CHAPTER 2 LITERATURE REVIEW

This chapter presents a review of research and literature on learning strategy with a Knowledge-Based Expert System for Car Faulty Diagnosis (KBESCFD) and the Computer-Assisted Concept Mapping (CA-CM) use, the development of automotive troubleshooting tasks by technicians. Items selected for review address each of the issues identified for this exploratory study as follow as:

2.1 Automotive service technicians
2.2 Design approaches to the knowledge-based system
2.3 Modeling framework of knowledge-based expert systems
2.4 Concept mapping as a support tool of KBESCFD model
2.5 Computer-assisted concept mapping in a KBESCFD model
2.6 Summary

2.1 Automotive service technicians

Automotive service technicians inspect, maintain, and repair automobiles and light trucks that run on gasoline, diesel, hybrid synergy drive, electricity, and or alternative fuels, such as ethanol. They perform basic care maintenance, such as oil changes and tire rotations, diagnose more complex problems, and plan and execute vehicle repairs. Automotive service technicians' responsibilities have evolved from simple mechanical repairs to high-level technology-related work (National Automotive Technicians Education Foundation, 2010).

In recently, the report provided that status increasingly need troubleshooters' that excellence skill and ready to learn to perform new tasks or to receive special tasks in the repair of system components. Motor vehicles dealers' providers upgrade and maintain employees' skills. Troubleshooter must have knowledge acquisition and knowledge representation within hands-on skills and affective (The Office of the National Education Commission, 2006; Thoranin, 2007; U.S. Department of Labor, 2008; Sudsomboon, 2007). The motor vehicles authorities strongly need that troubleshooter highly achievement in workplace. These are statement of problems that is emphasizing to promote the learning innovation in technology to develop manpower competition.

When mechanical or electrical troubles occur, technicians first get a description of problem from the owner or, in a large shop, from the repair service estimator or service advisor. To locate the problem, technicians use a diagnostic approach. First, they test to see whether components and systems are secure and working properly. Then, they isolate the components or systems that might be the cause of the problem. For example, if an air-conditioner malfunctions, the technicians might check for a simple problem, such as a low refrigerant level, or a more complex issue, such as a bad drive-belt connection that has shorted out the air conditioner.

As part of their investigation, technicians must test drive the vehicle or use a variety of testing equipment, including on-board and hand-held diagnostic computers or compression gauges. These tests may indicate whether a component is salvageable or whether a new one is required. Problem-solving skills are essentially. Accuracy and efficiency are critical in diagnosing and repairing vehicles, as parts are increasingly expensive, and timely repairs allow shops to take on more business. Technicians can repair or replace worn parts before they cause breakdowns or damage the vehicles. Technicians usually follow a previous experience that they examine every critical part. In order to make decision, other potentially troublesome items are watched closely. The analogical reasoning has influency for setting the mindset and how to perform and solving the problems underlying.

Also, problem-solving skills extend to learn the cognitive science behind these automobiles and how to repair them (Butler, 2005; Foran, 2005; Jones, 2002; Mills, 2005; Peatman, 1988). Automotive service technicians in large companies, which awesome does often troubleshooter in certain types of repairs. For example, transmission technicians and rebuilders work on gear trains, couplings, hydraulic pumps, and other parts of transmissions. Extensive knowledge of computer controls, the ability to diagnose electrical and hydraulic problems, and other specialized skills are needed to solve the problems on these complex components, which employ some of the sophisticated technology used in vehicles. Tune-up technicians adjust ignition timing and valves and adjust or replace spark plugs and other parts to ensure efficiency engine performance (Sudsomboon & Anmanatrakul, 2009).

2.2 Design approaches to the knowledge-based system

Expert System (ES) is Artificial Intelligence (AI) tools that capture the expertise of knowledge workers and provide advice to (usually) non-experts in a given domain. Thus, expert systems constitute a subset of the class of AI systems primarily concerned with transferring knowledge from experts to novices. Any successful decision-making is strongly dependent upon various capabilities that include the effective knowledge acquisition, storage, distribution, and sophisticated use of the knowledge of the human experts in the field. In the context of computer-aided systems for monitoring and information processing, these capabilities would be achieved through developing an expert system (Angeli & Altherton, 2001; Butler, 2005; Foran, 2005; Jones, 2002).

Nyberg and Krysander (2003) argued that the most successful application of Artificial Intelligence (AI) in decision making so far is the development of Decision Support System (DSS), particularly expert system, which is a 'consultant' or 'advisor' to decision makers (Persin & Tovornik, 2003). ES is cheaper compared to human experts in the long-term scenario. However, ES is relatively costly to develop but easy and cheap to operate. In addition, expert systems allow automation of many tasks that could not be effectively handled by human experts. An expert system attempts to emulate how a human expert solves a problem, mostly by the manipulation of symbols instead of numbers namely the knowledge-based systems (KBS).

KBS, also known as expert systems, are computerized systems that use information to provide relevant advice and problem solutions within a specific domain. Knowledge-based systems enable expert knowledge to be solved the problem, even when an expert is unavailable. They also provide a means to preserve information that otherwise might be lost when an expert retires. Figure 2.1 shows the basic structure of an expert system consisting of an inference engine, a knowledge base, and a fact base. The inference engine is a program that manipulates the knowledge base and fact base using a general problem solving technique. The knowledge base is the fixed set of information or data that is necessary to solve problems within a particular domain.

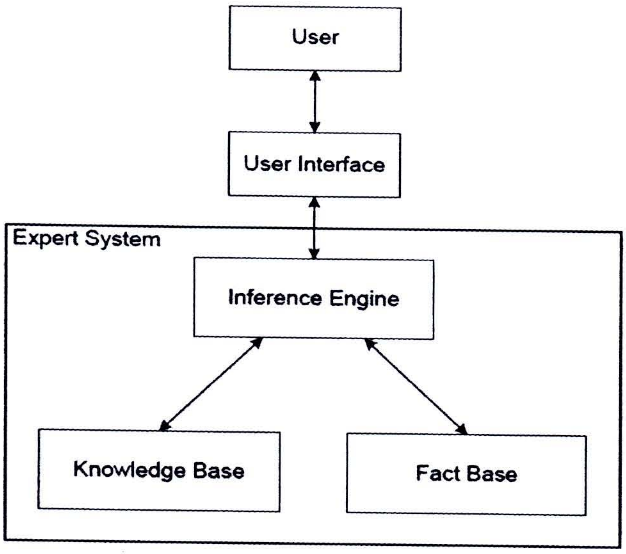

Figure 2.1 Expert system block diagram
(Isermann, 2005)

The fact base contains problem-specific data, such as user inputs and information derived from the knowledge base by the inference engine (Pouliezos & Stavrakakis, 1994; Preston, Chapman, Pinfold, & Smith, 2005). Unlike conventional algorithms that embed domain knowledge within the program, inference engines are problem independent.

2.2.1 KBS reasoning

For a KBS to produce accurate results, it must obtain its conclusions via some logical process. In logic, there are three fundamental ways of reaching a conclusion: deductive reasoning, inductive reasoning, and abductive reasoning. Deductive reasoning is a sound form of argument, meaning that if its premises are true its conclusion is guaranteed to be true as well. Inductive reasoning is inferring from specific to more general statements. Inductive reasoning is an unsound form of reasoning, meaning that even if the premises are true the conclusion is not guaranteed to be true (Reimann & Chi, 1989).

Abductive reasoning is drawing a hypothesis based on observed characteristics. Like inductive reasoning, abductive reasoning is unsound. In fact, abductive reasoning can be viewed as a form of inductive reasoning because it is reasoning from specific observations to draw generalized hypotheses that are plausible but not guaranteed (Isermann, 2005). An ideal KBS should offer the correct solution to every problem within its domain. To guarantee the validity of every solution, the system would have to contain all first principles within its domain and employ a sound reasoning technique, such as deductive reasoning.

Furthermore, KBS that generate their own governing principles for problem solving take less time to create because the programmer need not spend time determining the governing principles by hand. Instead, the system itself can determine its own rules by processing a database of examples.

2.2.2 Knowledge-based expert system architecture

The development of a knowledge-based expert system (KBES) involves: identifying a car real world problem solving task that is to be tackled, representing the key components of this task in the KBES, and implementing the inference process that produces solutions. Thus there are two key components involved in the knowledge engineering process. There is the task of producing a representation of the problem that captures the key features and the task of developing an inference mechanism that describes the causal interactions involved in deriving solutions, as shown in Figure 2.2.

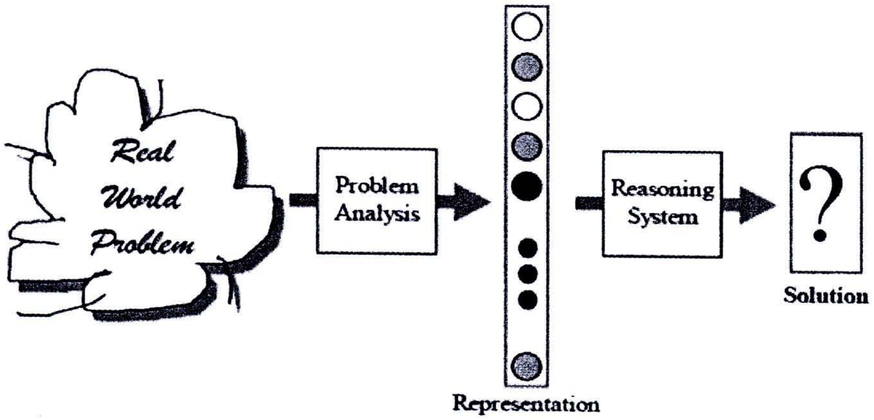

Figure 2.2 An architecture of knowledge-based expert system (Isermann, 2005)

Chen and Zhiming (2008) discussed the inference mechanism is implemented using a concept mapping of solved problems and a mechanism for retrieving and adapting this car faulty diagnosis. Many implemented the KBES involve little or no adaptation and the reasoning mechanism is simply a retrieval system with solutions being used intact or with adaptation performed by the user. The knowledge is encoded in the system in:

1. The knowledge representation used,
2. The faulty diagnosis themselves,
3. The similarity metric used in identifying faulty diagnosis to be reused,
4. The mechanism for adapting solutions, if any.

So in the KBES with no automatic adaptation the big knowledge engineering issue is the knowledge representation. If an appropriate representation is easy to identify then concept mapping has strong benefits; if not then there may be considerable knowledge engineering effort in determining a good representation. In the later sections we analyze an iterative process of improving the representation driven by an analysis of the faulty solutions produced by a KBES. Then, researchers present the background for this iterative knowledge acquisition process. The paper concludes with analysis of effectiveness of this process and some reflections on when there is a knowledge engineering associated with a KBES.

2.3 Modeling framework of knowledge-based expert systems

In this section researcher describe the modeling frameworks which address various aspects of model-based KBES approaches: CommonKADS (Schreiber et. al, 1994) is prominent for having defined the structure of the Expertise Model as the result of the knowledge acquisition phase, and exploits the notion of the knowledge representation. CommonKADS have cleared that there exist further approaches which are well known in the KE community on car faulty diagnosis. A knowledge-level description of a problem-solving process abstracts from details concerned with the implementation of the reasoning process and results in the notion of a Problem-Solving Method (PSM) as shown in Figure 2.3.

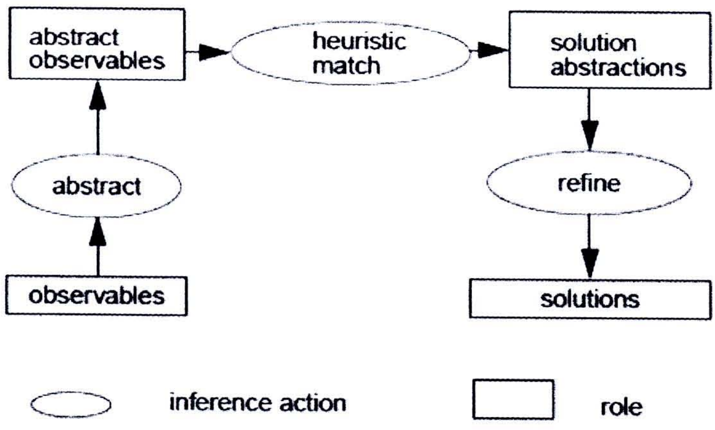

Figure 2.3 The problem-solving method heuristic classification (Schreiber et al. 1994)

Thus, the reuse of such a PSM in different domains is made possible. For example, when considering an automotive domain, an observable like "Engine malfunction lamp showed at overheat region" may be abstracted to "highly coolant temperature" by the inference action *abstract*.

This abstracted observable may be matched to a solution abstraction, e.g. the abnormal of coolant system, and finally the solution abstraction may be hierarchically refined to a solution, e.g. the coolant system faulty symptoms are pipe leak problem, loose belt problem, water deficient problem, thermostat problem, and water pump failure problem". In the meantime various PSMs have been identified, like e.g. *Cover-and-Differentiate* for solving diagnostic tasks (Schreiber et. al, 1994) or *Propose-and-Revise* (Quinlan, 1986) for parametric design tasks.

2.3.1 The CommonKADS Approach

Through this time, the notations used in the method have changed, and elements have been included or removed from the method. Even the expansion of the acronym has changed during its development from "Knowledge Acquisition and Documentation System" to "Knowledge Acquisition and Design System" among other things; the present version of KADS is termed "Common KADS", where KADS is used as a name rather than an acronym.

A prominent knowledge engineering approach is *KADS* (Isermann, 2005) and its further development to *CommonKADS* (Schreiber et al. 1994). A basic characteristic of KADS is the construction of a collection of models, where each model captures specific aspects of the KBES to be developed as well as of its environment. In CommonKADS the *Organization Model*, the *Task Model*, the *Agent Model*, the *Communication Model*, the *Expertise Model* and the *Design Model* are distinguished. Whereas the first four models aim at modeling the organizational environment the KBES will operate in, as well as the tasks that are performed in the organization.

Subsequently, we will briefly discuss each of these models and then provide a detailed description of the Expertise Model:

1. Within the *Organization Model* the organizational structure is described together with a specification of the functions which are performed by each organizational unit. Furthermore, the deficiencies of the current business processes, as well as opportunities to improve these processes by introducing KBES are identified.
2. The *Task Model* provides a hierarchical description of the tasks which are performed in the organizational unit in which the KBES will be installed. This includes a specification of which agents are assigned to the different tasks.
3. The *Agent Model* specifies the capabilities of each agent involved in the execution of the tasks at hand. In general, an agent can be a human or some kind of software system, e.g. a KBES.
4. Within the various interactions between the different agents are specified. Among others, it specifies which type of information is exchanged between the agents and which agent is initiating the interaction.

A major contribution of the KADS approach is its proposal for structuring the KBES Model, which distinguishes three different types of knowledge required to solve a particular task (Schreiber et. al, 1994). (See in Figure 2.3 respectively “domain layer”, “inference layer” and “task layer”):

1. *Domain layer*: At the domain layer all the domain specific knowledge is modeled which is needed to solve the task at hand. This includes a conceptualization of the domain, and a declarative theory of the required domain knowledge. One objective for structuring the domain layer is to model it as reusable as possible for solving different tasks.

2. *Inference layer*: At the inference layer the reasoning process of the KBES is specified by exploiting the notion of a Problem-solving method (PSM). The inference layer describes the *inference actions* the generic PSM is composed of as well as the *roles*, which are played by the domain knowledge within the PSM. The dependencies between inference actions and roles are specified in what is called an *inference structure*. Furthermore, the notion of roles provides a domain independent view on the domain knowledge. In Figure 2.3 (middle part) we see the inference structure for the PSM *Heuristic Classification*. Among others we can see that "patient data" plays the role of "observables" within the inference structure of *Heuristic Classification*.

3. *Task layer*: The task layer provides a decomposition of tasks into subtasks and inference actions including a goal specification for each task, and a specification of how these goals are achieved. The task layer also provides means for specifying the control over the subtasks and inference actions, which are defined at the inference layer.

In essence, the KBES Model captures the functional requirements for the target system. Based on these requirements the *Design Model* is developed, which specifies among others the system architecture and the computational mechanisms for realizing the inference actions. KADS aims at achieving a *structure preserving design*, i.e. the structure of the *Design Model* should reflect the structure of the *Expertise Model* as much as possible (Schreiber et al. 1994).

The following types of strategic knowledge in this study could be generated and modified namely the KBESCFD model as shown in Figure 2.4.

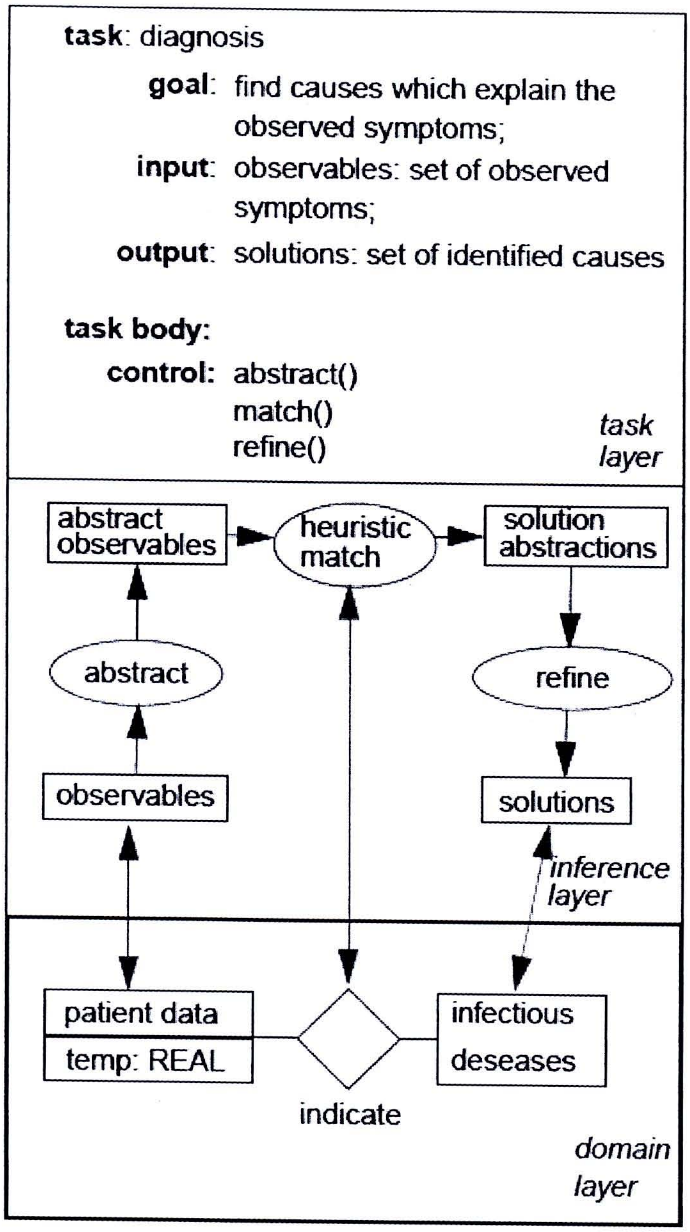

Figure 2.4 A knowledge-based expert system model for medical diagnosis (Schreiber et al. 1994)

All the development activities, which result in a stepwise construction of the different models, are embedded in a cyclic and risk-driven life cycle model similar to a rule-based expert system (Butler, 2005; Foran, 2005; Jones, 2002; Mills, 2005; Peatman, 1988).The basic structure of the KBESCFD model has some similarities with the data, functional, and control view of a system as known from knowledge engineering.

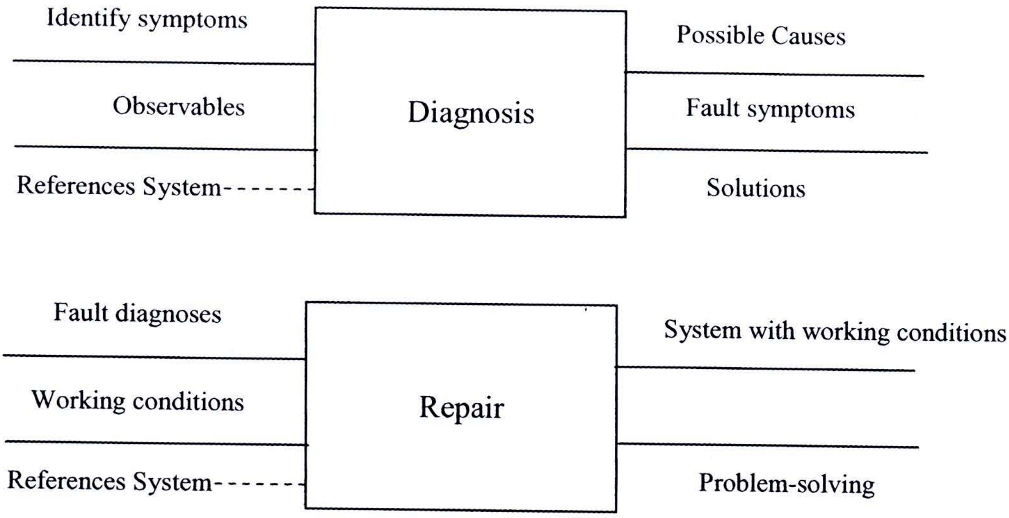

Figure 2.5 Generate KBESCFD model

However, a major difference may be seen between an inference layer with a typical data-concept mapping: Whereas an inference layer is specified in generic terms and provides - via roles and domain views - a flexible connection to the data described at the domain layer, a data-flow concept mapping is completely specified in domain specific terms.

Moreover, the data dictionary does not correspond to the domain layer; since the domain layer may provide a complete model of the domain at hand which is only partially used by the inference layer, whereas the data dictionary is describing exactly those data which are used to specify the data flow within the data flow concept mapping as shown in Figure 2.5.

Mappings are, on the one hand, similar to the schema translation rules as discussed in the area of interoperable semantic argumentation, and on the other hand, at providing a small collection of rather simple mappings to limit the reuse effort needed to specify these mappings as shown in Figure 2.6. Thus KBESCFD recommends reusing domain knowledge only in situations where the required concept mappings can be kept relatively simple (Gegele & Wang, 1998).

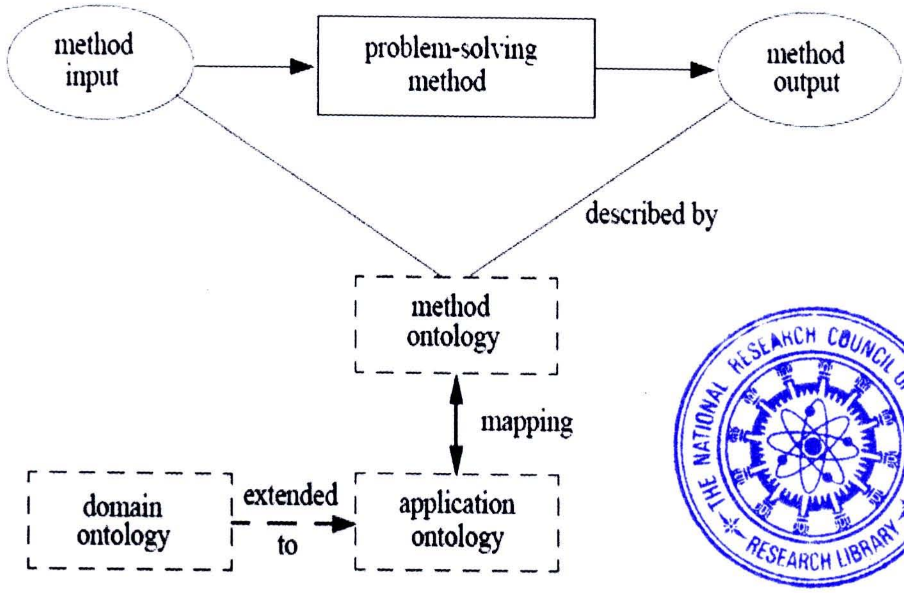

Figure 2.6 An inference layer with a typical data-concept mapping (Preston, Chapman, Pinfold, & Smith, 2005)

2.3.2 A development of knowledge-based expert system for car faulty diagnosis

2.3.2.1 Knowledge acquisition and representation

In common with all KBES, knowledge acquisition was the first and most difficult task in developing this prototype. This is because the knowledge to be represented should not only be based on correct facts and data, but should also include all possible alternatives with the concept mapping (Chang, Sung, & Chen, 2001, 2002). It may happen that the cause of the observed symptom is excluded, resulting in an incorrect diagnosis that leads to unnecessary repair or replacement. In spite of these inherent difficulties, the diagnostic knowledge was easily captured. The basic reason was that decision trees were utilized extensively to represent the expertise in a clear and compact way, allowing the possibility of visual guidance.

The developer's past experience as an auto mechanic and reference to auto engine troubleshooting catalogues and texts have also made this process simpler. In recent year, concept maps were widely used to list the possible causes for a given fault symptom, including the interdependence of failures and their causes. Knowledge representation systems, also called expert systems, are computerized models that capture the knowledge of one or more human experts and store it in the framework that is most appropriately suited to the reasoning processes that the experts use in their problem-solving behavior (Chen & Zhiming, 2008).

According to Milton 2007, the knowledge engineer then encodes the expert's knowledge into a knowledge base, which is a repository of the expert's knowledge in a particular representational structure. Some of the most common knowledge representations are described below. In addition to the knowledge base, an expert system includes an automated reasoning mechanism called an inference engine that performs calculations and/or logical processes to produce the results of a particular problem-solving session. Each knowledge representation has a corresponding inference technique. Three very common knowledge representations are rule-based systems, frame-based systems, and case-based systems (Hall, 1988; Halford, 1993).

The misfit of new, different experience to existing, inadequate schemata produces cognitive dissonance in the learner and a state of disequilibrium. Existing schemata must be restructured to fit or accommodate the unfamiliar experience and to return to equilibrium. In this study, researchers complies concept of addition must be extended to include fractions with previous experience. Increasing quantity and quality of experience with adding the knowledge constructed within concepts through assimilation and accommodation can vary in quantity and quality. Knowledge constructions consisting of greater quantity and quality of knowledge acquisition and knowledge representation advanced learning as shown in Table 2.1 (Hao, Kwok, Lau, & Yu, 2010; Haugwitz, Nesbit, Sandmann, 2010; Hilbert & Renkl, 2009; Jonassen, 1997, 2000, 2004; Jonassen & Hernandez-Serrano, 2002; Tzeng, 2009).

2.3.2.2 Structure of KBESCFD

KBESCFD is concerned with the general and most common passenger car and light truck failures that can be diagnosed off-line. Given a concrete problem for a specific car faulty diagnosis, the system is flexible to modify and update, so the concept mapping can generate specific design information such as electronic fuel injection control system, diesel common-rail fuel direct injection system, and transaxle system. Such the KBESCFD can be used in the diagnosis knowledge base and the system can refer to them under execution. The users is provided with various types via computer that fulfill a variety of functions.

The main idea of the KBESCFD illustrates primary differences between expert and novice troubleshooters are the amount and organization of system knowledge (Johnson & Rouse, 2001). An analysis of the cognitive processes through the KBESCFD required solving automotive troubleshooting tasks shows (Butler, 2005; Foran, 2005; Jones, 2002; Mills, 2005; Peatman, 1988) that technicians must:

1. Identify fault state and related symptoms, that is, define the current state of the system being troubleshot.
2. Construct a mental model of the problem by:
    - 2.1 Describing the goal state (how do you know when system is functioning properly).
    - 2.2 Identify the faulty subsystem (known as space splitting).
3. Diagnose the problem by:
    - 3.1 Examining the faulty subsystems;
    - 3.2 Remembering previously solved problems;
    - 3.3 Reusing or adapting the previously solved problem;
    - 3.4 If no previously solved problem is available, ruling out the least likely hypotheses;
    - 3.5 Generating an initial hypothesis and assumptions about the problem;
    - 3.6 Testing this hypothesis based on domain knowledge;
    - 3.7 Interpreting the results of test;
    - 3.8 Confirming or rejecting the validity of the hypothesis, and if it is rejected, generating a new hypothesis;
    - 3.9 Repair the process of generating and testing hypotheses until the fault is identified.
4. Implement the solution by replacing the defective part of subsystem.
5. Test the solution to determine if the goal state is achieved.
6. Record the results in a fault database (that is, remember the case for future reuse).

2.3.3 Fault symptoms and hypothesis generation

Associated with the KBESCFD is the inference mechanism. It is predominantly based on the backward-reasoning technique. Backward reasoning starts from a given goal that is mostly given by a hypothesis. The reasoning process begins from this hypothesis and solves for facts that support it. Diagnosis problem have a defined goal (the symptom) and can be easily represented by rule-based and concept maps; this makes backward chaining a good solving (Jonassen & Hung, 2006), hence it is used by most intelligence fault diagnosis systems.

KBESCFD proposed that concept mapping can be integrated synergize the troubleshooting potentially. The categories have the following:

2.3.3.1 Problem space construction

Researchers focused on the constructing problem space are the first step in solving problems (Newell & Simon, 1972). "Problem solving must begin with the conversion of the problem statement into an internal representation" (Reimann & Chi, 1989, p. 165). Therefore, the problem space of any troubleshooting problem is the mental model of the task environment that the troubleshooter constructs. For instance, the electronic fuel injection control systems are represented as wiring diagrams, exploded views of mechanical and electronic systems, and flowcharts of diagnostic procedures. External problem space representations guide troubleshooters construct internal representations of the system.

Later, researchers demonstrated a multi-layered external problem representation for guiding learners that includes topographic description of the system components, functional descriptions of the system flow, normal behaviors of the system components, symptoms or behaviors the system exhibit when operating correctly and faultily and representations of strategic decisions required during troubleshooting.

2.3.3.2 Identify fault symptoms

Researchers trained troubleshooters use strategic knowledge about which procedures to perform in order to identify discrepancies. Recognizing symptoms of faulty components is also aided by experience. The likelihood of symptoms becoming apparent is a function of historical knowledge.

2.3.3.3 Diagnose fault (s)

After constructing a problem space, the troubleshooter begins the diagnosis process by examining the faulty system and comparing the system states to similar problems those themselves solved. Throughout the process of "hypothesis generation and testing" cycles (Johnson et al., 1995, p. 10), the troubleshooters attempt to further narrow the problem space and isolate potential faults. Johnson (1989) explained that these potential hypotheses are generated to provide possible explanations for the causes of the system fault. Researchers classified hypotheses while troubleshooters create concept maps into four levels:

1. System: The hypotheses conjecture the fault at the system level but do not reduce the problem space beyond the entire equipment or complete system.
2. Subsystem: The hypotheses conjecture the fault at the subsystem level and reduce the problem space to a discrete subsystem within the complete system.
3. Device: The hypotheses conjecture the fault at the device level and reduce the problem space to a limited number of components within a subsystem.
4. Component: The most specific type of hypotheses that conjecture the fault at the component level and result in the identification of a single component as the potential fault cause.

2.3.3.4 Generate and verify solutions

Researcher suggested the troubleshooter needs to generate one or more solutions for repairing the system based on the results of tests. As with diagnosis, skilled troubleshooters rely first on their experiences. They must know that certain solutions are quicker, easier, cheaper, or more reliable. They must select the most plausible solution from the set of solutions generated (Johnson et al., 1993) and determine which best meets all the constraints (e.g., effectiveness, efficiency, system-specifies, or economic consideration).

2.3.4 Design of integrated KBESCFD model

Researchers is necessary to design new, more complex and powerful monitoring and car faulty diagnosis, due to the rapid development of automotive technology and the continuously increasing demands of the dealers. The vast majority of KBESCFD have human expert reasoning monitoring available for faults characterized by real world problems in their automotive troubleshooting tasks. These states can be obtained directly by using a concept mapping between the technicians and the monitoring and diagnosis system with computer-assisted concept mapping.

However, there is little evidence that the process conditions are continuously monitored with human expert reasoning. Hence, the computer-assisted concept mapping must be acquired by designing a data-representation system inside the KBESCFD. Hence, the inference engine of the integrating monitoring and diagnosis system with a modular structure is established and designed as shown in Figure 2.7. Therefore, there is a need for establishing a model of KBESCFD that integrated diagnosis expert system with the concept maps.

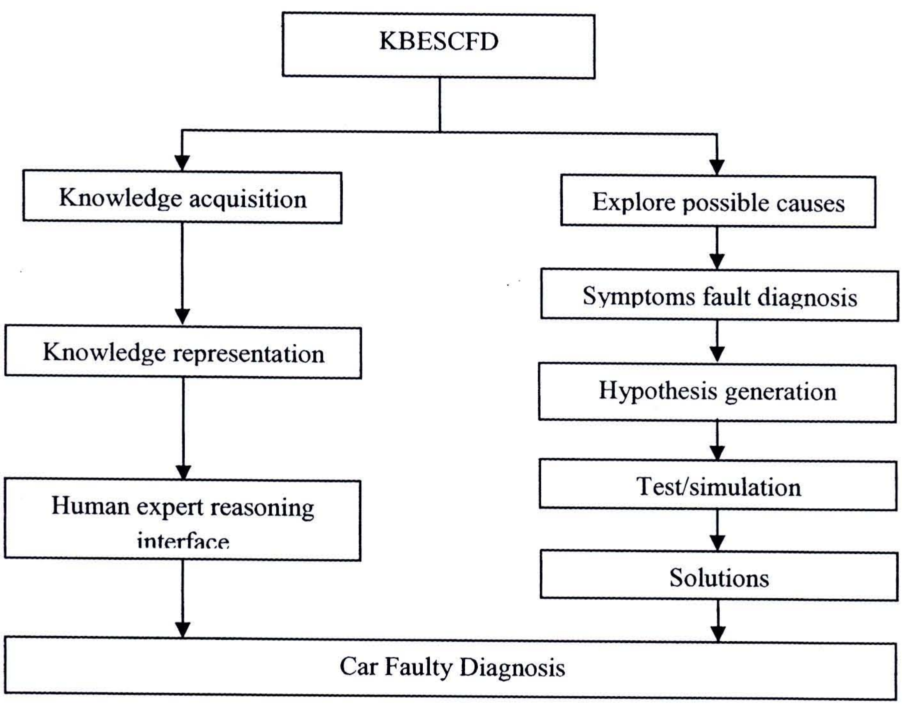

Figure 2.7 A block diagram of the KBESCFD

2.4 Concept mapping as a support tool of KBESCFD model

The use of concept mapping is diagnosis problem has a defined goal (the symptom) and can be easily represented by rule-based and concept maps generating ideas linked to the starting-point for training. Concept mapping (as developed by Novak, 1990, 1998) has been shown to be a classroom environment technique for enhancing learning in the sciences (e.g. Horton et al., 1993; Lawless, Smee & O'Shea, 1998). In this case, concept mapping can be a helpful the KBESCFD, promoting understanding in which new material interacts with the technician' existing cognitive structure as shown in Figure 2.8.

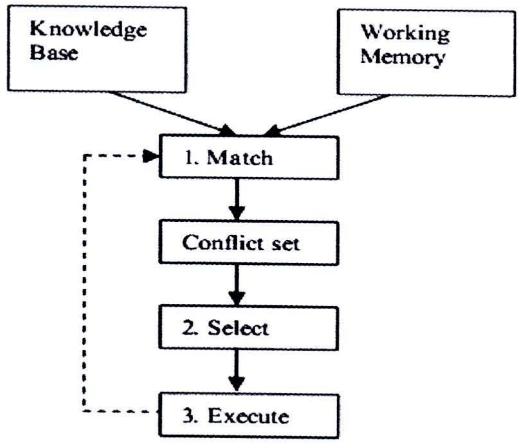

Figure 2.8 The applications of inference process
(Wang, Luo, & Shiech, 2006)

The interaction of new and existing knowledge is made easier if the existing knowledge is made explicit to both trainer and practitioner. This is described as 'meaningful learning' as shown in Figure. The concept mapping as an inference engine excepts user input queries and responses to question through the input/output interface and uses dynamic knowledge together with static knowledge of the database to derive conclusions about situations (Wang, Luo, & Shiech, 2006). The process is recursive and carried in three stages as shown in Figure 2.6.

When abnormal situation arises in the car, the KBS makes inferences by deciding which rules are satisfied by facts stored in the working memory and executes the rule with highest priority and propose proper correcting solution. The rules whose patterns are satisfied by facts in the working memory are stored in the agenda part of the inference engine. Figure 2.8 explains the inference process of the system using the rules listed. Figure 2.9 shows the relationships between the four rules used in this example.

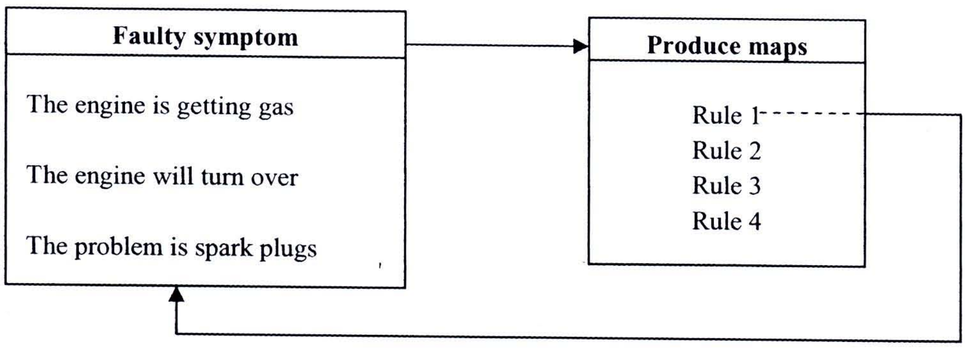

Figure 2.9 The inference process of the system using the rules listed

The system indicated that a full expert system will be practical and can be extremely useful in providing consistent car failure detection. KBESCFD is needed to improve the system by adding sufficient domain knowledge that represents domain knowledge thoroughly.

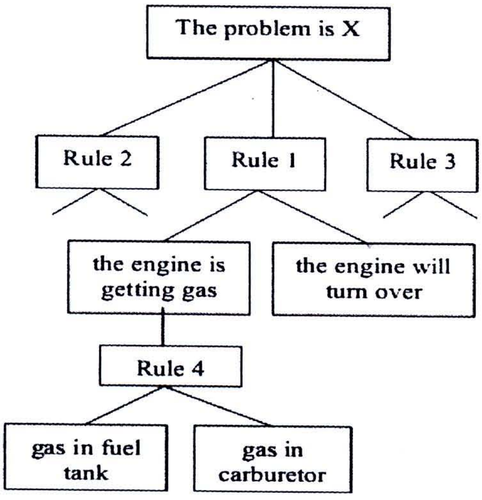

Figure 2.10 The concept mapping relationships between the four rules (Gegele & Wang, 1998)

Jonassen (2000) suggested that the construction of a concept map is intended to reveal the perceptions of the map's author, rather than a reproduction of memorized facts. According to Halford (1993), 'to understand a concept entails having an integral representation or mental model that reflects the structure of the concept' (p. 7). The structure of map is, therefore, unique to its author, reflecting his/her experiences, beliefs and biases in addition to his/her understanding of a topic. The ability to construct a concept mapping tools also illustrates two essential properties of understanding, the representation and the organization of ideas (Novak & Gowin, 1984). It takes one concept as the center, and related concepts and details emerge as the mapping develops from the central to the external (Fisher, Glietman, & Glietman, 1991; Boyle & Weisharr, 1997; Gould, 1987).

The expert-constructed concept map is another method of teaching and learning strategies. This concept map differs from the former learner-constructed concept map because it is developed by instructor. The expert-constructed concept map is used to train learners in comprehension of a text and to save instructors time in teaching (Hall, 1988; Jonassen, Beissner, & Yacci, 1993). The "learner-constructed concept map" and the "expert-concept constructed concept map" each have their appropriate times, and instructors can use these two ways of concept mapping alternately in order to trigger meaningful learning (Huang, 2005). This study is employed the "learner-constructed concept map" and the "expert-concept constructed concept map" as well for accuracy and efficiency in research conducting (Yin et. al, 2005).

2.4.1 Applications of concept mapping in a KBESCFD model

When a technicians is processing information, concept mapping can stimulate his/her metacognitive awareness so that it assists the leaner not only to establish an appropriate monitoring strategy but also to increase the use of retrieving and memorizing knowledge on case(s) complicatedly as shown in Figure 2.10 (Chen & Chang, 1997; Chiu, Huang, & Chang, 2000; Novak, 1990; Novak & Gowin, 1984).

To improve technicians' ability, effective KBESCFD model and supportive tools are being widely considered. Researchers have found that concept mapping troubleshooting strategies can enhance technicians' problem-solving and used as a support tool of KBESCFD model (Amadieu, Gog, Paas, Tricot, & Marine, 2009; Akinsanya & Williams, 2004; Cline, Brewster, Fell, 2010; Hao, Kwok, Lau, & Yu, 2010; Haugwitz, Nesbit, Sandmann, 2010; Hilbert & Renkl, 2009; Tzeng, 2009). A concept mapping automotive troubleshooting task strategy offers troubleshooters a more systematic and organized way to clarify the important concepts of problem-solving skills procedures (Johnson, 1989; Jonassen, 2000, 2004) as shown in Figure 2.11.

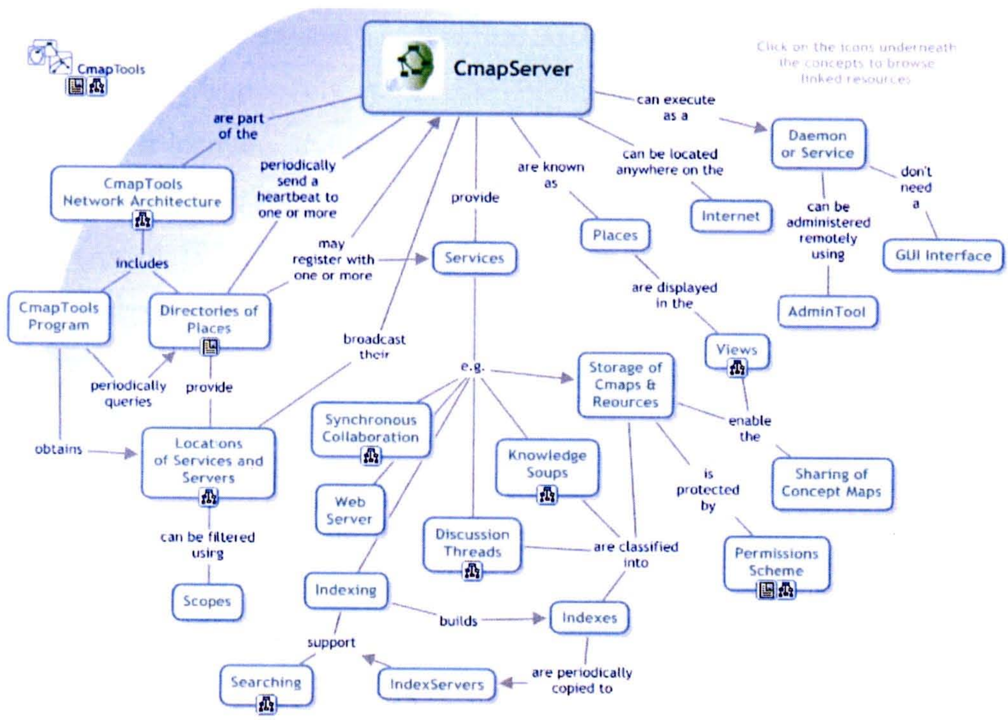

Figure 2.11 Concept mapping tools

Institute for Human and Machine Cognition (2009)

Nevertheless, two limitations are noteworthy in the process of drawing concept maps using traditional paper-pencil methods. First, if the concept map involves a number of concepts, it may be too complicated to use conveniently (Anderson-Inman & Zeitz, 1993; Reader & Hammond, 1994). Second, with the traditional paper-pencil method, instructors cannot conveniently provide immediate feedback to each learner.

2.4.2 Concept mapping as a knowledge inventory

The complexity of automotive problem-solving skills strategies remains a problem in especially with the changes in new innovation. Through the construction of a concept map, meaningful learning can be assisted (Ausubel, Novak, & Hanesian, 1978). Novak (1995) describes a variety of applications of concept mapping in knowledge representation. For example, concept maps can assist the preparation of lessons and the sequence of topics presented; they can serve as a basis for discussions, and they can be used as a tool for knowledge storage and evaluation. Furthermore, concept maps can assist learning from the knowledge inventory.

A variety of studies have demonstrated the effectiveness of concept mapping as a leaning strategy. In a meta-analysis, Horton, McConney, Gallo, and Woods (1993) found a generally positive effect of concept mapping on knowledge acquisition. Compared to other learning strategies, learners who used concept mapping as a learning strategy performed better than, for example, learners who co-learners who used underlining (Amer, 1994) discussing with co-learners (Chularut & Debacker, 2004), or outlining (Robinson & Kiewra, 1995).

Traditionally, concept maps are generated using paper-pencil method. However, using computer software to create concept maps allows learners to re-arrange, color-code, add, or delete concept nodes and links with relative ease. Learners usually prefer the higher flexibility of computer-generated concept mapping (Sturm & Rankin-Ericson, 2002; Hilbert & Renkl, 2008, 2009). Although concept mapping successfully fosters learning and understanding, beginners often lack the skills to productively use concept mapping tools and thus cannot their full potential.

Hence, the employment of worked-out concept maps that are provided by an instructor is a promising method (Chang, Sung, & Chen, 2001, 2002). Although learning from a worked-out concept map can be effective way on learning contents, creating concept maps on their own helped learners use this technique more effectively. O'Donnell, Densereau, and Hall (2002) state that training is a key factor in producing favorable outcomes when concept mapping is employed. Most studies merely report some anecdotes of the learners' difficulties during concept mapping (Jonassen, Beissner, & Yacci, 1993). Knowing beginners' specific deficits is necessary in order to develop effective training approaches.

2.4.3 What characterizes good and poor mappers?

With the aim of developing an effective concept mapping training, Hilbert and Renkl (2008) carried out a think-aloud study to analyze the relationships between cognitive processes during concept maps the learners produced and learner outcomes. Unsuccessful learners seldom labeled the links that connected the concept nodes. They were also characterized by employing very little planning and controlling strategies. In contrast, effective learners showed much effort in planning their mapping process with three steps:

1. Planning the concept map is the first step.

2. While actually constructing the concept maps, learners have to pay special attention to the relationships between the concepts nodes.

3. The concept map has to be steadily controlled for its correctness and completeness and – if necessary – learners have to encourage in a new planning activity to revise concept map.

Thus, begin the curricular process of concept mapping over again. In sum, to learn successfully by concept mapping, learners should engage in planning processes, should aim to construct a coherent concept map and should control the progress of their map (Hilbert & Renkl, 2008) as shown in Figure 2.12.

2.4.4 Concept mapping representation and evaluation methods

Two main issues of concept mapping in this study were considered: concept map representation, and methods for evaluating concept maps. Researchers searched for a concept map representation that would consequently two categories: First, a concept mapping representation that would help troubleshooters' think-aloud study to case-based reasoning on automotive troubleshooting tasks. Second, researchers needed a concept map representation that would lend itself to electronic evaluation. Because our study is targeted at troubleshooters can be solved the problems based on case(s) and because endeavors in learning troubleshooting environment (TLE) require a level of accuracy greater than some other disciplines, researcher elected to use a formal representation software IHMC Cmaps Tools version 4.18 see above Figure 2.12 (Institute for Human and Machine Cognition, 2009).

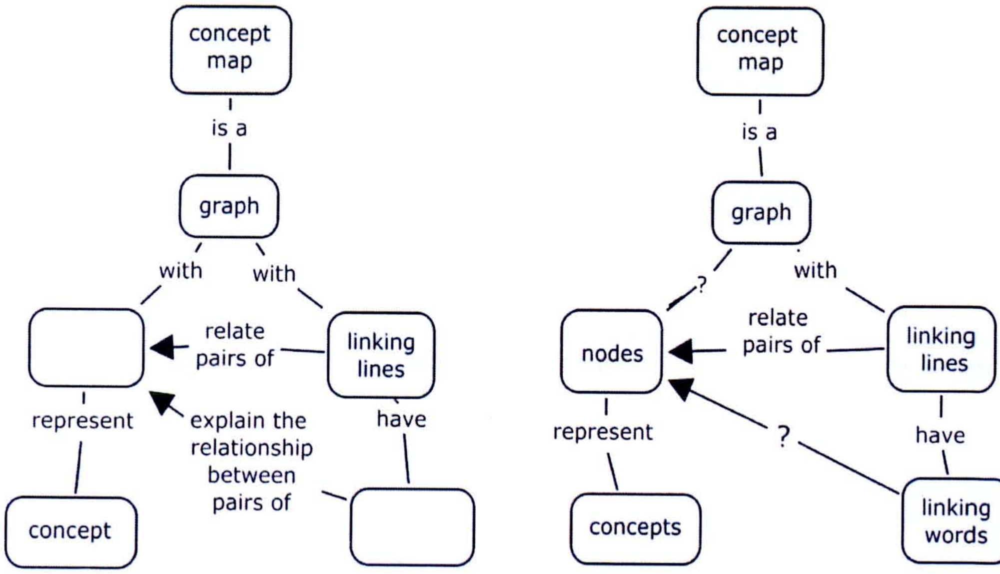

Figure 2.12 Examples of good mappers (Novak & Gowin, 1984)

In experiment group, computer-assisted construct concept node labels are unique, representation five automotive troubleshooting tasks to knowledge. The concept map has valid propositions for sub-graph and clearly shows that regarding is performed by a Novak Scoring Protocol (Novak, 1998; Novak & Gowin, 1984) and that is the process that compares the "learner-constructed concept map" and the "expert-concept constructed concept map". The development of concept mapping Novak and Gowin (1984) noted that "there is also an apparent arbitrariness in scoring concept maps as shown in Figure 2.13. For the evaluation of concept maps in this study, the following scoring method developed by Novak and Gowin (1984) was used scoring criteria for concept maps can be explaining that:

1. *Propositions.* Is the relationship between two concepts indicated by a connecting line and linking word(s)? Is the relationship valid? For each meaningful, valid proposition shown, score 1 point.

2. *Hierarchy.* Does the map show hierarchy? Is each subordinate concept more specific and less general than the concept drawn above it (in the context of the material being mapped)? Score 5 points for each valid level of the hierarchy.

3. *Cross links.* Does the map show meaningful connections between one segment of the concept hierarchy and another segment? Is the relationship shown significant and valid? Score 10 points for each cross link that is both valid and

significant and 2 points for each cross link that is valid but does not illustrate a synthesis between sets of related concepts or propositions. Unique or creative cross links might receive special recognition or extra points.

4. *Examples*: Specific events or objects that are valid instances of those designated by the concept label can be scored 1 point each.

In addition, a criterion concept map may be constructed, and scored, for the material to be mapped. Then divide the students' scores divided by the criterion map score to give a percentage for comparison. (Note that some students may do better than the criterion and receive more than 100 %)

In an earlier study, Ruiz-primo et al. (2001) described the use of a criterion map for manually scoring student concept maps. The criterion map Novak Scoring Protocol was a composite of concept maps produced by domain experts, teachers, and researchers. He found that students' concept maps were compared to the criterion map for proposition accuracy, convergence, and salience. Proposition accuracy is based on rating system that assigns scores of excellent, good, poor, and invalid to propositions.

Ruiz-Primo et al. (2001) consisted an excellent proposition to be both complete and correct, and one that demonstrated a deep understanding by the student of the concept map involved. A good proposition was one that was complete and accurate and missed some key attributes of the relation between concepts. A poor proposition was correct but showed only partial understanding by the student of the concept maps. An invalid proposition was incorrect.

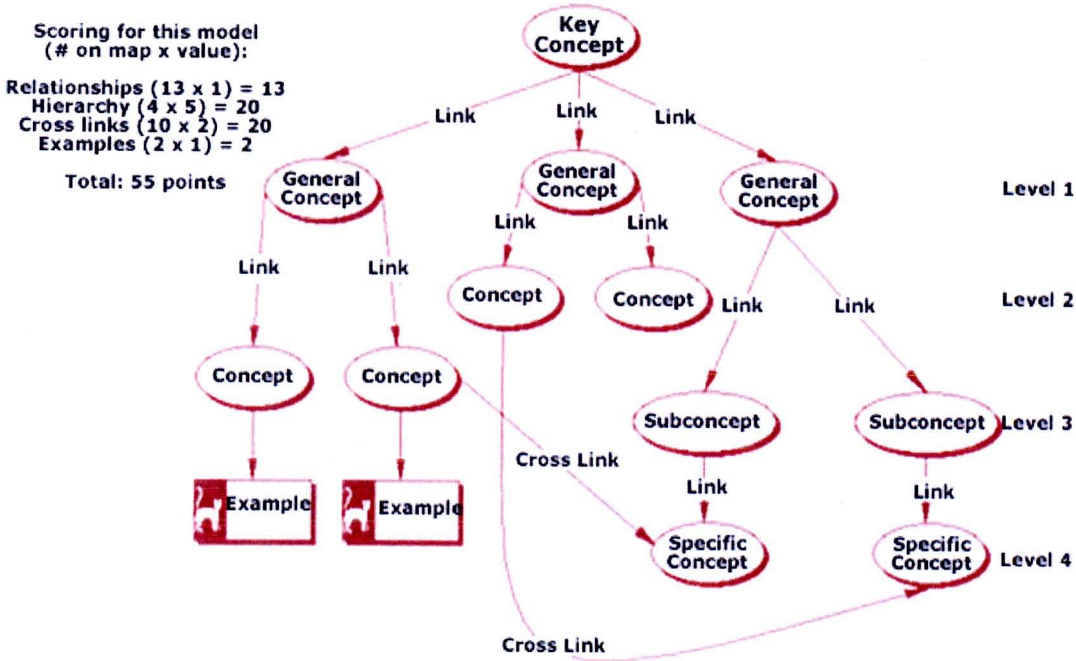

Figure 2.13 Novak Scoring Protocol

(Novak & Gowin, 1984)

2.5 Computer-assisted concept mapping in a KBESCFD model

In applications of KBESCFD, research of Chularut and DeBacker (2004) indicated that students with low proficiency benefited more from the Computer-Assisted Concept Mapping (CA-CM) strategies. They also found that the concept mapping group showed significantly greater gains from pre-test to post-test students, learning different concept mapping strategies. Moreover, Haugwitz, Nesbit, and Sandmann (2010), the concept mapping strategy was found to be advantageous only for students whose cognitive ability was below the median for the sample and who were placed in groups with other students having low cognitive ability. Thus, research results on the effects of concept mapping on automotive troubleshooting ability in specific and for troubleshooters gained proficiency knowledge structure and problem solving skills.

KBESCFD can computerize concept mapping is easily succeeded, and it attempt learners create concept maps quickly and accuracy. Thus, computerized concept maps strategies are more helpful in organizing information and promoting comprehension than traditional training strategies. Computers are linking both instructors and learners interactive as well (Anderson-Inman & Zeitz, 1993; chen & Chang, 1997; Novak & Gowin, 1984). In other words, computers can track and record learners' concept-constructing processes, analyze their thinking patterns, and re-solve test results (Shin, Deno, Robinson, & Marston, 2000; Schin, Jonassen, & McGee, 2003).

The IHMC CmapTools have potentially been made available; consequently, it use to employ in this study. Troubleshooters can download it from the internet. Messerotti (2010) undertook the IHMC CmapTools software in research and education, which its application for the high-level development of multi-level concept maps in the framework of Space Meteorology. In Messerotti's study, they are suitable to be published on the web: the coded knowledge can be exploited for educational purposes by the students and the public, as the level of information. The study provided evidence that CmapTools software can be naturally organized among linked concept maps in progressively increasing complexity level for high-level knowledge representation in research and education.

2.6 Summary

Automotive service technicians must have the thinking skills is the core of higher-order or advanced thinking. Thinking processes are a goal-oriented, strategic, and multi-step process that is required for solving real-world issues. Real-world issues include designing artifacts, making decisions, and solving problems. Designing artifacts consists of planning, performing, assessing, and revising a task.

The review literature summarized knowledge Engineering results in several important achievements which are also relevant for other disciplines like Software Engineering, Information Integration or Knowledge Management. Notable developments are:

1. Within the framework of model-based KE, model structures have been defined which clearly separate the different types of knowledge which are important in the context of Knowledge-based System (KBS). The knowledge-based expert system model is the most prominent example of these models.

2. The clear separation of the notions of task, problem-solving method, and domain knowledge provides a promising basis for making the reuse-oriented development of KBS more feasible.

3. The integration of a strong conceptual model is a distinctive feature of the KBESCFD.

Overall consensus is that knowledge management requires an interdisciplinary approach including technical support by human reasoning. A central technical aspect of knowledge management is the construction and maintenance of a working memory as a means for knowledge conservation, distribution and reuse. Furthermore, one should be aware, that although a considerable effort is put into knowledge management, the construction and application of organizational memories is still in a very early stage.

In general, the developments in several disciplines rely on extracting, modeling and exploiting various types of knowledge in order to address the demands which arise among others from the growing complexity of applications. Methods and concepts from KBES are certainly one of the promising approaches for developing solutions which are able to meet KBESCFD and the CA-CM.