Analyzing the Effect of Collaborative Cost Management in Supply Chain by Case-Based Reasoning

Jianxi Fu
Department of Mechanical Engineering, Texas A&M University, TX 77843, USA
Email: fujianxi@tamu.edu

Yuanlue Fu*
Center for Accounting Studies, Xiamen University, Xiamen, 361005, P.R. China
Email: ylfu@xmu.edu.cn

***Abstract*—Applying case-based reasoning (CBR) to analyze the effect of collaborative cost management (CCM) in supply chain is a new research topic. This paper illustrates a new method which combining four steps of CCM and procedures of CBR with fuzzy inference model. The method improves the traditional similarity assessment and obtains the most suitable case to solve new problems. Moreover, this study gives a new definition of information set on the CCM problem and emphasizes self-learning in CBR for CCM in order to make the selected case solution more suitable and obtain the more collaborative effect value of CCM.**

***Index Terms*—Collaborative cost management (CCM), multi-agent, case-based reasoning (CBR), supply chain**

I. Introduction

In the environment of economy globalization and fiercer competition, it is very important that each company uses the CCM (cost collaborative management) of network partners to reach its goal. Moreover, more general inter-organization cost management is a new pattern ([2], [3]) of organization between the traditional firm and the market model. Dubois et al. (2004) [4] argue that by evaluating performance within different boundaries is also highlighted and thus can be a platform for increasing awareness of interdependence existing across borders. Peng et al. (2012) [5] leverage three types of the complex and natural relationships in Multi-Agents System (MAS) to model the trust in MAS in this paper and try to bridge the gap in the area of MAS trust modeling based on social relationship. Fu & Fu (2011)[1] study the Multi-Agents System for Collaborative cost management (MAS-CCM)in supply chain and conduct a novel framework model of collaborative cost management in supply chain based on the application of case-based reasoning.

Generally, the alliance organization is set up a connected and operational mechanism by serious contracts (including agreements, corporate institutions and legal contracts) among the members of the supply chain [6]. The key goal of an established inter-organization is putting higher related firm into the supply chain, so that it can create more return of capital by synergic effect [7]. In recent years, agent technology has successfully been implemented for managing business processes ([8], [9], [10], [11] and [12]) and supply chain ([12] , [13] and [14]). The model proposed here, which is called an ‘intelligent agent-based system’, solves problems related to cost synergy management by viewing the process as a cost synergy agent.

This study introduces another approach CBR which is available to interactively construct dynamic and collaborative situations. Intelligent agents with learning ability are able to construct adaptive negotiation strategies depending on their knowledge, experience and information available from the use of CBR [15] in association with CCM. Loor et al. (2011) [16] conducted that the proposed solution stems from various case bases, which enable the similarity, between a target situation and all the cases in the base, to be calculated at any time.

This paper is focused more on showing the benefits of applying CBR in CCM. The purpose is: to propose a novel analysis method for the effect of CCM by applying case-based reasoning, to seek a new technique of case retrieval in CBR oriented specifically to CCM-problems. The approach is introducing new information on the problems and fuzzy inference models. This information will help us to choose the most suitable solution in a new stage, which applies similarity measures in addition to the information on the CCM of the attribute to obtain the most suitable case to be recovered. This methodology is conducive to achieve the objective: finding out the most suitable case (this case is no need to be the most similar) and obtaining the collaborative effect value of CCM.

The remainder of this paper is organized as follows: Section 2, a brief review on the research of CBR and CCM is given. The framework for integrating case-based reasoning into MAS-CCM is depicted in section 3. Section 4 discusses the methods combining the procedures of CBR with the four steps of MAS-CCM. And finally, a conclusion will be presented.

* Corresponding author: Professor Yuanlue Fu. Tel.:86-592-2186201; fax: 86-592-2181520; Email: ylfu@xmu.edu.cn.

doi:10.4304/jsw.8.2.367-374

II. Related Research: CBR and CCM

Multi-agents system for CCM extends main strategic management processes to external node firms beyond core company boundary [7] in order to seek the approaches of reducing the cost of the entire supply chain. The core company and node firms can utilize sufficiently synergic opportunities and synergic effect among partners of the network firms by the means of coordinating cost management projects among manufacturers, suppliers and customers. Fu & Fu (2012) [1] depict the architecture model (figure 1) focuses mainly on the cost collaboration multi-agent. The architecture of the system consists of four essential elements. Each agent in the conceptual market model is represented by a corresponding agent in the multi-agent system, and its name is derived from the role that it plays in the market. As shown in fig.1, the agents are the suppliers, the manufacturers, the customers, and the cost collaboration management. Each agent is autonomous and should be responsible for own decision making. Since the multi-agent has both social ability and reactivity, it can easily adjust its goals as a new uncertainty emerges. The detailed roles of each agent are described as follows [1]:

S-Agent: Produces components or materials. It receives raw materials from outside the supply chain and supplies the components or processed materials to the manufacturer (M-Agent).

M-Agent: Manufactures products by assembling components. It receives orders from the customer (C-Agent) and places component orders to the supplier (S-Agent).

C-Agent: Receives the customer's order and then sells the product if it is in inventory. If the agent cannot fill the order, it places an order for the product to the manufacturer (M-Agent) and the order is backlogged.

CC-Agent (Cost Collaboration Agent): Facilitates additional levels of coordination and information sharing for cost collaborative management. Its main priority is to maximize the overall supply chain profits by coordinating with other agents.

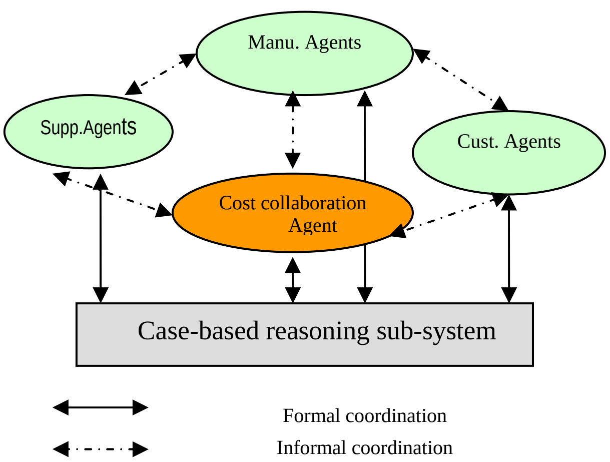

Fig.1. Multi-agent architecture for cost collaboration management base on case-based reasoning
(Figure source: [1] Fu & Fu (2012))

CBR is a well-known technique in Artificial Intelligence (AI). Attempting to imitate the way human beings reason, this technique solves problems by using or adapting solutions of old problems to solve the new ones. Although CBR has been implemented successfully and widely to solve many problems, it is not entirely congruent with the way that human beings act, since the future consequences of the decisions constitute very important information that will be taken into account before choosing one option or another. Recent studies have witnessed increasing interest in formalizing different aspects of the CBR methodology, including such areas as case and knowledge representation; acquisition and modeling of maintenance and management of CBR systems; case indexing; adaptation, etc. This paper focuses on the stage of case retrieval and CBR learning in CCM.

Many researchers have worked in this domain, and various retrieval techniques have been developed, which range from classical methods, such as Schaaf [20], to more sophisticated methods that mix neural networks [21, 22], genetic algorithms [23–25], fuzzy ant colony systems [26] or fuzzy logic [27–30]. Another technique used to improve accuracy in CBR retrieval is the approach of attribute weighting. Attributes with weights of zero are effectively ignored during similarity computation, while attributes whose weights are high having the most impact in determining similarity. There are many approaches to weighting include experience of the expert, Analytic Hierarchy Process (AHP) [31], decisions trees [32,34] and fuzzy logic [33].

Methods of CBR retrieval take many different approaches, as the following studies exemplify: [22] proposes a non-classical approach to measuring the temporal similarity of cases that are heterogeneous temporal event sequences. Given two or more sequences, the temporal similarity is measured by describing a unique temporal scenario of possibility temporal relations and calculating the uncertainty produced. In [29] the CBR system has been embedded within a deliberative agent and interacts with interface and commercial agents, which facilitate the construction of intelligent environments. Some studies also use statistical techniques [30,31]. Others research uses CBR with ruled-based reasoning, as in [32–33]. We propose combining CBR with ruled-based reasoning from a new perspective, using the valuable local information that effect of CCM to the problem in supply chain.

CBR is a problem-solving paradigm in the field of Artificial Intelligence, in which previous similar situations are retrieved and used to resolve new problems. An important argument for CBR is that situations recur with regularity. It is likely that the decision made for one case is applicable to another similar case. CBR allows businesses to treat past cases as a corporate resource and reuse them in future decision-making [15, 16] (Loor et al., 2011, Fang et al.,2010). This motivated us to use CBR as a key method for storing and reusing retailer profiles, manufacturer profiles, supplier profiles, relationship types, product characteristics, and associated market data for an

Enhanced Integration mechanism. Applying CBR to MAS-CCM systems is rather unique, though there are several works applying CBR to electronic commerce and negotiation problems [17,18,19]. There are several advantages of using CBR for MAS-CCM:

(1) CBR allows agents to propose new offers quickly without deriving them from scratch. This provides organizational memory-based intuition for a given supply chain management problem to avoid an inconsistent problem-solving process.

(2) CBR alerts agents to avoid repeating past mistakes because those mistakes are already captured in CBR.

(3) CBR helps agents to analyze the importance of features and issues of supply chain management, thus leads to better deals in future.

(4) CBR is flexible in handling inter-firms cost management uncertainty, and changes in relationships and strategies (e.g., the introduction of a new supplier).

The case base keeps track of all of the supply chain dynamics. If the partners (S-agent, C-agent, M-agent) change their relationships from transactional to strategic, the case base is updated to reflect this new relationship. Moreover, the subsequent supply chain strategies will be based on the new relationship. Similarly, if the manufacturer experiences uncertainty from the suppliers, it may add another supplier, or pool the production capacities, or inventories of its existing suppliers for risk pooling. The case base also records this new case.

III. The Framework for Integrating CBR into MAS-CCM

CCM is an important philosophy, an attitude and a set of techniques to create more value at lower cost. The critical success factors for CCM not only encompass financial factors, such as costs and revenues, but also encompass non-financial factors, for instance new product development, product quality, customer satisfaction. Therefore, the definition of CCM in supply chain is an integrated cost management, which integrates information management system into CCM system (Figure 2). It provides non-financial information, traditional financial information, and external information for decision maker in order to get the goals and the competitive advantages of the core company and node firms in the supply chain. Thus it builds a future new framework with three functions:

(1)Planning and decision-making in static CCM and dynamic CCM like managing cash flow, budgeting, purchase of raw materials, production scheduling, pricing, inter-firms designing and inter-firm cost management.

(2) Real time collaborative control beyond the firm boundary. Controlling and monitoring in the CCM implementation could be extended to upstream and lower stream by multi-agent system and CBR, and could be emphasized on matching with the company's strategic position.

(3) Optimal CCM not only for collaborative effect but also for multi-win requirements.

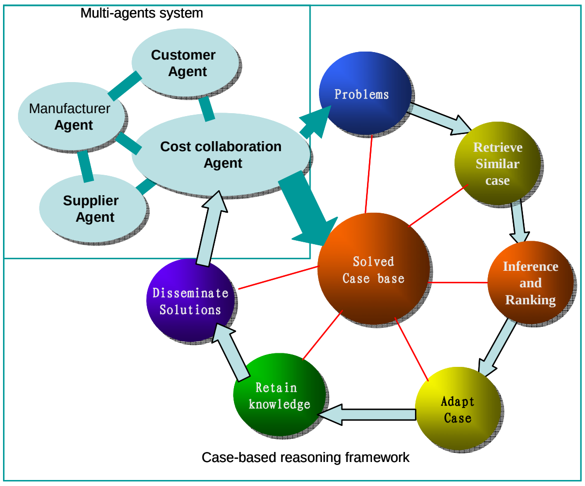

Figure 2. Integrating case-based reasoning into MAS-CCM
（Figure source: [1] Fu & Fu (2012)）

In this paper, the research of the CCM in supply chain is beyond the traditional cost management research. Is there a suitable model from those current models of CCM to satisfy the need in this paper? The answer is no. However, there are some models from current models and extend these specific chosen models. Of course, it is fine to choose the model—multi-agents system for CCM based on case-based reasoning (see figure 2).

The description of the framework model (figure 2): based on the network (supply chain) coordinating mechanism[13], taking the strategic objectives and financial objectives as basic goals of the system, taking the strategic cost plans as the action guidance of CCM, and integrating multi-agents system and case-based reasoning into an integrated CCM system, which are utilizing all resources (tangible assets, intellectual assets, information etc.) effectively and efficiently in supply chain to create value for a specific firm. The system is emphasized that inter-firms CCM and should match with strategic position of the specific firm.

The above model does pay attention not only to the cost drivers of a stand-alone company but also to the cost drivers of other node companies in supply chain and macro-economic policies, so that it makes up the deficiency that the earlier model of cost management only consider those factors of single company. The system emphasizes following: to set up an system connection between strategic objective (such as lower product cost strategy and product technique differentiation) and suppliers, company purchasing, design, manufacturing, sale, distribution and logistic; furthermore, to integrate financial management, accounting, risk management, information system and human resource management into the system of CCM in supply chain. Moreover, traditional standard cost, overall budgeting, pricing and cost analysis have become ones of the basic parts which are integrated into the system (including the real time control and management of logistic and fund flow, financial report and other decision information report, performance evaluation and incentive, strategy management decision support subsystem, and so on).

The CCM process is executed in four steps （in detail to see [1]）: cost driver identification; cost driver impact assessment; decision; implementation of CCM actions and optimization. The process involves collaboration amongst supply chain partners through exchange of information and allocation of specific roles, in order to get the goal of CCM in the supply chain.

IV. Combining the Procedures of CBR with the Four Steps of MAS-CCM

In most CBR systems, one case only consists of the problem, the solution and the outcome parts. One new approach is designed by combing the procedures of CBR with four steps of MAS-CCM. This approach is implemented as the following five sub-sections:

A．New Problem is Defined

The cost drivers of CCM are identified through the use of qualitative and quantitative analysis. A new problem of CCM is defined at the informational set P={B, C,V, S}. B is the case base associated with the problem P; C = {C_i}, i = 1, . . ., n is the set of all cost drivers in the case base, such as product research and development, product cost, product quality, delivery lead times and the level of an in-stock inventory, production throughput, utilization of capacity; V ={v_{ci}}, i = 1,. . ., n is the set of effect values, where a cost driver C_i takes its value from the solution action S; S= {S_j}, j = 1,. . . ,m, is the set of all solutions in the case base.

These sets indicate the suitability of applying the solution, S_j, to solve the new problem, when the cost driver produces the effect v_{ci}, i.e. the solution effect of S_j is for solving the problem.

We have chosen a fuzzy inference system because it is useful and efficient for analyzing imprecise, rough information and because it is able to provide linear and non-linear information. In order to build this system, we shall introduce a formula（4）to obtain the suitability of a case by making it dependent on the effect, weight (w_i) and local similarity $Sim(C_i^{base}, C_i^{new})$. The weight w_i presents important degree of the cost driver C_i (see table 1 and table 2). Thus, the weight of the cost drivers can be used not only to identify an abnormal situation that may involve a potential opportunity cost, but also to identify the actual effect values from those cost drivers，which are monitored within a specific time frame and compared with predefined values from S-Agent, M-Agent and C-Agent that are described in an agreement among partners (agents)

B．Similar Cases Research

We are interested in the effect of CCM in supply chain, as they seem to represent an interesting business proposition. Since CBR is useful for various types of problems and domains (as seen in [16–22]), it may be able to determine whether or not the effect of executing in a certain event of CCM is positive. Consider the following situation: firstly, the local similarity between cost drivers is calculated by several local measurements ([18–20]). The following local similarity measurement will be used:

$$Sim(C_i^{base}, C_i^{new}) = 1 - \frac{|C_i^{base} - C_i^{new}|}{|C_i^{max} - C_i^{min}|} \qquad (1)$$

where C_i^{base} is the ith cost driver of the case in case base, C_i^{new} is the ith cost driver of the current case and C_i^{max}, C_i^{min} are the maximum and minimum values between all the cases (including the target case) for the ith cost driver, respectively. Secondly, the overall similarity is calculated by using the following arithmetic average formula:

$$TotalSim(C^{base}, C^{new}) = \frac{\sum_{i=1}^{n} Sim(C_i^{base}, C_i^{new})}{n} \qquad (2)$$

where C^{base} is the case in case base, C^{new} is the target case, and n is the number of attributes in each case. In order to avoid confusion, the overall similarity is referred as *TotalSim* and the local similarity is referred as *Sim().* The next step is to make the measurement more accurate. This can be done by incorporating the relative importance of the attributes, since certain attributes are more important than others in our problems.

The importance degree of the cost driver is introduced as a new variable, which is called the weight variable. This variable measures the importance of the i^{th} cost driver, which is expressed as w_i. Although the valuation of weights is a crucial element in determining the most similar case, our example used a human expert to assign the values and important degree by table I. And the relation between important degree and triangular fuzzy number is set up.

TABLE Ⅰ.
IMPORTANT DEGREE VARIABLES FOR THE RATING

Weight w_i	Important Degree (Linguistic term)	Triangular fuzzy number $\tilde{a} = (a_1, a_2, a_3)$
Z_4	Very important (VI)	(0.75, 1.0, 1.0)
Z_3	Important (I)	(0.5, 0.75, 1.0)
Z_2	Fair (F)	(0.25, 0.5, 0.75)
Z_1	Poor (P)	(0, 0.25, 0.5)
Z_0	Very poor (VP)	(0, 0, 0.25)

In table I, weight w_i may presents as important degree in linguistic term and in triangular fuzzy number $\tilde{a}$. The present study uses triangular fuzzy numbers. A triangular fuzzy number $\tilde{a}$ can be defined by a triplet (a_1, a_2, a_3). This triplet will be used in formula (5) and make calculation of case suitability become realistic.

By using the weights, w_i, associated with each cost driver, the overall similarity measurement is modified. Thus the weighted sum of the similarities between cost driver and weights will be correspondingly determined as:

$$TotalSim(C^{base}, C^{new}) = \frac{\sum_{i=1}^{n} w_i Sim(C_i^{base}, C_i^{new})}{\sum_{i=1}^{n} w_i} \qquad (3)$$

A fuzzy inference model is chosen because it is useful and efficient for analyzing imprecise, rough information and because it is able to provide linear and non-linear information. In order to build this system, a formula should be introduced to obtain the suitability of a case by making it dependent on the effect (Vci), weight (wi) and local similarity $Sim(C_i^{base}, C_i^{new})$:

$$Suit(C^{base}, C^{new}) = \frac{\sum_{i=1}^{n} w_i f_{w_i}(Sim(C_i^{base}, C_i^{new}))}{\sum_{i=1}^{n} w_i} \quad (4)$$

where n is the number of the attributes. The function f(.) is obtained implicitly with a fuzzy inference function and is calculated as a weighted average of the outputs from all of the rules. The fuzzy inference system provides the following advantages in overall suitability assessment:

1) The local information obtained from the effect variable enables us to make the decision.

2) The decision is shared between the risks and the weights, thereby alleviating its effect on retrieval.

3) Solution is better and more realistic.

The fuzzy inference model used in formula (4) is a direct application of the fuzzy model [33]. For each triangular fuzzy number of important degree (see table I) of the ith cost driver, the model function f(.) is depicted as the following :

$$f_{\tilde{a}}(x) = \begin{cases} x + \dfrac{a_3 - a_1}{2}, & x \le a_1, \\ x + \dfrac{x - a_1}{3}, & a_1 < x \le a_2 \\ x, & a_2 < x \le a_3 \\ x - \dfrac{a_3 - a_1}{2}, & x > a_3 \end{cases} \quad (5)$$

Formula (4) uses the function $f_{\tilde{a}}(x)$ to make selected case more suitable for the CCM problem cases. In these rules, the linguistic terms (such as 5 terms in table I) are defined based on w_i and Sim respectively. They are defined by the different experts who make the decision about what values are suitable (see table Ⅱ and table Ⅲ).

C. Application of the Suitable Model

The formula (2) and (4) mentioned above are applied to determine similar degree and suitable degree of specific case, and to case inference and ranking of CBR, in two different models. An illustration (table II and table Ⅲ) is used to verify that the suitable degree formula (4) is more adaption than similar degree formula (2) in CBR. In this illustration, there are six cost drivers and their Sim() values of two selected cases from the case base. The data in table Ⅱ show similar numbers, important degrees w_i and triangular fuzzy number of the cost drivers, and function values($F_1()$,$F_2()$) of $f_{\tilde{a}}(x)$ in two cases (case1 and case2).

TABLE Ⅱ.

CALCULATION OF SUITABLE DEGREE

Cost driver	Case1	Case2	W_i	Triangular fuzzy number $\tilde{a}$	$F_1(.)$	$F_2(.)$
	Sim()	Sim()				
C1	0.75	0.6	0.9	(0.75,1.1)	0.875	0.725
C2	0.55	0.7	0.85	(0.75,1,1)	0.675	0.825
C3	0.65	0.3	0.35	(0.25,0.5,0.75)	0.65	0.55
C4	1	0.8	0.3	(0.25,0.5,0.75)	0.75	0.45
C5	0.6	0.97	0.2	(0,0.25,0.5)	0.35	0.72
C6	0.7	1	0.5	(0.25,0.5,0.75)	0.70	0.7
T-Sim	0.70833	0.72833	3.1			

In table Ⅱ, overall similar of case 2 equals to 0.72833, which is more than that 0.70833 of case1. However, these suitable degree calculation of table Ⅲ shows that suit() value of case 1(0.72056) is more than that (0.70169) of case2. That means the important degree of the cost driver produces some effect on the values of suitable degree by formula (5) and (4).

TABLE Ⅲ.

CALCULATION OF SUITABLE DEGREE

Cost Driver	W_i	Triangular fuzzy number	F1(.)	F2(.)	$W_i*F_1(.)$	$W_i*F_2(.)$
C1	0.9	(0.75,1,1)	0.875	0.725	0.78750	0.6525
C2	0.85	(0.75,1,1)	0.68	0.825	0.57375	0.70125
C3	0.35	(0.25,0.5,0.75)	0.65	0.55	0.22750	0.1925
C4	0.3	(0.25,0.5,0.75)	0.75	0.45	0.22500	0.135
C5	0.2	(0,0.25,0.5)	0.35	0.72	0.07000	0.144
C6	0.5	(0.25,0.5,0.75)	0.70	0.7	0.35000	0.35
Suit()	3.1				0.72056	0.70169

This paper improves the calculation method of similar number in CBR. In the table Ⅲ, the weights w_i of cost drivers present the various important degree of effect value in CCM. Managers could use those weights to balance off their management activities in supply chain. Because of complexity for CCM, this fuzzy suitable degree model provides a possibility for checking and monitoring whether the program and objective of CCM are being pursued.

Thus, the success of a decision applied to a specific most suitable case is taken into consideration during the retrieval and inference process. The most suitable similar case responses to cost drivers of the problem is selected, through the multi agents of CCM improving the quality of supply chain management by cases being updated in real time. In case an alarm is triggered at the side of a supplier due to the identification of an abnormal cost drivers, all the potential loss cost that arise are identified by the root identifier in the field “type of loss cost”.

Furthermore, it suggests that the new method of suitable degree calculation in this sub-section must be integrated into cost driver assessment from multi-agents for CCM. Potential remedies are then evaluated by the built-in simulator initially in terms of their feasibility and based on specific constraints (e.g. contractual agreements). To get customer’s local optimal policy by invoking C-Agent; and get manufacturer’s local optimal policy by invoking M-Agent using retailer’s local optimal policy; and get supplier’s local optimal policy by invoking S-Agent using retailer’s and manufacturer’s local optimal policies. Then, the expected effects of those feasible local optimal policies are calculated, generating a list of remedies for the cost driver event that emerges along with CCM.

D．Suitability and Recommended CCM Solutions

To further rank these candidate source cases, their relative similarity levels are computed according to the user’s targets. In this subsection, case ranking and adapt case are main content. We focus on the analysis of a case suitable content, such as applying formula (4). Moreover, we ensure that the case model we propose is adapted to the whole CBR process steps.

A solution for CCM problem is recommended, which is a new problem used to retrieve a most suitable case from a collection of previous cases.

In order to retrieve the most suitable cases, different and successive indexation mechanisms can be implemented according to the type of CCM (transaction, technical, information, intellectual asset. . .), the decision referential, the type of causes, effects, the management actions, …. These successive indexations can lead to different sets of potential solutions. The case retrieval should also be done by considering the union of the identified satisfying cases. This type of filtering processes can really be interesting to give a quite exhaustive retrieval of solution cases. The case model {B, C, V, S} is stable: only the number of causes and/or effect events and the number of management actions are undetermined. However, usual retrieval mechanisms like similarity techniques are adapted to aggregation processes and the application does not present a particular problem in this way.

Moreover, since a case is made of linked events (conjunction, disjunction of events,…), particular indexes can be constructed to choose the management actions. As an example, a CCM event made of multiple and independent causes and of a single effect will probably be managed by reducing the effect.

Actually, the recommended solution is the optimal corrective strategy for the cost driver identified at the end of the cost driver impact assessment process. Specifically, the recommended solution is informed by the coordination agent about the feasible corrective scenarios for the collaborative effect. This initiates a process that intents either to eliminate or to reduce the prominent loss risk, or to further dichotomize it, in order to be shared to the supply network. The selected corrective actions are transferred again to the built-in simulator, where the optimization process begins (towards improving performance for the entire supply chain).This step can be characterized as the backbone of the database, where successful strategies are also constructed by using CBR (see figure 2), in order to form the whole data into a database legible to the system—so that past successful decisions are transformed as knowledge for the adaption case and retain knowledge of CBR into decision of CCM agent in supply chain.

E. Optimization and Self-learning in CCM

The final step of CBR is the optimization of the recommended solution, including retaining knowledge (self-learning) and disseminating solutions of CBR. Firstly, CCM process, the collaborative effect is calculated initially through a statement for the recommended solution. Then, through the application of ‘‘what-if’’ scenarios by the built-in simulator, the collaborative effect is managed in order to: (i) achieve a optimal collaborative effect in CCM, that is, the collaborative effect is increased and the risk (cost) is decreased, or (ii) to retain more efficiency in the same level, decreasing in this manner both the cost and the risk. Furthermore, the output of this process is the selection of the recommended solution strategy that is considered as beneficial for all the members of the supply chain. The problem of adaptation of an optimal strategy for a new CCM problem is modeled as an optimization problem. The different layers of swarms evolve independently but work in coordination with optimization to balance the “exploration” and the “exploitation” searches.

On the other hand, with parallel action of the optimization is learning of CBR in CCM. In the process of CBR, the case-base can gain more exact knowledge from the solutions of the problems, and find out better CCM skills and then get the effective value of CCM. These new results may affect and even change the strategies, decisions and behaviors of agents in subsequent CCM processes. The main learning tasks include the following four activities:

(1) Construct the new case and fuzzy inference model – after completion of the previous three phases, the actual actions of CCM can be observed and obtained. All these interactions are recorded as the cases in the case-base. The interactions (a set of offers and counteroffers) are used to construct its fuzzy inference model which simulates the CCM behaviors of a particular supplier in a particular situation. The fuzzy inference model is saved in the evaluation part of this new case.

(2)Measure of CCM skills – based on this fuzzy inference model, the negotiation strategy used in the previous phases is evaluated and a better collaborative strategy may be found out. Similar to the adaptation of the collaborative strategy in the second phase, fuzzy optimization is also used to solve this strategy optimization problem.

(3)The optimal (or near optimal) strategy in the last stage of CCM by CBR helps agents to find out what factors contribute to execute CCM and to identify the useful skills or conversely what factors contribute to the

CCM failure to avoid similar mistakes in future applications.

(4)The recommended CCM solutions are adapted in interactive learning, and the best matched case is recorded and listed. If a user chooses to amend the effect value of a CCM issue for a particular satisfaction level, the respective case content will be updated accordingly. The strategy recommended by the most suitable case has to be adjusted to help the C-agent and S-agent to achieve the maximum collaborative effect in CCM process. In this regard, the knowledge of the C-agent itself as well as that of its counterpart (S-agent) need to be elicited. Moreover, the knowledge of the CCM coordinator helps agents to predict the coordinator preference, the similar decision solution elicited from the best matched case is used to help the coordinator to predict the CCM actions in the succeeding phase.

V. CONCLUSIONS AND FUTURE WORK

In this study, based on [1] having built a novel framework for effective MAS-CCM, we seek only the most suitable case rather than the most similar one by our new method of suitability calculation in CBR. Existing CBR techniques include only the weight and similarities of each attribute instead of taking all of the problems' information into account. In order to compensate for these deficiencies, our paper introduces a new concept, effect information of cost driver through the facilitation of software agents and through the utilization of CBR which chooses previous successful corrective actions as cases for future decisions in CCM. There are definitely many benefits from the utilization of MAS-CCM initiatives. Moreover, this study develops a new method to integrate CBR into MAS-CCM, which includes the four key steps: cost driver and problem identification, cost driver impact assessment and ranking, decision of collaborative cost management actions, optimization and solution. This integrated method, in the model, can deal with cost drivers associated with important degree on the effect value of CCM, and improve the calculation of similar degree for fuzzy inference in seeking the most suitable solutions. In reasoning procedures, it can significantly facilitate decision making and self-learning in MAS-CCM, providing substantial information for CCM by the method of CBR. Moreover, managers could use those models to balance off their management activities in supply chain and to provide a possibility for checking and monitoring whether the program and objective of CCM are being pursued.

These results demonstrate that the new effect concepts improve the best case retrieval in effect of CCM and guide the weights towards better retrieval. The definition of effect measures enables us to seek the most suitable case for our problem in CCM, depending on local similarity and on the solution of the case in the system. To enhance this new method, we shall continue to working on this topic of research by case-based reasoning from a series of cases. Some issues for further research that this paper has identified are: (1) to study further theory on intelligent CCM in supply chain; (2) to conduct empirical studies about the synergic effect on CCM.

ACKNOWLEDGMENT

The authors are grateful that this paper is supported by National Natural Science Foundation of China (Grant No.70872096）and by the MOE Project of Key Research Institute of Humanities and Social Sciences in Universities of China (Grant No. 12JJD790011) and by Center for Accounting Studies of Xiamen University in China.

REFERENCES

[1] J. Fu and Y. Fu, "Case-based reasoning and multi-agents for collaborative cost management in supply chain" , *Procedia Engineering*, Vol.29, pp.1088–1098, 2012.

[2] W.W. Powell, "Neither market nor hierarchy: network forms of organization", *Research in Organization Behavior*, Vol.12, pp.20-30, 1990.

[3] Y. Fu, "The new method of value management: strategic management accounting based on value flow", *Accounting Research (Chinese)*, 2004(6),pp. 28-35.

[4] A. Dubois, K. Hulthen and A. Pedersen, "Supply chains and interdependence: a theoretical analysis", *Journal of Purchasing & Supply Management*, Vol.10,pp.3–9, 2004.

[5] M. Peng, Z. Xu, S. Pan and R. Li, "AgentTMS: A MAS Trust Model based on Agent Social Relationship", *Journal of Computers*, Vol. 7(6), pp. 1535-1542,2012

[6] Y. Fu, "Cost synergy management in e-supply chain", *Pacific-Asia Management Accounting Journal*, Vol.2(1),pp.35-53, 2007.

[7] H. L. Lee, K.C. So and C.S. Tang, "The value of information sharing in a two-level supply chain", *Management Science*, Vol.46 (5), pp.626–643, 2000.

[8] C. Berry, A. Hobbs and M.A. Meroney, " O'Neill RP and Steward Jr WR. Understanding how market power can arise in network competition: a game theoretic approach", *Utilities Policy, Vol.*8,pp.162-172, 1999.

[9] P.S. Adler, "Market, hierarchy, and trust: the knowledge economy and the future of capitalism", *Organization Science*, Vol.12 ,pp.215–234, 2001.

[10] P. Kajüter and H.I. Kulmala, "Open-book accounting in networks: potential achievements and reasons for failures", *Management ccounting Research*, Vol.16 , pp.179–204, 2005.

[11] M.J. Tarokh and J. Soroor, "IE-SCM: intelligent electronic supply chain management", in: *IEEE International Conference on Service Operations and Logistics, and Informatics*, Beijing, China, August 2005.

[12] M.J. Tarokh and J. Soroor, "Developing the next generation of the web and employing its potentials for coordinating the supply chain processes in a mobile real-time manner", *International Journal of Information Technology*, Vol.12 (9) ,pp.1–40, 2006.

[13] J. Soroor and M.J. Tarokh, "Innovative SCM – A wireless solution to smartly coordinate the supply processes via a web-based, real-time system", *The Journal of Information and Knowledge Management System*, Vol.36 (3), pp.183-195, 2006.

[14] W. Zhao, H. Wu, W. Dai, X.Li, F. Yu and C. Xu, "Multi-agent Middleware for the Integration of Mobile Supply Chain", *Journal of Computers*,Vol. 6(7), pp. 1469-1476,2011.

[15] F. Fang and T. N. Wong, "Applying hybrid case-based reasoning in agent-based negotiations for supply chain management," *Expert Systems with Applications,* Vol.37, pp.8322-8332, 2010.

[16] P.D. Loor, R. Bénard and P. Chevaillier, "Real-time retrieval for case-based reasoning in interactive multi-agent-based simulations", *Expert Systems with Applications,* Vol.38,pp.5145-5153, 2011.

[17] M.A. Shirazi and J. Soroor, "Employing the synergy of DM and IA technologies for real time supply chain coordination", in: *IEEE International Conference on System of Systems Engineering* (SoSE 2006), Los Angeles, California, USA, April 2006.

[18] P. Cunningham, R. Bergmann, S. Schmitt, R. Traphoner, S. Breen and B. Smyth, "Intelligent support for online sales: the WEBSELL experience",in: *Workshop program at the fourth international conference on case-based reasoning,* pp.87–93, 2001.

[19] O. Kwon, G. P. Im and K.C. Lee, "MACE-SCM: A multi-agent and case-based reasoning collaboration mechanism for supply chain management under supply and demand uncertainties", *Expert Systems with Applications,* Vol.33, pp.690–705, 2007.

[20] J.W. Schaaf, "Fish and shrink: a next step towards efficient case retrieval in large scaled case bases", in: *Advances in Case-based Reasoning: Third European Workshop*, Lausanne, Switzerland, pp. 362–377, 1996.

[21] K.H. Im and S.C. Park, "Case-based reasoning and neural network based expert system for personalization", *Expert Systems with Applications,* Vol.32 (1),pp.77–85, 2007.

[22] P.C. Chang, J. J. Lin and W.Y. Dzan, "Forecasting of manufacturing cost in mobile phone products by case-based reasoning and artificial neural network models", *Journal of Intelligent Manufacturing,* Vol.23, pp.517–531, 2012.

[23] J. Jarmulak, S. Craw and R. Rowe, "Genetic algorithms to optimize CBR retrieval, lecture notes in computer science", in: *Advances in Case-base Reasoning* , pp.136–147, 2000.

[24] M.J. Huang, H.S. Huang and M.Y. Chen, "Constructing a personalized e-learning system based on genetic algorithm and case-based reasoning approach", *Expert Systems with Applications,* Vol.33 (3), pp.551–564, 2007.

[25] S. Passone, P.W.H. Chung and V. Nassehi, "Incorporating domain-specific knowledge into a genetic algorithm to implement case-based reasoning adaptation", *Knowledge-Based Systems,* Vol.19 (3),pp.192–201, 2006.

[26] R.J. Kuo, Y.P. Kuo, and K.Y. Chen, "Developing a diagnostic system through integration of fuzzy case-based reasoning and fuzzy ant colony system", *Expert Systems with Applications* Vol.28, pp.783–797, 2005.

[27] V. Marques, J.T. Farinha and A. Brito, "Case-based reasoning and fuzzy logic in fault diagnosis", *WSEAS Transactions on Computers,* Vol.8 (8), pp.1408–1417, 2009.

[28] S. Begum, M.U. Ahmed, P. Funk, N. Xiong and B. Von Schele, "A case-based decision support system for individual stress diagnosis using fuzzy similarity matching", *Computational Intelligence,* Vol.25 (3), pp.180–195, 2009.

[29] S. Chaudhury, T. Singh and P.S. Goswami, "Distributed fuzzy case based reasoning", *Applied Soft Computing,* Vol.4 (4),pp. 323–343, 2004.

[30] T.Y. Slonim and M. Schneider, "Design issues in fuzzy case-based reasoning", *Fuzzy Sets and Systems*, Vol.117 (2),pp. 251–267, 2001.

[31] C.S. Park and I. Han, "A case-based reasoning with the feature weights derived by analytic hierarchy process for bankruptcy prediction", *Expert Systems with Applications,* Vol.23 (3),pp. 255–264, 2002.

[32] S.Z. Dogan, D. Arditi and H.M. Gnaydin, "Using decision trees for determining attribute weights in a case-based model of early cost prediction", *Journal of Construction Engineering and Management,* Vol.134 (2), 146–152, 2008.

[33] B. L. Su, M. S. Wang and Y.M. Huang, "Fuzzy logic weighted multi-criteria of dynamic route lifetime for reliable multicast routing in ad hoc networks", *Expert Systems with Applications,* Vol.35 (1–2), pp. 476–484, 2008.

[34] O.M. Akanle and D.Z. Zhang, "Agent-based model for optimizing supply chain configurations", *International Journal of Production Economics,* Vol.115(2), pp.444-460, 2008.

[35] T. Takagi and M. Sugeno, "Fuzzy identification of systems and its application to modeling and control", *IEEE Transaction on Systems, Man, and Cybernetics,* Vol.15 (1) , pp.116–132, 1985.

Yuanlue Fu was born in 1953, and received his M.S. degree of Statistics in 1987 and Ph.D. degree of Accounting in 1997 both at Xiamen University, China. Now he is a professor and doctoral supervisor at School of management, Xiamen University; he also is a vice director of the center for accounting studies of Xiamen University in China. His main research interests cover accounting information system, intelligent inference engines, cost management, multi-agent systems, supply chain management, finance theory and computerized auditing. He was as a senior visiting scholar, engaged in collaborative research in Haas business school of University of California at Berkeley (USA) from 2002-2003. He was project leader of 5 national research Projects from NSFC and SSFC. More than 50 papers of him were published in key Chinese journals or international journals &conferences, 22 of which are cited by EI/SSCI/CSSCI. Five books were published by him in Press companies of China and he obtained 5 national and provincial awards in science achievement. He also is a Chairman of 2012 APMAA 8th conference and Vice President of APMAA (Asia Pacific Management Accounting Association). He is the corresponding author of this paper.

Jianxi Fu was born in 1983, and got his bachelor's degree in measuring & control technology and instrumentations from Tsinghua University, Beijing, China in 2005 and got M.S. degree in mechanical engineering from Texas A&M University, USA in 2010. And now he is pursuing Ph.D degree at Texas A&M University in the same major. His research fields are system control, artificial intelligence, machine learning, fractal theory, DSP&ARM, fuzzy-neural networks, rotating machinery diagnosis, condition based maintenance and maintenance cost control.