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Modeling of a Fuzzy Expert System for Choosing an Appropriate Supply Chain Collaboration Strategy

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ABSTRACT
Nowadays, there has been a great interest for business enterprises to work together or collaborate in the supply chain. It is thus possible for them to gain a competitive advantage in the marketplace. However, determining the right collaboration strategy is not an easy task. Namely, there are several factors that need to be considered at the same time. In this regard, an expert system based on fuzzy rules is proposed to choose an appropriate collaboration strategy for a given supply chain. To this end, firstly, the factors that are significant for supply chain collaboration are extracted via an extensive review of literature. Then, a simulation model of a supply chain is constructed to reveal the performance of collaborative practices under various scenarios. Thereby, it is made possible to establish fuzzy rules for the expert system. Finally, feasibility and practicability of our proposed model is verified with an illustrative case.

KEYWORDS
Supply chain management; fuzzy expert system; vendor managed inventory; collaborative, planning, forecasting and replenishment; simulation

1. Introduction

Supply chain management (SCM) is interested in all enterprises that take a part in creation and delivery of a product in some way. This wide scope of SCM makes it necessary to consider various activities from procurement and manufacturing to distribution. In general, SCM has two main objectives (Simchi-Levi, Kaminsky, & Simchi-Levi, 2008). These are; (1) to cope with the uncertainties observed in demand and supply sides, and (2) to achieve the global optimization. In fact, the members of a supply chain need to work together on key business activities to achieve these objectives (Golicic, Foggin, & Mentzer, 2003; Simatupang & Sridharan, 2002). This practice is referred to as supply chain collaboration (SCCOL).

By means of SCCOL, it is possible to have a greater performance improvement than the enterprises would achieve individually (Cannella & Ciancimino, 2010; Ramanathan, 2014). In addition, SCCOL is also utilized as an effective risk mitigation strategy (Chen, Sohal, & Prajogo, 2013) and a tool for increasing supply chain resilience (Scholten & Schilder, 2015). For these reasons, it has become very popular in the business world. For instance, Procter & Gamble, Boeing, Glaxosmithkline, and Motorola deploy some sort of SSCOL with some of their major retailers (Danese, 2004; De Toni & Zamolo, 2005; Liao & Kuo, 2014; Micheau, 2005; Yao, Kohli, Sherer, & Cederlund, 2013).

However, in spite of its popularity, there is no one way of description for SCCOL. For instance, Cao, Vonderembse, Zhang, and Ragu-Nathan (2010) conceptualize it in seven interconnecting elements as information sharing, goal congruence, decision synchronization, incentive alignment, resource sharing, collaborative communication and joint knowledge creation. However, Kohli and Jensen (2010) define SCCOL simply with two components as information sharing and joint planning. According to Barratt (2004), on the other hand, it has four dimensions as cross functionality, process alignment, joint decision-making and shared performance metrics.

In fact, in parallel to the differences in its conceptualization, the way of implementation for SCCOL is also different. In this regard, Holweg, Disney, Holmström, and Småros (2005) categorize SCCOL into three main groups according to their level of integration. These are; information exchange supply chain (IESC), supply chain with vendor managed inventory (VMI) and synchronized supply chain (SSC). More recently, a very similar classification is also done by Danese (2011).

In this classification, IESC represents the simplest form of collaboration. Here, sales information at retailers is shared with suppliers. For example, efficient customer response (ECR) (Andraski, 1994) or quick response programs (Choi & Sethi, 2010) can be included into this group. In a typical IESC program, the main purpose is to reduce the lead times along the supply chain. In a VMI program, on the other hand, not only sales information is shared, but also the inventory decisions are left to the suppliers (Waller, Johnson, & Davis, 1999). Thus, compared to an IESC program, a VMI program requires a collaboration that is more intensive. Finally, in a SSC program, forecasting and replenishments decisions are made with the contribution of all members. This program is the most intensive type of SCCOL. A Collaborative Planning, Forecasting, and Replenishment (CPFR) program is a good example for this category (Chen, Yang, & Li, 2007; Danese, 2006).

Therefore, it is vital to determine the most appropriate SCCOL strategy for a given enterprise as there are multiple options (De Leeuw & Fransoo, 2009). Indeed, it is intuitively attractive to implement full level of collaboration (e.g. SSC) as it promises more benefits (Kohli & Jensen, 2010). Nevertheless, the decision situation is not that simple, because of the implementation cost and management difficulties. In addition, it is also a reality that the benefits of SCCOL are not equal for all supply chains (Sari, 2008a). For instance, while a SSC program (i.e. full level of collaboration) provides huge benefits for a given enterprise, it can create only a limited improvement for

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another enterprise that suffers from the errors in inventory records (Sari, 2008b). Thus, determining the right SCCOL strategy is a very challenging problem in SCM area. In this research, we aim to concentrate on this problem.

In fact, two groups of studies are performed previously in an attempt to solve this problem. The first category of studies (e.g. Angulo, Nachtmann, & Waller, 2004; Cannella, Framinan, Bruccoleri, Barbosa-Póvoa, & Relvas, 2015; Danese, 2011; Fry, Kapuscinski, & Olsen, 2001; Gavirneni, 2002; Lau, Huang, & Mak, 2004; Sari, 2008a; 2008b) concentrate on evaluating the performance of SCCOL by means of analytical and simulation methods. On the other hand, the studies in the second category (e.g. Holweg et al., 2005; Barros, Póvoa, & Castro, 2008; Danese, 2011), analyze the factors that are important for SCCOL via case study analyses. In spite of their contributions, both groups of studies have some limitations from our research perspective.

Firstly, only one part of the problem is examined by those studies. This is actually a result of modeling difficulties. For instance, Sari (2008a, 2008b) and Waller et al. (1999) concentrate on lead-time and demand uncertainty. Similarly, Gavirneni (2002) considers the capacity limitations. On the other hand, Cannella et al. (2015), Sari (2015a) and Kwak & Gavirneni (2014) pay more attention on the errors in inventory records. In addition, SCCOL is not explored fully by these studies. Namely, Sari (2008a, 2008b) makes a comparative analysis of CPFR and VMI programs; however, an IESC program is not taken into consideration. Similarly, Angulo et al. (2004) and Waller et al. (1999) evaluate the performance of a VMI program only.

Secondly, some of the results obtained from those studies include ambiguity and vagueness. For example, Bourland, Powell, and Pyke (1996) indicate that the value of a SCCOL program is greater under high level of demand uncertainty. Similarly, Lee, So, and Tang (2000) reach exactly the same conclusion. However, high level of demand uncertainty is not defined in the same way by these studies. In addition, Holweg et al. (2005) and Danese (2011) reveals that a SCCOL program creates lower value for supply chains with large geographical dispersion. However, in both studies, large geographical dispersion is not defined clearly.

Therefore, in this study, we aim to develop a framework that rectifies the limitations observed in the previous studies. By the way of this framework, the managers can analyze their own supply chains and then obtain a suggestion about the right SCCOL strategy. To achieve this purpose, a fuzzy rule based expert system is designed as the decision situation is complex and involves some degree of vagueness and ambiguity. In addition, a simulation analysis is conducted to explore the factors related with SCCOL. In reality, it is best way to use a fuzzy rule based expert system under these conditions (Sari, 2013).

To the best of our knowledge, the only work that uses an expert system by using fuzzy rules or artificial intelligence for SCCOL is the study by Sari (2015b). However, some important factors such as "shelf life of a product" or "geographical dispersion of logistics network" are not taken into consideration by Sari (2015b). In fact, these factors are worth considering. In addition, only past studies are considered by Sari (2015b) to form the fuzzy rules. In reality, a simulation model is needed to have a better understanding of the situation.

The outline of this study is as follows: Proposed expert system is explained in Section 2. Construction of fuzzy rules along with simulation model is presented in Section 3. In Section 4, an illustrative case is provided to indicate the feasibility and practicability of the expert system. Finally, conclusion and directions for future research are presented in Section 5.

2. Proposed Expert System based on Fuzzy Rules

An expert system based on fuzzy rules is a systematic reasoning methodology to explain the complex behavior of a system by using fuzzy set theory (Tang, Chen, Hu, & Yu, 2012). Over the past few decades, these systems are successfully used in a wide range of areas. For instance, they are used in SCM (Olugu & Wong, 2012), in medical sciences (Lee & Wang, 2011), and in investment decisions (Fasanghari & Montazer, 2010). They are data driven systems in which a relationship is established between the input variables and the output variables, based on a set of IF-THEN rules. As an example, a fuzzy rule is represented in Equation 1.

$$\text{IF } X \text{ is } A_i \text{THEN } Y \text{ is } B_i, \quad i = 1, \ \ldots, \ n \tag{1}$$

Here, X and Y are input and output variables, respectively. In addition, A_i and B_i represent vague linguistic expressions (i.e. low, medium, high).

In our proposed expert system, more than one input variable is considered as SCCOL is influenced from many factors. Those are identified by means of an extensive review of SCM literature. In addition, the benefits obtained from SCCOL are determined as the output variable of the system. In modeling of our expert system, the steps shown in Figure 1 are followed. As it is shown in Figure 1, there are two phases in our modeling approach. In the first phase, construction of our expert system is achieved. In second phase, however, a module is provided to analyze a given supply chain for its appropriateness for SCCOL.

2.1. Input Variables of the Expert System

Danese (2011) considers four factors as important for SCCOL. They are; goals of collaboration, demand elasticity, product diversity, and supply network spatial complexity. Similarly, geographical dispersion of logistics network, demand pattern of the product, and product characteristics are regarded as prominent factors by Holweg et al. (2005). In addition, Barros, Barbosa, and Castro (2008) identify six factors. They are defined as; purchasing volume, risk of supply, demand volatility, importance of buyer to supplier, lead time, and shelf life. Finally, De Leeuw and Fransoo (2009) regard five influencing factors by developing a conceptual model of SCCOL. They are; demand uncertainty and lead time, supply uncertainty, product criticality, product customization level, capabilities and skills of suppliers.

In addition, some analytical and simulation studies are also performed to investigate the value of SCCOL. They reveal to us that manufacturing capacity (Gavirneni, 2002; Lau et al., 2004; Simchi-Levi & Zhao, 2003), replenishment lead times (Lee et al., 2000; Sari, 2008a), demand uncertainty (Bourland et al., 1996; Fry et al., 2001; Lee et al., 2000), and errors in inventory records (Angulo et al., 2004; Cannella et al., 2015; Kwak & Gavirneni 2014; Sari, 2008b) are very important factors.

As a result, we determine seven factors as the main drivers of SCCOL. They are; geographical dispersion of logistics network (GEO), lead-time (L), demand uncertainty (DU), error rate in inventory records (ERI), value of the product (PV), capacity limitations (CAP) and shelf life or selling period of products (SL).

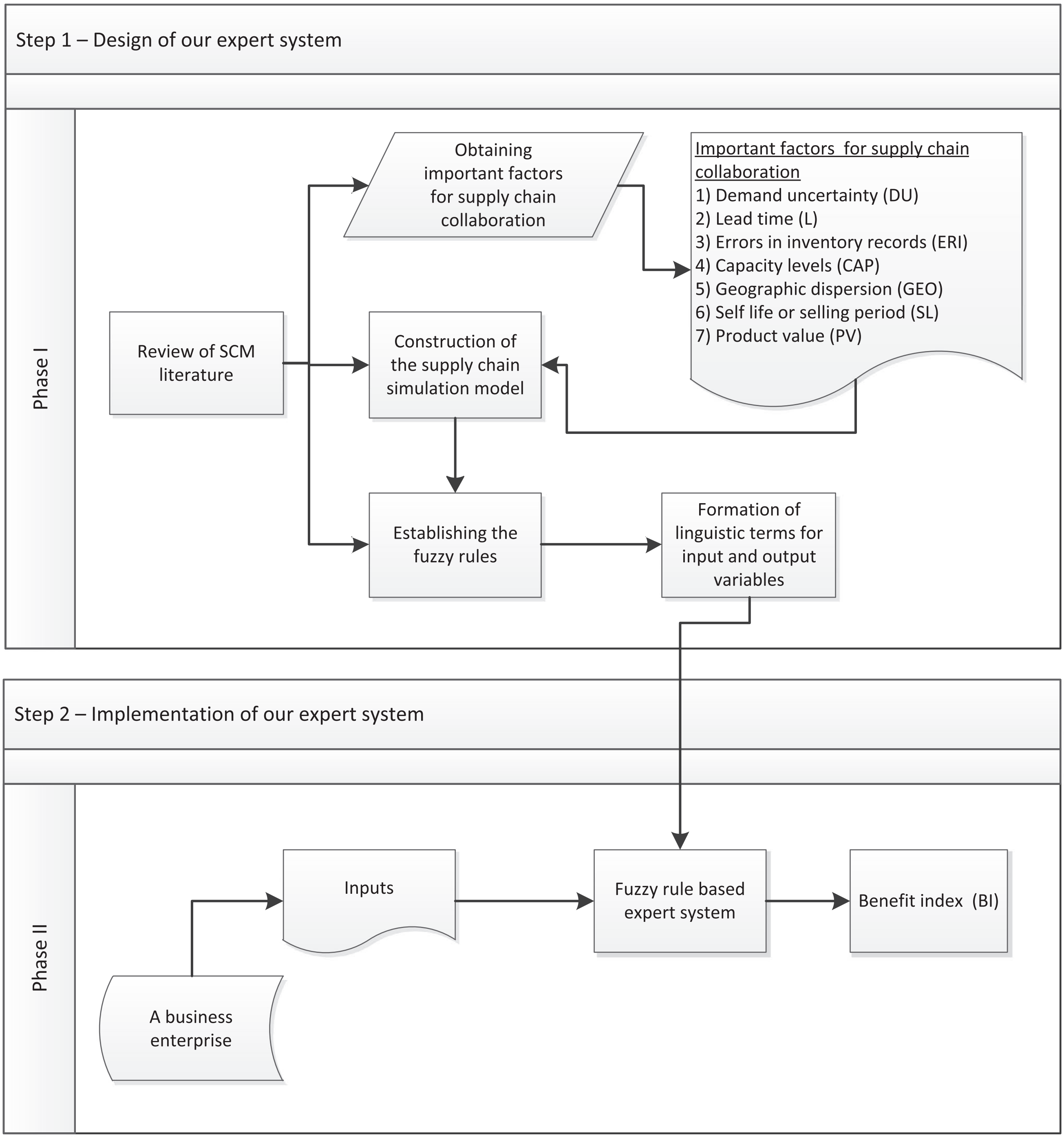

Figure 1. The Steps Followed in Constructing the Fuzzy Expert System.

2.2. *Output Variable of the Expert System*

As shown in Figure 1, the proposed expert system produces a Benefit Index (BI). This index indicates the potential benefit that is obtainable from a SCCOL program. It is assumed that BI can take a value in the range of 0 and 100 points. By creating BI, it is made possible to evaluate a specific supply chain for its aptness to collaborative practices. For example, if the value of BI is produced high as 80 points by the expert system, then it will be understood that deploying a program within the set of SSC (i.e. CPFR) is more appropriate for this case. On the other hand, it will be suggested using a very low level of collaboration (e.g. QR) in case that BI is produced very low as 5 or 10.

3. Establishing the Relationship between Variables of the Expert System

The implications obtained from SCM literature is very clear for three of the input variables. These are; GEO, PV and SL. Namely, as PV and SL of a product increases, the benefit obtained from a SCCOL program also increases (see e.g. Barros et al., 2008; Holweg et al., 2005). In addition, it is also observed that a SCCOL program provides greater advantage for the supply chains with a small GEO (e.g. Danese, 2011; Holweg et al., 2005). Therefore, these implications are used in establishing the fuzzy rules. For the other input variables, on the other hand, a simulation model is constructed. Indeed, the fuzzy rules for these variables can also be extracted from related

SCM literature. However, as each of the past studies considers only a few of those variables under various assumptions, we prefer to make a simulation analysis here to investigate all the input variables together. By this way, we believe that the big picture about SCCOL is emerged.

3.1. Assumptions and Parameters of the Simulation Model

A supply chain structure that is also used in The Beer Distribution Game is considered (Jacobs, 2009). It consists of one capacitated plant, one warehouse, one distributor, and one retailer. In this setting, a single product is manufactured at the plant and sold at the retailer. In addition, customer demand is assumed to be normally distributed with a mean of 100 units.

A full factorial simulation run is performed by considering five independent factors each taking two levels. These are; ERI with levels of 0% and 20%, L with levels of 1 week and 5 weeks, CAP, which represents the ratio of available capacity of the plant to the market demand, with levels of 1.10 and 1.50, and DU with a standard deviation of 20 units and 60 units. At this point, 20 units of standard deviation represent the low level of demand uncertainty (LDU) and 60 units of standard deviation represents high level of demand uncertainty (HDU). In addition, two levels of SCCOL are represented. These are a non-collaborative, traditionally managed supply chain (TMSC) and a synchronized supply chain (SSC). While selecting these values for the levels of experimental design, past simulation studies are considered (Sari, 2008a, 2008b).

The base stock level (Simchi-Levi et al., 2008, p.45) is used with a review interval of 1 week as an inventory control policy. Here, note that the base-stock level is calculated in a different way for TMSC and SSC (e.g. Sari, 2008a). In the design of experiment, three response measures are used as performance indicators. These are total cost per week for all system (TSCC), average supply chain inventory (INV) and customer service level at the retailer (CSL). A simple, but a realistic cost structure is chosen. They are as follows: The unit back-order costs per week for the plant, the distributor, the warehouse and the retailer are \$15, \$25, \$35, and \$50, respectively. In addition, respective inventory holding cost per week of \$0.70, \$0.80, \$0.90, and \$1.00 are chosen for each supply chain member.

3.2. Analysis of Simulation Results

Ten replications are made for each combination of independent variables to remove the impact of random variations. The simulation run is performed for 500 weeks and data for the last 400 weeks are considered for output analysis. The simulation output analysis is performed with DEO (Design of Experiment) Module of Minitab 16.

The results bring out that SCCOL has a significant impact on all three response variables at 5 percent significance level. Namely, while SCCOL creates substantial reduction in TSCC and INV, it has some negative impacts on CSL. The interaction plots for TSCC, CSL, and INV are shown in Figures 2–4, respectively.

From Figure 2, it is revealed that SCCOL results in substantial reductions in TSCC. However, the cost reduction created by SCCOL is greater when the DU is high (DU = HDU) and/or when the L is long (L = 5) and/or when the CAP is high (CAP = 1.50). On the other hand, Figure 3 shows that SCCOL can create performance reductions in CSL under certain conditions. These are the conditions where the ERI is high (ERI = 20%) and/or when the DU is low (DU = LDU). Finally, Figure 4 indicates that SCCOL results in substantial reductions in INV. However, the reduction amount is greater when the ERI is high (ERI = 20%) and/or when the L is long (L = 5).

From these results, we can state that the benefit of a SCCOL program is greater when DU is higher and/or when L is longer,

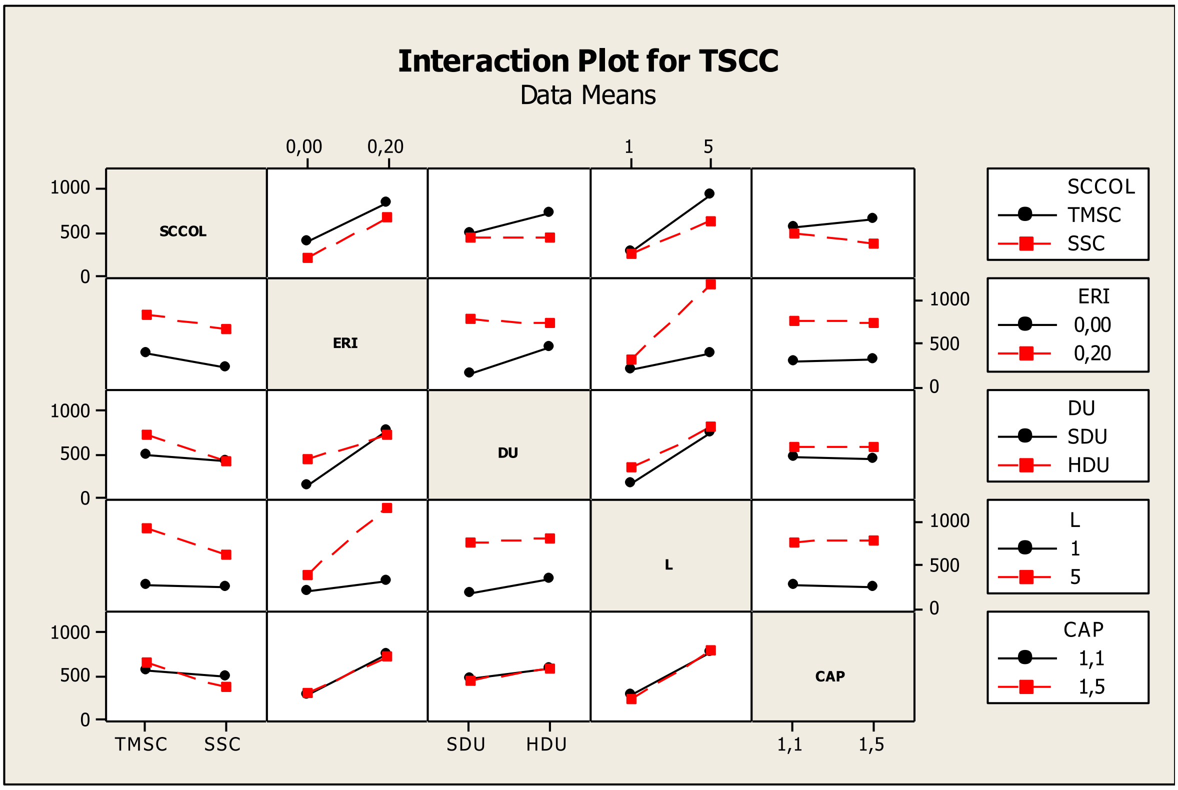

Figure 2. Interaction Plot for Total Supply Chain Cost per Week (TSCC).

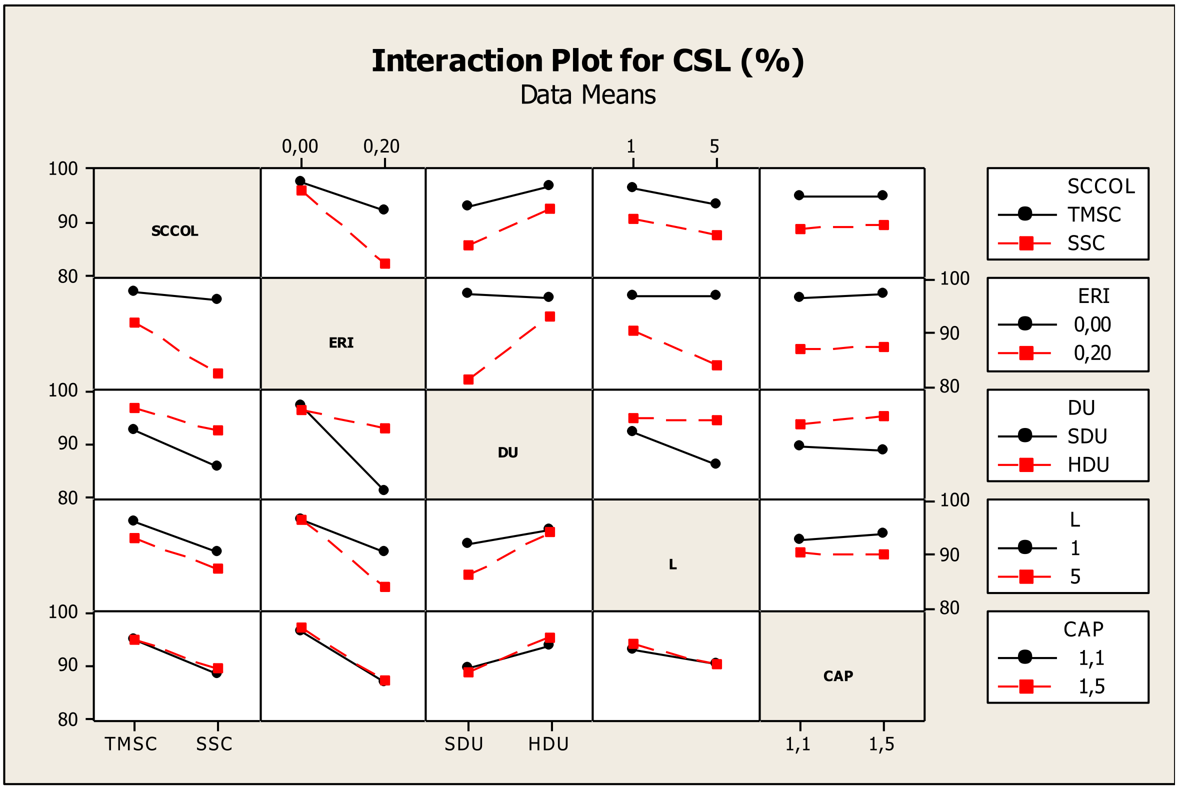

Figure 3. Interaction Plot for Customer Service Level (CSL).

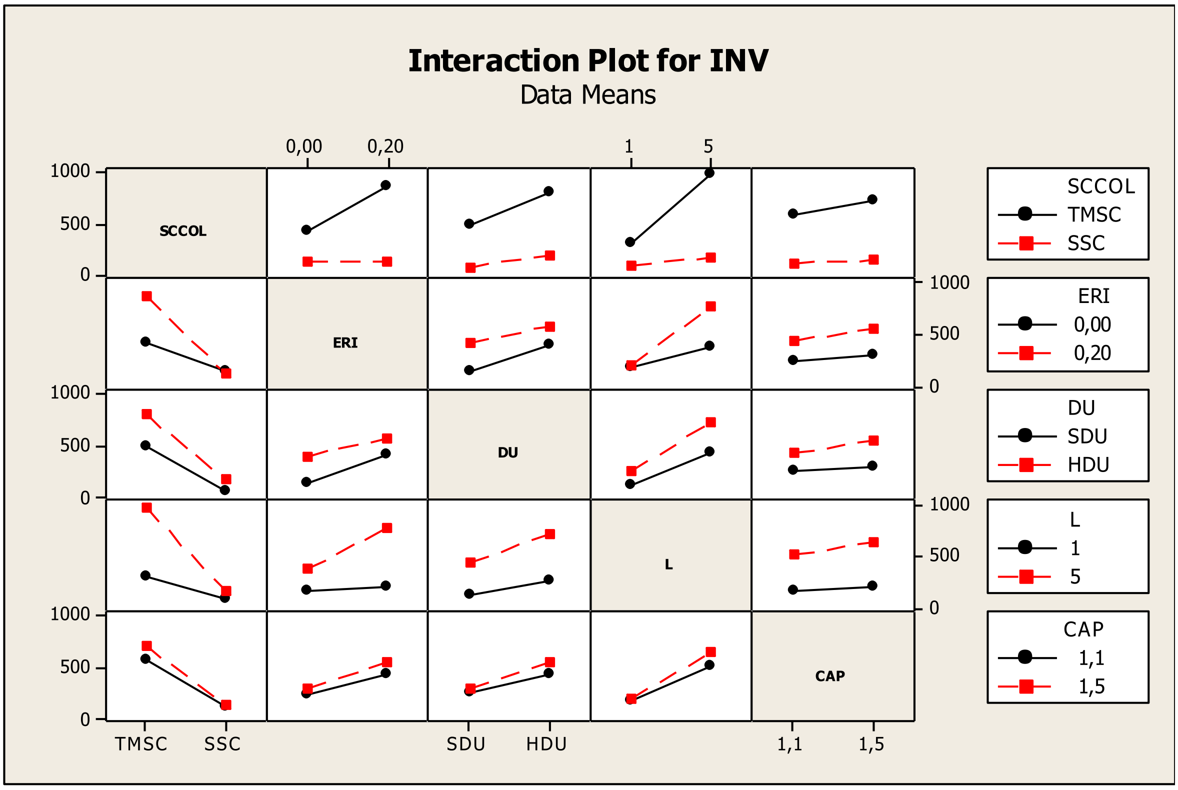

Figure 4. Interaction Plot for Average Inventory Level (INV).

and/or when CAP is higher and/or when ERI is lower. In fact, past studies on SCM area also support our results. Namely, the studies by De Leeuw and Fransoo (2009), Sari (2008a), and Lee et al. (2000) provide the same result for L. Similarly, the studies by Cannella et al. (2015), Kwak & Gavirneni (2014), Sari (2015a), and Angulo et al. (2004) come forward for ERI. For CAP, on the other hand, the studies by Lau et al. (2004), Simchi-Levi and Zhao (2003), and Gavirneni (2002) give a similar result. Finally, the studies by De Leeuw and Fransoo (2009), Fry et al. (2001), Lee et al. (2000), and Bourland et al. (1996) present the same findings for DU. Thus; we use these findings while establishing the fuzzy rules of our expert system.

3.3. Fuzzy Rule Construction

For the purpose of fuzzy rules, three linguistic terms (e.g. low, medium, and high) are used to describe the input and the output variables of our expert system (Zadeh, 1965). As a result, six groups of fuzzy rules are established. At this point, results of the simulation analysis and results of the past studies are evaluated together. All fuzzy rule groups are listed in Table 1 along with their source of inspiration. As an example, rules in group 1 of Table 1 indicate the relationship between GEO and BI.

According to Liang and Wang (1994), triangular fuzzy numbers (TFNs) are the most commonly used fuzzy numbers to capture the vagueness of linguistic assessments. For this reason, TFNs are used to represent the linguistic assessments for input and output variables of the expert system. As it is known, a TFN can be represented with three parameters of l, m, and u. These parameters indicate the smallest possible value, the most promising value, and the largest possible value, respectively. The membership functions of the variables are shown in Table 2.

At the end, our expert system is completed. That is to say, we have the input and output variables and we have membership functions of these variables. In addition, we have fuzzy rules that express the relationship between input and output variables. Therefore, it is possible to get a recommendation about the level of SCCOL. At this point, the necessary steps are to enter the input variables, make the fuzzy calculations, and then get the output variable. Indeed, these steps can be done manually or by computer software. In this study, Matlab Fuzzy Toolbox is used for this purpose.

4. An Illustrative Case

The managers of a manufacturer try to obtain a recommendation about the level of collaboration for their supply chain. At this point, the following input variables are provided to our expert system. These are a ratio of 0.80 for DU, 5 weeks for L, ratio of 0.10 for ERI, ratio of 1.50 for CAP, PV of 4, 12 months for SL, and 3000 km for GEO. These input variables are provided as crisp numbers. Later, by using membership functions shown in Table 2, these are converted to the linguistic variables.

As an output, we expect to obtain BI. This index represents the potential usefulness of SCCOL and it can take a value between 0 and 100. The fuzzy rules provided in Table 1 are adopted to obtain the BI for the given input parameters. The process is completed by Mamdani model available in Matlab Fuzzy Toolbox. Meanwhile, the max-min method is performed for the aggregation of fuzzy rules. In addition, the centroid method is utilized for the defuzzification of fuzzy outputs. At the end, a score of 62 is obtained for BI. The details of the computations are shown in Figure 5.

As shown in Figure 5, a score of 62 for BI indicates that implementation of a SCCOL program can result in a moderate level of benefit for the manufacturer. Hence, a VMI program requiring mid-level collaboration can be proposed for this case.

Table 1. The Fuzzy Rules Established for Supply Chain Collaboration (SCCOL).

Fuzzy Rules					Related Literature
Rule Group 1	If GEO is	Low Medium High	BI is	High Medium Low	Danese (2011), Holweg et al. (2005)
Rule Group 2	If L is	Low Medium High	BI is	Low Medium High	De Leeuw and Fransoo (2009), Sari (2008a), Lee et al. (2000)
Rule Group 3	If ERI is	Low Medium High	BI is	High Medium Low	Cannella et al. (2015), Kwak & Gavirneni (2014), Sari (2015a), Angulo et al. (2004)
Rule Group 4	If CAP is	Low Medium High	BI is	Low Medium High	Lau et al. (2004), Simchi-Levi and Zhao (2003), Gavirneni (2002)
Rule Group 5	If DU is	Low Medium High	BI is	Low Medium High	De Leeuw and Fransoo (2009), Fry et al. (2001), Lee et al. (2000), Bourland et al. (1996)
Rule Group 6	If SL is	Low Medium High	BI is	Low Medium High	Barros et al. (2008), Holweg et al. (2005)
Rule Group 7	If PV	Low Medium High	BI is	Low Medium High	De Leeuw and Fransoo (2009), Holweg et al. (2005)

Table 2. Linguistic Terms Used to Define the Input and Output Variables.

		Linguistic Term		
Variables	Explanation	Low	Medium	High
GEO	kilometers	(0, 0, 4000)	(2000, 5000, 8000)	(6000, 15000, 15000)
L	weeks	(0, 0, 4)	(1, 5, 9)	(6, 10, 10)
ERI	error rate in inventory information	(0, 0, 0.10)	(0.05, 0.15, 0.25)	(0.15, 0.30, 0.30)
CAP	ratio of available capacity to the total demand	(1.10, 1.10, 1.40)	(1.20, 1.50, 1.80)	(1.60, 1.90, 1.90)
DU	ratio of standard deviation of demand to the average demand	(0, 0, 0.80)	(0.4, 1, 1.60)	(1.20, 2, 2)
SL	months	(0, 0, 6)	(2, 7, 12)	(8, 15, 15)
PV	10 is the highest value, 0 is the lowest value product	(0, 0, 4)	(1, 5, 9)	(6, 10, 10)
BI	100 is the best, 0 is the worst case	(0, 0, 40)	(10, 50, 90)	(60, 100, 100)

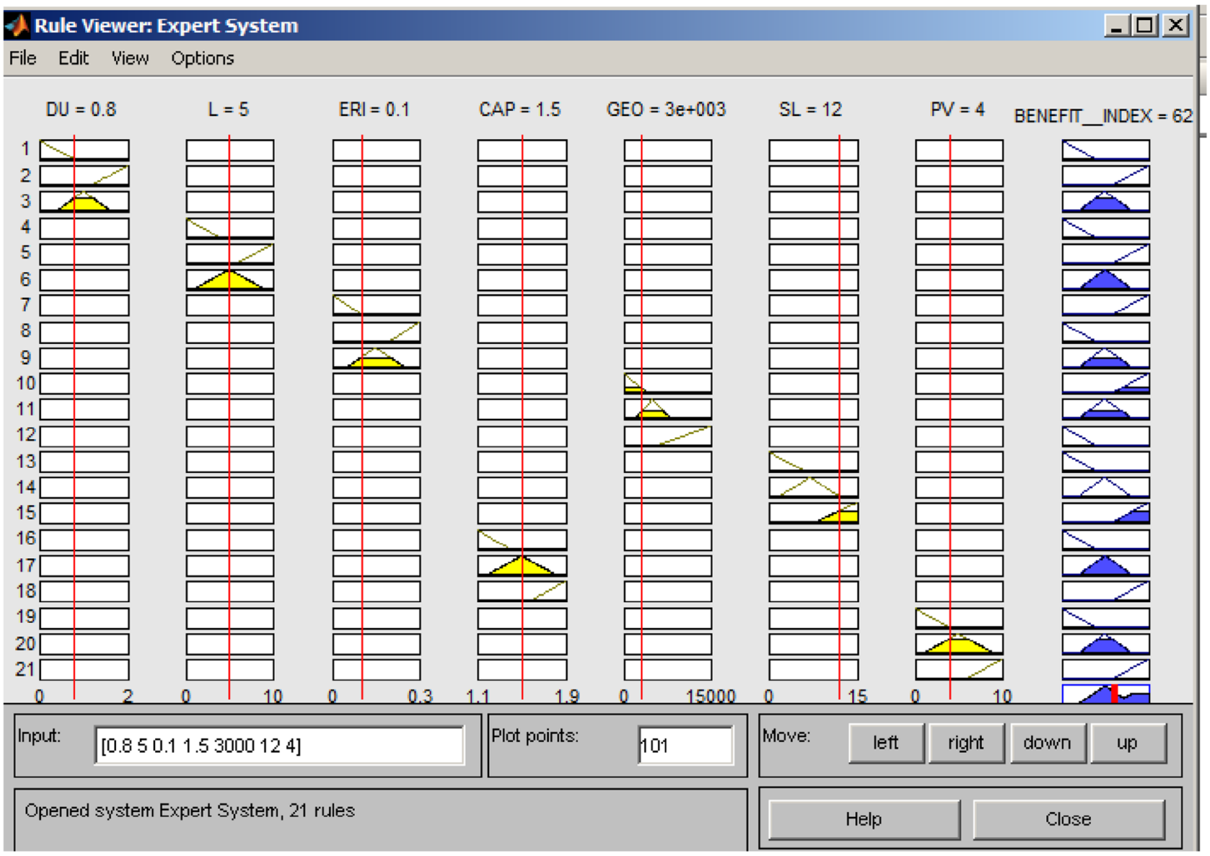

Figure 5. An Illustrative Example.

5. Conclusion

In this study, an expert system is designed for determining the best suitable type of SCCOL for a given enterprise. By this way, we aim to fill an important gap in SCM area. In modeling of this expert system, key factors that are influential on the value of a SCCOL program are extracted from related SCM literature. Later, a number of fuzzy rules are established along with a supply chain simulation model. Finally, feasibility and practicability of our proposed expert system is verified with an illustrative case.

Today, we observe that most of the enterprises adopt a SCCOL program just because of its popularity. However, this is not a good decision for two reasons. First, the choice of a SCCOL program is a strategic decision and has a long term impact. Second, the benefits obtained from a SCCOL program are different from one supply chain to another. Therefore, a very careful analysis has to be performed while making a decision about SCCOL. At this point, our expert system can be a useful tool for the managers. Through our expert system, the managers can evaluate the special conditions of their business and then determine the most appropriate SCCOL program. In this process, our expert system allows them to analyze up to seven input variables and then indicates the potential benefits of a SCCOL program.

In spite of its usefulness, this study has some shortfalls, which we need to state. First, three types of SCCOL is considered in this study. However, it is possible to categorize SCCOL practices in more than three levels. Therefore, it would be an interesting study to investigate other categorizations as well. Second, it is assumed that each group of fuzzy rules has an equal level of importance. In fact, a study that prioritizes the fuzzy rules may extend the findings obtained in this study.

Disclosure Statement

No potential conflict of interest was reported by the author.

Notes on Contributor

Kazim Sari earned his Ph.D. in Industrial Engineering from Istanbul Technical University, Istanbul, Turkey. He currently serves as an associate professor and chairman of the Industrial Engineering Department at Beykent University, Istanbul, Turkey. His principle research areas include analysis and design of supply chains and logistics systems through optimization and simulation modeling. His studies have been published in various prestigious journals including European Journal of Operational Research (EJOR), International Journal of Production Economics (IJPE), Computers & Industrial Engineering (CAIE), and International Journal of Physical Distribution and Logistics Management (IJPDLM). He is a member of Production and Operations Management Society (POMS).

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