CHAPTER 3

KNOWLEDGE BASED SYSTEM, GAUGING ABSENCES OF PRE-REQUISTES AND ANALYTIC HIERARCHY PROCESS

3.0 Introduction

This chapter presents a review on Intelligent System (IS) with the emphasis on one of its type, Knowledge Based System (KBS). The structure of KBS is discussed along with a description of the development tool used in the research. This is then followed by a discussion on the application of KBS in Production and Operations Management (POM) area. Published papers on Gauging Absences of Pre-requisites (GAP) and Analytic Hierarchy Process (AHP) techniques, which are embedded in the developed KBS, are also reviewed.

3.1 Review of Intelligent Systems

Intelligent System is a term for a system that uses Artificial Intelligence (AI) technology [Hopgood (2001)]. According to Awad (1996), "*Artificial intelligence (AI) is a field of computer science or the science of making machines do things that would require intelligence if done by humans*". This agrees with Luger's (2005) definition as "*the branch of computer science that is concerned with the automation of intelligent behaviour*". From these definitions, it is clear that an intelligent system consists of two major elements: it is a discipline of computer science, and it mimics the human intelligence.

Various types of intelligent system that have been applied to POM area were listed in many papers [Teti and Kumara (1997), Proudlove *et. al.* (1998), Meziane *et. al.* (2000), Luger (2005)]. These include five of the most applied tools based on study by Proudlove *et. al.* (1998) and Meziane *et. al.* (2000), i.e. Knowledge Based System (KBS), Case based reasoning (CBR), Genetic Algorithms (GA), Neural Network (NN), and Fuzzy Logic (FL). The explanations of each of these five tools and the applications of these tools in POM area are described in the following sub-sections.

3.1.1 Knowledge Based Systems (KBS)

Knowledge Based System (KBS) is defined as "*a branch of AI that applies human knowledge of a specific area of expertise to solve very difficult problems within that area*" [Awad (1996)]. As a KBS is expected to perform like a human who has expertise and special skills in a certain area, it is also known as an Expert System (ES) [Giarratano and Riley (2005)]. KBS first appeared in the seventies and basically comprises three main elements: knowledge base, inference mechanism and user interface [Teti and Kumara (1997)]. The structure of KBS will be discussed in detail in Section 3.2 since the system developed in this research is based on this type of intelligent system.

3.1.2 Neural Network (NN)

Neural Network (NN) is an approach to problem solving that simulates how the human brain works, and has been applied broadly to classification and optimisation tasks [Proudlove *et. al.* (1998)]. The structure of a NN includes a set of artificial neurons (nodes) that are grouped in a number of layers [Teti and Kumara (1997), Akyol and Bayhan (2007)]. A typical structure consists of an input layer, output layer, and at least one hidden layer. An example of NN structure with two hidden layer is shown in Figure 3.1.

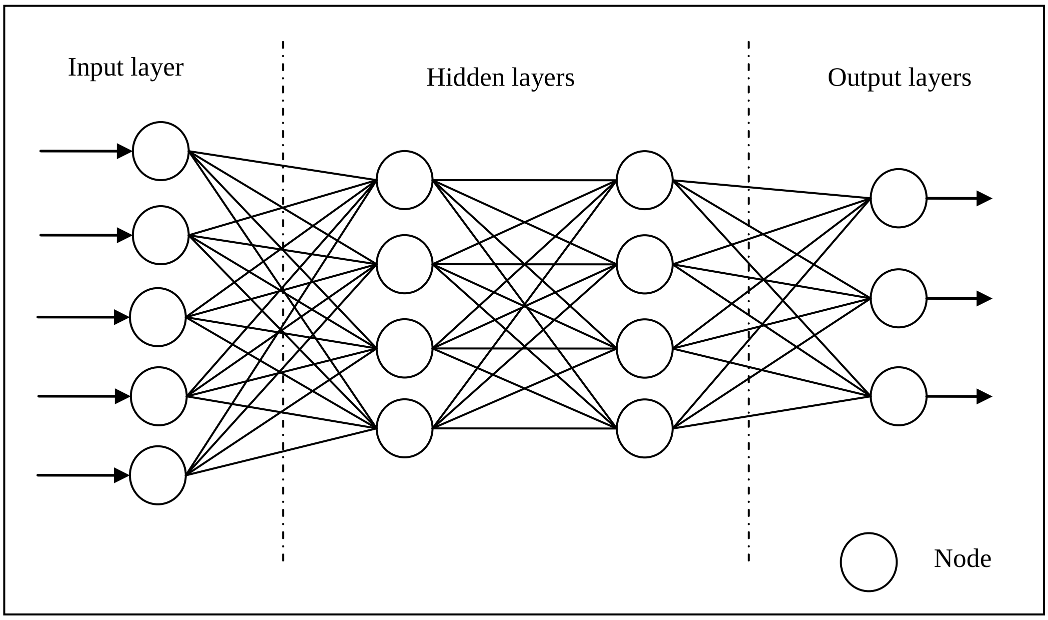

Figure 3.1: Structure of Multi-layer Neural Network (adapted from Akyol and Bayhan (2007))

A node in input layer processes an input before delivering a single output, which is an input to the intermediate layer. The output is transmitted to other layer (until output layer) by amplifying it through its weight factor, an element of NN which expresses the relative importance of each input node. [Udin (2004)]. The NN has to be trained such a way that the application of a set of inputs produces the desired set of outputs [Choudhury *et. al.* (2007)]. The training methods include the setting of weight factor using priori knowledge or by feeding it patterns and letting it change its weighs according to some learning rule [Choudhury *et. al.* (2007), Anonymous (2008)].

3.1.3 Genetic Algorithms (GA)

Genetic Algorithms (GA) refer to a computerised stochastic search technique that is inspired by the process of natural genetics and evolutionary biology such as inheritance, selection, mutation and cross-over. Based on the principle that solutions can be evolved, the population then evolves through successive iterations called generations [Huang *et. al.* (2005)]. Turban *et. al.* (2005) emphasise that the basic goal of GA is to develop a system that can learn and adapt to changes.

GA starts with a population composed of a set of random solutions known as numerical chromosomes. Then by randomly combining all portions of chromosomes, it forms a new set of solutions with infrequent alterations. These new solutions are tested and the most feasible solutions are selected for the next alteration until reaching an optimal solution for the problem. The GA process flow is shown in Figure 3.2.

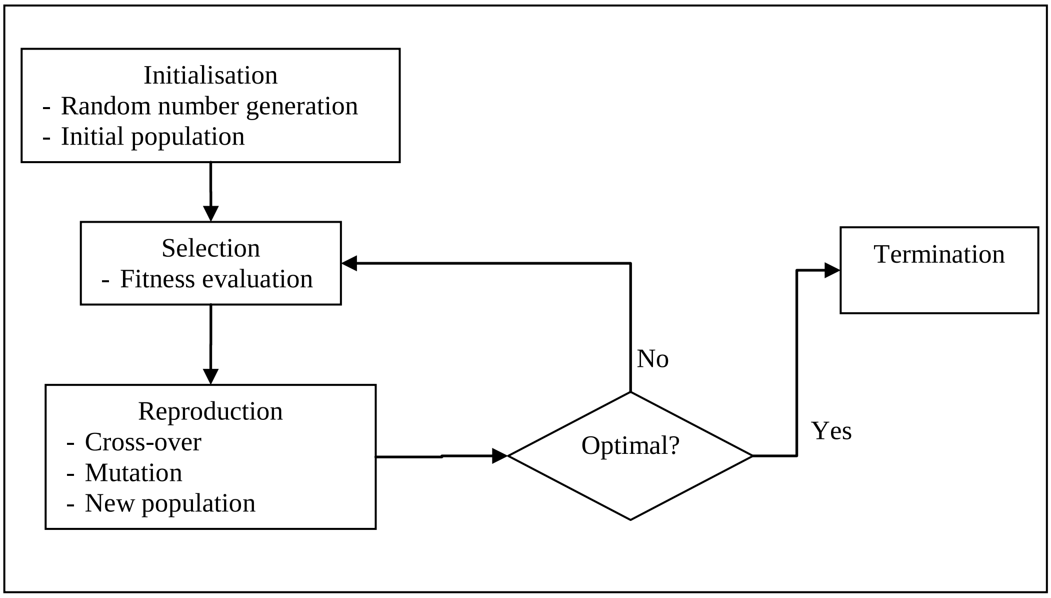

Figure 3.2: Process flow of Genetic Algorithm (GA) (adapted from Sun *et. al.* (2007))

3.1.4 Fuzzy Logic (FL)

In the conventional or Boolean logic, the truth of any statement is valued as either TRUE or FALSE. To compensate the uncertainty of the statement, Fuzzy Logic (FL) is introduced to handle the concept of partial truth, which is the value between completely TRUE and completely FALSE [Metaxiotis *et. al.* (2003)]. In mathematical form, the truth of any statement in FL is in the interval [0, 1] i.e. any value between 0 (FALSE) and 1 (TRUE). For example, for the rule: IF room temperature is *warm* THEN air-conditioner is *on*, both variables, *warm* and *on*, map to ranges of values. A typical structure of FL consists of a rule base, membership functions and an inference procedure, as illustrated in Figure 3.3.

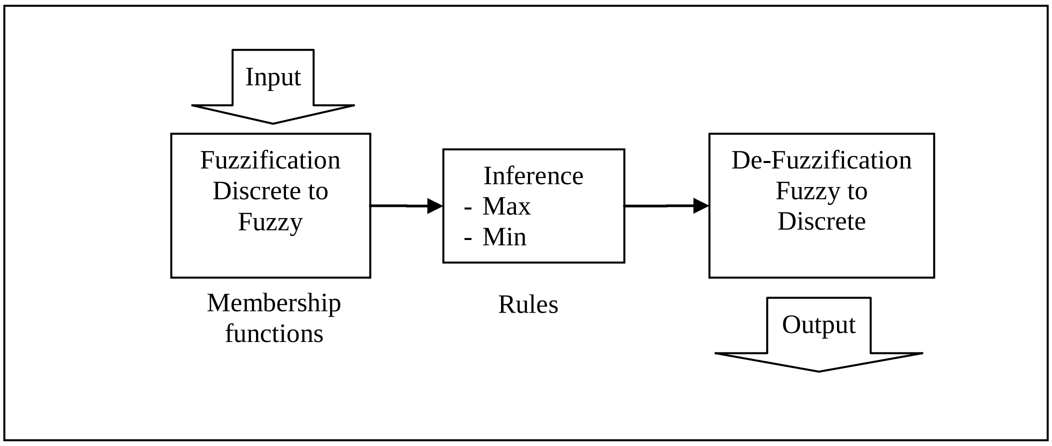

Figure 3.3: Structure of Fuzzy Logic System (adapted from Metaxiotis *et. al.* (2003))

3.1.5 Case Based Reasoning (CBR)

Case Based Reasoning (CBR) is an approach to problem solving that depends on past similar cases to find solutions to new problems [Kolodner (1993)]. According to Aamodt and Plaza (1994) and supported by Belecheanu *et. al.* (2003) the CBR process can be represented by four **R**s as shown in Figure 3.4.

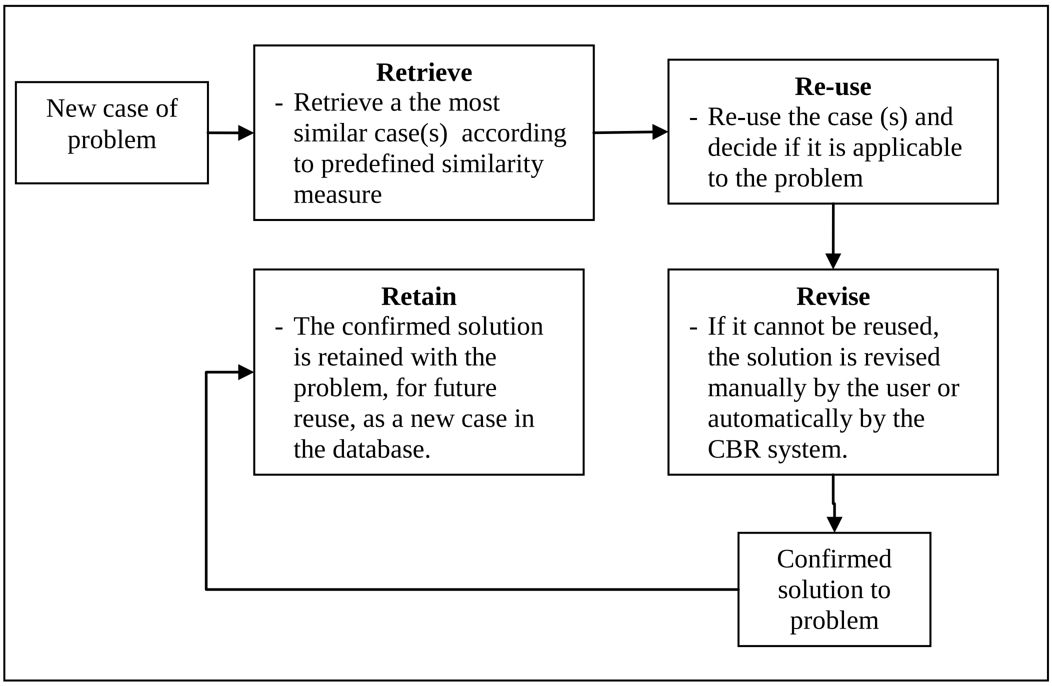

Figure 3.4: Process flow of Case Based Reasoning (CBR) (adapted from Belecheanu *et. al.* (2003))

3.1.6 Applications of Intelligent Systems in Production and Operations Management (POM)

Since the 1980s, many manufacturing organisations have been applying intelligent systems in their Production and Operation Management [Proudlove *et. al.* (1998), Meziane *et. al.* (2000), Delen and Pratt (2006)]. Many researchers have realised the capabilities of intelligent systems in improving the manufacturing operations including product and process design, quality, scheduling, planning and control. Table 3.1 highlights a summary of previous researches related to the applications of five dominant intelligent systems in various operations areas of POM.

Table 3.1: Summary of Intelligent System Applications in Production and Operations Management

	KBS	Neural Network	Fuzzy Logic	Genetic Algorithms	Case-Based Reasoning
Product Design	Planning for product design using integrated KBS [Hung *et. al.* (2008)]	Development of customer utility prediction system based on NN for product conceptualisation [Chen and Yan (2008)]	FL used for the Design for Environment (DFE) evaluation for parts, assembly and operations analysis [Mascle and Zhao (2008)]	GA used in shape optimisation for product design [Sun *et. al.* (2007)]	The application of case based reasoning to decision support in new product development [Belecheanu *et. al.* (2003)]
Process	A Knowledge Based Design Methodology for manufacturing assembly lines [Khan and Day (2002)]	NN applied to estimate process capability of non-normal processes [Abbasi (2008)]	Application of FL based decision support system for material handling selection problems [Kulak (2005)]	GA used on product life cycle and production function at LCD TV manufacturer [Che (2008)]	Application of CBR to identify Printed Circuit Board (PCB) principal process parameter [Tsai and Chiu (2007)]
Quality	Quality Function Deployment based expert system for machining [Chakraborty and Dey (2007)]	Quality prediction in a plastic injection moulding process using NN [Chen *et. al.* (2008)]	FL approach to define sample size for attributes control chart in multistage processes [Engin *et. al.* (2008)]	GA used to achieve the desired product qualities for a nano-particle milling [Su and Hou (2008)]	A CBR approach for specifications quality design given by customers [Suh *et. al.* (1998)]
Scheduling	Creating an expert system for detailed scheduling [Benavides and Prado (2002)]	NN with competitive scheme to solve real-time job scheduling problem [Chen *et. al.* (2007)]	FL based decision support system for parallel machine scheduling/ rescheduling in the presence of uncertain in a pottery company [Petrovic and Duenas (2006)]	Tool developed for Flexible Manufacturing Systems using Hybrid GA [Noor (2007)]	Application of CBR for predictive production scheduling [Schmidt (1998)]
Planning and Control	Application of analytic hierarchy process-driven expert system in planning [Razmi *et. al.* (2000)]	NN prediction model to optimize work-in-process inventory level for wafer fabrication [Lin *et. al.* (2008)]	FL approach used to load-oriented manufacturing control for job-shop [Bonfatti *et. al.* (2006)]	GA used for batch selection decisions in flexible manufacturing system [Deng (1999)]	CBR algorithm used to construct new BOM in mass customisation environment [Tseng *et. al.* (2005)]
Supply Chain	Application of KBS in collaborative supply chain management design and planning [Udin *et. al.* (2006)]	NN evaluation model for ERP performance from SCM perspective to enhance enterprise competitive [Chang *et. al.* (2008)]	Development of FL for reduction of bullwhip effect in supply chain systems [Zarandi *et. al.* (2008)]	A genetic algorithm for determining optimal replenishment cycles to minimize maximum warehouse space [Yao and Chu (2008)]	Application of CBR model in logistics outsourcing [Isiklar *et. al.* (2007)]

In this research, the rule-based KBS is selected to support the planning and designing of Collaborative Lean Manufacturing Management (CLMM) System, since it is the most established AI technique and many commercial shells and software are available to support the development. With the availability of the shell, the process of building the KBS is simple compared to other AI techniques [Udin (2004)]. Knowledge and information acquisition from literature and user interactive sessions are easily structured using the KBS rule-base. In addition, the application of KBS is widely used in business organisations and the capabilities of KBS are proven in improving the effectiveness and efficiency of the organisation's decision-making processes.

3.2 Structure of KBS

Figure 3.5 shows a typical KBS structure, where each of these components is described in the following sub-sections.

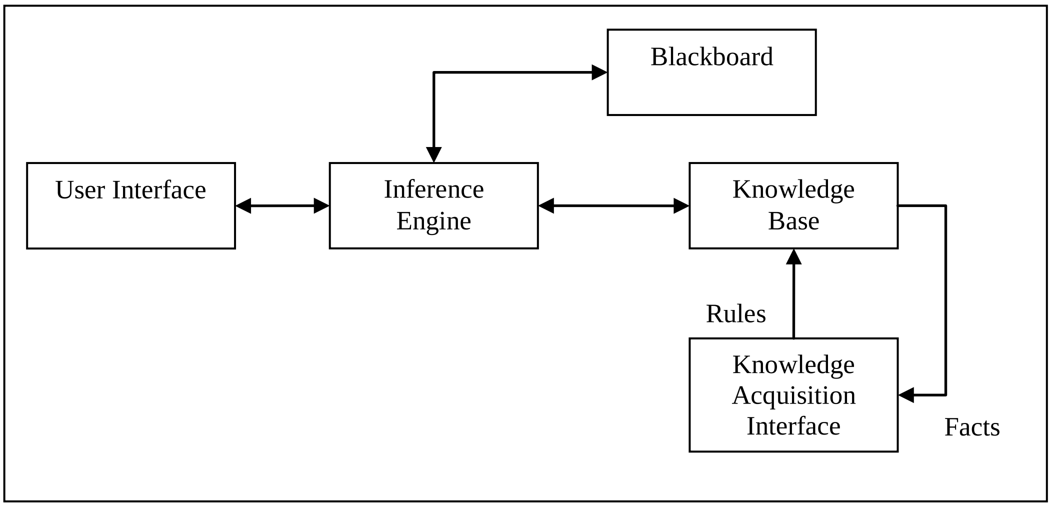

Figure 3.5: Structure of a typical KBS (adapted from Udin (2004))

3.2.1 Knowledge Base (KB)

The KB is the main component of KBS where rules, facts, and knowledge acquired from human expert are stored. The knowledge contained in the knowledge base is needed to understand, formulate and solve specific problem of particular domain [Turban *et. al.* (2005)]. There are various approaches including production rules, logic representation, semantic networks, and frames to represent the knowledge [Pigford and Baur (1990), Turban *et. al.* (2005)]. As most of KBSs use production rules, KBSs are also known as rule-based systems [Awad (1996), Giarratano and Riley (2005)].

3.2.2 Production Rules

Production rules are the most common approach of representing knowledge [Hussain (1998), Wibisono (2003)]. In this approach, premise-action or IF ... THEN is the basic structure of representing knowledge [Awad (1996)]. Other structures in production rules include *connectors* (AND and OR), and *alternative action* (ELSE). An example of production rules is:

IF *the number of full time employee is more than 150*
OR *the company annual sales turnover is more than £3.68 million*
THEN *the company is classified as a large company*
ELSE
IF *the number of full time employee is between 51 and 150*
AND *the company annual sales turnover is between £1.47 million and £3.68 million*
THEN *the company is classified as a medium company*
ELSE *the company is classified as a small or micro company*

The statements of "*the number of full time employee is more than 150*" and "*the company annual sales turnover is more than £3.68 million*" are known as *procedural* parts. Since OR represents *connector* to these statements, if at least one of these statements is true, then the action will result the statement of "*the company is classified as a large company*", which is called *consequence* or conclusion.

If both statements are false, the next statements of "*the number of full time employee is between 51 and 150*" and "*the company annual sales turnover* *is between £1.47 million and £3.68 million"* will be tested. Since AND represents *connector*, both statements need to be true to result the statement of "*the company is classified as a medium company*". Otherwise, the action will result the statement of "*the company is classified as a small or micro company*".

The explanations of other components of KBS in the subsequent sections refer specifically to this type of production rule-based system.

3.2.3 Inference Engine

The inference engine is the brain of the KBS and refers to the control program or rule interpreter [Turban *et. al.* (2005)]. It decides how and when facts and rules in the knowledge base are to be used in making decisions. In making inferences to the knowledge base, the inference engine utilises reasoning techniques before the conclusion and suggestion can be obtained [Udin (2004)]. In controlling the mechanism of inferencing, backward chaining and forward chaining approaches are used. These approaches are illustrated in Figure 3.6.

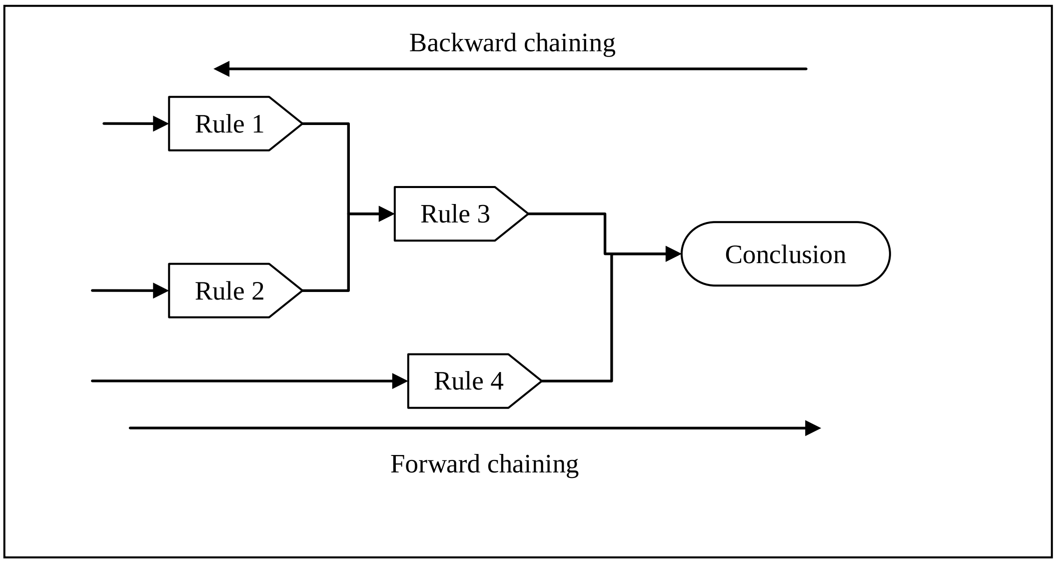

Figure 3.6: Forward Chaining and Backward Chaining Approaches (adapted from Udin (2004))

In the backward chaining approach, the chaining checks the premise or consequence of every rule in the KB based on existing assertions. Also known as goal-driven approach, it works backward from the goal to find supporting data [Awad (1996)]. This backtracking process tests every rule and fact that leads to the conclusion. On the other hand, in the forward chaining approach, the basic data are tested against the rules in the KB until a conclusion is drawn [Udin (2004)]. This approach is also known as data-driven approach.

3.2.4 Blackboard

The blackboard or working memory is an area for the description of a current problem according to the user-input data. According to Turban et al. 2005), the blackboard records an immediate hypothesis and three types of decisions: plan, agenda and solution. The Blackboard is different from database, in that it is similar to the concept of Random Access Memory (RAM) in computer systems. The contents of the blackboard are changed according to the problem situation.

3.2.5 Knowledge Acquisition Interface

In KBS, human participation is divided into two categories. The first category is where the end user of the KBS is a non-expert user who uses the system in seeking expert advice relating to a particular domain of problem. The second category of human participation in the KBS is in the knowledge acquisition process [Awad (1996)].

There are many sources of knowledge acquisition which include knowledge from the published materials, interview with the experts, observations of experts at work, and induction of rules from examples. The most common way identified is the comprehensive interview with the experts [Hussain (1998), Wibisono (2003)]. In this process, specific steps used are listed in Table 3.2.

Table 3.2: Steps of Knowledge Acquisition (adapted from Wibisono (2003))

Step	Description
Problem discussion	The knowledge engineer and domain expert(s) explore the kind of data, knowledge and procedures needed to solve specific problems.
Problem description	The expert describes a prototype problem for each category of answer in the domain.
Problem analysis	The knowledge engineer asks a series questions from the expert to solve the problem while looking for the rationale behind the reasoning steps.
Refinement	The knowledge engineer solves a series of problems using the rules and procedures acquired during the interview with experts.
Verification	The expert examines and criticise the prototype rules and evaluates the control strategies used to select the rules.
Validation	The knowledge engineer presents the cases solved by the expert and prototype system to other experts to compare their strategies and problem solving approaches

The knowledge acquisition process involves the knowledge engineer and the expert. The knowledge engineer, normally the system developer, is the person who interviews and listens to the human expert and is able to interpret and structure the knowledge into the language that is understood by the KBS in a particular problem domain [Wibisono (2003)].

3.2.6 Domain Expert

The domain expert is the person who possesses the special knowledge, experience, skills and judgement in solving problems in a particular problem domain. The expert knows the importance and relationship of the facts and provides this to the knowledge engineer or directly to the knowledge base. In addition, the expert also provides the skill on how to solve the problem that the KBS will perform. Apart from the expert, the knowledge engineer also extracts the knowledge from written documents and translates it into the system. The extracted knowledge should be consistent, accurate and complete in order to make the KBS work effectively [Udin (2004)].

3.2.7 End User

The user interface is the location where the end user communicates with the system by providing all the inputs, conditions and other relevant information to the problem being tackled. In designing the user interface, there are two important components that should be considered: firstly, the screen display and secondly, the user interaction through input devices. The effectiveness of these components can contribute in enhancing the performance of the system [Giarratano and Riley (2005)].

3.2.8 Advantages and Disadvantages of KBS

KBS have the capabilities in providing solutions and justifications for the given solutions. Furthermore, KBS also play a significant role in transferring and reproducing expertise. According to Mallach (2000), there are some advantages and disadvantages of KBS when compared to human experts and these are listed in Table 3.3.

Table 3.3: Advantages and Disadvantages for Human Experts and KBS (Source: Udin (2004))

Dimensions	**KBS**		**Human Expert**	
	Advantages	**Disadvantages**	**Advantages**	**Disadvantages**
Speed	Faster			Variable
Cost	No cost while not use	High initial cost	No development cost	Regular payment
Performance	Consistent	Knowledge updated periodically	Knowledge updated constantly	Variable
Availability	Normally weekdays		Always available	
Sustainable	Yes			No
Emotion	No	No common sense	Able to use common sense	Yes

The development of KBS is not to replace the human in the decision-making, but is used as a supportive tool in order to assist in providing guidance for the decision-making process. In addition, KBS is limited to a narrow domain of expertise and in certain cases there is a difficulty in knowledge acquisition when the knowledge is limited or cannot be accessed.

3.3 Tools for KB System Development

There are many tools that have been used for building KB Systems (KBS). The tools vary from general programming languages, such as *C* and *Pascal* to special purpose AI languages such as *PROLOG* and *LISP*. However, using these kinds of languages requires the developer to build the KB system's user interface from beginning and implement appropriate inference engine [Darlington (1997)]. To avoid this time-consuming process, software programs known as "shells" are mostly used nowadays.

Shells offer an easy starting point for KBS building because they are KB systems which have been emptied of their knowledge. This means that developers can concentrate on entering the KB without having to build everything including the inference engine and user interface. Even non-programming experts can familiarise themselves with shells fairly rapidly. Also, many ES shells contain tools which can simplify the knowledge acquisition process. There are several shells commercially available. These include: XPERT RULE, AM for Windows, and Leonardo [Darlington (1997)].

In this research, the KBS shell known as *Application Manager for Windows* (AM) is used in developing the KBS, due to its availability, ease of use, and previous successful researches [Khan and Hafiz (1999), Khan and Day

(2002), Wibisono (2003), Udin (2004)]. AM is designed and developed by Intelligent Environments Inc. as an upgraded version of *Crystal* which was based on the DOS environment. AM uses a highly interactive interface and includes a wealth of database access with remote system connectivity. This enables users or developers to develop a powerful stand alone or client/server applications easily and quickly. AM uses production rules techniques in representing knowledge that is stored in the application. The base component available in AM software is called modules which consists of *procedures*, *commands*, *variables*, *windows*, *functions* and *menus* [AM (2002)]. Appendix A explains in detail each of these elements.

3.4 Review of Gauging Absences of Pre-requisites (GAP)

Gauging Absences of Pre-requisites (GAP) analysis is a technique that is used to measure the performance disparity between the organisation's actual environment and an ideal one, resulting in knowledge of the desirable prerequisites for an effective implementation [Wibisono (2003), Udin (2004)].

According to the scope of this research, GAP analysis has three objectives. The first objective is to identify the main elements for initiatives implementation from the proposed KBS. The second objective is to provide a quantitative basis for comparing the status in the present condition with the future requirement for the effective functioning of the initiatives. Finally, the third objective is to identify the strengths and weaknesses of current practices in manufacturers, suppliers, and customers so that some practices can be aligned or amended for suitability in the new collaborative environment [Udin (2004)].

The GAP analysis in the proposed KBS is conducted through the responses of the user to the questions provided. The problems highlighted for each negative reply are classified into five categories, which are structured in descending order of importance [Wibisono (2003), Udin (2004)] and shown in Table 3.4.

The code is used to identify whether the response given by users is in the Good Point (GP) Category or Bad Point (BP) Problem Category (PC). The PCs is ranked from 1 to 5 (PC1 to PC5), as shown in Table 3.4, with PC1 being the most critical condition. Due to the aim of the system to identify the missing pre-requisites that are needed in order to make the implementation of improvement initiatives a success, only the BPs are categorised into PCs.

Table 3.4: Problem Categories and Description of GAP Analysis Technique (Source: [Kochhar *et. al.* (1991), Wibisono (2003), Udin (2004)])

Problem Category	Code	Description
1	PC1	This indicates a serious problem, which should and can be resolved in the short term and the result of the problem is quite likely to provide a real short-term benefits.
2	PC2	This indicates a serious problem, which is likely to have pre-requisites and is better dealt with as part of an appropriate and logical improvement and implementation plan.
3	PC3	This is not a serious problem and can be dealt with now. If resolved, it is likely to produce short-term benefits.
4	PC4	This is not a serious problem. Although it could be dealt with now, it is unlikely to produce short-term benefits. Therefore, it should only be dealt with if it is a pre-requisite for other things.
5	PC5	This is not really a Good or Bad point it self. The questions associated with this category are primarily asked to identify certain situations in the environment, which upon subsequent probing by succeeding questions may well reveal problems.

From this result, the missing pre-requisites of the current position of manufacturers, suppliers, and customers can be identified through the number of PCs.

3.5 Review of Analytic Hierarchy Process (AHP)

Decision-making is a process of selecting the best alternative from the various alternatives to achieve a specific goal or objective. Based on the literature, there are several techniques of decision-making that are used in organisations. Apart from utilising the application in IS, one technique that is currently accepted in supporting the decision-making process is Analytic Hierarchy Process (AHP). AHP was first developed and introduced by Saaty in 1970s [Saaty (2001)], and is a decision making tool that supports in dealing with complex, unstructured and multi-attribute problems.

The application of AHP is widely accepted in various areas such as operation management, manufacturing, economics, business, and information technology [Render *et. al.* (2006)]. With its ability to mimic human opinions in structuring a complex and multi-attribute problem, AHP has significantly improved the performance of the decision-making process in organisations. Razmi *et. al.* (2000) stress that the AHP is a powerful tool, which can be used to deal with multi-attribute and complex problems particularly in selecting and prioritising an alternative for improvement purposes. AHP has the capability to compare the alternatives and make a comparison amongst the alternatives before the optimum solution can be suggested.

3.6 Application of AHP in Production and Operations Management (POM)

AHP has been applied to several decision problems related to POM. Some of the recent areas of research are shown in Table 3.5.

Table 3.5: Application of AHP in POM

Authors	Area of Application	Description
Sharma and Agrawal (2008)	Production control	AHP is used to analyse production policies of Kanban, CONWIP and Hybrid Push-Pull as alternatives for controlling the engineering manufacture
Aguilar-Lasserre *et. al.* (2008)	Design	Integrating AHP with AI techniques to design batch plants with imprecise demands in product amounts.
Rabelo *et. al.* (2007)	Supply Chain	Analysis the service and manufacturing activities of the global supply chain of a multinational construction equipment corporation using hybrid AHP/simulation.

3.7 AHP Development Process

There are three basic steps or principles in AHP, which are structuring hierarchies, setting priorities and logical consistency [Saaty (2001)]. Each of these steps is described in the following sections.

3.7.1 Structuring Hierarchies

AHP divides the complex multiple criteria of problems into a hierarchy, where each layer consists of specific elements. The structure of this hierarchy is shown in Figure 3.7.

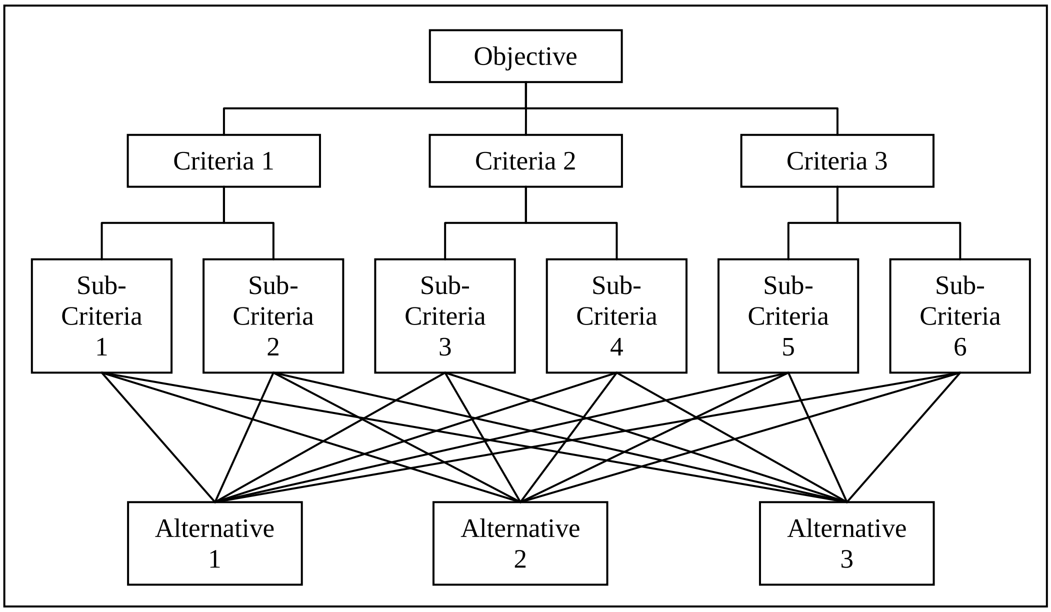

Figure 3.7: Structure of Hierarchy within AHP

The top layer of the hierarchy, referred to as a goal or objective, is the focus of the analysis. The lowest level of the hierarchy is called alternatives, which contribute positively or negatively towards the main objective through their impact on the criteria in the intermediate level. The intermediate level consists of criteria or attributes that may have several elements that affect the decision.

3.7.2 Setting Priorities

Once the problem is constructed into a hierarchy, the pair-wise judgement is conducted, which starts at the second level and finishes in the lowest level. This pair-wise judgement is done in order to prioritise each of the elements to determine their importance. Each pair-wise comparison is quantified accordingly to Saaty (2001), by assigning it a number from 1 to 9. The scale for the comparison is shown in Table 3.6.

Table 3.6: Scale for Pair-Wise Comparisons

Intensity of Importance	Definition
1	Equal importance
2	Very Weak importance
3	Weak importance
4	Moderate importance
5	Importance
6	Strong importance
7	Very strong importance
8	Almost absolute importance
9	Absolute importance

For pair-wise comparison, these elements are structured into the form of a matrix. The matrix is a simple tool that provides a framework for consistency testing. Following Saaty (2001), to begin the comparison process, the property or basis (C) is selected from the top of hierarchy, while elements in the next level of hierarchy are selected for comparison. Figure 3.8 below illustrates the sample of a matrix for the pair-wise comparison.

C	A1	A2	A3
A1	1	A1/A2	A1/A3
A2	A2/A1	1	A2/A3
A3	A3/A1	A3/A2	1

Figure 3.8: Matrix for Pair-Wise Comparison

Based on the normalised matrix, the test of consistency is done in order to make sure the judgement made by the decision-maker is good. The AHP measures the judgement presented in the matrix by using Consistency Ratio (CR) [Saaty (2001)].

3.7.3 Logical Consistency

The consistency of the matrix is important to maintain, since it reflects the decision made by the decision–maker [Saaty (2001)]. Since the judgement made by users cannot be so certain, consistency could be forced into the matrix. On this principle, the AHP process determines the consistency of the matrix based on the Consistency Ratio (CR). The value of CR should be 10% or less, and if it is more than 10%, the decision-maker should review the judgement. The mathematical process integrates the weights to develop overall evaluation of the decision alternatives. The example of the mathematical process for performing the calculation in the AHP is explained in Appendix B.

3.8 Hybrid System

Based on algorithm developed by Wibisono (2003), supported by Udin (2004), the utilisation of this hybrid approach (the combination between the GAP analysis and the AHP approach) required specific algorithms in the process to match the five-point scales of Problem Categories (PC) in the GAP analysis and the nine-point scales of Intensity of Importance in the AHP technique. Since these nine-point scales are used in the prioritisation process of AHP, there is a need to transfer all five-point scales of PC into AHP point scales. The detail explanations of the transfer algorithm and the performance score are discussed in Appendix C. Table 3.7 shows the guide for transferring performance scores in GAP in intensity of importance in AHP.

Table 3.7: Guide for Transferring Performance Scores into Intensity of Importance

Intensity of importance in AHP	**Definition**	**Explanation**	**Performance Score (S) in GAP**
1	(A) is equal importance with (B) in improvement priority	Two activities contribute equally to the objective	S = 0
2	(A) is very weak importance with (B) in improvement priority	Experience and judgement very slightly favour one activity over another	$0 < S \leq 50$
3	(A) is weak importance of (B) in improvement priority	Experience and judgement slightly favour one activity over another	$50 < S \leq 100$
4	(A) is moderate importance of (B) in improvement priority	Experience and judgement moderately favour one activity over another	$100 < S \leq 150$
5	(A) is importance than (B) in improvement priority	Experience and judgement favour one activity over another	$150 < S \leq 200$
6	(A) is strong importance than (B) in improvement priority	An activity is favoured strongly over another	$200 < S \leq 250$
7	(A) is very strong importance than (B) in improvement priority	An activity is favoured very strongly over another; its dominance is demonstrated in practice	$250 < S \leq 300$
8	(A) is almost absolute importance than (B) in improvement priority	The evidence favouring one activity over another is almost of the highest possible order of affirmation	$300 < S \leq 350$
9	(A) is absolute importance than (B) in improvement priority	The evidence favouring one activity over another is of the highest possible order of affirmation	$350 < S \leq 400$

Based on Table 3.7, each component is assigned with the Intensity of Importance scale in the form of matrices, where the mathematical process starts, in order to normalise and find the priority weights for each matrix. Since the consistency of the pair-wise comparison is important to confirm the result validity, the Consistency Ratio (CR) for each matrix is measured and if the CR is bigger than 0.10, it implies that there is a 10% chance that the elements have not been compared well and the decision-maker must review the comparison again.

The utilisation of AHP and GAP analysis in the KBS makes it more manageable and the possibility of accurate calculation is higher. In essence, the AHP analysis determines the priority of importance between the main modules (criteria) whereas the GAP analysis determines the priority of improvement internally to each module (criteria).

3.9 Summary

This chapter has provided review of Knowledge Based Systems (KBS), and the proposed embedded techniques, GAP and AHP. In the business and manufacturing environments, the applications of KBS are widely used for supporting management in decision making, planning and designing processes. In the manufacturing environment, the application of KBS can be classified into five main areas, which are design, process planning, quality, scheduling, planning and control activities. In manufacturing system, KBS is used in the area of procurement or purchasing, and relates to issues such as planning, production, and quality management. This application provides some advantages to organisations in managing the collaborative lean manufacturing, and helps organisations in satisfying customer through quality improvement and cost reduction.

In this research, the *AM for Windows* (AM) software is used as a development tool for KBS system in developing a CLMM along with Analytic Hierarchy Process (AHP) which is embedded in the system. Basically, the AHP is a tool that is used to support management in problem-solving processes that relate to multi-attribute problems that occur in day-to-day (but complex) operations. In developing CLMM, the AHP is used to prioritise the factors that are needed for improvement, and based on a series of questions that have been analysed by the GAP analysis technique. Furthermore, the description on how transferring, calculating and displaying the AHP prioritisation result has been discussed.

The following chapter will now propose a framework for a KB for Collaborative Lean Manufacturing Management (KBLMM) system that is specific for the planning and design of Lean Manufacturing Management in the collaborative environment.