IMPROVING RISK IDENTIFICATION BY UTILIZING HYBRID INTELLIGENT REASONING

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Risk management is an important project management tool that is in order the understanding of the scope and potential problems related to projects to support decision making. Despite the wide variety of methods in existence, the application of risk management in practice is still limited. One reason relates to the level of accuracy and complexity of current analysis tools, accurate analysis relies upon the identification of realistic risk factors. Risk identification is about trying to forecast potential sources of risk that might impact on successful completion of a project. Risk identification is a key part of risk management and it identifies the potential sources of risk. Risk forecasting considers the probability and impact of these sources. Popular risk identification methods are mostly based on expert knowledge, so identification largely depends on the involvement and the sophistication of experts. Subjective judgement and intuition usually accompany the experts' opinion; this could be expressed as the impact of human behaviour. In order to reduce such subjectivity and enhance knowledge sharing, artificial intelligent techniques can be utilised. An intelligent system provides storage to accumulate retrievable knowledge and reasoning in an impartial way so that a common acceptable solution can be achieved. This paper introduces a hybrid approach to modelling risk identification in construction projects. Case-based reasoning and rule-based reasoning are two artificial intelligent paradigms that have already proved to be successful in managing knowledge. The integration of Case-based reasoning and Rule-based reasoning is particularly useful for project knowledge in relation to risk. Case-based reasoning matches the manner that humans solve problems by remembering past similar experience, which can provide compelling support for forecasting and then decision making. Rule-based reasoning provides suggestions on the basis of a situation detection mechanism that relies on structured prior knowledge when there are no matching cases in case base. A pilot study has shown that the approach is feasible and this will soon be fully tested using project data.

Keywords: case-based reasoning, decision support, reasoning, risk identification, rule-based reasoning.

INTRODUCTION

The increasing complexity of both projects and project environments causes many projects to fail to meet their expected goals. Risk management is an important tool to aid decision making in projects leading to a higher probability of a successful outcome.

As most data storage and complex calculation demands have been met, the research focus of computer science has now moved to knowledge management, helping humans cope with intricate problems with non-numerical information. This is similar to the development of the project risk management approach: in the 1980s, the quantitative theory was successfully established; then in the 1990s, the relevant theory was integrated into various risk analysis software. More recently the qualitative stage

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of risk management has became more important, as it decide whether or not the quantitative stage carry on and what quantification elements should be. Obviously, the main purpose of risk identification is to gain knowledge about uncertain situations and potential problems that might arise in a given project. For such work, present procedures largely depend upon the involvement and the empirical knowledge of the experts. In addition, subjective judgement and psychological influence usually accompany experts' decisions; this could be expressed as the impact of human behaviour. In the present paper, it will be argued that to reduce such subjectivity and to manage the project knowledge in a dependable manner, a hybrid system that combines case-based reasoning (CBR) and rule-based reasoning (RBR) is an ideal tool.

The system proposed will works as follows. The project risk documents are retained in a case-base as problem description and solution. When a new project is instigated, the relevant description is selected, and then the system retrieves from the case-base to find the nearest matching cases by providing a matching list. This has descending matching scores and an explanation of why the case has been selected. The procedure also generates a suggested solution by reusing the solutions of the matching cases. The user can also review details of the matching cases and they are able to retrieve the previous solutions for these cases. The system is intended to support the decision making in risk identification, so the user can decide whether or not they use the output solution. They can revise the solution, and the common accepted one will be retained in the case base as a new piece of knowledge for the future use. As the available data in construction projects is not abundant as in medical diagnosis, occasionally there might not be satisfactory matching cases in the case-base, so the RBR can be used. Rule-based system makes a forward chain with If-Then rules, seeking a solution in a deductive way. The solution found from rule-case reasoning can also be retained in the case-base. Such integration enhances the flexibility of the system and ensures that it can provide solutions in the majority of situations.

PROBLEM DESCRIPTION

Risk identification provides fundamental information for subsequent forecasting stages: assessment, ranking, classifying, and judging the probability and impact of potential risks. However, in practice, researchers have paid more attention to quantitative analysis. Raftery [17] suggested that the risk identification stage has not been adequately addressed in risk management literature. Williams [20] advocated a 'risk register' component in the management system of a project to generate an accessible database of risk experiences. Edwards and Bowen [9] concluded: "risk management techniques were only useful as the willingness of the project participants to become knowledgeable and skilled in them".

In order to identify risks in an effective way, previous experience is important. The management of knowledge relating to project risks is the key to improve qualitative risk forecasting. Chapman [6] noted "for both parties to manage their risks effectively, it may be important to move towards a cooperative shared information approach to management."

Traditional methods

The traditional methods used for risk identification include checklists, brainstorming, examining historic data, and Delphi method.

Checklists are a simple and inexpensive way of generating information. However, the possibility of ambiguities and subjective alter the accuracy of results [8].

Brainstorming enables the project personnel to hear what the other members of the project team see as risks and then to use this idea to give themselves inspiration in identifying additional project risks. It is one of the most popular methods when carry out the risk identification because of its simplicity and speed. Merna [15] addressed limitations of this technique as its dependence on the group composition, conformance, personality characteristics, compatibility, and peer pressure.

The examination of historic data from previous projects ensures that corporate knowledge is utilized. However, an organization may not deal with same project twice and the data from a previous similar project may not be recorded. Therefore, this technique can only be successfully used in limited cases.

Delphi methods provides a communication process allowing a group of individuals as a whole to deal with complex problems. Nevertheless, the drawbacks of the Delphi method are insufficient reliability, over sensitivity of results to ambiguity of questions, time consuming [5] and it is expensive in terms of the resources used, the cost of resources, the time undertaken and the success of this method largely rely upon selection of the panel of experts.

Further more, with the advent of Artificial Intelligences, innovative applications such as Artificial Neural Network (ANN), Knowledge-Based Systems, Expert Systems and Machine Learning can enrich risk identification and management.

Limitation of current risk identification

Currently, risk identification is largely based on the subjective judgement of human experts. Decision-making is commonly based upon incomplete, contradictory information. The identified risk sources can be classified to uncertainty, risk, complexity, and opportunity. Group techniques, such as brainstorming and Delphi might broaden the perspective, "but the limitations of human processing information still will often preclude optimal decision-making" [16]. Psychological research finds that humans make future planning decisions averagely based on the three most recent decisions made by the same manager. According to Pender [16], it seems that about nine decision attributes that a person can effectively encompass each time, which illustrates that human have a limited information processing capability. Because people have limited information-processing capability, they cannot directly deal with complex problems even though the information may be available in some form. Psychologists found that modelling a judge's decision-making process, the results provided by using that model were more accurate than the judge's own decision [16].

On account of the complexity associated with construction projects, simple modelling systems cannot carry out risk identification. Compared with traditional risk management methods, artificial intelligent techniques have more flexibility. However, the main problem in deploying successful new systems is user acceptance: no system is useful unless its users accept its results. ANN has the advantage of self-learning, self-organizing and real time operation. However, ANN is like a black box that cannot provide explanations of their decisions. The Knowledge-based system must explains decisions by referencing to rules which the user may not fully understand or accept, and the process of obtaining rules is also time consuming. CBR learns from previous experience and solves problems by reference to earlier solutions. The reasoning process is retrievable and it can deal with textual information easily, so the output solution might more easy to understand and accept.

THE POTENTIAL FOR THE USE OF HYBRID REASONING

In construction, there are many situations where quantitative and detailed information to evaluate uncertainty is not available. The intelligent systems, like humans, solve hard problems despite limited and uncertain knowledge and their performance improves with experience. Jung *et al.* [12] explained that the CBR technique is good for the risk analysis process because it is useful for tasks that are experience-intensive, that lead to inconsistent outcomes, that have incomplete rules to apply, and that are hard to acquire domain experience. Bellazzi, *et al.* [5] stated that because of its 'inductive' nature, CBR use well suited for integration with other reasoning paradigms grounded on more general knowledge such as rule-based or model-based reasoning.

Case-based reasoning

Case-based Reasoning is a problem-solving paradigm that solves a new problem by remembering a previous similar situation and by reusing information and knowledge of that situation [2]. It usually contains four processes: retrieve the similar cases, reuse the retrieved cases to seek solution, revise the proposed solution and retain the new case. In a problem solving system, each case would describe a problem and a solution to that problem. It is concerned with solving new problems by adapting solutions that worked for similar problems in the past. When a problem is solved, the reasoner remains the case description and solution in the case base. Different from database query, it provides approximate matching according to attribute matching criteria. It could be applied to solve problem where no explicit model existed or with incomplete information, and CBR can learn by acquiring new cases and so improve their performance with time [10].

CBR has the advantage to handle non-numerical information. Attributes expressed mostly by textual items, solutions is output in text as well, so CBR is easily accepted by users because of its intuitive feel and retaining rich context of knowledge.

Rule-based reasoning

Rule-based programming is motivated by the observation that humans often detect a set of conditions in their environment and respond with a particular set of behaviours. In this sense, rules can be viewed like the IF-THEN statements in procedural programming: if a particular set of conditions exist, then respond with a particular set of behaviours [18]. RBR as a deductive reasoning approach is widely used by most of the existing domain knowledge as the rules to inference about new problems are considered as an effective reasoning mechanism when the theory of the underlying problem domain can be well-defined [7]. Rule-based system reasons from rules, which the experts do not use but observe. It explains decisions by citing rules. However, its inferences are static and predictable, therefore it is difficult to build, update and maintain.

Hybrid System

RBR and CBR have both been applied to a diversified collection of problems with some success. However, each reasoning approach has its weakness. Chi and Kiang [7] address CBR cannot easily take advantage of existing domain knowledge and sometimes makes decision intuitively, while RBR requires a complete theory of the domain but suffers from lacking of knowledge that can be derived from past experience. The integration of these two paradigms can overcome these limitations.

Indurkhya and Weiss [11] introduced ‘using case data to improve on ruled-based function approximation’, which relies on searching for the most relevant cases using a rule-based system, and then using these cases for determine the function value. Surma and Vanhoof [19] argued that when an activity has repeated frequently enough, it becomes rule- like in nature. So the algorithm presented in their ‘integrating rules and cases for the classification task’ as: IF a new case is covered by some rule, THEN apply a solution from a rule with the highest priority, ELSE adapt the solution from the most similar case. Later, An *et al.* [3] explained an approach of integrating rule induction and CBR to enhance problem solving: a set of decision rules are induced from a set of training data; rules are applied to make decisions; if there is a conflict between matched rules, CBR is performed.

CBR is particularly applicable to highly dynamic or poorly-understood domains, or where expert knowledge is difficult to divine or encode, while RBR is more concrete and tangible and require the information provided to them to be equally concrete and complete. A system that combines rule- and CBR technologies will lead to a better use of intelligence to a given process or problem. It may learn from preview experience and can continue the learning process as they are used and developed. The power of this system can be harnessed to help human experts more quickly solve a complex problem of risk forecasting [18].

In relation to project risk identification: where knowledge is gained from previous cases and experts, the integration of CBR and RBR is particular useful. CBR can be used to generalize solutions from non-standard situations, provide enough evidence to support decision-making. Meanwhile, it accumulated experience through coping with new case. Rules provide suggestions on the basis of a situation detection mechanism that relies on structured prior knowledge [5]. If a particular project class is not sufficiently covered by cases, the use of rules may be exploited to try to learn suitable situations, in order to improve the competence of the case-based component.

PROPOSED SYSTEM ARCHITECTURE

When carrying out risk identification for construction projects, the integration of CBR and RBR seems a natural solution: the widely recognized knowledge is formalized in the system as a set of rules, while additional knowledge, consisting of evidence-based information, is represented through a database of past collected cases [5]. The proposed system architecture is introduced from two angles: the application layer, which provide the basic information about how the data be managed and how can user access to the system, what information will be provided through the interface and the system framework about the internal process and methodology.

Application Layer

The application layer of this risk assessment system includes three parts: a graphic user interface (GUI), an application model, and a database mapping.

Graphic User Interface.

The user interface provides the communication environment between the user and computer. The user can access to the system through an intranet within a particular organization or internet under relevant authority. This makes knowledge can be broadly shared. The data transaction between web page and case base will be achieved through a template document on the server.

The input of the system is project features, such as project size, location, total project coast, project team membership, stakeholders, staff experience, contract type, schedule pressure, safety and health, change control, technical complexity, commercial/ contractual complexity, financing plan, source and amount, implementation period, contractor selection and governing law etc.

The output of the system includes: identified risk factors, the potential impact level, which is classified as opportunity, uncertainty, complexity and risk, and risk allocation strategy: avoid, transfer, mitigating, accept or maximize.

Application Model

Application model bridges the communication between database and user interface. It is built by constructing a set of risk forecasting object classes with a mechanism to automatically generate the object model.

For the CBR system, the project description will be classified in categories/ subcategories, which are defined as classes/subclasses in the system. The project detail is described by attributes under classes/subclasses. The cases will stored as different instances in the system. Each attribute has three scores to contribute CBR matching: match contribute score, absent penalty score and mismatch penalty score. Different match score calculation methods will be used:

For the symbolic string:

$$Case-score=\frac{\frac{attribute-score}{\max imum-stored-score}*100+\frac{attribute-score}{\max imum-presented-score}*100}{2}$$

For the numeric scoring:

$$Case-score=match-contribution-\frac{|SV-PV|}{match-\text{int}erval}*(match+mismatch)$$

SV=stored case attribute value
PV=presented case attribute value

In RBR part, rules are defined through: if condition fact 1, 2, 3…happened, then risk factors selected or actions should be taken will be…, else alternative actions… will be taken. Such kind of rules involves main information of the project make up a forward chain. To trace this chain, the solution that based rules will be found out.

Database Mapping

When forecast risks in a project, it is necessary to determine the consequences of project risks together with the magnitude of their impact and chance of occurrence as well as the exposure of project risk may well be presented by a hybrid reasoning system. This paper uses the risk breakdown tree as the way to construct project description in the case base, as shown in Fig. 1. Various external risk factors in terms of six major classes are identified: environment, finance, politics, society, and market. Similarly, the internal risk factors are divided into five major classes, which include communication, construction, geography, legal, and technology.

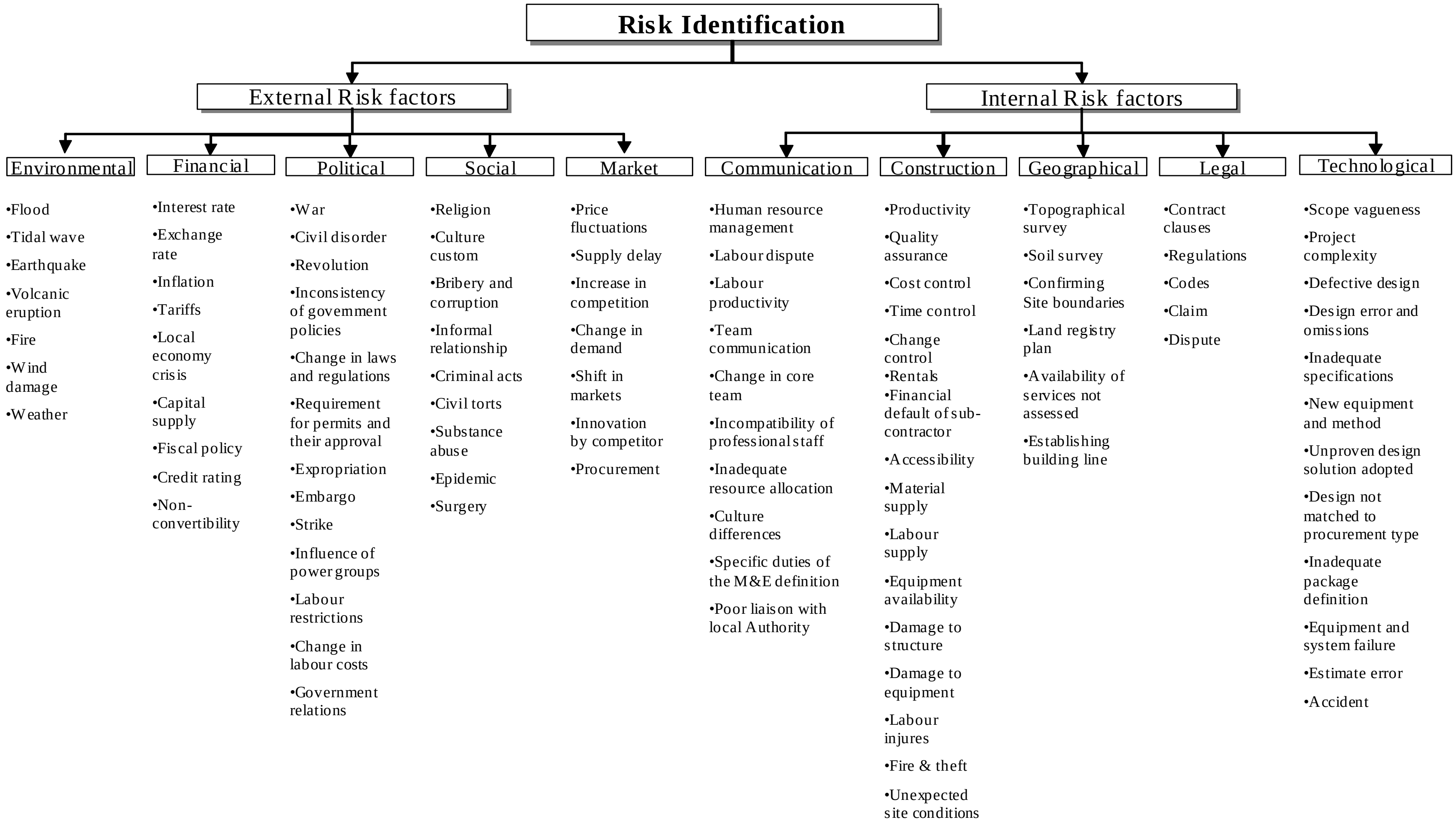

Figure 1 Data Mapping Structure

System Framework

CBR could takeover most of the identification tasks of project risk management. It depends upon general domain knowledge in contingency concerned with risks, the mechanism to select matching cases and knowledge update in the case base.

In practice, if reasoning from case-specific knowledge fails, for example when no similar situation is found in the case library, general knowledge in forms of If-Then rules may be used in an attempt to solve the problem[1]. Fig.2 shows the potential architecture of the hybrid system, which provides the procedure of how to build and maintain the system to support the organizational knowledge creation. The cycle of system evolution as shown defines a user interface, a system development process, a case-based development process, a RBR process and a knowledge base.

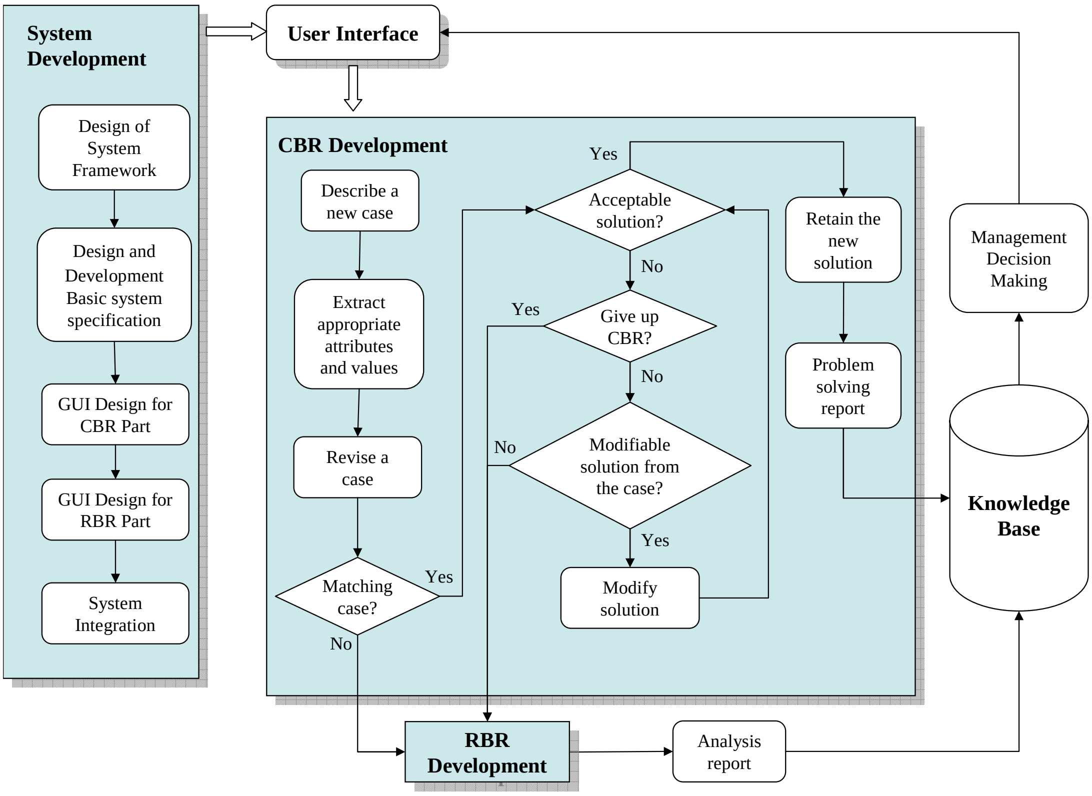

Figure 2 The Framework of Hybrid System

The “System development” process designs and develops a framework for the overall graphic user interface. It also provides space for structured data resources for case-base reasoning process and decides the way to manage knowledge gained from the rules. This can only be accessed by the system designer.

The “Case-base reasoning development” process starts after relevant problem features have been extracted from the problem description. The problem description is entered as data to the system, which interprets the data into information that can be used for programming. If the problem features match a certain problem, the case based problem solving solution is provided; if the solution is acceptable, or even not acceptable but can be modified to an acceptable one, the solution will be used. Otherwise, the RBR is processed. Most problems are solved by case-based method, while the rule-base supports the exceptional situation. The CBR/RBR reasoning will report its solution respectively, which elaborates a formatted case report to knowledge base, then output to facilitate users making their own decision.

These processes form one cycle of knowledge creation and system evolution. When the system passes relevant validation and verification, the system should hold a case-base consisting of appropriately represented and indexed high quality cases and a set of extracted rules specific to the application domain [13].

To forecast risk in construction project is particularly complex when compares with other application of commercial forecasting, such as product demand. It is the first time that the process of human adaptation knowledge has been imitated and used for risk forecasting by learning from similar previous cases through CBR and supported by RBR. The undertaken research is currently carried out in University of Leeds. The first hand data are provided by BNFL (British Nuclear Fuel plc.), and the secondary data seeks from World Bank project documents and information in various case study.

CONCLUSION AND FUTURE WORK

This paper has explored the feasibility of using a hybrid system for modelling human reasoning when carrying out risk identification in a construction project. CBR is an appropriate approach to manage project knowledge regarding risks and provides easy acceptable solution. The integration with RBR improves system flexibility. This approach intends to exploit the advantage of knowledge sharing, increasing confidence and efficiency in investment decisions, and enhancing communication among the project participants. This should bring about a focus change to risk identification and promote the application of risk management to construction industry.

The future research objectives focus on two points, one is to develop a hybrid reasoning based approach to forecast project risk system based on current framework; and the other is to validate and verify the result of the research and any guidelines arrived at through this research.

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