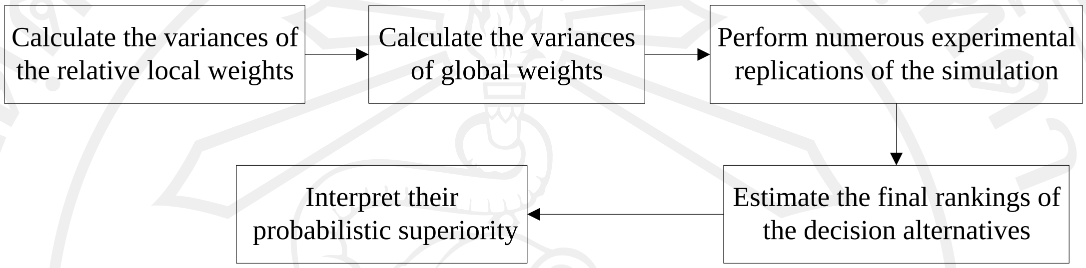

Figure 3.5 Overview of a stochastic approach

Next, variances of the global relative weights were calculated by employing the local weights and their variances. A simple decision problem (with a three layers comprised three criteria and three alternatives) was used to demonstrate as shown in Figure 3.6.

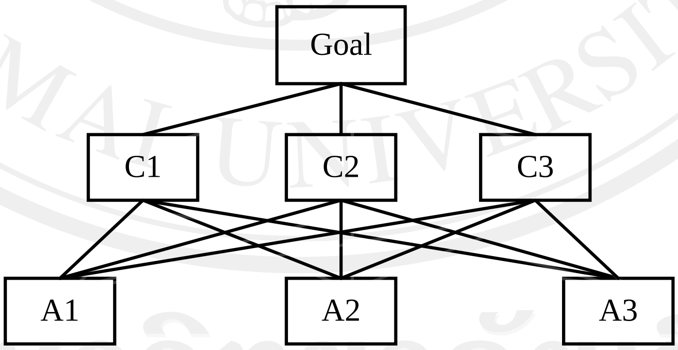

Figure 3.6 A simple decision problem

From the hierarchy, the relative weights were represented in a matrix form as

$$\begin{matrix} W_{1,3}^{1,1} \\ W_{2,3}^{1,1} \\ W_{3,3}^{1,1} \end{matrix} = \begin{bmatrix} W_{1,3}^{1,2} & W_{1,3}^{2,2} & W_{1,3}^{3,2} \\ W_{2,3}^{1,2} & W_{2,3}^{2,2} & W_{2,3}^{3,2} \\ W_{3,3}^{1,2} & W_{3,3}^{2,2} & W_{3,3}^{3,2} \end{bmatrix} \begin{bmatrix} W_{1,2}^{1,1} \\ W_{2,2}^{1,1} \\ W_{3,2}^{1,1} \end{bmatrix} \tag{3.25}$$

where $W_{i.j}^{k,l}$ states relative weights of element i at layer j with respect to element k at layer l.

Each variance of the global weight was calculated by an obtained matrix equation

$$\begin{bmatrix} \left(\sigma_{1,3}^{1,1}\right)^2 \\ \left(\sigma_{2,3}^{1,1}\right)^2 \\ \left(\sigma_{3,3}^{1,1}\right)^2 \end{bmatrix} = \begin{bmatrix} \left(W_{1,3}^{1,2}\right)^2 & \left(W_{1,3}^{2,2}\right)^2 & \left(W_{1,3}^{3,2}\right)^2 \\ \left(W_{2,3}^{1,2}\right)^2 & \left(W_{2,3}^{2,2}\right)^2 & \left(W_{2,3}^{3,2}\right)^2 \\ \left(W_{3,3}^{1,2}\right)^2 & \left(W_{3,3}^{2,2}\right)^2 & \left(W_{3,3}^{3,2}\right)^2 \end{bmatrix} \begin{bmatrix} \left(\sigma_{1,2}^{1,1}\right)^2 \\ \left(\sigma_{2,2}^{1,1}\right)^2 \\ \left(\sigma_{3,2}^{1,1}\right)^2 \end{bmatrix} +$$

$$\begin{bmatrix} \left(\sigma_{1,3}^{1,2}\right)^2 & \left(\sigma_{1,3}^{2,2}\right)^2 & \left(\sigma_{1,3}^{3,2}\right)^2 \\ \left(\sigma_{2,3}^{1,2}\right)^2 & \left(\sigma_{2,3}^{2,2}\right)^2 & \left(\sigma_{2,3}^{3,2}\right)^2 \\ \left(\sigma_{3,3}^{1,2}\right)^2 & \left(\sigma_{3,3}^{2,2}\right)^2 & \left(\sigma_{3,3}^{3,2}\right)^2 \end{bmatrix} \begin{bmatrix} \left(W_{1,2}^{1,1}\right)^2 \\ \left(W_{2,2}^{1,1}\right)^2 \\ \left(W_{3,2}^{1,1}\right)^2 \end{bmatrix} + \tag{3.26}$$

$$\begin{bmatrix} \left(\sigma_{1,3}^{1,2}\right)^2 & \left(\sigma_{1,3}^{2,2}\right)^2 & \left(\sigma_{1,3}^{3,2}\right)^2 \\ \left(\sigma_{2,3}^{1,2}\right)^2 & \left(\sigma_{2,3}^{2,2}\right)^2 & \left(\sigma_{2,3}^{3,2}\right)^2 \\ \left(\sigma_{3,3}^{1,2}\right)^2 & \left(\sigma_{3,3}^{2,2}\right)^2 & \left(\sigma_{3,3}^{3,2}\right)^2 \end{bmatrix} \begin{bmatrix} \left(\sigma_{1,2}^{1,1}\right)^2 \\ \left(\sigma_{2,2}^{1,1}\right)^2 \\ \left(\sigma_{3,2}^{1,1}\right)^2 \end{bmatrix} +$$

where $\sigma_{i,j}^{k,l}$ denotes standard deviation of element i at layer j with respect to element k at layer l.

Utilizing the global AHP weights and their corresponding estimated variances, Monte Carlo simulation was employed for handling the related uncertainty in the global AHP weights. This simulation approach is a powerful and practical tool to observe whether the differences among alternatives are statistically significant or not.

Monte Carlo simulation was implemented as follows. The global weights of decision alternatives were found as random variables. Each alternative had a specified range of global weight due to judgmental error. The simulation replications were obtained by generating these random global weights variables at numerous times. The decision alternatives ranking was documented. Final rankings of the decision alternatives were estimate with obtained 95% confidence interval (C.I.) of the global weights. Aggregated results of the rankings were employed to obtain the probabilistic interpretation of final rankings of alternatives and to test whether or not there were statistically significant differences among alternatives. This type of analysis provided more information for the DM to make more precise discriminations among competing alternatives (Wanitwattanakosol et al., 2010). Finally, each method was compared results.

3.3 A Hybrid Algorithm for Cobacabana

Chapter 6 is based on the Cobacabana which works under the WLC concept. This research comprised three phases as shown in Figure 3.7. The various steps were described below.

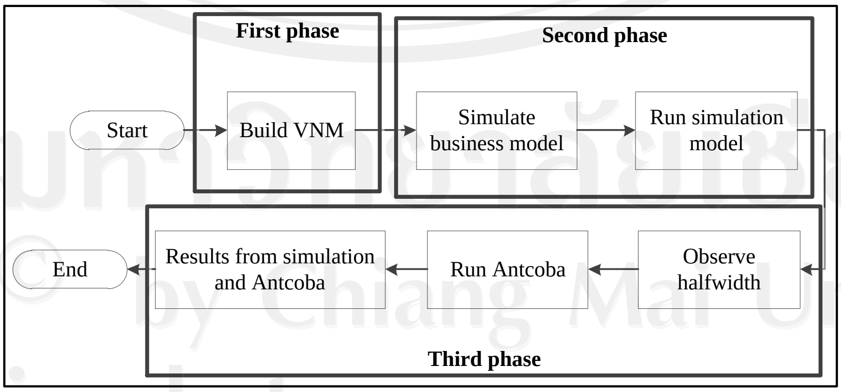

Figure 3.7 An overview of the hybrid algorithm for Cobacabana

A first phase presented VNM for supporting data in order entry level of WLC as shown in Figure 3.8. All necessary data were clearly shown for production planner in order to prepare for performing an analysis in order release phase (Sopadang et al., 2012).

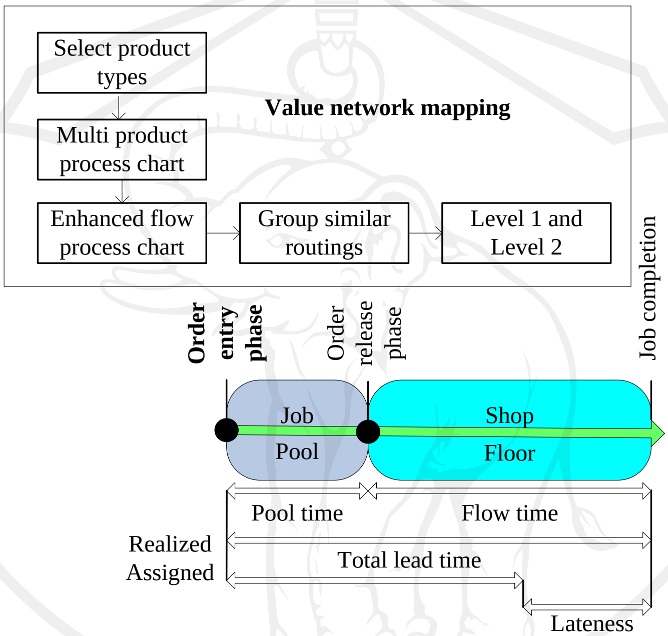

Figure 3.8 A schematic diagram of the first phase

A first step was to select product types by using a combination of a product quantity analysis (PQ analysis) and a product cost analysis (PC analysis). The PQ analysis is a powerful tool for product mix segmentation which is used to display the product mix in the form of a Pareto chart. An essential logic was that high product quantities were accountable for the largest part of non value-added actions. Consequently, focusing on a high-volume value stream should increase the company's overall performances. Moreover, the PC analysis sorted the product types in order to decrease cost. Hence, the two Pareto analyzed combination represents to the classification of nine distinct products ranging from AA (superior grade) to CC (inferior grade).

At step two and two, the MPPC, that brought all items together on one sheet of paper, was adopted to implement into a second step. Across the top were arranged the various products or items involved at a separate column. It listed down from the left side of a sheet and displays the product's operations. In addition, it was easy to make comparison the product flow paths. For step three, the enhanced FPC was applied to collect necessary data as previously explained in section 2.4.

In step four, data were collected and observed for grouping product families on the basis of the pair-wise similarity coefficients (PWSC) which was obtained by the "Jaccard" similarity function as below

$$S_{ij} = \frac{X_{ij} + \sqrt{X_{ij} \bullet Y_{ij}}}{X_{ij} + A_i + B_j + \sqrt{X_{ij} \bullet Y_{ij}}} \tag{3.27}$$

where, $0 \le S_{ij} \le 1, X_{ij}$ = number of machines used by both part 'i' and part 'j' (number of matches), A_i = number of machines used by part 'i' only, B_j = number of machines used by part 'j' only and Y_{ij} = number of machines that are used neither by part 'i' nor by part 'j' (number of misses).

The level 1 (product family) and level 2 (component family) were drawn in the final step. These maps of VNM stated the material handling information associated with every flow of parts on any machines.

Next, an application of the Cobacabana was evaluated via simulation study in the second phase. Cobacabana was chosen with the aim of providing an example of practice and also to test the proposition via a discrete event simulation. The model was kept as simple as possible to avoid any noise that affects the results.

The simulation model was developed using the simulation commercial software ARENA 11.0 (Kelton et al., 2007). It should be noted that the proposed structural models had been extensively developed previously from Patrick et al. (2008). The simulation comprised six sub-models: the entry level, release level, dispatching level, production level, statistics and chart, as illustrated in Figure 3.9.

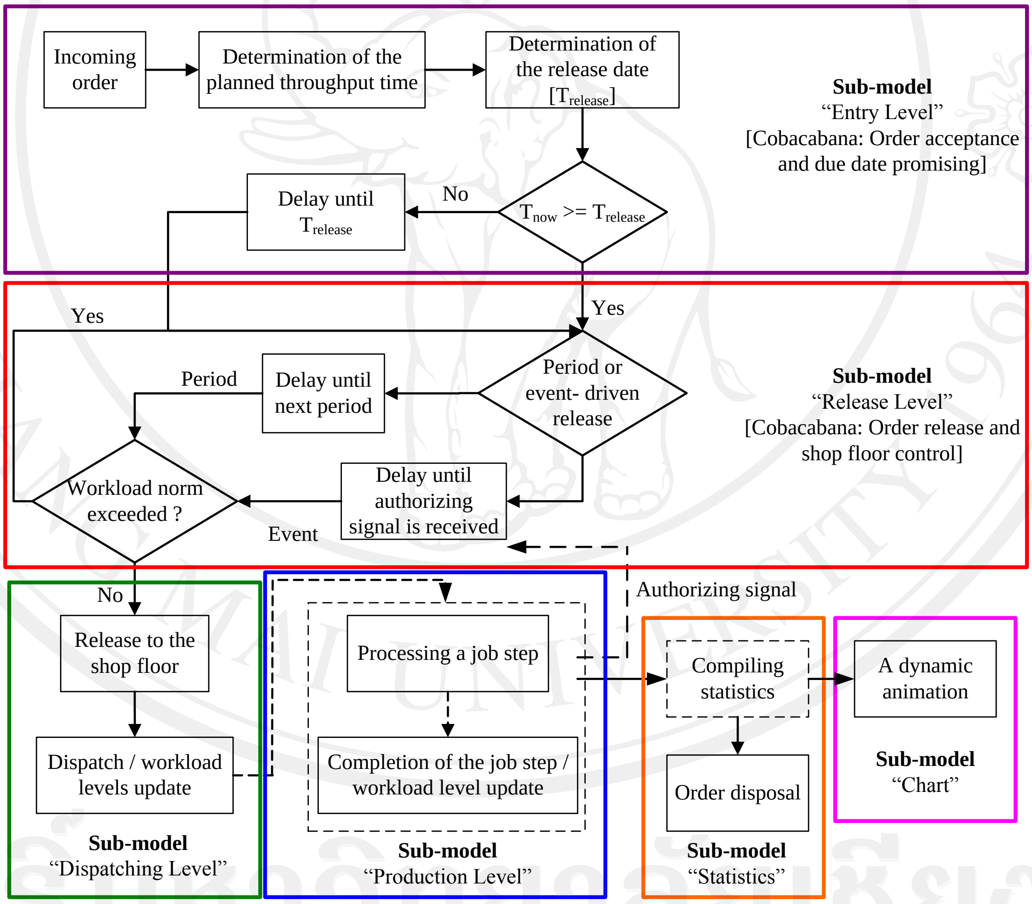

Figure 3.9 Algorithm of the simulation model

In the entry level sub-model, each new order determines the release date at the order pool. When the planned release date of order threatens to be late, it is immediately released to the shop floor. On the other hand, the unreleased orders are preserved in the job pool until a period signal and an event signal are given which are sent from the production sub-model.

The period signal is time-limit based and the release mode is activated in predefined intervals. The event signal analyses current shop floor capacities. Both signals are sent to the pool with respect to the current values of adjustment aggregate workload at each workstation. If the condition of workload norm is not exceeded, the qualified orders are released to the dispatching level sub-model. The direct and indirect loads for each released order are updated according to the sequence. Otherwise, the order has to wait until the next release procedure.

The production sub-model is employed not only to calculate workload orders but also to send an authorizing signal of the event driven. In addition, this sub-model is performed to compute the contribution cards of Cobacabana. The statistical sub-model is designed to collect statistical data during the experiments. Finally, the chart sub-model shows a dynamic animation of parameters of interest, such as the lead time, throughput time and Cobacabana display.

When a simulation model is built, verification is concerned with ensuring that an error-free computer program has been used. It is known as debugging the model. This study adopted a structured walkthrough technique to verify the simulation model. Event validity and internal validity of the model were used in determining model validity. If the simulated results were compared with existing systems output data to determine similarity, then the simulation model had event validity (Law, 2008). Several replications were needed to determine the amount of stochastic variability in the simulation model for internal validity (Sargent, 2008).

The hybrid algorithm was used to find value parameters for Cobacabana system in the third phase. ACO was employed for the hybrid algorithm to improve the computational time by dealing with a model parameter identification issue for minimizing an objective function as

$$g(\phi) = \frac{\sum_{i=1}^{n} T_i^l}{n} \tag{3.28}$$

s.t. $$d(\phi) = \delta_i / \left(\delta_i - \left(\gamma_i + \vartheta_i\right)\right) \tag{3.29}$$

where g is the objective function, ϕ is the vector of input parameters, n is a number of jobs, T_i^l is the lead time which comprises of T_i^p is the pool time and T_i^f is the floor time, d is the constraint function δ_i is the due date, γ_i is the tardy delivery date and ϑ_i is the early delivery date.

Beside, we had to add a case study constraint that the delivery reliability had to greater than or equal to 67.57 % as

$$d(\phi) \geq 0.6757 \tag{3.30}$$

The complete algorithm, which was elaborated by MATLAB® 7.12.0.635 (R2011a), was exhibited as below.

Algorithm Antcoba

Step 1 form an initial pheromone trails by set $\tau_{ij} = 1 \times 10^{-4}$ and set all parameters.

Step 2 place m ants to the complete parameter space.

Step 3 generate construction steps. Each ant k choose a probabilistic action choice rule to decide which stratum to visit next as

$$p_{ij}^{k}=\frac{\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}}{\sum l\in N_{i}^{k}\left[\tau_{ij}\right]^{\alpha}\left[\eta_{ij}\right]^{\beta}},ifj\in N_{i}^{k} \tag{3.31}$$

where η_{ij} is a heuristic value that is adopted from simulated delivery reliability values, α and β are two parameters which determine the relative influence of the pheromone trail and the heuristic information and N_i^k is the feasible neighborhood of ant.

Step 4 update pheromones after all ants have constructed their path. This is done by lowering the pheromone value on all paths by a constant factor and adding pheromone on the paths that ants have moved in their paths as

$$\tau_{ij}\leftarrow\left(1-\rho\right)\tau_{ij}+\sum_{k=1}^{m}\Delta\tau_{ij}^{k},\forall\left(i,j\right)\in L \tag{3.32}$$

where $o<\rho\leq 1$ is the pheromone evaporation rate, $\Delta\tau_{ij}^{k}$ is the amount of pheromone ant k deposits on the paths it has visited. It is defined as follows

$$\tau_{ij}^{k}=\begin{cases}\dfrac{1}{C^{k}}, if\ \ path(i,j) belongs\ to\ T^{k}\\ 0, otherwise\end{cases} \tag{3.33}$$

where C^k is adopted from simulated lead time values in the path T^k.

When applying ACO to combinatorial optimization problems, a first step is the definition of the construction graph. However, it was no explicit path in this problem. Thus, a discretization of a search space was applied to build up a path and a route for solving this problem. The objective of ACO was to find the state of the interval $\left[\phi_i^-,\phi_i^+\right]$ of each parameter c into a number, S_i, of strata. There will be $S=s_1,s_2,...,s_b$ permutations or feasible pathways through the space of input parameters. Let $\phi_{ij}\left(i=1,...,b \text{ and } j=1,...,m\right)$ be the stratum j of parameter ϕ_i in the search space.

The discretization scheme of this research is depicted in Figure 3.10 for two parameters (workload norms and release period lengths), with each parameter period $\left[\phi_i^-,\phi_i^+\right]$ divided into ten strata. There were no hard rules for selecting the parameter stratification, except that primarily they should uniformly enclose the complete parameter space. Abbaspour et al. (2001) suggested that a number of random subset $\geq 0.1S$ generally leads to optimum solutions. Hence, each ant must trail only one path as the constraint of ACO. A path-structure list was shown also in Figure 3.10.

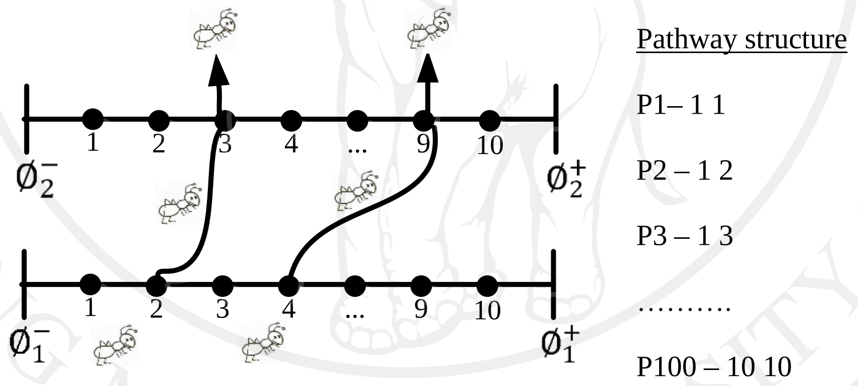

Figure 3.10 Graphical representation of parameter space

Next, the ARENA was run with all parameters values of workload ratio and release period length at ten replications for forming outputs of lead time and delivery reliability. These prepared output values were used for building paths in the path list for an Antcoba algorithm.

Antcoba uses the path list to find parameter values of workload ratio and release period length. After that, it sends parameter values to the ARENA. The

ARENA was run with obtained parameters values at approximate replications to achieve a confidence interval with a pre-specific desired half width for forming outputs of lead time and delivery reliability as follows

$$n \cong n_0 \times \left(\frac{h_0^{\,2}}{h^2}\right) \tag{3.34}$$

where n_0 is the number of initial replications and h_0 is the half width from initial replications, h is a pre-specified desired half width.

This hybrid algorithm repeated several times until a stopping rule was satisfied. The stopping rule of this research was the value of the objective function that was no more changes in consecutive iterations. The results from proposed approach were compared with earliest due date (EDD) rule.

3.4 Conclusion

Literatures, basic principles and theories have been already presented in Chapter 2. In this Chapter, the research methodology was presented and it could be mainly divided into 3 phases. The first phase performed the roadmap for lean manufacturing system. This phase used IDEF0 to investigate all shop floor activities before evaluating the finalized SHEN model by factor analysis. The second one focused on supplier selection. The problem of selecting a qualified supplier is increasingly complex for DMs. Two types of MCDM method were proposed through the illustrative example. A workload-based job release system was presented in the last phase. Simulation optimization of the production system was studied by using Antcoba to find parameter values for simulation model in ARENA to evaluate the performance of the workload based job release mechanism. An overview of the relationship between the individual sectors in Chapter 2 and Chapter 3 is displayed in Figure 3.11.

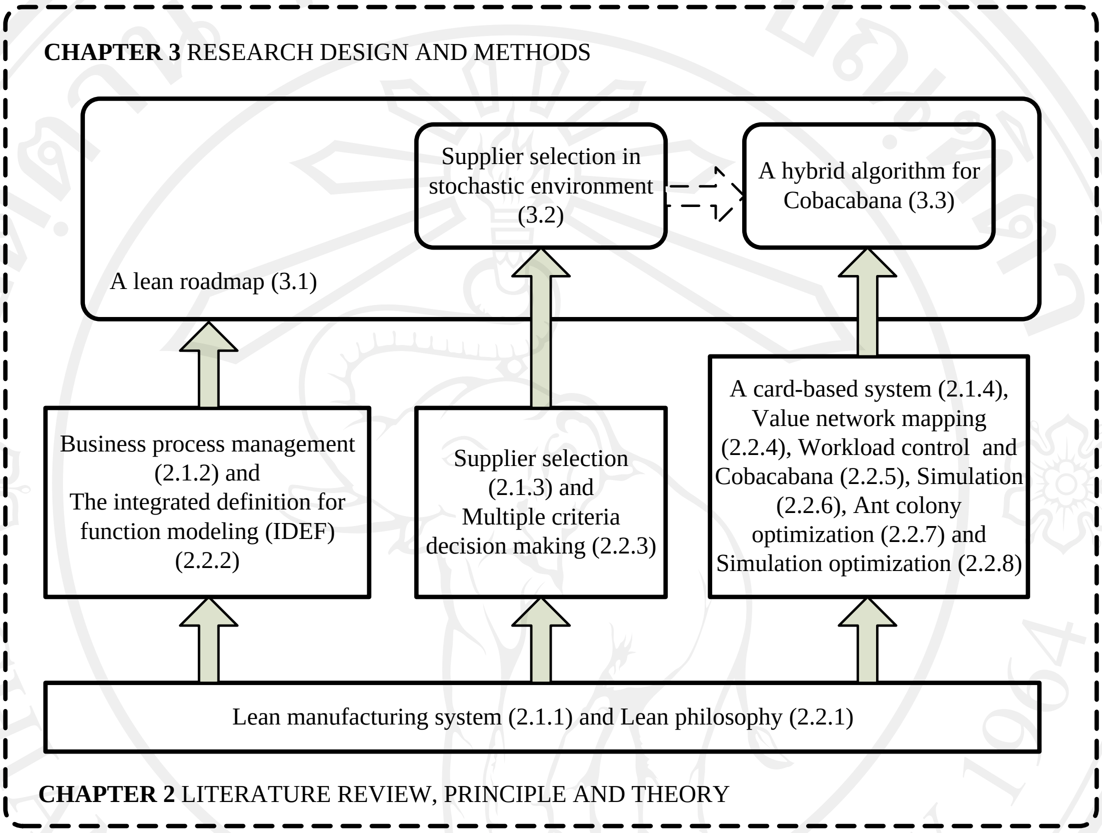

Figure 3.11 An overview of Chapter 2 and Chapter 3