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A case-based reasoning based multi-agent cognitive map inference mechanism: An application to sales opportunity assessment

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Abstract In order to propose a new cognitive map (CM) inference mechanism that does not require artificial assumptions, we developed a case-based reasoning (CBR) based mechanism called the CBRMCM (Case-Based Reasoning based Multi-agent Cognitive Map). The key idea of the CBRMCM mechanism involves converting all of the factors (nodes) that constitute the CM into intelligent agents that determine their own status by checking status changes and relationship with other agents and the results being reported to other related node agents. Furthermore, the CBRMCM is deployed when each node agent references the status of other related nodes to determine its own status value. This approach eliminates the artificial fuzzy value conversion and the numerical inference function that were required for obtaining CM inference. Using the CBRMCM mechanism, we have demonstrated that the task of analyzing a sales opportunity could be systematically and intelligently solved and thus, IS project managers can be provided with robust decision support.

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1 Introduction

Causal Maps (CMs) or Fuzzy Cognitive Maps (FCMs) are useful decision making tools for resolving nonstructural problems with various quantitative and qualitative elements having cause and effect relationships. CMs are composed of (a) concept nodes (i.e., variables or factors) that represent the factors describing a target problem, (b) arrows that indicate causal relationships between two concept nodes, and (c) causality coefficients on each arrow that indicate the positive (or negative) strength with which a node affects another node. Its main virtue lies in the ability to see whether one node has influenced on the state of another node.

The CM has proven to be of particular use in attempts to solve unstructured problems with many variables and causal relationships. Examples include geographical information systems (Liu and Satur 1999), electronic commerce web site design (Lee and Lee 2003), knowledge management (Noh et al. 2000), business process redesign (Kwahk and Kim 1999), and neuroscience (Jeffery and Burgess 2006; Kumaran and Maguire 2005;). Although CM has been applied in various fields of the social and natural sciences (Styblinski and Meyer 1991), the majority of these applications have involved using the CM to solve specific problems and evaluate cause-and-effect relationships among elements of a problem, using the CM in the decision-making process of nonstructural problems via the CM inference function (Kardaras and Karakostas 1999), or applying the CM as a single mechanism of artificial intelligence (Miao et al. 2001). Taking into consideration the number of CM application studies that have been conducted in a variety of fields, it is apparent that relatively little research has been focused specifically on the process by which a CM is constructed.

Simply applying CM to a sales opportunity assessment is not enough since most existing causal relationships are hard to identify and measure exactly. Moreover, in order to apply the inference functions of CM in a decision-making situation the relationship strengths, inference functions, and fuzzified status values are still required. For the purpose of devising a new inference mechanism capable of providing inference without artificial and subjective assumptions, this study proposes the case-based reasoning based multi-agent cognitive map (CBRMCM). CBRMCM introduces the concept of the multi-agent which involves CM containing internal case-based reasoning. To demonstrate the validity of this proposed approach, the CBRMCM was applied to a real dataset (sales opportunity assessment cases) extracted from a multinational IT company. For the experimental platform of the CBRMCM, we adopted a *NetLogo* environment where decision makers can build their own multi-agents simulation mechanism for various decision problems.

The remainder of this paper is structured as follows. Section 2 presents a research background review focused on case-based reasoning applications. Section 3 describes the proposed CBRMCM using an illustrative example and elucidates its inference mechanism and implementation process. Some experimental results are presented and analyzed in Section 4 and finally our concluding remarks are provided in Section 5.

2 Applications of CBR

The case-based reasoning (CBR) approach is one of the popular methodologies currently in use in knowledge management. CBR is a novel paradigm that solves a new problem by remembering a previous similar situation and reusing information and knowledge of that situation (Huang and Tseng 2004). CBR is similar to the decision making process that human beings use in many real-world applications. It has often shown significant promise for improving the effectiveness of complex and unstructured decision-making. A general CBR cycle as described by Aamodt and Plaza (1994) is comprised of four activities: retrieve, reuse, revise, and retain cases. A case is defined as a situation or problem in terms of natural language descriptions and answers to questions and associates with each situation a proper business action.

(1) Retrieve the most similar case or cases.
(2) Reuse the information and knowledge in that case to solve the problem.
(3) Revise the proposed solution.
(4) Retain the parts of this experience likely to be useful for future problem solving.

In the retrieval process, many CBR models retrieve multiple similar neighbors rather than the single nearest neighbor. The results of the retrieved neighbors can be different from each other, thus CBR uses integrated results considering the degree of similarity and the number of neighbors. After that, it makes classification decisions by comparing the integrated results with the cut-off point. Utilizing these activities provides CBR the following advantages: knowledge acquisition is improved, existing data and knowledge are fully leveraged, domain knowledge is completely formalized, and the acquisition of new cases is made easier (Huang and Tseng 2004).

CBR applications can be broadly classified into two main problem types, namely, classification tasks and synthesis tasks. Classification tasks cover a wide range of applications that share all certain features in common. A new case is matched against those in the case-base to determine what type, or class, of case it is. The solution from the best matching case is then reused. Classification tasks have been successfully applied in many domains, for example, in medical diagnosis (Althoff et al. 1998), diagnosis of machinery breakdown (Varma and Roddy 1999), on-line services to help desk application (Göker and Roth-Berghofer 1999), electronic commerce (Vollrath et al. 1998), and military control (Liao 2000). There are over 130 companies (e.g. IBM, Intel, Apple, and Compaq et al.) currently using CBR methodologies to solve various problems (Vollrath et al. 1998; Watson 1999).

Synthesis tasks attempt to create a new solution by combining parts of previous solutions. Synthesis tasks are inherently complex because of the constraints between elements used during synthesis. CBR systems that perform synthesis tasks must make use of adaptation and are usually hybrid systems combined with other artificial intelligence techniques. In some application domains there is a need to combine CBR with other reasoning techniques such as Model-based Reasoning (MBR) or Rule-based Reasoning (RBR). Some examples are CABARET (Rissland and Skalak 1991) that integrates RBR and CBR to facilitate applying rules containing ill-defined terms; MoCas (Pews and Wess 1993) that combines CBR and MBR for technical diagnosis applications; BOLERO (Lopez 1993) which integrates RBR at the domain level with CBR at the meta-level in such a way that the cases guide the inference process at the domain level thereby allowing the system to learn control knowledge by experience; and MMA (Arcos and Plaza 1994) which is a reflective architecture capable of integrating different inference and inductive learning algorithms. Finally, we believe that the use of fuzzy logic

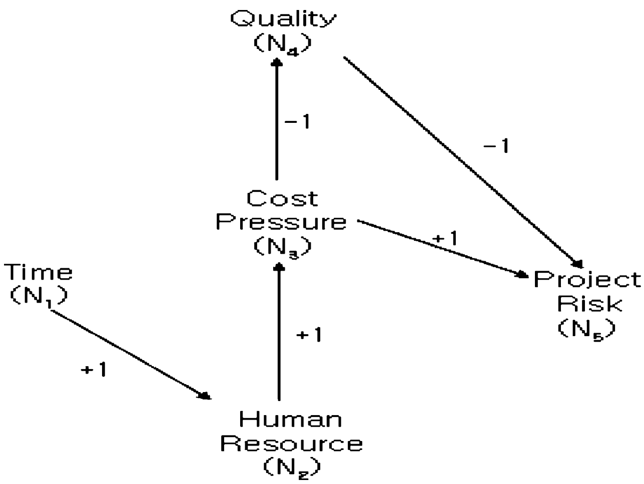

Fig. 1 Simple example of CM

techniques may be relevant in case representation thus allowing for imprecise and uncertain values in features. Case retrieval by means of fuzzy matching techniques and also for case adaptation by using the concept of gradual rules may also be relevant. Plaza and Lopez de Mantaras (1990) have performed studies on fuzzy CBR. Although there have been a number of studies conducted regarding the integration of CBR and other artificial intelligence techniques, hardly any studies have dealt with CM integration. One of the recent studies on the integration of CBR and CM include the proposition of the B2B negotiation mechanism based on the integration of FCM and the CBR technique by Lee and Kwon (2006). However, it involves selecting a FCM according to the circumstances from several FCMs rather than a complete integral mechanism of CBR and FCM. It also bears fundamental differences with the proposed technique for CM inference using CBR.

CBR has been criticized because its prediction accuracy is usually much lower than the accuracy of

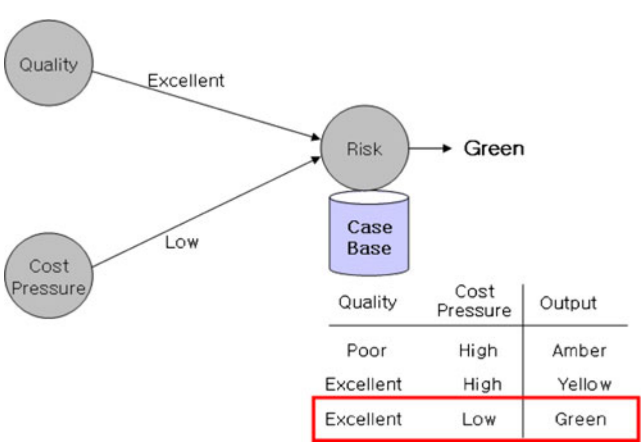

Fig. 2 Basic concept of CBRMCM

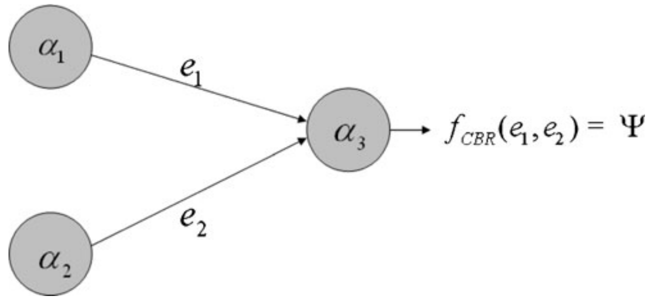

Fig. 3 CBRMCM inference mechanism

other artificial intelligence techniques, especially artificial neural networks (ANNs). Thus, there have been many studies to enhance the performance of CBR. Among them, mechanisms to enhance the case retrieval process such as the selection of the appropriate feature subsets (Domingos 1997; Glasgow et al. 2006), utilizing instance subsets (Chiu 2002; Liao et al. 2000; Wettschereck et al. 1997), the determination of feature weights (Babu and Murty 2001; Huang et al. 2002), and the number of neighbors that are combined (Ahn and Kim 2009) have been most frequently studied. Ahn and Kim (2009) proposed GOCBR (Global Optimization of CBR) which optimizes three parameters of CBR simultaneously using genetic algorithms: (1) the weights of the features, (2) the training instances, and (3) the number of neighbor cases that are combined. To validate the usefulness of GOCBR, Ahn and Kim (2009) applied it to the real-world case of breast cytology diagnosis.

3 CBRMCM

3.1 Background

The general process of extracting a CM for a particular problem involves in (1) extracting factors (nodes) that constitute the problem, (2) expressing the relationships among the extracted nodes with arrows, and (3) providing a relation strength to each relationship (Lee and Lee 2003;

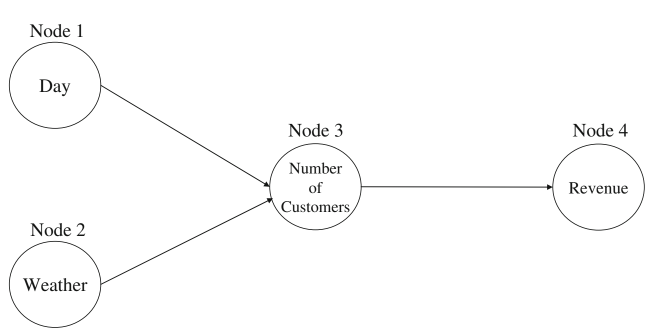

Fig. 4 Simple example of CBRMCM inference

Table 1 Case base of Node 3

No.	Input node value		Output node value
	Day	Weather	Number of customers
1	Weekday	Sunshine	500
2	Weekend	Sunshine	1,000
3	Holiday	Sunshine	1,000
4	Weekday	Rain	700
5	Weekend	Rain	1,500
6	Holiday	Rain	1,500
7	Weekday	Snow	600
8	Weekend	Snow	1,200
9	Holiday	Snow	1,200

Miao and Liu 2000). In order to utilize the completed CM as a decision making tool such as a *what-if* simulation tool, the fuzzy conversion mapping rule must also be defined in order to convert a node status into a fuzzy value. For the example given in Fig. 1, if we define the status of the "Quality" factor with four grades (excellent, satisfied, need to be improved, and poor), each status must be mapped with a fuzzy value for making inference. For example, a fuzzy value conversion gauge is defined as excellent (1.0), satisfied (0.5), need to be improved (−0.5), and poor (−1.0), then, the quality factor status is converted into a fuzzy value between −1.0 and 1.0. Identical conversion is required for the strength among the factors according to the relationship strength to be comparable. However, such fuzzy value conversion is very artificial and uses subjective assumption. One CM designer could assign a value of 1.0 to the grade "excellent" whereas a value of 0.9 could be assigned by another CM designer. Another problem with the conventional CM is that it generally uses the Tanh or 1/2 threshold function as the inference function. Expressing the cause and effect relationship between factors with a simple function could be regarded as an artificial assumption that skews real world facts.

Table 2 Case base of Node 4

No.	Input node Number of customers	Output node Revenue
1	400	3,200
2	500	4,000
3	600	4,800
4	700	5,600
5	800	6,400
6	900	7,200
7	1,000	8,000
8	1,200	9,600
9	1,300	10,400
10	1,400	11,200
11	1,500	12,000

In order to propose a new CM inference mechanism that does not require such artificial assumptions, we implemented a CBR based mechanism called the CBRMCM (Case-Based Reasoning based Multi-agent Cognitive Map). The key idea of the CBRMCM is shown in Fig. 2. The mechanism involves all of the factors (nodes) that constitute the CM being converted into intelligent agents that determine their own status by checking the status changes of and relationships with other agents, and the results being reported to other related node agents. Furthermore, the CBR technique is deployed when each node agent references the status of other related nodes to determine its own status value. This approach eliminates the artificial fuzzy value conversion and the numerical inference function that were required for obtaining CM inference.

3.2 CBR mechanism in CBRMCM

Every node in a CBRMCM is an intelligent agent and each contains an independent internal case base. The node agent detects the cause and effect relationship arising from the changes in the related node status and determines its own status according to the CBR technique. If we define the status change of the node agent as Event e as in Fig. 3, e affects the target node from the node created according to the causal relationship defined within the CM. In this case, Node α_3 receives e_1 and e_2 generated by Nodes α_1 and α_2

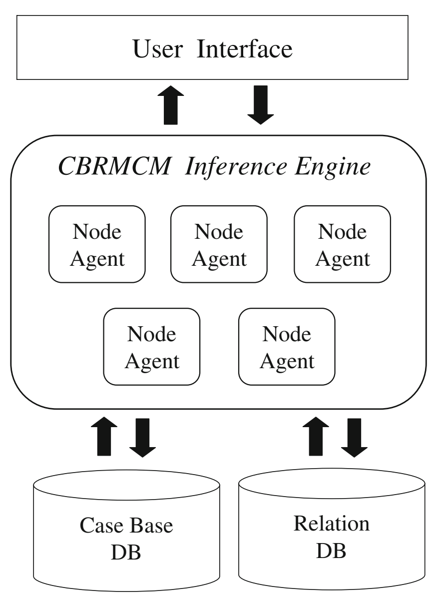

Fig. 5 Architecture of the CBRMCM

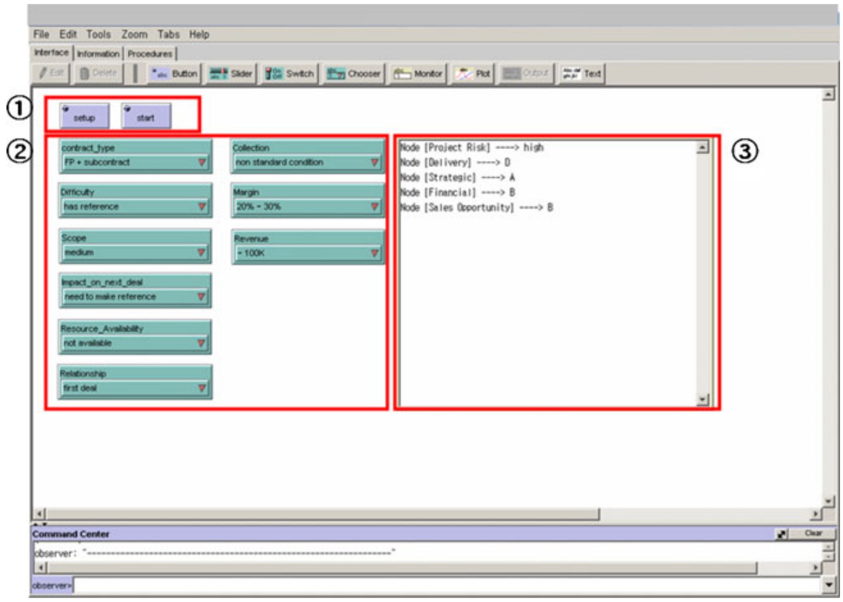

Fig. 6 User interface of the CBRMCM

as variables and determines the output value Ψ through the CBR inference as in Eq. 1.

$$f_{CBR}(e_1, e_2) = \Psi \tag{1}$$

Here, the CBR inference function looks for the case as in Eqs. 2 and 3 that minimizes the similarity measure φ_m and selects the corresponding output value.

$$f_{CBR}(e_1, e_2, ..., e_n) = \Psi \tag{2}$$

$$Min\ \phi_m = \sum_{i=1}^{n} w_i \phi_{type}(i, m) \tag{3}$$

type: ordinal text, non-ordinal text, and numeric.

$$\phi_{ot} = \sqrt{(S(e) - S(\theta))^2} \tag{4}$$

ϕ_{ot} similarity measure for ordinal text value data, normalized value.
$S(e)$ converted number of ordinal text e.
$S(\theta)$ converted number of ordinal text θ.

$$\phi_{nt} = T(e, \theta) \tag{5}$$

ϕ_{nt} similarity measure for non-ordinal text value data, 0 or 1.

$T(x_1, x_2) = \omega$, *if* $x_1 = x_2$ then $\omega = 1$, otherwise $\omega = 0$.

$$\phi_{nu} = \sqrt{(e - \theta)^2} \tag{6}$$

ϕ_{nu} similarity measure for numeric value data, normalized value.
e_i effect value of node i
θ_i^m case base value of node i recorded in m^{th} case base record.

```
For i=1 to Total_node_number
 Read node_number (i), node_name(i), number_of_relation(i)
 For j=1 to number_of_relation (i)
   Read related_node_list [node_number, relation_strength, relation_time_delay]
 Next j
 Create Node_Agent[i] with [ node_number(i),
                             node_name(i),
                             related_node_list(i)
                             node_status_value (0)
                             ]
Next i
End
```

Fig. 7 Pseudo code of node agent creation

Fig. 8 Pseudo code of event creation

```
For i=1 to Total_node_number
 Ask node_agent with [node_number =i][
                         current_status_value_new = CBR (input_node_value_list)
                                    ]
 If (current_status_value_new <> current_status_value_old) [
  Foreach related_node_list(i) [
             Create Event with [
                  originated_node = i
                    Target_node = node_number
                    Effect_value= current_status_value
                                   ]
               Add Event into Event_queue(related_node_number) ]
Next i
```

Ψ selected output value from case base.
ϕ_m similarity measure.
w_i weighted value for node.

The similarity measure ϕ_m that indicates the level of similarity between an event generated by the cause and effect relation from another node and the case base data for the corresponding node stored in the case base has three types of functions. Node status value data can be largely categorized as text and numeric values. Text values would be further classified into ordinal texts that can be sequenced according to the degree of significance and non-ordinal texts that cannot be sequenced. In the case of ordinal texts, a sequence is assigned for unique values among the event value of the corresponding node and the sequence number is acknowledged as the status value of the node. The case base data related to the corresponding node is converted into a numeric value in a similar manner. Consequently the ordinal text value is converted into a numeric value using the function and similarity between and is calculated with Eq. 4. When a sequence cannot be assigned according to the degree of similarity between the node status and value

Fig. 9 Pseudo code of CBR

```
To CBR (input_node_value_list)
For i=1 to end of CBR_record
If (type of input_node_value_list = numeric) [
    For j=1 to number of factors
    similarity(i) =  ∑w(i)*SQRT ((factor(j) –CBR_Data(i,j))^2)
    Next j                                  ]
If (type of input_node_value_list = ordinal_text) [
    For j=1 to number of factors
    similarity(i) =  ∑w(1)*SQRT ((order_num (factor(j)) – order_num (CBR_Data(i,j)))^2)
    Next j                                  ]
If (type of input_node_value_list = non_ordinal_text) [
    For j=1 to number of factors
      if (factor(j) = CBR_Data(i,j)) [temp_similarity = 1 ]
      if (factor(j) <> CBR_Data(i,j)) [temp_similarity = 0 ]
         similarity(i) = similarity(i) + temp_similarity
    Next j                                  ]
Next i
Return CBR_Data(i , out) with Min similarity (i)
End
```

Table 3 Nodes and status value of target problem

No.	Node name (Factor)	Description	Node status (Attributes)	Value type
1	Project Risk (PR)	Overall project risk	Very high High Medium Low Very low	Ordinal text
2	Contract Type (CT)	Time & material or fixed price	Subcontractor and time and material Prime contractor and time and material Subcontractor and fixed price Prime contractor and fixed price	Non-ordinal text
3	Difficulty (DI)	Difficulty of implementation	Stable product and industry reference and experienced resource New product and no reference and no experienced resource	Non-ordinal text
4	Scope (SC)	Clarity of project scope definition	Clear Medium Unclear	Ordinal text
5	Impact on next deal (IN)	Degree of impact the outcome of this deal will have on subsequent deals	Need to make reference No special impact Market has much potential Already matured market	Non-ordinal text
6	Resource Availability (RA)	Available personnel for presales activities and project implementation for this deal	Available Not Available	Non-ordinal text
7	Relationship (RL)	Relationship with the customer	Strategic account First deal Normal Bad site (Bad customer)	Non-ordinal text
8	Collection (CO)	Potential problems with collection	No issue expected Non standard collection condition Historical credit issue	Non-ordinal text
9	Margin (MA)	Expected margin	A: more than 30% B: 20~30% C: 10~20% D: less than 10%	Ordinal text
10	Revenue (RE)	Revenue scale of the deal	A: more than 1 M USD B: 500 K~1 M USD C: 100 K~500 K USD D: less than 100 K USD	Ordinal text
11	Delivery (DE)	Evaluation from the delivery of project execution	A: No issue B: Execution is possible but caution required C: Difficult execution D: Expected to be a very difficult project	Ordinal text
12	Strategic (ST)	Evaluation from strategic aspect rather than financial or project delivery perspective	A: Strategically very important deal B: Average deal C: Strategically unimportant deal	Ordinal text
13	Financial (FI)	Financial evaluation	A: Deal with good financial conditions B: Small revenue but no problems in terms of margin and collection C: Margin less than 20% or collection issues expected D: Not a good deal in terms of revenue, margin and collection	Ordinal text
14	Sales Opportunity Index (SOI)	Evaluation of overall sales opportunity	A: Green B: Yellow C: Amber D: Red	Ordinal text

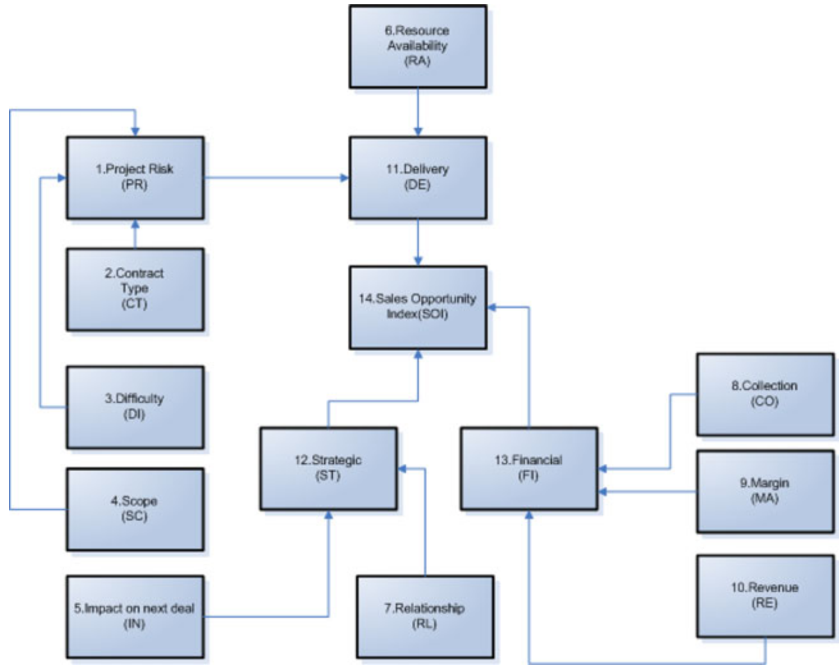

Fig. 10 CM of target problem

data, two text values are compared and it is assigned a value of 1 for a match and 0 otherwise. If the value data is of a numeric value, similarity measure ϕ_{nu} is calculated using the differential between the two values.

3.3 CBRMCM inference mechanism

Figure 4 displays a simple example for explaining the CBRMCM inference mechanism. The CM consists of four nodes and is designed to predict sales at a movie theater. It has a causal relationship which indicates that the day of the week and the weather affects the number of visitors which in turn determine the sales at the movie theater. Nodes 3 and 4 contain case bases exhibited in Tables 1 and 2, respectively. If we assume a condition where Day = "Weekend" and Weather = "Rain", Node 3 calculates an output of 1,500 from CBR inference (See Table 1). Since the status values of Nodes 1 and 2 are non-ordinal texts, similarity measure was used. Node 4 receives as input the output 1,500 from Node 3 and calculates the result (revenue) of inference based on the case base data shown in Table 2. Since the input value of 1,500 is numeric data similarity measure was used. Therefore, output value of each node is as follows: Node 1 (Weekend), Node 2 (Rain), Node 3 (1,500), and Node 4 (12,000).

3.4 CBRMCM application development

An application was developed using the agent-programming tool *NetLogo* in order to test the utility of

Table 4 Case base of Node 1 (Project risk)

Case	Input node			Output node
	Contract type	Difficulty	Scope	Project risk
1	Subcontractor and time and material	New product and no reference and no experienced resource	Clear	Low
2	Prime contractor and time and material	Stable product and industry reference and experienced resource	Medium	Low
3	Subcontractor and fixed price	New product and no reference and no experienced resource	Unclear	High
4	Prime contractor and fixed price	Stable product and industry reference and experienced resource	Clear	Low
5	Subcontractor and time and material	Stable product and industry reference and experienced resource	Clear	Very Low
6	Prime contractor and time and material	Stable product and industry reference and experienced resource	Clear	Very Low
7	Prime contractor and fixed price	New product and no reference and no experienced resource	Unclear	Very High
8	Subcontractor and time and material	New product and no reference and no experienced resource	Unclear	High
9	Prime contractor and time and material	New product and no reference and no experienced resource	Unclear	High

Table 5 Case base of Node 11 (Delivery)

Case	Input node		Output node
	Project risk	Resource availability	Delivery (A~D)
1	Low	Available	No issue (A)
2	Low	Not Available	Difficult execution (C)
3	High	Available	Execution is possible but caution required (B)
4	Very Low	Available	No issue (A)
5	Very Low	Not Available	Difficult execution (C)
6	Very High	Available	Difficult execution (C)
7	High	Not Available	Expected to be a very difficult project (D)

the CBRMCM proposed in this study. As depicted in Fig. 5, the CBRMCM mainly consists of the case base DB, relationship DB, CBRMCM inference engine, and user interface. The relationship DB contains information regarding the nodes and node relationships. The case base DB stores the case base data of each node which is used for the node agent to deploy CBR inference. The CBRMCM inference engine is constructed with the node agents converted with the intelligent agent. These node agents have effects among themselves based on the information stored in the relationship DB according to the changes in the node statuses and the changes are defined as effective evens in this study. The event values received from the related nodes become the input values and the values determined through CBR inference becomes the output which in turn affects other nodes in the form of events. The CBRMCM inference engine involves these procedures where the node agents process the events. The inference procedure terminates when there are no more events to process.

Figure 6 displays the user interface of the CBRMCM application developed with *NetLogo*. Number ① is the control button for reading the data from the relation DB and carrying out inference. Number ② is the chooser for selecting the status value and Number ③ is the output window that displays the inference result. Every node is created and activated by reading the relationship DB data as shown in Fig. 7 pseudo code. Node agent attributes include the node number, node name, node list with a relationship to the corresponding node, and node value. When a node agent detects an event generated at a related node while checking the events created from their related nodes, the node agent determines its output value based on CBR inference. It then creates a new event and registers it in the event queue as shown in Fig. 8. When a node agent conducts CBR inference, it calculates similarity according to the input value and finds the closest case and returns the corresponding output as indicated in Fig. 9.

4 Experiments

4.1 Target problem

This section demonstrates how to apply the aforementioned CBRMCM approach described through analyzing a sales opportunity for a consulting project of a multinational

Table 6 Case base of Node 12 (Strategic)

Case	Input node		Output node
	Impact on next deal	Relationship	Strategic (A~C)
1	Need to make reference	Strategic account	Strategically very important deal (A)
2	No special impact	First deal	Strategically unimportant deal (C)
3	Market has much potential	Normal	Strategically very important deal (A)
4	Already matured market	Normal	Strategically unimportant deal (C)
5	No special impact	Bad site (Bad customer)	Strategically unimportant deal (C)
6	Market has much potential	First deal	Average deal (B)
7	Market has much potential	Strategic account	Strategically very important deal (A)
8	No special impact	Strategic account	Average deal (B)
9	No special impact	Normal	Strategically unimportant deal (C)
10	No special impact	Bad site (Bad customer)	Strategically unimportant deal (C)

Table 7 Case base of Node 13 (Financial)

Case	Input node			Output node
	Collection	Margin	Revenue (USD)	Financial (A~D)[a]
1	No issue expected	Less than 10%	More than 1 M	C
2	Non standard condition	10~20%	500 K~1 M	C
3	Historical credit issue	20~30%	100 K~500 K	C
4	No issue expected	More than 30%	Less than 100 K	B
5	Non standard condition	Less than 10%	100 K~500 K	C
6	Historical credit issue	10~20%	Less than 100 K	D
7	No issue expected	20~30%	More than 1 M	A
8	Non standard condition	More than 30%	500 K~1 M	A
9	Historical credit issue	10~20%	100 K~500 K	C
10	Non standard condition	20~30%	More than 1 M	B
11	No issue expected	More than 30%	More than 1 M	A
12	Non standard condition	20~30%	More than 1 M	B
13	Non standard condition	20~30%	500 K~1 M	B
14	No issue expected	Less than 10%	More than 1 M	D
15	No issue expected	20~30%	100 K~500 K	C

Financial[a] A: Deal with good financial conditions

B: Small revenue but no problems in terms of margin and collection

C: Margin less than 20% or collection issues expected

D: Not a good deal in terms of revenue, margin and collection.

software company. To prepare the CBRMCM, we must consider a number of past instances of the information systems project risk management and sales opportunity index. For this purpose, we gathered them from a multinational IT consulting firm located in Seoul, South Korea. This organization got involved in corporate software implementation consultation including enterprise resource planning (ERP), customer relationship management (CRM), and package products. There are approximately 80 consultants. Additional work staff can be outsourced or recruited from overseas depending on the circumstances. There may be a lack of work forces in a particular area at a certain time point. However, as the target utilization for an individual consultant is 70%, new consultants cannot be hired at every instance at which additional work force is required. In order for a potential sales opportunity to lead to an actual contract, fierce competition occurs among the competitors and additional people are required at the pre-sales stage. Although every sales representative claims that his account is important and requests priority in personnel

Table 8 Case base of Node 14 (Sales opportunity index)

Case	Input node			Output node
	Delivery[a]	Strategic[b]	Financial[c]	Sales opportunity index (A~D)
1	A	A	A	Green (A)
2	B	B	B	Yellow (B)
3	C	C	C	Amber (C)
4	D	D	D	Red (D)
5	A	B	B	Yellow (B)
6	B	C	A	Yellow (B)
7	C	A	C	Yellow (B)
8	C	B	C	Amber (C)
9	D	A	A	Yellow (B)
10	C	C	B	Amber (C)
11	D	A	C	Amber (C)
12	B	A	A	Green (A)
13	C	B	A	Yellow (B)
14	C	C	B	Amber (C)
15	B	C	B	Yellow (B)
16	B	C	C	Amber (C)

Delivery[a] A: No issue, B: Execution is possible but caution required

C: Difficult execution, D: Expected to be a very difficult project

Strategic[b] A: Strategically very important deal, B: Average deal, C: Strategically unimportant deal

Financial[c] A: Deal with good financial conditions

B: Small revenue but no problems in terms of margin and collection

C: Margin less than 20% or collection issues expected

D: Not a good deal in terms of revenue, margin and collection

Table 9 Case base of Node 14 (Sales opportunity index)

No.	Node	Opportunity 1	Opportunity 2	Opportunity 3	Opportunity 4	Opportunity 5	Opportunity 6	Opportunity 7	Opportunity 8
2	Contract Type (CT)	Prime contractor and fixed price	Subcontractor and time and material	Prime contractor and fixed price	Prime contractor and fixed price	Subcontractor and time and material	Subcontractor and fixed price	Subcontractor and fixed price	Subcontractor and time and material
3	Difficulty (DI)	Stable product and industry reference and experienced resource	New product and no reference and no experienced resource	New product and no reference and no experienced resource	New product and no reference and no experienced resource	Stable product and industry reference and experienced resource	New product and no reference and no experienced resource	New product and no reference and no experienced resource	New product and no reference and no experienced resource
4	Scope (SC)	Clear	Clear	Medium	Unclear	Clear	Unclear	Unclear	Unclear
5	Impact on next deal (IN)	Market has much potential	Need to make reference	Need to make reference	Market has much potential	No special Impact	No special impact	No special impact	Need to make reference
6	Resource Availability (RA)	Available	Not Available	Not Available	Available	Available	Available	Available	Not available
7	Relationship (RL)	Strategic account	Strategic account	First deal	First deal	Strategic account	Strategic account	First deal	Strategic account
8	Collection (CO)	No issue expected	No issue expected	No issue expected	No issue expected	No issue expected	No issue expected	No issue expected	No issue expected
9	Margin (MA)	20~30%	More than 30%	20~30%	20~30%	More than 30%	20~30%	10~20%	More than 30%
10	Revenue (RE)	More than 1 M USD	500 K~1 M USD	More than 1 M USD	More than 1 M USD	More than 1 M USD	500 K~1 M USD	More than 1 M USD	100 K~500 K USD

assignment, a work force cannot be extra supported at every opportunity from the perspective of the organization managing the consultants. There is always the problem of selecting the most important opportunities for the allocation of additional staffing. This organization holds weekly meetings attended by a consulting project manager, four resource managers and four sales managers. The weekly meetings help the organization to determine which sales opportunities should receive priority for additional staffing. Major decision criteria include financial revenue and margin, stability in project delivery, and the strategic aspects with regard to the market situation and the client. However, the process by which priority is determined at a meeting attended by people with differing interests is subject to debate and there is a definite need for a more systematic method of assigning priority.

4.2 CM construction

The Sales Opportunity Index (SOI) indicating the importance of a sales opportunity was established as the final node and 21 major factors related to SOI were determined by three experts each with 10 or more years of experiences. From the 21 nodes drawn, the experts conducted discussions to eliminate similar factors and ultimately leaving 14 in the final node pool as shown in Table 3 and Fig. 10.

A CM in Fig. 10 was drawn based on the traditional approach of the experts determining the factors and indicating their cause and effect relationships with arrows. Since fuzzy value conversion is not necessary for CBRMCM, fuzzy value mapping was not performed for the node status value and relation strength. Among the 14 nodes, 6 were non-ordinal text nodes and 8 were ordinal nodes.

4.3 Prepare case base

CBRMCM does not require a mathematical inference function but does need the CBR data to conduct CBR inference. In particular every node that has a relationship affected by other nodes requires a case base. For this study, case bases were required for five nodes in the target problem (Nodes 1, 11, 12, 13, and 14). The three experts participated in drawing the case base CM for the five nodes. An input case list was first created for each node and the output value was determined based on discussion of the corresponding input case to complete the case base. There were 1 through 4 input factors and 1 through 2 output factors for each node. The process of determining the output value for the node's input case was not a difficult task (See Tables 4, 5, 6, 7 and 8).

4.4 Data analysis and result

4.4.1 Situation

There are eight new sales opportunities and more consultants are needed for pre-sales activities. There should be 2~3 pre-sales consultants assigned to each sales opportunity. However, due to major projects under way there are only five consultants available that are not engaged in other projects. Therefore, the degrees of importance for the eight opportunities shall be analyzed to provide priorities for assigning personnel. The circumstances surrounding the eight opportunities are listed in Table 9.

4.4.2 Results

Table 10 displays the results of simulating the information regarding the eight opportunities of Table 9 using the CBRMCM application. The simulation results revealed that Opportunity 1 and Opportunity 5 are the most attractive and it is advisable that the consulting headquarters to place priority for assigning personnel to these two opportunities.

Although difficulties can be expected in terms of delivery for Opportunity 1, winning the deal signifies high gains in terms of strategy and financial aspects. Opportunity 5 has weak strategic implications but the project can be easily carried out and positive financial outcome can be expected.

4.5 Evaluation

To test the usefulness of CBRMCM proposed in this study, focus group interview (FGI) and a survey were done after the experts experienced the three methodologies (CBRMCM, Multi-Agent Inference Mechanism, and traditional manual FCM inference) and the time required for each task of the three methods was also assessed. The experiment implemented on 5 experts who have worked in IT consulting companies for 10 to 15 years. The experts' experiences of the 3 methods are done by random sequence. 14 nodes are provided as the starting experiment pool for more efficient comparison between methods and three scenarios are provided as the target problem. The experts were required to solve these three problems using each method.

The interview questionnaire consisted of questions asking their feeling on the pros and cons of each method and the survey items are regarding 'Perceived Usefulness (PU)' and 'Perceived Ease of Use (PEU)' (See Table 11).

Tables 12 and 13 show the interview result and time check result. According to the interview results and time checks, CBRMCM was the easiest method for end users because end users do not need to understand fuzzy concept and also do not need to prepare fuzzy conversion. However, end users felt there was difficulty in preparing case base data. Regarding this point, CBRMCM has some drawbacks when the number of factors increases.

The response results for the survey regarding PU and PEU of the three methods were analyzed statistically using the Wilcoxon signed-rank test. Tables 14, 15 and 16 show the results of Wilcoxon signed-rank test to evaluate the performance of the suggested method. Both CBRMCM and MAIM are better than traditional FCM in terms of PU and PEU. Moreover, CBRMCM is better than MAIM in the

Table 10 CBRMCM simulation results

Node Opportunity	Project risk	Delivery[a]	Strategic[b]	Financial[c]	Sales opportunity index
Opportunity 1	High	B	A	A	Green (A)
Opportunity 2	Low	C	A	B	Yellow (B)
Opportunity 3	High	D	A	A	Yellow (B)
Opportunity 4	High	B	B	A	Yellow (B)
Opportunity 5	Very Low	A	B	A	Green (A)
Opportunity 6	Very High	C	B	A	Yellow (B)
Opportunity 7	Very High	C	C	C	Amber (C)
Opportunity 8	High	D	A	B	Yellow (B)

Delivery[a] A: No issue, B: Execution is possible but caution required

C: Difficult execution, D: Expected to be a very difficult project

Strategic[b] A: Strategically very important deal, B: Average deal, C: Strategically unimportant deal

Financial[c] A: Deal with good financial conditions

B: Small revenue but no problems in terms of margin and collection

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D: Not a good deal in terms of revenue, margin and collection

Table 11 Survey questionnaire

Factor	Variable	Question	Reference
Perceived Usefulness (PU)	PU1	Using the system (method) improves my performance.	Davis (1989)
	PU2	Using the system (method) in my task increases my productivity.	
	PU3	Using the method enhances my effectiveness in my task.	
	PU4	I find the system (method) to be useful in my task.	
Perceived Ease of Use (PEU)	PEU1	My interaction with the system (method) is clear and understandable.	
	PEU2	Interacting with the system (method) does not require a lot of my mental effort.	
	PEU3	I find the system (method) to be easy to use.	
	PEU4	I find it easy to get the system (method) to do what I want it to do.	

Table 12 Interview result

Method	CBRMCM	MAIM	FCM
Pros	Easy to understand inference mechanism. Once case base is prepared, it is very easy to solve new problem.	It is not easy to understand inference mechanism. Information regarding causal relations between nodes is provided clearly. It looks efficient when target problem is consisted of many numbers of factors.	We can trace all inference calculation steps.
Cons	Preparing case base data is painful and boring task. We cannot use this method in the situation that we cannot prepare case base data. Cannot get information which relation between nodes more important. If number of nodes increase, it seems difficult to prepare and maintain case base data.	Fuzzy conversion for node status and relation strength is subjective. Fuzzy conversion value needs to be adjusted after check the inference result of sample problem. And this adjustment task is not easy.	It is difficult understand and learn inference using mathematical matrix. It takes much time to calculate inference result. Fuzzy conversion for node status and relation strength is subjective. Fuzzy conversion value needs to be adjusted after check the inference result of sample problem. And this adjustment task is not easy. Using one single inference function is not realistic.

CBRMCM Case Based Reasoning based Multi-agent Cognitive Map, *MAIN* Multi-Agent Inference Mechanism, *FCM* Fuzzy Cognitive Map

Table 13 Time check result

Method	CBRMCM	MAIM	FCM
Task and average time	1. Factor extraction - 4.4 min. 2. Draw relation - 10.2 min. 3. Prepare case base - 42.2 min. 4. Input data into CBRMCM - 33.5 min. 5. Problem solving (inference) - 4.7 min.	1. Factor extraction - 4.3 min. 2. Draw relation - 11.0 min. 3. Prepare fuzzy conversion value - 46.4 min. 4. Input data into MAIM - 28.2 min. 5. Draft inference - 8.8 min. 6. Adjust fuzzy conversion value - 32.5 min. 7. Problem solving (final inference) - 8.2 min.	1. Factor extraction - 4.2 min. 2. Draw relation - 11.0 min. 3. Prepare fuzzy conversion value - 50.5 min. 4. Draft inference - 86.5 min. 5. Adjust fuzzy conversion value - 67.5 min. 6. Problem solving (final inference) - 68.0 min.
Total time	95.0 min	139.4 min	287.7 min

CBRMCM Case Based Reasoning based Multi-agent Cognitive Map, *MAIN* Multi-Agent Inference Mechanism, *FCM* Fuzzy Cognitive Map

Table 14 Statistical test result (CBRMCM vs. MAIM)

Var.	CBRMCM		MAIM		Mean difference	*t*-test		Wilcoxon test	
	Mean	std	Mean	std		*t*	Sig.	*z*	Sig.
PU1	6.200	0.837	6.200	0.837	0.000	0.000	1.000	0.000	1.000
PU2	6.200	0.447	6.200	0.447	0.000	0.000	1.000	−1.732	0.083
PU3	5.800	0.447	5.600	0.548	0.200	0.535	0.621	−0.577	0.564
PU4	6.600	0.548	6.400	0.548	0.200	1.000	0.374	−1.000	0.317
PEU1	5.600	0.548	3.800	0.837	1.800	3.087	0.037	−1.841	0.066
PEU2	5.200	0.447	3.600	0.548	1.600	6.532	0.003	−2.070	0.038
PEU3	4.800	0.837	2.600	0.548	2.200	5.880	0.004	−2.041	0.041
PEU4	5.400	0.548	4.600	0.548	0.800	1.633	0.178	−1.414	0.157

CBRMCM Case Based Reasoning based Multi-agent Cognitive Map, *MAIN* Multi-Agent Inference Mechanism, *PU* Perceived usefulness, *PEU* Perceived ease of use

Table 15 Statistical test result (MAIM vs. FCM)

Var.	MAIM		FCM		Mean difference	*t*-test		Wilcoxon test	
	Mean	std	Mean	std		*t*	Sig.	*z*	Sig.
PU1	6.200	0.837	3.200	0.837	3.000	6.708	0.003	2.041	0.041
PU2	6.200	0.447	3.800	0.837	2.400	4.707	0.009	2.032	0.042
PU3	5.600	0.548	2.600	0.548	3.000	9.487	0.001	2.060	0.039
PU4	6.400	0.548	2.800	0.447	3.600	14.697	0.000	2.121	0.034
PEU1	3.800	0.837	1.600	0.548	2.200	11.000	0.000	2.121	0.034
PEU2	3.600	0.548	1.400	0.548	2.200	5.880	0.004	2.041	0.041
PEU3	2.600	0.548	1.400	0.548	1.200	6.000	0.004	2.121	0.034
PEU4	4.600	0.548	1.200	0.447	3.400	13.880	0.000	2.070	0.038

MAIN Multi-Agent Inference Mechanism, *FCM* Fuzzy Cognitive Map, *PU* Perceived usefulness, *PEU* Perceived ease of use

Table 16 Statistical test result (FCM vs. CBRMCM)

Var.	FCM		CBRMCM		Mean difference	*t*-test		Wilcoxon test	
	Mean	std	Mean	std		*t*	Sig.	*z*	Sig.
PU1	3.200	0.837	6.200	0.837	−3.000	6.708	0.003	−2.060	0.039
PU2	3.800	0.837	6.200	0.447	−2.400	4.707	0.009	−2.032	0.042
PU3	2.600	0.548	5.800	0.447	−3.200	9.487	0.001	−2.121	0.034
PU4	2.800	0.447	6.600	0.548	−3.800	14.697	0.000	−2.121	0.034
PEU1	1.600	0.548	5.600	0.548	−4.000	11.000	0.000	−2.041	0.041
PEU2	1.400	0.548	5.200	0.447	−3.800	5.880	0.004	−2.041	0.041
PEU3	1.400	0.548	4.800	0.837	−3.400	6.000	0.004	−2.070	0.038
PEU4	1.200	0.447	5.400	0.548	−4.200	13.880	0.000	−2.041	0.041

FCM Fuzzy Cognitive Map, *CBRMCM* Case Based Reasoning based Multi-agent Cognitive Map, *PU* Perceived usefulness, *PEU* Perceived ease of use point of PEU. These statistical results are consistent with the interview results shown in Table 12.

5 Concluding remarks

As demonstrated in the case study of Section 4, CBRMCM provides the possibility of performing CM inference without the artificial fuzzy value conversion and the mathematical inference functions that had been problematic for the decision-making mechanism based on traditional CM inference. The key idea of the CBRMCM mechanism involves all of the nodes that constitute the CM being converted into intelligent agents that determine their own status by checking the status changes and relationship with other agents and the results being reported to other related node agents. Furthermore, the CBRMCM is deployed when each node agent references the status of other related nodes to determine its own status value. This approach eliminates the artificial fuzzy value conversion and the numerical inference function that were required for obtaining CM inference.

The theoretical and practical contributions of this study are as follows:

(1) CBRMCM end users can easily understand inference process without need to know about the CM's fuzzy value or mathematical functions. Moreover, CBRMCM can also be easily applied to other decision-making situations. The CBRMCM mechanism provides a means of easy inference without fuzzy value conversion and mathematical inference functions for the node status value and relationship strength that have been subject to criticism in applying CMs to real world problems.

(2) CBRMCM can help sales representatives and consulting project managers in explaining why sales opportunity for a consulting project is classified as either bad or good. Furthermore, CBRMCM is powerful management tools that the task of analyzing a sales opportunity could be systematically and intelligently solved. In this way, IS project managers can be provided with robust decision support.

(3) This enhancement in predictability of potential sales opportunity can significantly contribute to the correct project risk evaluation of institutional investors, and hence financial institutions can make use of CBRMCM for the better lending decision makings, which may lead to higher profits and firm values eventually.

There are several points requiring improvements if the CBRMCM to be fully utilized. Firstly, studies on the methodology of easily obtaining the case base data of the CBR that plays key roles for CBRMCM inference need to be performed. Secondly, the mechanism by which the node agent constantly updating the case base data should be examined. Thirdly, a time delay concept should also be introduced for CBRMCM. These subjects are potential key topics for future studies.

In spite of the many positive findings regarding CBRMCM observed in this study, our study includes limitations as well. Firstly, the results from the study should be generalized. Our study only uses one chosen dataset for system validation and only one chosen dataset may not be reliable to make a general conclusion. It is necessary to consider a certain number of different datasets for system validation. It would be better to investigate additional problem domains in order to generalize the results of this study. Secondly, the target problem is a relatively simple CM consisting of 14 total nodes. The effectiveness of CBRMCM should be further examined in future studies based on a complex CM containing more than 14 nodes.

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