Expert Systems With Applications 184 (2021) 115455

Contents lists available at ScienceDirect

Expert Systems With Applications

journal homepage: www.elsevier.com/locate/eswa

Evaluation of the impact of blockchain technology on supply chain using cognitive maps

Ayşenur Budak [a,*], Veysel Çoban [b]

[a] Gebze Technical University, Industrial Engineering Department, Gebze, Kocaeli, Turkey
[b] Bilecik Seyh Edebali University, Industrial Engineering Department, Bilecik, Turkey

ARTICLE INFO

Keywords:
Blockchain technology
Supply chain management
Probabilistic-linguistic fuzzy cognitive map (PL-FCM)
Hesitant fuzzy cognitive map (HFCM)
Rough set cognitive map (RS-CM)
Blockchain impacts evaluation

ABSTRACT

Blockchain technology have gained importance in the supply chain with its transparency, robustness, and elimination of intermediaries. Different impacts are expected with the integration of blockchain technology in supply chain processes. Comprehensive evaluation methods are required to take important strategic decisions about blockchain technology. To examine the impact of blockchain technology, factors of cost, risks, business, and customer related benefits should be considered comprehensively. The purpose of this paper is to investigate the causal relationships among the factors to evaluate blockchain technology impact on supply chain. Cognitive maps (CM) methods which are hesitant fuzzy cognitive map (HFCM), probabilistic linguistic fuzzy cognitive map (PL-FCM) and rough set cognitive map (RS-CM) are used in this study. Also, PL-FCM that is generated based on probabilistic linguistic term sets is used for the first time in this study as a novel cognitive model. This study provides a contribution by developing cognitive map methods to measure and examine the impact of blockchain technology on supply chain for the first time. Firstly, the impacts of blockchain technology on supply chain and their relations are formed according to expert views and literature review. Then, five scenarios are considered using cognitive mapping methods, future predictions in terms of supply chain management are determined. Sensitivity analysis is performed. In this way, firms can analyze various implications and under what conditions how blockchain technology will have an impact on the supply chain.

1. Introduction

The supply chain is a complex structure with a large number and variety of inputs and outputs, as well as a large number of stakeholders, and it is very difficult to manage (Bozarth et al., 2009). Therefore, it faces many problems. The most common problems are lack of transparency, low traceability, smuggling, counterfeiting in products and / or documents, intense paperwork, high rates of human errors and follow-up of financial transactions. It is possible to find solutions to many of these problems with blockchain technology (BCT) (Abeyratne and Monfared 2016, Tian 2016).

All these complexities negatively affect performance in the supply chain and increase risks. Delays in transactions, increased costs, and loss of confidence between the stakeholders are some of the prominent risks. Blockchain is seen as a potential solution to some of these and similar key problems in the supply chain (Francisco and Swanson 2018, Wang et al., 2019). It provides some solutions to the problems that have become more complex with globalization in the logistics and supply chain. Basically, blockchain offers some important solutions such as transparency and accessibility of transaction records, establishing confidence in commercial transactions, security structure that prevents data falsification, removing intermediaries, saving costs and speed in transactions (Chen et al., 2018). In order to reduce this complexity in the supply chain, companies have started to implement BCT to perform more efficient supply chain processes. (Kshetri, 2018).

BCT has aroused great interest in both the academic world and the supply chain industry in recent years and started to be used in supply chain processes (Wang et al., 2019). It is important for the supply chain industry, which is intertwined with technology, to analyze and evaluate the impacts that will arise with the integration of BCT. Thus, companies can better control the future outputs and fluctuations. The cost, benefit and risk factors expected to be revealed after a new technology integration should be determined and the relationship between them should be analyzed.

The purpose of this paper is to provide a conceptual framework for analyzing the impacts among BCT's integration, benefits, cost and

* Corresponding author.
E-mail addresses: abudak@gtu.edu.tr (A. Budak), veysel.coban@bilecik.edu.tr (V. Çoban).

https://doi.org/10.1016/j.eswa.2021.115455
Received 10 July 2020; Received in revised form 26 March 2021; Accepted 18 June 2021
Available online 24 June 2021
0957-4174/

performance in the supply chain context. In the literature, there is a lack of comprehensive quantitative evaluation model of the impacts BCT. Therefore, our study focuses on evaluating the factors that arise with the integration of BCT into the supply chain using the cognitive mapping methods. The impacts of the factors on each other and their complex network structure are taken into consideration, the complexity of the system is evaluated by considering cognitive mapping (CM). Relationships among the factors in CM are defined based on the experts' knowledge and experience. The correct expression and reflection of the evaluations is very important to reflect the long-term behavior of the factors. In this paper causal relations are defined by using the hesitant fuzzy linguistic term set (HFLTS)(Rodriguez et al., 2012), probabilistic linguistic term set (PLTS) (Pang et al., 2016) and rough set (RS) theory (Pawlak 2012), and cognitive maps developed with these expression tools are used to quantify the impact of BCT on a supply chain process in the long term. Fuzzy logic theory (Zadeh and Aliev, 0000) and rough set theory (Pawlak, 2012) are used to describe causal relationships involving uncertainty and ambiguity condition. Thus, the consistency of experts who use different identification tools for the same causal relationships is observed in the evaluation process. In addition, the consistency of the proposed causal relationship map based on BCT is confirmed by different methods. The expected impacts in the supply chain can change with the integration of BCT. The proposed models foresee the effects of BCT's integration on the supply chain. The motivations that led to carry out this study and the main contributions of the study into the literature are as follows:

)i) **Motivations**

- Identifying active BCT factors affecting the supply chain by referring to the literature review and revealing the causal relationships among factors.
- To reveal the long-term effects of BCT factors on the supply chain and to contribute to the decision-making process of businesses with the results obtained.
- Examination of the claim that rough sets are more flexible and objective than fuzzy sets (Fang, Li et al., 2018).
- Observing the effects of different evaluation methods (HFLTS, PLTS and RS) on the results obtained from cognitive maps.
- Contributing to the supply chain management of organizations and supporting them in a competitive environment.

)ii) **Main Contributions**

- It is the first study that quantifies the impact of BCT on a supply chain process. The proposed framework can help experts to observe and analyze how supply chain performance improved after BCT integration.
- The main contribution of this study is to develop a framework which investigates the impact of BCT on the supply chain through cognitive map methods.
- There is no previous research about evaluation of blockchain impacts on supply chain. Therefore, this study aims to fill this gap, notably by using the cognitive mapping based on HFLTS, PLTS, and RS to understand the impacts of BCT in the logistics and supply chain.
- This study also contributes to the literature by integrating CM methods based HFLTS, PLTS and RS into the blockchain area. Also, the cognitive map developed on the basis of PLTS is added to the literature as a novel method. In addition, this study checks the claim that rough set theory is more flexible and objective than fuzzy set theory (Fang, Li et al., 2018).

The rest of this paper has been organized as follows: Section 2 includes some details about the concept of BCT, advantages and disadvantages in supply chain management. Moreover, literature of blockchain is presented. Definitions of factors for BCT impacts on supply chain management are given in Section 3. In Section 4, the proposed CM methods for the analysis of the blockchain impact on the supply chain are explained. Section 5 considers application of the proposed methodology and presents results. Section 6 applies sensitivity analysis. Finally, the obtained results and future research directions have been discussed into Section 7.

2. Blockchain technology in supply chain

Blockchain is a database that ensures safe and consistent transactions by a large number of nodes in the network. BCT provides a distributed, transparent, irreversible and secure data structure where the reliability of transactions is verified by stakeholders in the network (Swan, 2015).

Blockchain is seen as secure because, it is very difficult to destroy, change or delete the records entered into the blockchain database (Zhang et al., 2019). The date and time of the transaction are processed for each new record added to the blockchain database. Every user on the network has access to information in the database. In addition, records added to the database cannot be deleted, and remain a permanent record (Dobrovnik et al., 2018). Thus, the records cannot be falsified, which is one of the most important difference from the traditional databases of BCT. With this feature, counterfeiting in registration, transactions and information can be prevented.

There are many blocks in the blockchain. These blocks are connected to each other in a linear and chronological manner (Tian, 2016). Strong encryption algorithms are used for the operations performed in blockchain. When a user wants to perform any action, this process is encrypted, and a new block is created. The created block is added to the end of the other blocks. Adding blocks to each other also creates a chain (Muhr and Laurence 2017); (Çolak, et al. 2020).

BCT have innovative features that can provide very effective solutions in supply chain management. It provides ease in financial activities and transparency is provided. With blockchain application, all transactions performed in supply chain management can be monitored simultaneously and transparently at all stages through RFID, barcode, automatic ID scanners. The stakeholders in the chain can obtain information such as where the products come from, lot numbers, factory and processing data, expiration dates, shipping details and which stores they are delivered (Chang et al., 2019);(Apte and Petrovsky 2016). Traceability is increased by keeping track of the processes passed by all stakeholders in the supply chain of raw materials, materials, and products in the supply chain. The blockchain provides an accurate and stable record from the product's origin to the destination (Madhwal and Panfilov, 2017). Thus, the product and process can be followed from the end to the beginning. It is possible to monitor the origin, route, manufacturer company, the processes applied, the costs at each stage of the supply process, the temperature and pressure levels that occur during transportation or storage (Hackius and Petersen, 2017). Moreover, time delays, human errors and cost factors can be eliminated, and also fraud, or theft of products can be prevented (Muhr and Laurence, 2017).

BCT also contains some adoption challenges. A lot of energy is consumed in blockchain and very expensive computer systems are operated. The ability of each node on the network to store a copy of all data and access its content may damage the privacy of users. Once smart contracts are created, they cannot be changed and are kept accessible to everyone in the blockchain. This can leave smart contracts vulnerable to malicious attacks. On the other hand, management and employees can resist to new technology (Janssen et al., 2020).

Studies on the application of BCT in supply chain processes have started to increase recently. Liu and Li (2019), proposed a framework which is based on blockchain product information traceability framework to e-commerce supply chain. Helo and Hao (2019), designed a blockchain system that was programmed and tested based on Ethereum. The aim of the study is to track in supply chain network and to provide an open history record for each transaction. Azzi et al. (2019), introduced benefits and challenges in supply chain management. Longo et al. (2019), integrated BCT into supply chain and real case study was considered. Moreover, a simulation model has been developed to

Table 1
Evaluation factors of blockchain impact on supply chain.

Factors	Definitions	References
Transparent and Efficient Transactions (traceability) **(TET)**	Ensuring transparent, accurate and effective data transfer. Verifiable and permanent record of transactions between different parties	(Swan 2015); (Awwad et al., 2018)
Fraud and Theft **(FT)**	Loss of products, smuggling, theft, and counterfeit products	(Yli-Huumo et al., 2016); Gupta 2017)
Managerial Adoption Risk **(MAR)**	Management's inability to adapt to the blockchain-based environment. (e.g difficulty in changing organizational culture, lack of knowledge and expertise, lack of new organizational policies)	(Saberi et al., 2019)
Privacy and Security Risks **(PS)**	Data protection security issues, cyber security risks. The possibility of hacking information about customers stored on central servers, criminal activities	(Dorri et al., 2016; Mougayar, 2016; Yli-Huumo et al., 2016; 2019)
Bullwhip Effect **(BE)**	The effect of the amplification of the demand in the supply chain, increasing in the variance of demand when moving from the end consumer to the suppliers in a supply chain.Increasing fluctuations in inventory.	(van Engelenburg, et al., 2018; Kim and Shin, 2019)
Cost **(C)**	Expected cost in the supply chain	(Pettersson and Segerstedt 2013)
Customer Satisfaction **(CS)**	Meeting customer needs at the right amount at the right time and the satisfaction rate after meeting his request.	(Heikkilä 2002)
Customer Demand **(CD)**	The amount of product or service requested by the customer.	(Chen et al., 2017)
Partnership Efficiency and Growth (relationship between partners) **(PEG)**	Cooperation, strategic partnership level.Efficiency level in collaboration and partnership between supply chain partners.	(Ahram et al., 2017); Kim and Shin 2019)
Qualified Personnel and Talent **(QPT)**	Talented and trained staff to blockchain technology, developers proficient in this technology	(Ahl et al., 2020)

recreate the supply chain operations. Chang et al. (2019), focused on the feasibility and inceptive application of supply chain processes. Current and proposed frameworks were compared. Queiroz and Fosso Wamba (2019), proposed an empirical investigation in BCT adoption challenges in supply chain. Technology acceptance model and partial least squares structural equation modeling (PLS-SEM) were used to investigate blockchain adoption behavior at the individual level. Kamble et al. (2020), developed a combined Interpretive Structural Modelling (ISM) and Decision-Making Trial and Evaluation Laboratory (DEMATEL) methodology to evaluate complex between the BCT enablers. Model was applied on agriculture supply chains. Ar et al. (2020), investigated the feasibility of blockchain technology in logistics industry by using a multi-criteria method such as AHP into VIKOR under Intuitionistic Fuzzy Theory. Tang et al. (2019), evaluated public blockchains by using entropy and TOPSIS.

Lin et al. (2018), developed a blockchain-based system for secure mutual authentication to enforce fine-grained access control polices. Therefore, the conceptual framework empowered efficiently to implement a flexible and reconfigurable smart factory. Xu et al. (2019), designed a real-world project called as "originChain". It was a blockchain-based traceability system that restructures the current system by replacing the central database with blockchain. This system provided transparent tamper-proof traceability data with high availability. Jangirila et. al (2019), developed a new efficient lightweight blockchain-enabled radio frequency identification (RFID)-based authentication protocol for supply chains in 5G mobile edge computing environment. It can be revealed that this protocol sustained security against various attacks. Fan et al. (2020), proposed a novel decentralized, reliable and efficient remote outsourced data auditing scheme with blockchain smart contract for industrial IoT which named as Dredas. It was a scheme that could choose the current blockchain nonce as a random seed also could use the number blocks on the Ethereum as the security timestamp. Challa et al. (2020), designed a new authentication scheme related to the cloud-assisted CPS. Two aspect were taken into consideration. First one was authentication between a user and a cloud server, second one was authentication between a smart meter and a cloud server. It was shown that proposed scheme was more efficient than other related existing schemes.

When analyzing literature, it can be revealed that there is no quantitative fuzzy set and rough set-based study for the evaluation of blockchain impacts on the supply chain. Therefore, this study uses the different cognitive mapping based on HFLTS, PLTS, and RS to understand and quantify the impacts of BCT in the logistics and supply chain. For this aim, ten factors and causal relationships among them are explained with the help of the literature and seven blockchain experts. Also, the PLTS based CM method is used for the first time. In this way, this study provides a new perspective to the literature in terms of both application area and developed methodology.

The expected strategic advantages and challenges of BCT are deeply analyzed by developed methodology. This approach can dynamically model causal relationships between the factors that occur in the supply chain after the integration of BCT with the help of cognitive mapping.

3. Cognitive mapping to evaluate the impacts of blockchain technology

In this study, ten factors are described that impacts of BCT on supply chain and causal relations among them. Causal relationships are evaluated by using CM methods. At each iteration, states of the factors can be evaluated, and their levels can be observed in the long term. Table 1 depicts impacts of BCT on supply chain.

Ten factors are defined for "Evaluation of the Impact of BCT on supply chain". In Fig. 1, the causal relationships among factors are represented graphically which is generated by the help of the literature and seven BCT experts. Negative causality is shown by orange lines on the other hand blue lines depicts a positive causality relation between the factors in CM.

The developed methodology can be seen in Fig. 2. Firstly, the relationship map of BCT impact on supply chain is created according to expert opinions and literature review. Cognitive maps based on HFLTS, PLTS and RS are used to evaluate these factors. Five different scenarios are identified to consider various inferences about BCT impact on supply chain. Results are obtained and expected effects are analyzed. Finally, sensitivity analysis is performed for the model's robustness and applicability.

4. Methods (Preliminaries)

The causal relationships among the factors in the supply chain CM model under the influence of BCT are determined based on the experts' knowledge and experience. Tools used to identify causal relationships should minimize experts' uncertainty and hesitations, and also reflect experts' opinions at the highest level. The HFLTS, PLTS and RSs that are selected for this purpose allow specialists to make comfortable and objective evaluations. In this study HFCM, PL-FCM and RS-CM methods are used to examine the impact of BCT. Therefore, the consistency of results could be ensured with using three CM methods.

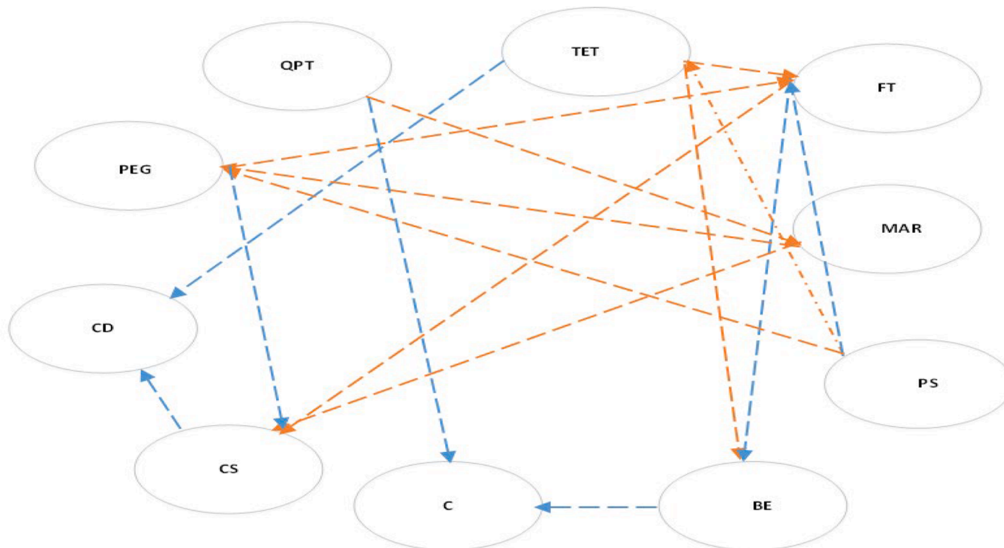


Fig. 1. CM of evaluation the impact of BCT on supply chain.

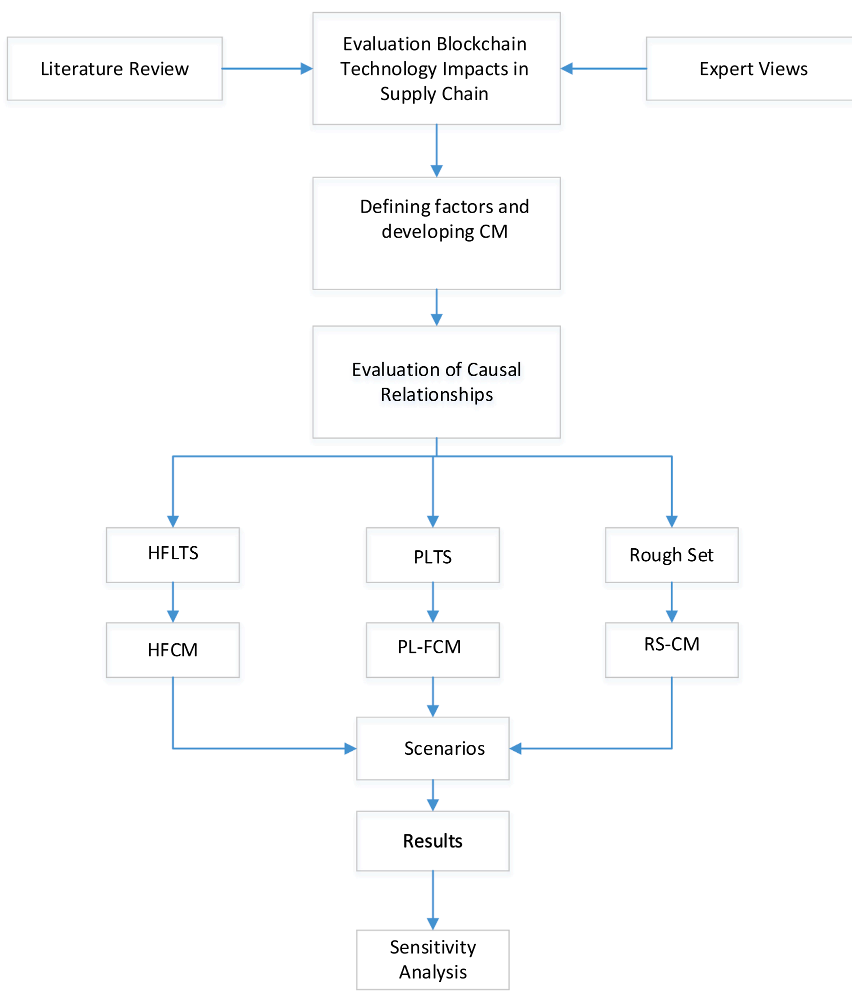
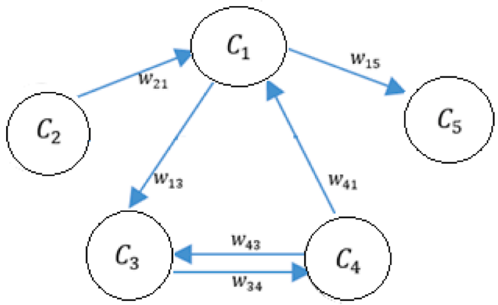


Fig. 2. Flowchart of the developed methodology.

4.1. Fuzzy cognitive maps

Fuzzy Cognitive Maps (FCMs) are fuzzy graphics that explain the relationships between concepts with causal reasoning (Kosko 1986). FCMs are developed based on fuzzy logic to express uncertain and vague causal relationships in cognitive maps. A FCM consists of nodes and edges that represent the criteria and causal relationships between criteria respectively. Edge defines the strength of directional causal



	C_1	C_2	C_3	C_4	C_5
C_1	0	0	w_{13}	0	w_{15}
C_2	w_{21}	0	0	0	0
C_3	0	0	0	w_{34}	0
C_4	w_{41}	0	w_{43}	0	0
C_5	0	0	0	0	0

Fig. 3. A sample Fuzzy Cognitive Map and connection matrix.

relationships between nodes (C_i and C_j) as weight (w_{ij}). Uncertain weights in FCM are defined by fuzzy numbers or fuzzy expressions based on the knowledge and experience of experts (Glykas 2010, Papageorgiou 2013). The graphical representation of FCM enables the definition of complex interactions between concepts and the creation of possible new relationships. Sample FCM (Fig. 3) consists of five concepts and six causal relationships.

The relationship between the concepts is defined in the weight (relationship) matrix in the range [-1, 1]. Positive, negative, and zero weight values indicate the same direction, inverse direction, and no relation, respectively. FCM shows that change in concepts will cause the chain effects in the system due to their causal relationships. The chain effect in the system causes to change the initial states of the concepts. The concept in FCM has no causal relationship on itself, and therefore the diagonal of the weight matrix is defined as zero. Fuzzy causal relationships are defined either by referring to experts' evaluations or by using the information obtained through literature review.

The weights of causal relationships shown in FCM are defined by fuzzy numbers (such as triangular, trapezoidal, sigmoid, Gaussian) or fuzzy linguistic expressions. The weights of causal relationships defined by fuzzy expressions are converted to crisp values in the range [-1,1] by defuzzification methods and the state vector of concepts is defined. $\mathrm{A}_{\mathrm{m}}^{\tau}$ represents the state value of the concept C_{m} in time τ, and the state values of concepts are defined in the state vector as $\mathrm{A}^{\tau} = \left[\mathrm{A}_1^{\tau}, \mathrm{A}_2^{\tau}, \cdots, \mathrm{A}_s^{\tau}\right]$. The new state values resulting from the chain effect in the FCM are calculated as follows.

$$A_m^{\tau+1} = f\left(\sum_{k=1}^{s} A_k^{\tau} w_{mn} + A_m^{\tau}\right) \tag{1}$$

where $A_m^{\tau+1}$ is a new state value of the concept C_{m} in time $\tau+1$ and f() represents the threshold function that is used to transform the sum of the causal effects on the concepts C_m and the previous state value of concepts C_m ($\mathrm{A}_{\mathrm{m}}^{\tau}$). In this study, the hyperbolic tangent function (Eq. (2)) which defines causal relationships in the same direction and in the opposite direction in the range [-1,1] is used as the threshold function.

$$f(x) = tanh(\alpha x) = \frac{e^{\alpha x} - e^{-\alpha x}}{e^{\alpha x} + e^{-\alpha x}} \tag{2}$$

where α parameter determines the slope of the function and is defined as greater than zero by researcher according to the study. The iteration is repeated until the difference between the two consecutive state values ($\mathrm{A}_{\mathrm{m}}^{\tau+1} - \mathrm{A}_{\mathrm{m}}^{\tau}$) is less than 0.001, and the state where the iteration ends is called the steady state. All CMs based on the HFLTSs, PLTSs and RSs are built on a similar operation process, and their iteration methods are based on similar calculation methods.

4.2. Hesitant fuzzy linguistic term sets

Numerical values may be insufficient in measuring and evaluating real life problems. Linguistic expressions are an important assessment tool for solving such problems. Fuzzy set theory is used to define linguistic variables and to resolve uncertainties in linguistic expressions. The insufficiency of single linguistic terms in reflecting experts' evaluations causes the development of new fuzzy linguistic approaches. Hesitant Fuzzy Linguistic Terms Sets (HFLTS) is developed as a solution to eliminate decision-makers' instability between linguistic terms (Liu and Rodríguez 2014). $\mathrm{H_s}$ (HFLTS) is an ordered finite subset of the linguistic term set $\mathrm{S} = \{\mathrm{s}_0, \mathrm{s}_1, \cdots, \mathrm{s}_t\}$. Experts express the causal relationship between the criteria linguistically and linguistic evaluations are quantified and included in the calculations. The transformation steps followed in this process are as follows:

1. Hesitating linguistic terms are an important identification tool for experts in evaluating qualitative problems that cannot be identified by numerical expressions. Natural linguistic terms used by experts are created with context-free grammar G_H (Bordogna and Pasi 1993). $\mathrm{S} = \{\mathrm{s}_0 : \mathrm{nothing}, \mathrm{s}_1 : \mathrm{verylow}, \mathrm{s}_2 : \mathrm{low}, \mathrm{s}_3 : \mathrm{medium}, \mathrm{s}_4 : \mathrm{high}, \mathrm{s}_5 : \mathrm{veryhigh}, \mathrm{s}_6 : \mathrm{perfect}\}$ is a linguistic term set, and sample hesitant linguistic expressions defined using $\mathrm{G_H}$ are as follows: atmosthigh, lowerthanmedium, greaterthanverylow, and betweenmediumandhigh.

2. Causal relationships defined using context-free grammar are transformed into hesitant fuzzy linguistic term set (HFLTS, H_S) by transformation functions (E_{G_H}) (Liu and Rodríguez 2014). The transform functions are as follows:

- $E_{G_H}(s_i) = \{s_i | s_i \in S\}$
- $E_{G_H}(atleasts_i) = \{s_j | s_j \in Sands_j \geq s_i\}$ or $E_{G_H}(atmosts_i) = \{s_j | s_j \in Sands_j \leq s_i\}$
- $E_{G_H}(lowerthans_i) = \{s_j | s_j \in Sands_j < s_i\}$ or $E_{G_H}(greaterthans_i) = \{s_j | s_j \in Sands_j > s_i\}$
- $E_{G_H}(betweens_iands_j) = \{s_k | s_k \in Sands_i \leq s_k \leq s_j\}$

For example, the transformation of "*atleasthigh*" linguistic expression defined by context-free grammar into HFLTS is $\{high, veryhigh, perfect\}$.

3. The enveloping method is used to easily compare HFLTSs. The parameters defined by the enveloping method create a fuzzy membership function for HFLTS. In this study, the fuzzy envelope of the HFLTS is defined with a trapezoidal fuzzy membership function as $env_F(H_S) = T(a,b,c,d)$. All points of membership functions in the HFLTS $H_s = \{s_i, s_{i+1}, \cdots, s_j\}$ is defined in the set of elements to aggregate as $T = \left\{a_L^i, a_M^i, a_L^{i+1}, a_R^i, a_M^{i+1}, a_L^{i+2}, a_R^{i+1}, \cdots, a_L^j, a_R^{j-1}, a_M^j, a_R^j\right\}$(Liu and Rodríguez 2014). The simplified form of the set of elements to aggregate can be defined as $T = \left\{a_L^i, a_M^i, a_M^{i+1}, \cdots, a_M^j, a_R^j\right\}$.

The parameters are calculated as follows (Liu and Rodríguez 2014):

$$a = min\{a_L^i, a_M^i, a_M^{i+1}, \cdots, a_M^j, a_R^j\} = a_L^i$$

$$b = OWA_{W^s}\left(a_M^i, a_M^{i+1}, \cdots, a_M^j\right)$$

$$c = OWA_{W^t}\left(a_M^i, a_M^{i+1}, \cdots, a_M^j\right)$$

$d = max\{a_L^i, a_M^i, a_M^{i+1}, \cdots, a_M^j, a_R^j\} = a_R^i$

OWA aggregation operator is used to calculate the intermediate parameters (b, c) (Filev and Yager 1998, Liu and Rodríguez 2014). Weight vectors (W^s, W^t) of orness OWA aggregation method reveal intermediate values (b, c) of trapezoidal fuzzy membership function.

4. The linguistic expressions of the experts converted to trapezoidal fuzzy membership function are defuzzified to crisp values with Eq.(3). Crisp values that reflect the causal relationships between the factors come together to form the weight matrix.

$$D = (a + 2b + 2c + d)/6 \tag{3}$$

Although HFLTSs are sufficient to reflect the ideas of decision makers, it is insufficient to reflect the weight of the decision makers' ideas in group decision making studies (Pang, Wang et al. 2016). Therefore, PLTS are recommended as an alternative approach to HFLTS to reflect the linguistic evaluations of experts.

4.3. Probabilistic linguistic term sets

Decision makers remain undecided in reflecting their opinions among different linguistic expressions. PLTS are generated by expanding HFLTS to prevent loss of information in the linguistic evaluations of experts (Pang et al., 2016). PLTS reflects the probability information of the value set, and provides more accurate information from the evaluations of the experts.

$S = \{s_0, s_1, ..., s_t\}$ is the linguistic term set (LTS) and PLTS is defined as follows (Pang, Wang et al. 2016)

$$L(p) = \left\{ L^{(e)}(p(e)) | L^{(e)} \in S, p^{(e)} \geq 0, e = 1, 2, \cdots, \#L(p), \sum_{e=1}^{\#L(e)} p^{(e)} \leq 1 \right\}$$

$L^{(e)}(p(e))$ represents the probabilistic $(p(e))$ expression of linguistic terms $(L^{(e)})$. The number of linguistic terms (cardinality) in $L(p)$ is denoted by $\#L(p)$. The sum of probabilities of linguistic terms $(\sum_{e=1}^{\#L(p)} p^{(e)})$ indicates the level of lack of information.

The order of the elements in a PLTS is arbitrarily changed and probability values are regulated to overcome the lack of information in $L(p)$. $r^{(e)}$is a subindex of the linguistic term set, $L^{(e)}$. Ordered PLTS is obtained by arranging $L(p) = \{L^{(e)}(p^{(e)}) | e = 1, 2, ..., \#L(p)$ decreasing according to $r^{(e)}p^{(e)}$ product value. For example, PLTS is defined as $L(p) = \{s_1(0.3), s_2(0.4), s_3(0.3)\}$. Multiplication values of linguistic terms with their sub-indexes are calculated $(1 \times 0.3 = 0.3; 2 \times 0.4 = 0.8; 3 \times 0.3 = 0.9)$ and sorted in descending order. Ordered PLTS is defined as $L(p) = \{s_3(0.3), s_2(0.4), s_1(0.3)\}$.

In order to estimate the probabilistic lack of information and to ensure cardinality equality, which are necessary for performing transactions between PLTSs, PLTSs are normalized. If $\sum_{e=1}^{\#L(p)} p^{(e)} < 1$, there is a partial lack of information (ignorance) and this ignorance must be estimated. The ignorance identified by the missing probability is distributed to the linguistic terms in $L(p)$ on average as follows:

$$\overset{\hat{A}}{p}^{(e)} = p^{(e)} / \sum_{e=1}^{\#L(p)} p^{(e)} \tag{4}$$

and revised PLTS is defined as;

$$\overset{\hat{A}}{L}(p) = \{L^{(k)}\left(\overset{\hat{A}}{p}^{(e)}\right)(e = 1, 2, ..., \#L(p)) \tag{5}$$

$L_1(p) = \left\{L_1^{(e)}(p_1(e)) | e = 1, 2, \cdots, \#L_1(p)\right\}$ and $L_2(p) = \left\{L_2^{(e)}(p_2(e)) | e = 1, 2, \cdots, \#L_2(p)\right\}$ are two different PLTSs. If the PLTSs' linguistic term number is $\#L_1(p) > \#L_2(p)$, the number of linguistic terms is added to $L_2(p)$ as much as $\#L_1(p) - \#L_2(p)$. The added linguistic term is the smallest term in the linguistic term set and its probability is defined as zero. For example, $L_1(p) = \{s_1(0.3), s_2(0.2), s_3(0.3)\}$ ve $L_2(p) = \{s_2(0.5), s_3(0.4)\}$ are two different PLTSs.

a. PLTSs are ordered;

a. $L_1(p) = \{s_3(0.3), s_2(0.2), s_1(0.3)\}$
b. $L_2(p) = \{s_3(0.4), s_2(0.5)\}$

5. The ignorance of the PLTS is checked and, if necessary, ignorance is distributed in linguistic terms;

a. $\sum_{e=1}^{\#L_1(p)} p_i^{(e)} = 0.8 < 1$ then, $\overset{\hat{A}}{p}^{(e)} = p^{(e)} / \sum_{e=1}^{\#L_1(p)} p^{(e)}$ and $\overset{\hat{A}}{L}_1(p)$ is defined as;

$$\overset{\hat{A}}{L}_1(p) = \{s_3(0.375), s_2(0.25), s_1(0.375)\}$$

b. $\sum_{e=1}^{\#L_2(p)} p_i^{(e)} = 0.9 < 1$ then, $\overset{\hat{A}}{p}^{(e)} = p^{(e)} / \sum_{e=1}^{\#L_2(p)} p^{(e)}$ and $\overset{\hat{A}}{L}_2(p)$ is defined as;

$$\overset{\hat{A}}{L}_2(p) = \{s_3(0.44), s_2(0.56)\}$$

6. Since $\#L_1(p) > \#L_2(p)$, then the smallest linguistic term, s_2 is added to $\overset{\hat{A}}{L}_2(p)$;

$$\overset{\hat{A}}{\overset{\hat{A}}{L}}_2(p) = \{s_3(0.44), s_2(0.56), s_2(0)\}$$

Thus, normalized PLTS can be used in operations as $L_1(p) = \{s_3(0.375), s_2(0.25), s_1(0.375)\}$ and $L_2(p) = \{s_3(0.44), s_2(0.56), s_2(0)\}$.

PLTSs are considered to be normalized and ordered in operations. $L_1(p)$ and $L_2(p)$ are two different PLTS; $\sum_{e=1}^{\#L_1(p)} p_1^{(e)} = \sum_{e=1}^{\#L_2(p)} p_2^{(e)} = 1$ and $\#L_1(p) = \#L_2(p)$. Basic operations in the PLTS are defined as follows:

$$L_1(p) \oplus L_2(p) = \cup_{L_1^{(e)} \in L_1, L_2^{(e)} \in L_2} \{p_1^{(e)} L_1^{(e)} \oplus p_2^{(e)} L_2^{(e)}\} \tag{6}$$

$$L_1(p) \otimes L_2(p) = \cup_{L_1^{(e)} \in L_1, L_2^{(e)} \in L_2} \{\left(L_1^{(e)}\right)^{p_1^{(e)}} \oplus \left(L_2^{(e)}\right)^{p_2^{(e)}}\} \tag{7}$$

$$\lambda L(p) = \cup_{L^{(e)} \in L^{(e)}} \lambda p^{(e)} L^{(e)}, \lambda \geq 0 \tag{8}$$

$$(L(p))^{\lambda} = \cup_{L^{(e)} \in L^{(e)}} \{(L(p))^{p^{(e)}\lambda}\} \tag{9}$$

where $L_1^{(e)}$,$L_2^{(e)}$ present the *eth* linguistic terms in the PLTSs $(L_1(p), L_2(p))$ respectively and the corresponding probability values are $p_1^{(e)}$ and $p_2^{(e)}$.

$L_i(p) = \{L_i^{(e)}(p_i^{(e)}) | e = 1, 2, ..., \#L_i(p)\} (i = 1, 2, ..., n)$shows the n PLTSs and *ith* PLTS is presented as $L_i(p)$, where *eth* linguistic term and corresponding probability value are represented as $L_i^{(e)}$ and $p_i^{(e)}$ respectively. n PLTSs can be aggregated with the probabilistic linguistic averaging (PLA) operator as follow (Pang et al., 2016).

$$\begin{aligned} PLA(L_1(p), L_2(p), \cdots, L_i(p)) &= \frac{1}{n}(L_1(p) \oplus L_2(p) \oplus \hat{A}\cdot\hat{A}\cdot\hat{A}\cdot \oplus L_n(p)) \\ &= \frac{1}{n}\left(\cup_{L_1^{(e)} \in L_1, L_2^{(e)} \in L_2, \cdots L_n^{(e)} \in L_n} \left\{p_1^{(e)} L_1^{(e)} \oplus p_2^{(e)} L_2^{(e)} \right.\right. \\ &\quad \left.\left. \oplus \cdots \oplus p_n^{(e)} L_n^{(e)} \right\}\right) \end{aligned} \tag{10}$$

4.4. Rough sets

Rough set theory (Pawlak and Skowron, 2007) is another method used to identify uncertainties. Rough set theory is considered to be more flexible and objective than fuzzy set theory since it does not require prior knowledge in identifying and analyzing uncertainty (Fang et al., 2018). In rough set theory, precise concepts can be captured by expressing

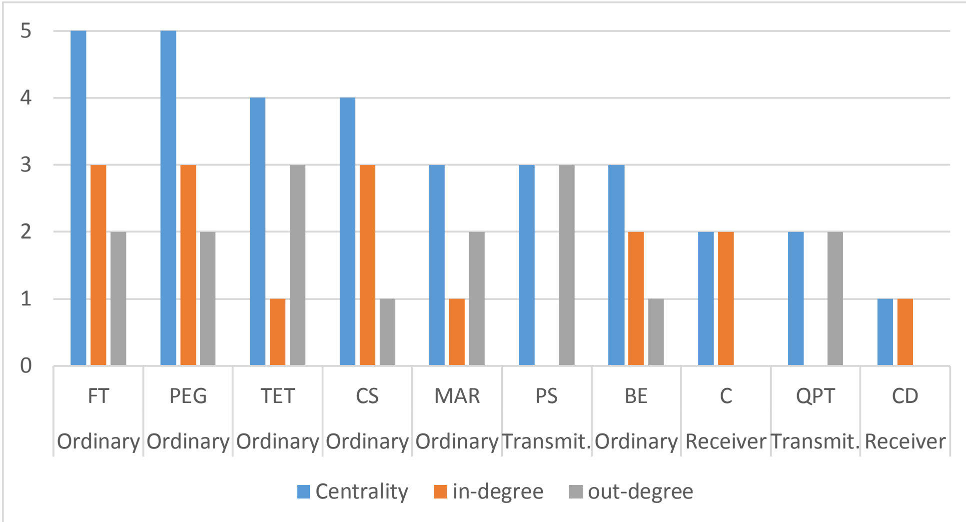


Fig. 4. Centrality, in-degree and out-degree values.

uncertain evaluations with lower and upper approximations. The uncertainty in the evaluations stems from the personal knowledge and experience of the experts. A variable precision parameter ($\alpha \in [0,1]$) is defined to determine the degree of uncertainty of experts. Evaluation steps with rough sets are as follows:

1. Experts define the degree of causal relationship between factors as 1 lowest score and 10 highest score. Experts' crisp evaluations reflect the certainty of the causal relationship.

$$\xi_{ij} = \left\{\xi_{ij}^1, \xi_{ij}^2, \cdots, \xi_{ij}^s, \xi_{ij}^k\right\}, s = 1,2,\cdots,k \tag{11}$$

ξ_{ij}^s shows the causal relationship between i factor and j factor evaluated by sth expert.

2. Causal relationships defined by crisp values are converted to precision rough interval. Imprecise and subjective evaluations defined by experts can be converted into precise evaluations using the rough set theory (Pawlak, 2012). The cognitive vagueness, which originates from the different knowledge and experience of the experts, is defined by the variable precision parameter (ρ) ranging from [0, 1] (Fang et al., 2018). As the ρ value increases from 0 to 1, the cognitive vagueness in the experts' evaluations grows. In this study, the vagueness degree is considered to be 0.5. Crisp evaluations defined by experts are converted into variable precision rough numbers (VPRN) taking into account the cognitive uncertainty levels of the experts.

$$LA^\rho\left(\xi_{ij}^s\right) = \cup\left\{\xi_{ij}^a \in \xi_{ij} | \xi_{ij}^a \le \xi_{ij}^b; \left(\xi_{ij}^b - \xi_{ij}^a\right) \le \rho R\right\} = \cup\left\{\xi_{ij}^a \in \xi_{ij} | \xi_{ij}^b - \rho R \le \xi_{ij}^a \le \xi_{ij}^b\right\} \tag{12}$$

$$UA^\rho\left(\xi_{ij}^s\right) = \cup\left\{\xi_{ij}^a \in \xi_{ij} | \xi_{ij}^a \ge \xi_{ij}^b; \left(\xi_{ij}^a - \xi_{ij}^b\right) \le \rho R\right\} = \cup\left\{\xi_{ij}^a \in \xi_{ij} | \xi_{ij}^b \le \xi_{ij}^a \le \xi_{ij}^b + \rho R\right\} \tag{13}$$

The vague range of the evaluation set (ξ_{ij}) is defined as $R = \max_s \xi_{ij}^s - \min_s \xi_{ij}^s$. The $\rho \times R$ value indicates the vagueness distances of the lower $\left(LA^\rho\left(\xi_{ij}^s\right)\right)$ and upper $\left(UA^\rho\left(\xi_{ij}^s\right)\right)$ approximation values. The VPRN of the experts' crisp evaluations is calculated as follows:

$$\xi_{ij}^{sL} = \sqrt[\alpha]{\prod \xi_{ij}^a | \xi_{ij}^a \in LA^\rho\left(\xi_{ij}^s\right)} \tag{14}$$

$$\xi_{ij}^{sU} = \sqrt[\beta]{\prod \xi_{ij}^a | \xi_{ij}^a \in UA^\rho\left(\xi_{ij}^s\right)} \tag{15}$$

The lower and upper limits of the variable precision rough number (ξ_{ij}^s) are defined as ξ_{ij}^{sL} and ξ_{ij}^{sU}, respectively. The number of elements in $LA^\rho\left(\xi_{ij}^s\right)$ and $UA^\rho\left(\xi_{ij}^s\right)$ are represented as α and β, respectively.

$$VPRN^\rho\left(\xi_{ij}^s\right) = \left[\xi_{ij}^{sL}, \xi_{ij}^{sU}\right] (\rho \in [0,1]) \tag{16}$$

3. Experts' variable precision rough evaluations are aggregated and common evaluations for each causal relationship are defined in the VPRN form with lower (ξ_{ij}^L) and upper limits (ξ_{ij}^U) as follows.

$$VPRN_{agr}^\rho(\xi_{ij}) = \left[\xi_{ij}^L, \xi_{ij}^U\right] \tag{17}$$

$$\xi_{ij}^L = \sqrt[k]{\prod \xi_{ij}^{sL}} \tag{18}$$

$$\xi_{ij}^U = \sqrt[k]{\prod \xi_{ij}^{sU}} \tag{19}$$

4. Variable precision rough values of causal relationships between factors are converted into deterministic values as follows (Song et al., 2017).
   a. The lower (ξ_{ij}^L) and upper (ξ_{ij}^U) limits of the group rough values are normalized.

$$\xi_{ij}^{NL} = \frac{\xi_{ij}^L - \min_i \xi_{ij}^L}{\max_i \xi_{ij}^U - \min_i \xi_{ij}^L} \tag{20}$$

$$\xi_{ij}^{NU} = \frac{\xi_{ij}^U - \min_i \xi_{ij}^L}{\max_i \xi_{ij}^U - \min_i \xi_{ij}^L} \tag{21}$$

where ξ_{ij}^{NL} and ξ_{ij}^{NU} represent the normalized form of ξ_{ij}^L and ξ_{ij}^U.

b. Deterministic values (ξ_{ij}^D) are calculated as follows;

$$\xi_{ij}^D = \min_i \xi_{ij}^L + \omega_{ij}(\max_i \xi_{ij}^U - \min_i \xi_{ij}^L) \tag{22}$$

Table 2
Sample evaluations using hesitant linguistic terms.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		(-) at leasth			(-) greaterthan h				(+) betweenm/vh	
FT					(+) between l/h		(-) lowerthan m			
MAR							(-) at most m		(-) at mosth	
PS	(-)at most h	(+) greaterthan vh							(-) betweenh/a	
BE						(+) greaterthan m				
C										
CS								(+) is a		
CD										
PEG		(-) at most m					(+) at mosth			
QPT			(-) greaterthan vh			(+) between m/h				

where ω_{ij} is called the causal relationship coefficient and calculated for each causal relationship as follows:

$$\omega_{ij} = \frac{\xi_{ij}^{NL}\left(1-\xi_{ij}^{NL}\right)+\left(\xi_{ij}^{NU}\right)^2}{1-\xi_{ij}^{NL}+\xi_{ij}^{NU}} \tag{23}$$

5. Deterministic values are normalized to define causal relationships in the [0,1] interval as follows:

$$\xi_{ij}^{N} = \frac{\xi_{ij}^{D}}{\max_{i}\xi_{ij}^{D}} \tag{24}$$

5. Application and results

In this study, the effects of BCT on the supply chain are evaluated on the cognitive map. Factors affecting the supply chain on the basis of BCT and causal relationships among factors are defined by literature review and expert evaluations. Causal relationships among factors are defined using PLTS, HFLTS and the Rough Set, and thus, probabilistic fuzzy cognitive map (PL-FCM), hesitant fuzzy cognitive map (HFCM) and rough cognitive map (RS-CM) models are developed. Factors are named ordinary, transmitter and receiver according to in-degree and out-degree values that refers the directions into a node and out of a node respectively (Fig. 1). Centrality, in-degree and out-degree values reflect the effects and importance of the factors in the map (Fig. 3). FT and PEG factors having the highest centrality values are important connection edge in the causal relationship network within the map. Transmitter factors that are not affected by other factors but affect other factors are PS and QPT. On the contrary, the receiver factors that do not affect but are affected are C and CD (Fig. 4).

Causal relationships between factors are evaluated by seven experts using PLTS, HFLTS and rough set, and the relationship weight matrix is created. The scales used in the evaluation and obtained weight matrices for each method are as follows:

i. HFLTS; $H(d_j, s_i) = \{d_j | d_j \in D and s_i | s_i \in S\}$, $D = \{d_1$:is, d_2 :at least, d_3 : at most, d_4 :lower than, d_5 : greater than, d_6 :between$\}$ $S = \{s_0$:nothing (n), s_1 : very low (vl), s_2 :low (l), s_3 :medium (m), s_4 : high (h) , s_5 : very high (vh), s_6 :perfect (p)$\}$.

Causal relationships are evaluated by experts using hesitant linguistic terms (Table 2). Linguistic evaluations are converted to HFLTS with transformation functions (Table 3). Trapezoidal fuzzy membership functions are obtained from HFLTS using the enveloping methods. OWA aggregation operator is applied to calculate the intermediate values (b, c) of trapezoidal fuzzy membership functions. Crisp values are obtained from trapezoidal fuzzy membership functions using defuzzification function (Eq. (3)). Weight matrix (Table 4) is formed to represent the strengths of causal relationships and is used in HFCM applications.

ii. PLTS; $L(p) = \left\{L^{(e)}(p(e))|L^{(e)} \in S, p^{(e)} \geq 0, e = 1, 2, \cdots, \#L(p), \sum_{e=1}^{\#L(e)} p^{(e)} \leq 1\right\}$, $S = \{s_0$:nothing (n), s_1 :very low (vl), s_2 :low (l), s_3 :medium (m), s_4 :high (h), s_5 :very high (vh), s_6 :perfect (p)$\}$.

Causal relationships among factors are defined by experts in linguistic terms (Table 5). Experts' linguistic evaluations (Table 6) are brought together and the probability values of the linguistic expressions are calculated for each evaluation. The weight matrix (Table 7) is created by combining the ordered and normalized PLTS with the aggregation operator (Eq. (10)).

iii. Rough set; 1 lowest score and 10 highest score.

First of all, experts define causal relationships between factors with a crisp value such that 1 represents the lowest value and 10 is the highest (Table 8). Experts' crisp evaluations (Table 9) are converted into precision rough intervals and variable precision rough numbers (VPRN) are obtained (Eq. 11–16). Causal relationships defined by VPRN are converted into deterministic values (Eq. 20–23). Deterministic values are normalized in the range [0,1] and weight matrix is obtained (Eq. (24)).

The weight matrix (W) (Table 10) obtained at the end of the

Table 3
Conversion of the sample hesitant linguistic terms into HFLTS.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		(-)$\{h, vh, p\}$			(-)$\{vh, p\}$				(+)$\{m, h, vh\}$	
FT					(+)$\{l, m, h\}$		(-)$\{n, vl, l\}$			
MAR							(-)$\{n, vl, l, m\}$		(-)$\{n, vl, l, m, h\}$	
PS	(-) $\{n, vl, l, m, h\}$	(+)$\{p\}$							(-)$\{h, vh, a\}$	
BE						(+) m$\{h, vh, p\}$				
C										
CS								(+)$\{a\}$		
CD										
PEG		(-)$\{n, vl, l, m\}$					(+) at most h			
QPT			(-)$\{p\}$			(+)$\{m, h\}$				

Table 4
Weight matrix for HFCM.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		−0.690			−0.354				0.378	
FT					0.479		−0.228		0	
MAR							−0.385		−0.548	
PS	−0.343	0.578							−0.863	
BE						0.390				
C										
CS								0.623		
CD										
PEG		−0.313					0.716			
QPT			−0.520			0.388				

Table 5
Sample linguistic evaluations of an expert.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		$s_5 : vh$			$s_4 : h$				$s_3 : m$	
FT					$s_3 : m$		$s_2 : l$			
MAR							$s_3 : m$		$s_4 : h$	
PS	$s_4 : h$	$s_5 : vh$							$s_5 : vh$	
BE						$s_4 : h$				
C										
CS								$s_6 : p$		
CD										
PEG		$s_2 : l$					$s_4 : h$			
QPT			$s_5 : vh$			$s_3 : m$				

Table 6
Experts' evaluations with LTS.

	TET	TET	TET	FT	FT	MAR	MAR	PS	PS	PS	BE	CS	PEG	PEG	QPT	QPT
	FT	**BE**	**PEG**	**BE**	**CS**	**CS**	**PEG**	**TET**	**FT**	**PEG**	**C**	**CD**	**FT**	**CS**	**MAR**	**C**
E_1	s_5	s_4	s_3	s_3	s_2	s_3	s_4	s_4	s_5	s_5	s_4	s_6	s_2	s_4	s_5	s_3
E_2	s_3	s_4	s_4	s_4	s_1	s_0	s_6	s_4	s_2	s_1	s_4	s_5	s_0	s_2	s_1	s_4
E_3	s_2	s_4	s_6	s_5	s_2	s_3	s_3	s_3	s_0	s_1	s_4	s_4	s_2	s_3	s_4	s_4
E_4	s_4	s_1	s_0	s_5	s_1	s_6	s_4	s_6	s_6	s_0	s_5	s_3	s_2	s_0	s_3	s_3
E_5	s_4	s_2	s_3	s_1	s_2	s_2	s_3	s_3	s_3	s_5	s_1	s_3	s_2	s_4	s_3	s_2
E_6	s_3	s_3	s_4	s_2	s_2	s_1	s_3	s_2	s_3	s_4	s_2	s_2	s_3	s_4	s_2	s_3
E_7	s_5	s_3	s_4	s_3	s_2	s_4	s_3	s_5	s_4	s_4	s_2	s_3	s_2	s_5	s_5	s_2

Table 7
Weight matrix for PL-FCM.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		−0.619			−0.500				0.572	
FT					0.548		−0.286			
MAR							−0.452		−0.619	
PS	−0.643	0.548							−0.476	
BE						0.524				
C										
CS								0.619		
CD										
PEG		−0.310					0.52381			
QPT			−0.548			−0.500				

evaluations reflects the strength and direction of the causal relationship. The strength of the relationship between the C_i and C_j factors is indicated as w_{ij} and the self-relationship is defined as zero ($w_{ii} = 0$). The initial state values (A^0) of the factors are defined under different scenarios. New states (A^t) of the factors are created using Eq. (1) and iterations are repeated until the factors reach a steady state. Table 11 represents sensitivity analysis results.

5.1. Scenarios

In this section, different scenarios are considered for evaluation impact of BCT on supply chain. Therefore, long term changes and impacts of factors can be observed. Values of initial states (A^0) are given between [-1,1] that represents the existence and existence level of factors in the system. Behavior of developed system can be analyzed by using different scenarios.

Scenario 1: In the first scenario, the situation where the high level of

Table 8
Sample crisp evaluations of an expert.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		9			8				8	
FT					5		3			
MAR							5		7	
PS	8	8							9	
BE						7				
C										
CS								9		
CD										
PEG		2					6			
QPT			10			6				

Table 9
Experts' crisp evaluations.

	TET	TET	TET	FT	FT	MAR	MAR	PS	PS	PS	BE	CS	PEG	PEG	QPT	QPT
	FT	**BE**	**PEG**	**BE**	**CS**	**CS**	**PEG**	**TET**	**FT**	**PEG**	**C**	**CD**	**FT**	**CS**	**MAR**	**C**
E_1	9	8	8	5	3	5	7	8	8	9	7	9	2	6	10	6
E_2	4	6	7	7	7	2	8	7	9	4	6	8	5	2	7	8
E_3	1	3	4	6	4	4	6	2	5	2	6	8	7	2	5	5
E_4	5	2	3	6	3	4	5	2	6	4	10	5	2	3	2	10
E_5	7	3	5	2	4	4	5	5	6	7	3	5	3	7	5	4
E_6	4	5	6	3	5	3	6	4	6	7	3	5	5	7	3	5
E_7	7	4	6	5	3	4	6	7	6	8	3	4	3	7	6	2

Table 10
Weight matrix for RS-CM.

	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
TET		−0.451			−0.388				0.549	
FT					0.446		−0.446			
MAR							−0.342		−0.625	
PS	−0.43188	0.673							−0.551	
BE						0.498				
C										
CS								0.614		
CD										
PEG		−0.322					0.418			
QPT			−0.501			−0.540				

Table 11
Sensitivity analysis table.

		TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
Ordinary	**TET**	0.201	−0.809	0	0	−0.875	−0.851	0.906	0.897	0.617	0
Ordinary	**FT**	0	0.201	0	0	0.616	0.794	−0.543	−0.820	0.000	0
Ordinary	**MAR**	0	0.736	0.201	0	0.831	0.842	−0.921	−0.899	−0.649	0
Transmitter	**PS**	−0.605	0.933	0	0.201	0.926	0.859	−0.936	−0.902	−0.860	0
Ordinary	**BE**	0	0	0	0	0.201	0.608	0	0	0	0
Receiver	**C**	0	0	0	0	0	0.201	0	0	0	0
Ordinary	**CS**	0	0	0	0	0	0	0.201	0.655	0	0
Receiver	**CD**	0	0	0	0	0	0	0	0.201	0	0
Ordinary	**PEG**	0	−0.546	0	0	−0.782	−0.833	0.794	0.879	0.201	0
Transmitter	**QPT**	0	−0.779	−0.627	0	−0.840	−0.850	0.958	0.905	0.838	0.201

risk factors is taken into consideration. How the increasing in risk levels will change the influence of the cost, customer satisfaction and impact on customer demand and other factors have been analyzed. The values of fraud and theft, managerial adoption risk and privacy & security risk are considered to be high and the initial state is defined as $A^0 = [\,0, 1, 1, 1, 0, 0, 0, 0, 0, 0]$.

The system is simulated in HFCM, PL-FCM and RS-CM models according to the initial state (A^0) defined in the scenario. The interactions of the factors and their steady-state points from the initial states are shown in the Figs. 5–7. General comparisons of the models according to scenario 1 are shown in Fig. 8.

The scenario reflects the existence of problems in the supply chain. The highest impact of these problems occurs as a decreasing in customer satisfaction (CS). Accordingly, the decrease in customer satisfaction brings with it a decrease in customer demand. The contraction in demand and existing problems cause deterioration of partnership efficiency and grow (PEG). The deteriorated relationship the partners prevents correct demand forecasting and causes high fluctuations in

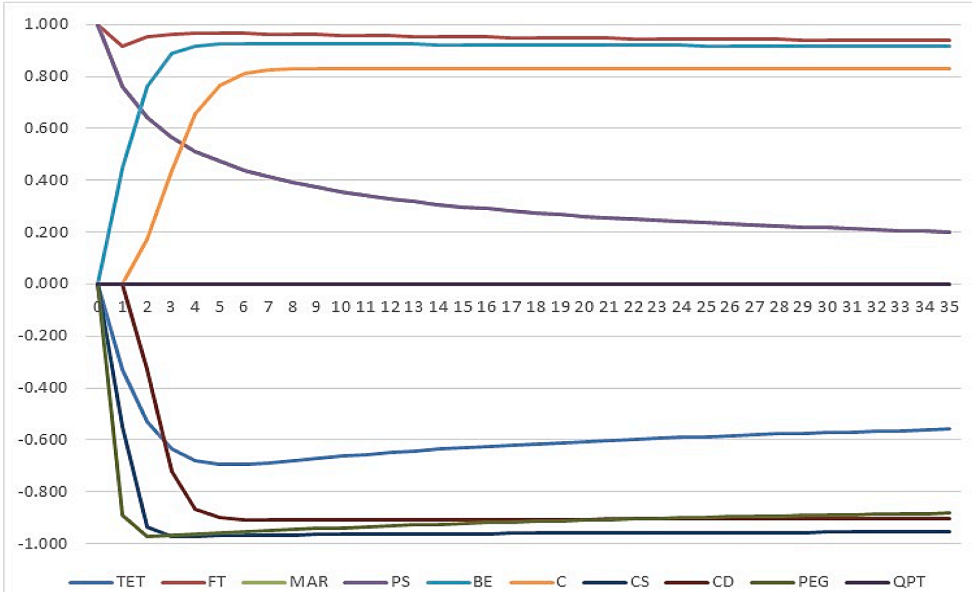


Fig. 5. HFCM simulation result for Scenario 1.

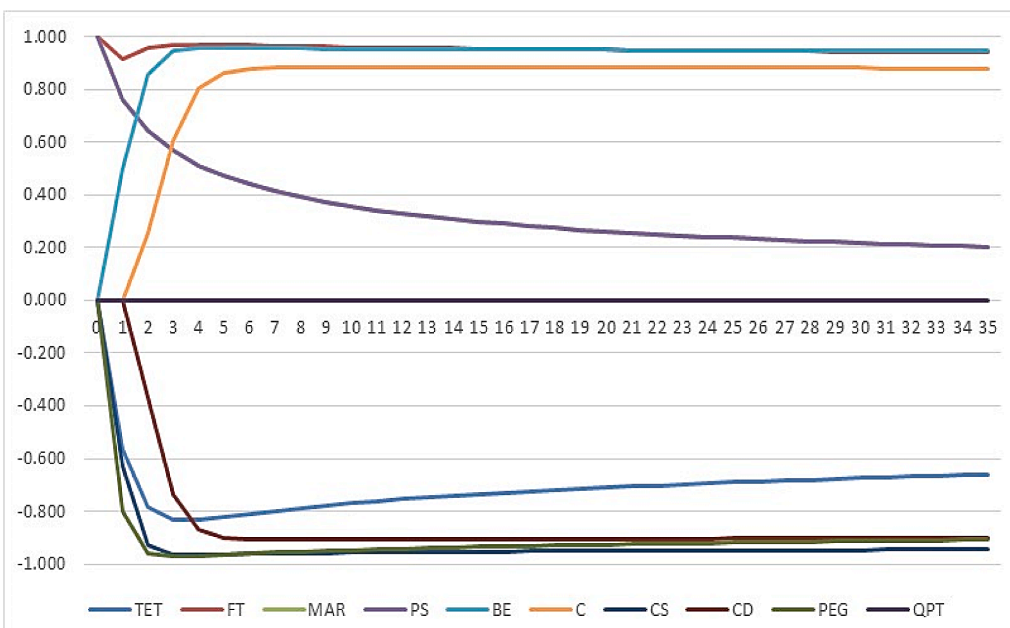


Fig. 6. PL-FCM simulation result for Scenario 1.

demand hereby bullwhip effect (BE) occurs. The imbalance between demand and supply causes total cost (C) to increase. Vulnerabilities and adaptation problems to BCT cause decrease in transparent and efficient transaction (TET). The long-term negative risk conditions cause adoption (MAR) and security (PS) problems to continue at a low level. Blockchain adaptation problems and the fact that the BCT is not implemented correctly in the supply chain causes FT to continue its existence at a high rate. QPT level remains at zero level since qualified and trained personnel are not available at the beginning and there is no factor that enables the formation of QPT factor.

According to this high risk scenario, it has been observed that the expected decrease in customer demand and satisfaction in the supply chain in the long term has led to increase in the factors such as cost, bullwhip effect which caused negativity in the system.

Scenario 2: The situation to be considered in the second scenario is about traceability and transparency benefits that the BCT provides to the system. The low level of risk factors and high level of transparency are considered. So the changes in the level of the cost, customer demand, customer satisfaction levels and other factors will be carried out. Therefore, fraud and theft, managerial adoption risk, privacy and security risk initial values are low as well as transparent and efficient transactions (traceability) initial value is high. The initial state is shown as $A^0 = [1, -0.9, -0.8, -0.9, 0, 0, 0, 0, 0, 0]$.

The interactions of the factors and their steady-state points from the

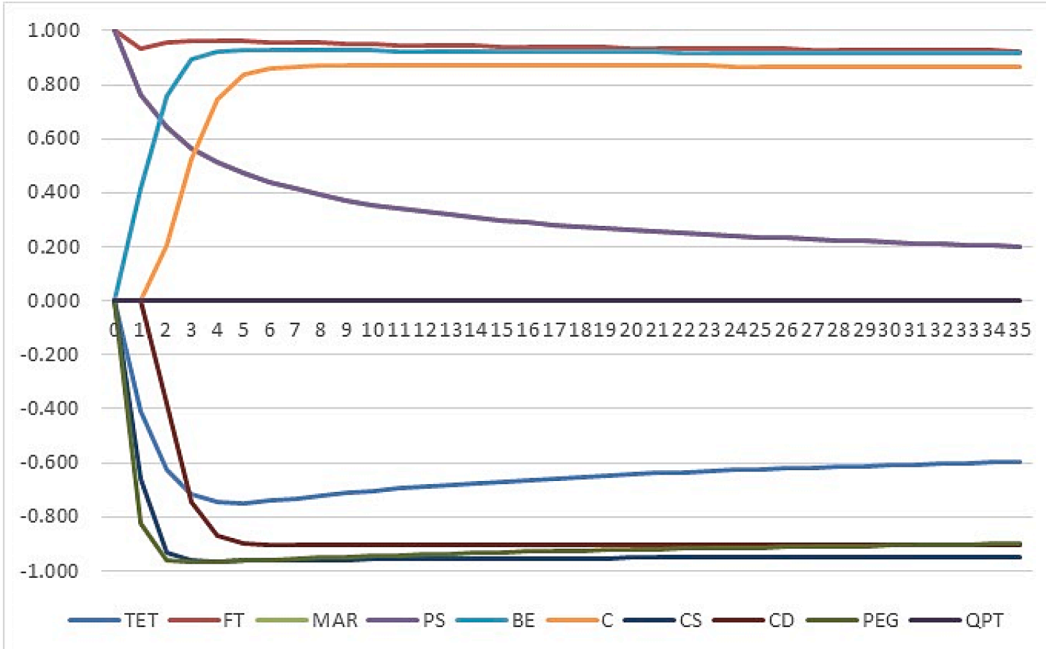


Fig. 7. RS-CM simulation result for Scenario 1.

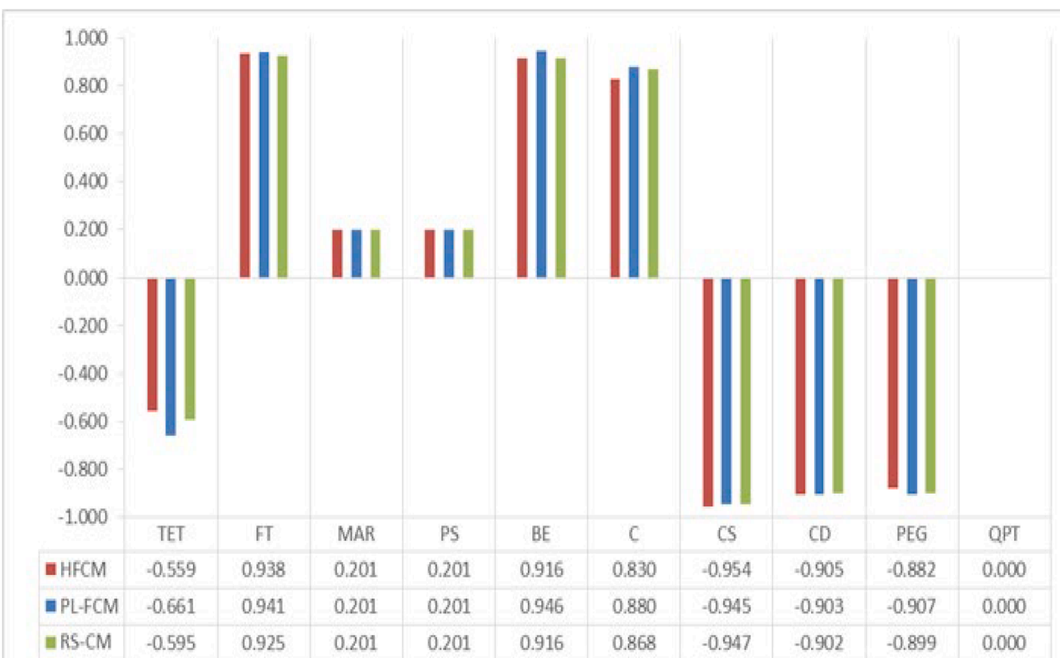


Fig. 8. Steady states of factors in different CM models for Scenario 1.

initial states can be seen in the Figs. 9, 10 and 11 that represent the HFCM, PL-FCM and RS-CM results respectively. General comparisons of the models according to scenario 2 are shown in Fig. 12. The expected effects in case of high benefit factors on the supply chain with the integration of the BCT system are given below.

The first reaction is about increasing partnership efficiency & growth (PEG) and customer satisfaction (CS) as the bullwhip effect decreases in the system. Increasing interaction between actors (PEG) in the supply chain reduces fluctuations in demand so the impact of bullwhips effect (BE) decreases. The flow of information between the actors is transparent (TET).

As the products have high traceability, theft and smuggling factors decrease. Moreover, cooperation between actors in supply chain with low risk levels, prevents fraud and theft (FT). The cost in the supply chain decreases with preventing fraud and theft. Managerial adoption risk (MAR) and privacy & security (PS) risk maintains its low level in the long term.

According to this scenario, the level of customer satisfaction (CS)

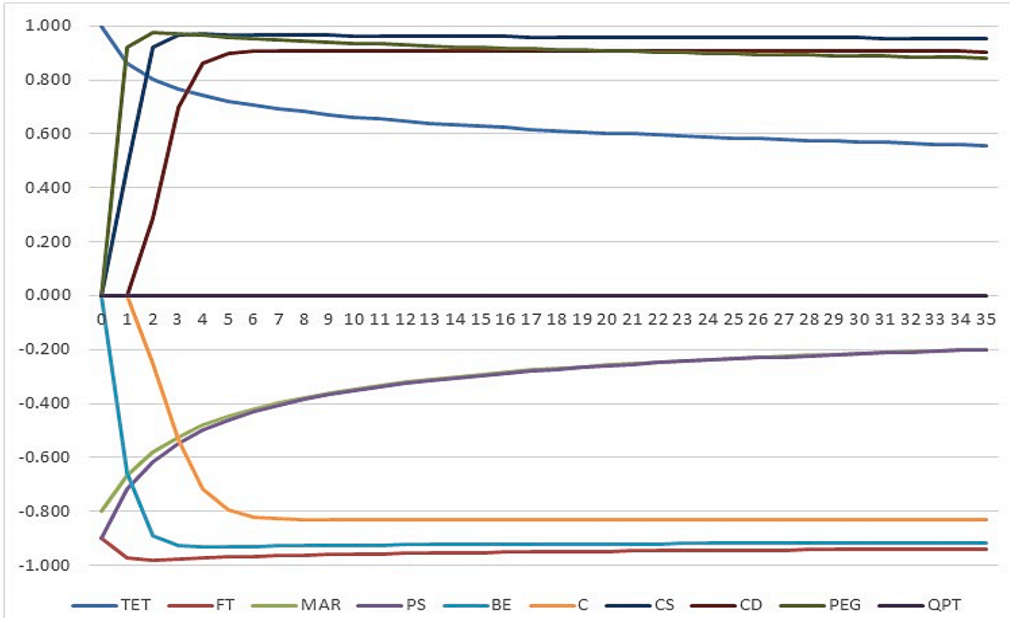


Fig. 9. HFCM simulation result for Scenario 2.

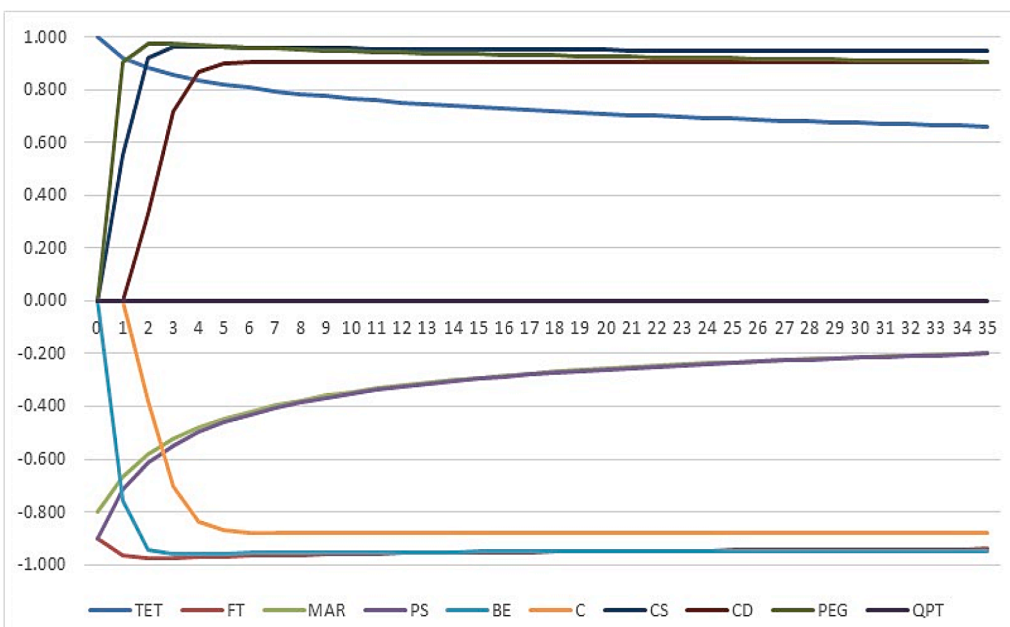


Fig. 10. PL-FCM simulation result for Scenario 2.

increases and the cost (C) decreases in the long run. It can be observed that the performance of the supply chain increase. Inventory management is provided effectively. Despite minor managerial adaptation problems, supply chain reliability increases.

Scenario 3: In this scenario, lack of qualified personnel and talent and how this low level will change the influence of the other factors will be examined.

The initial state is $A^0 = [0, 0, 0, 0, 0, 0,0,0,0, -1]$.

The system is simulated according to the initial state (A^0) defined in the scenario. The interactions of the factors and their steady-state points from the initial states are shown in the Figs. 13, 14 and 15 that represent the HFCM, PFCM and RS-CM results respectively. General comparisons of the models according to scenario 3 are shown in Fig. 16.

In the first reaction, it is observed that the lack of qualified personnel and talent significantly increases the managerial adoption risk and cost. Lack of personnel and talent causes integration of BCT system difficultly. Only in HFCM as seen in Fig. 12, the cost decreases first. After the 5th iteration cost factor increases. Lack of qualified personnel may have had a positive effect on cost at first, but in the long term, this lack causes loss of customers and increase cost in the supply chain. Customer satisfaction

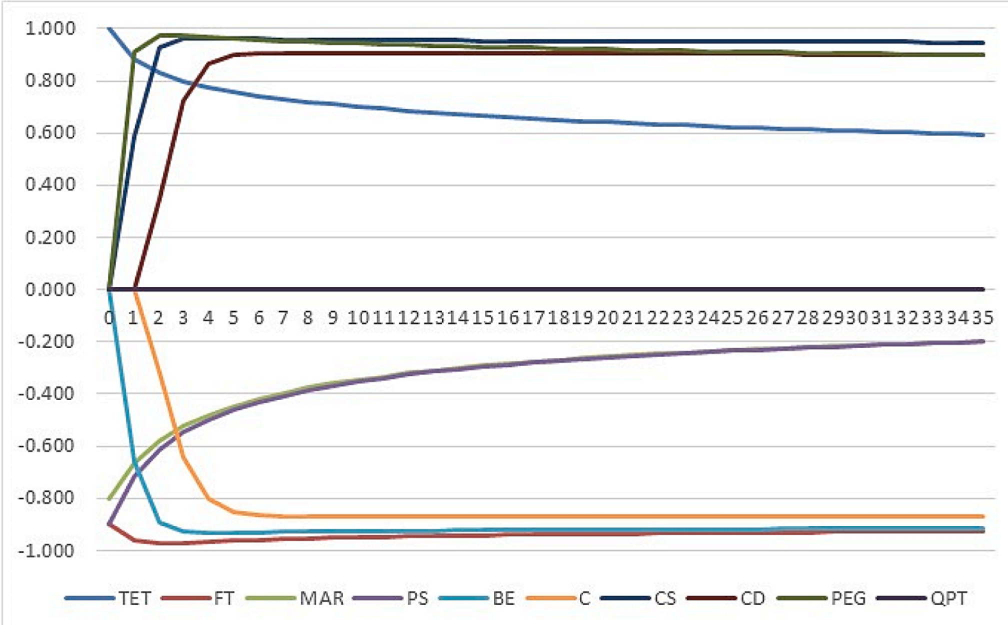
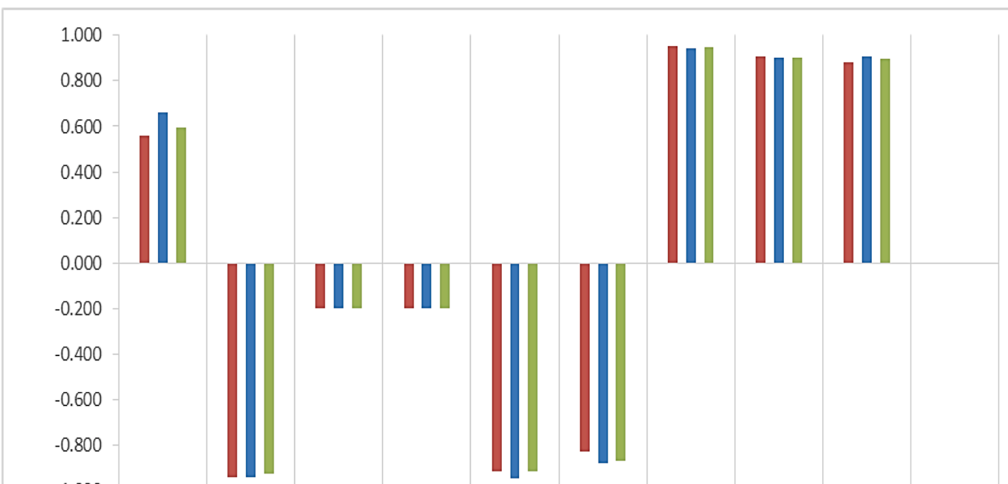


Fig. 11. RS-CM simulation result for Scenario 2.



	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
HFCM	0.558	-0.938	-0.199	-0.201	-0.916	-0.830	0.954	0.905	0.881	0.000
PL-FCM	0.660	-0.941	-0.199	-0.201	-0.946	-0.880	0.945	0.903	0.907	0.000
RS-CM	0.595	-0.925	-0.199	-0.201	-0.915	-0.868	0.947	0.902	0.899	0.000

Fig. 12. Steady states of factors in different CM models for Scenario 2.

and partnership efficiency and growth decrease. Lack of cooperation between partners in supply chain leads to customer dissatisfaction. With the decrease of PEG, it leads to a decrease in transparency and cooperation in the supply chain and this causes increasing FT. Lack of qualified personnel affects performance in the supply chain. It can be observed, as seen in graphs by reducing customer demand. As theft increase, uncertainty is revealed in demand and forecasting becomes difficult. It is observed fluctuations in demand. These effects increase the bullwhip effect in the third iteration. The level of privacy and security is not affected by any concept. Initially, there is no privacy and security risk (PS) situation. No factor causing PS has been found.

Long-term lack of qualified personnel and talent is observed to increase customer dissatisfaction, risk levels and cost factors in the supply chain. This situation is undesirable in the supply chain.

Scenario 4: This scenario is based on a positive approach. The low levels of bullwhip effect and high level of partnership efficiency and growth are considered.

The initial state of the system can be shown as $A^0 = [0, 0, 0, 0, -0.9, 0, 0, 0, 1, 0]$.

The simulation results of scenario 4 can be seen in Fig. 17, Fig. 18 and Fig. 19 that represent HFCM, PL-FCM and RS-CM results respectively Fig. 20 gives steady states of factors in different CM models for scenario

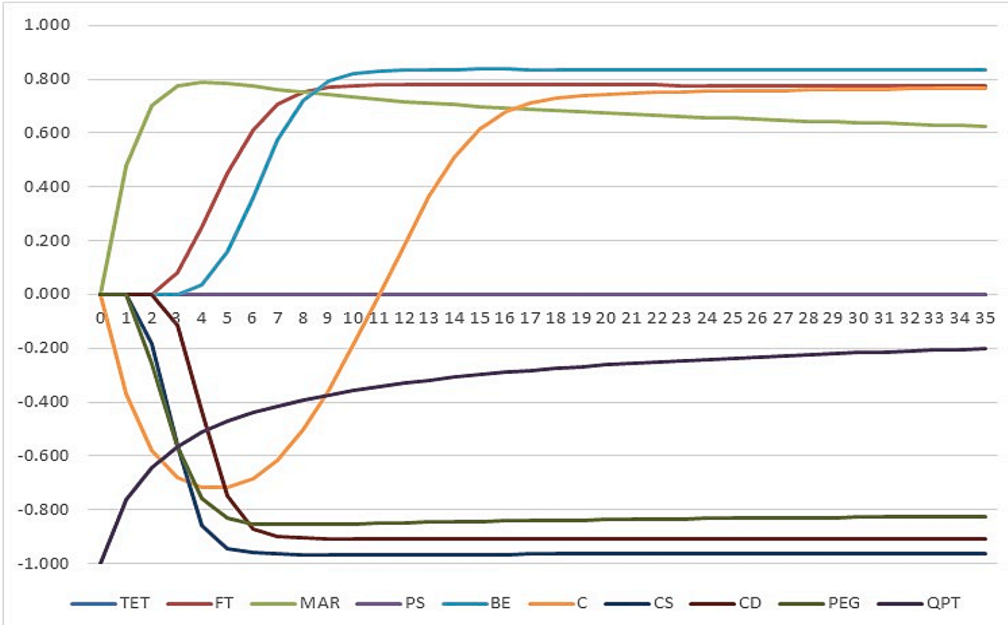


Fig. 13. HFCM simulation result for Scenario 3.

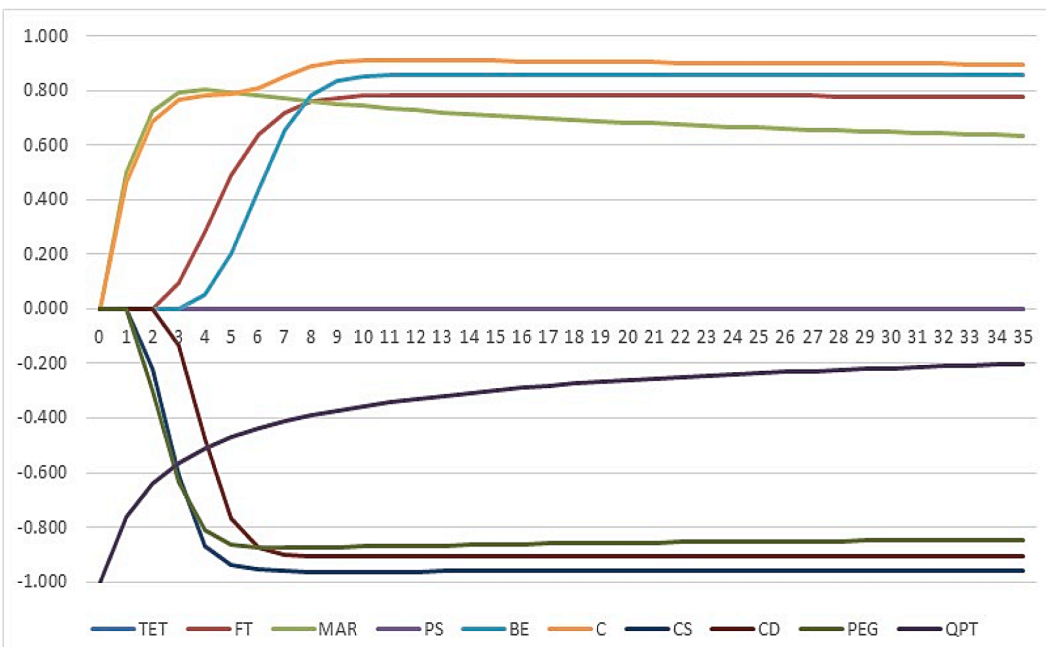


Fig. 14. PL-FCM simulation result for Scenario 3.

4.

The following results are obtained in this scenario. The first reaction shows increasing the level of customer satisfaction by reducing fraud and theft. Products can be easily tracked in the supply chain and transparency increases. Therefore, customer demand has increased at the first iteration. This leads to decreasing of cost in supply chain. Fluctuations in demand are not observed with transparency and cooperation provided by BCT. This leads to reduction in the bullwhip effect. QPT and MAR levels are not affected by other factors. In the long run, the level of partnership efficiency and growth decreases slightly. Nevertheless, expected and desired performance is provided in the supply chain.

Scenario 5: This scenario is developed to determine the dominant factors in the system. Initially, all factors are considered to have the highest level and the initial state vector of the system is defined as $A^0 = [1, 1, 1, 1, 1, 1, 1, 1, 1, 1]$. The system is simulated in HFCM, PL-FCM, and RS-CM models and the steady state of the factors are reflected in Fig. 21, Fig. 22 and Fig. 23. General comparisons of the models according to scenario 5 are shown in Fig. 24. Fig. 25 represents cumulative influence of factors from initial state vectors.

The main factor that maintains the initial state at the highest level is FT (0.919). This also constitutes the root cause of system corruption. The

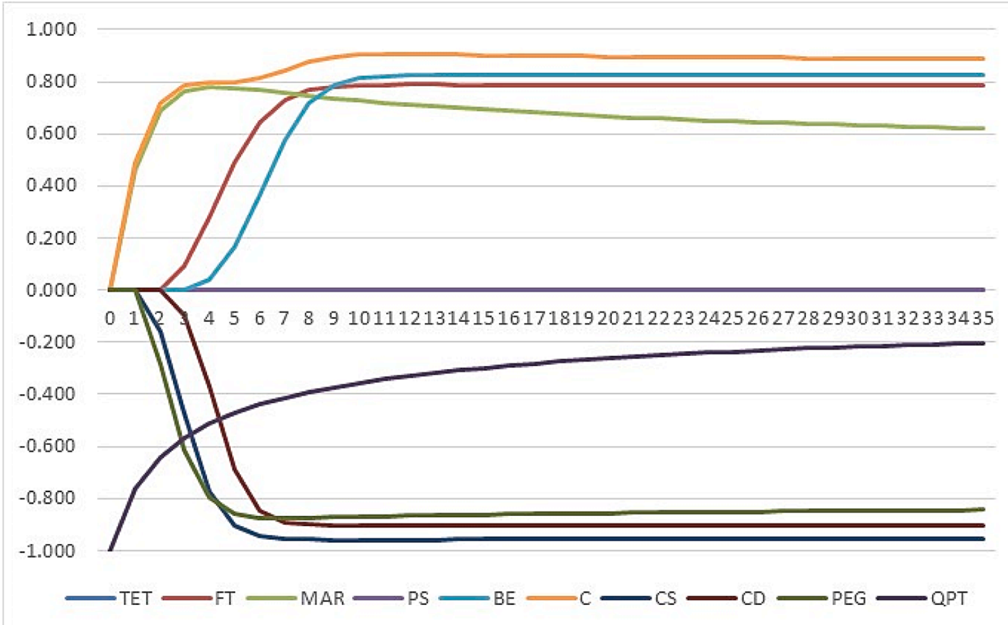
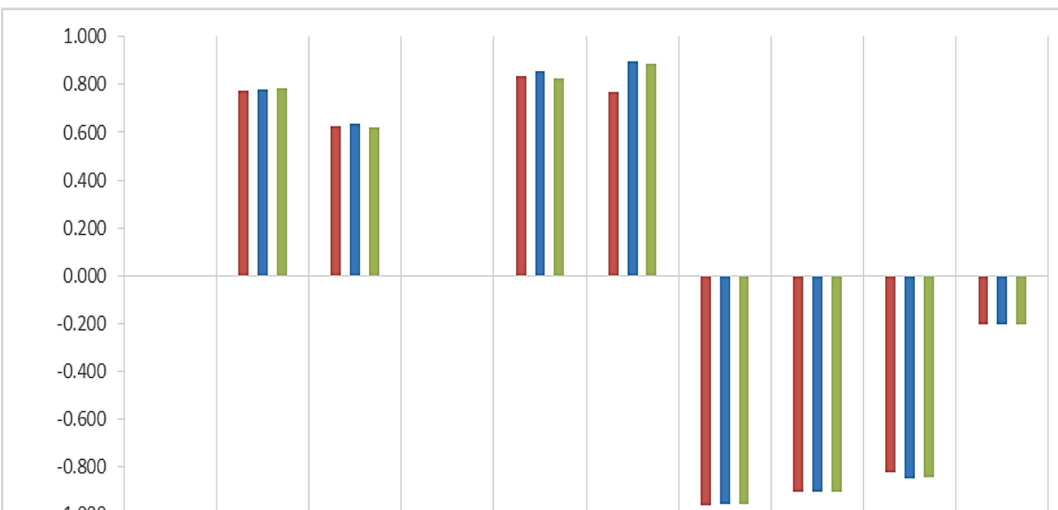


Fig. 15. RS-CM simulation result for Scenario 3.



	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
HFCM	0.000	0.775	0.626	0.000	0.836	0.767	-0.962	-0.906	-0.824	-0.201
PL-FCM	0.000	0.778	0.634	0.000	0.857	0.895	-0.957	-0.905	-0.846	-0.201
RS-CM	0.000	0.784	0.620	0.000	0.826	0.887	-0.954	-0.903	-0.843	-0.201

Fig. 16. Steady states of factors in different CM models for Scenario 3.

corrupted organization system with FT causes to increase the customer dissatisfaction (CS, −0.818), arise the adaptation problems (MAR, −0.626) and disrupt the data flow system (TET, −0.559) and partner relationships (PEG, −0.501), and decrease the demand uncertainties (BE, 0.914). Demand uncertainties and customer dissatisfaction lead to a significant decrease in demands (CS) and an increase in costs (C, 0.861). In this cycle, the supply–demand balance is disturbed and the scale of the economy cannot be realized. The presence of competent personnel (QPT) and data security (PS) remain their existence at low rates against FT. The low presence of QPT (0.201) and PS (0.201) prevents the system collapse. The PS must have a dominant role on the FT in order to prevent FT which causes system breakdown. PS forms the basis of corporate security and customer trust and is the most important factor for the existence of the organization.

HFLTS, PLTS and RS were preferred as the most suitable tools to transfer the knowledge and experience of the experts. HFCM, PL-FCM and RS-CM models developed on these assessment tools were used to evaluate the impact of BCT on the supply chain. Although the CM

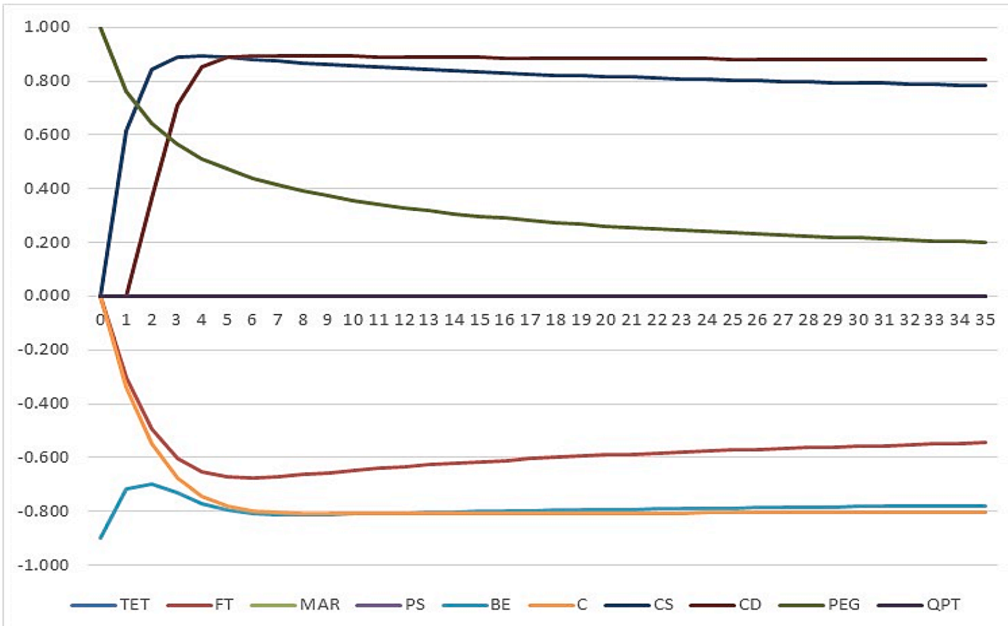


Fig. 17. HFCM simulation result for Scenario 4.

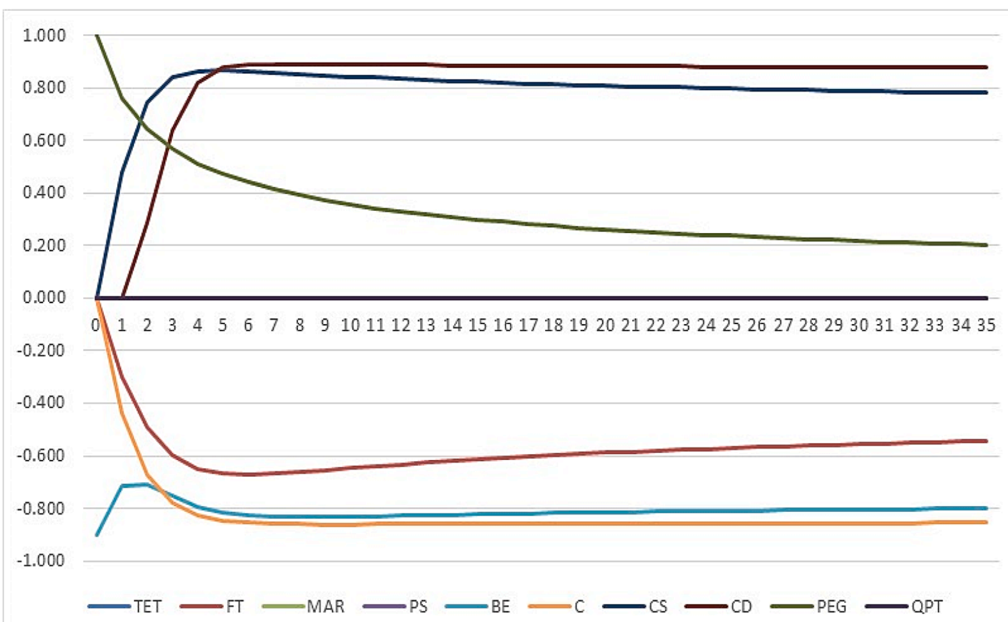


Fig. 18. PL-FCM simulation result for Scenario 4.

models do not show exactly the same feature, they do not have a significant difference. Small differences in converged values can be resulted from the different perception of the evaluation criteria defined in the models and the different expression of the causal relationships among the factors. The results show that CM models are sufficient to explain the causal relationships of BCT-based supply chain factors.

6. Sensitivity analysis

The sensitivity analysis study aims to observe the effects of the individual existence of the factors on other factors in the model. The initial state vector of the system is considered one for a vector and zero for other vectors. In other words, the system starts the simulation with the high level presence of a single factor. For example, if the Transparent and Efficient Transactions (TET) is considered to be at the highest level in the system, the initial state vector is defined as $A^0 = [\ 1, 0, 0\ ,0\ ,0\ ,0,0,0,0,0]$.

All of the factors whose initial states are defined as one converge to 0.201. Although these factors show an extinction, they continue their existence at a low level. While transmitter factors (PS and QPT) have important effects on the system, receiver factors (C and CD) have no effects on the system. The main reason is that C and CD do not affect the

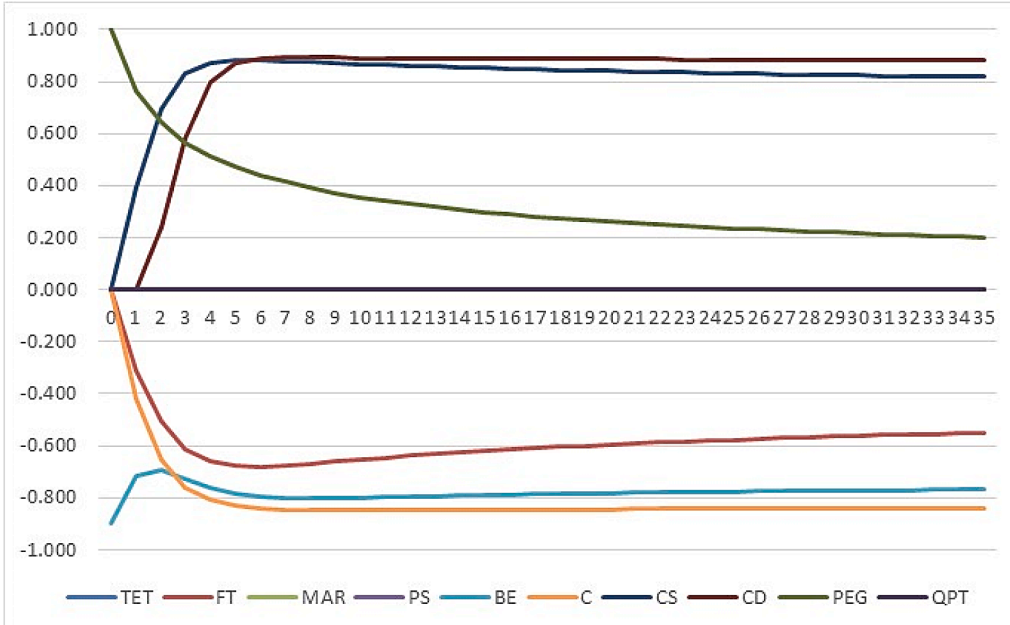
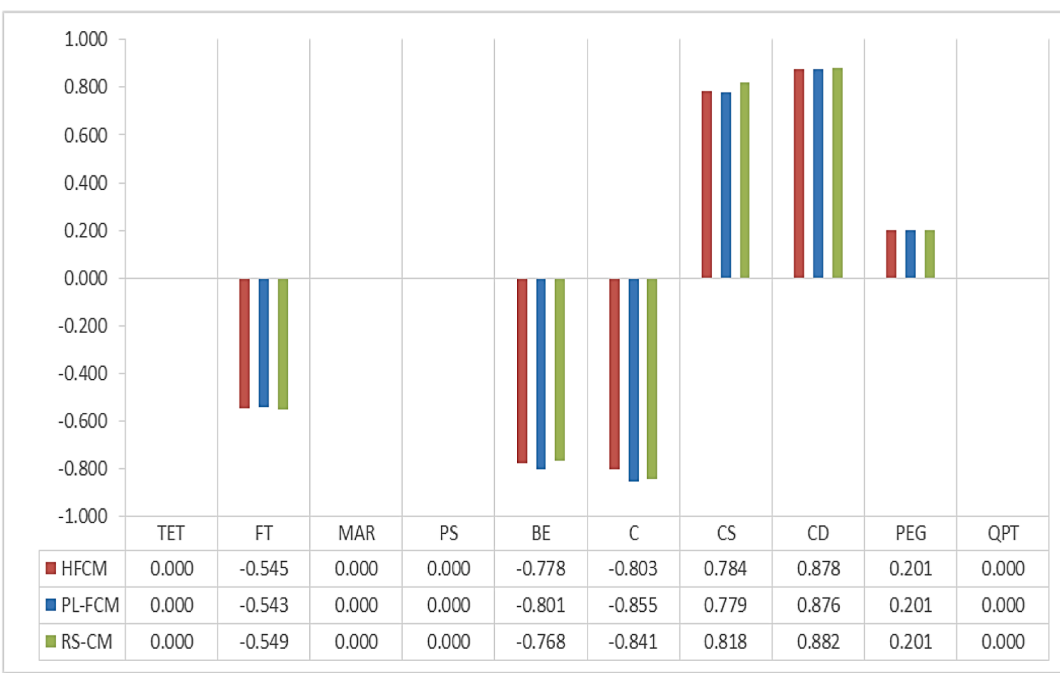


Fig. 19. RS-CM simulation result for Scenario 4.



	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
HFCM	0.000	-0.545	0.000	0.000	-0.778	-0.803	0.784	0.878	0.201	0.000
PL-FCM	0.000	-0.543	0.000	0.000	-0.801	-0.855	0.779	0.876	0.201	0.000
RS-CM	0.000	-0.549	0.000	0.000	-0.768	-0.841	0.818	0.882	0.201	0.000

Fig. 20. Steady states of factors in different CM models for Scenario 4.

system and they are the factors affected by the system change. The main reason is that C and CD do not affect the system, on the contrary, they are the factors most affected by system change. Other factors that are most affected from the initial states are BE, CS, FT and PEG.

7. Conclusion

The traditional supply chain operations have some managerial problems. Some improvements such as transparency, trust, security, demand flexibility, speed and quality can be achieved with the implementation of BCT in the supply chain. Although BCT has significant advantages on supply chain, it also has some disadvantages such as managerial adoption risks, technical infrastructure problems, and vulnerability. This situation creates uncertain and vague conditions for firms about their decisions on the BCT adoption.

The aim of this study is to evaluate impacts of BCT on supply chain and to design a model in which firms can determine their status and what situations will arise after this integration. For the first time, a numerical study guiding the evaluation of the impact of BCT in the supply chain is carried out.

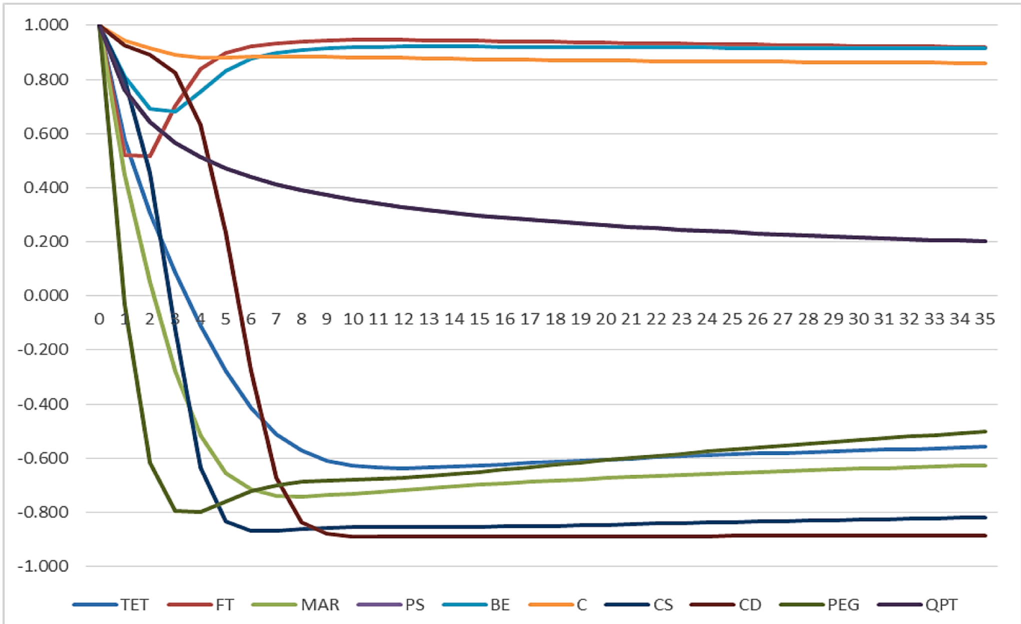


Fig. 21. HFCM simulation result for Scenario 5.

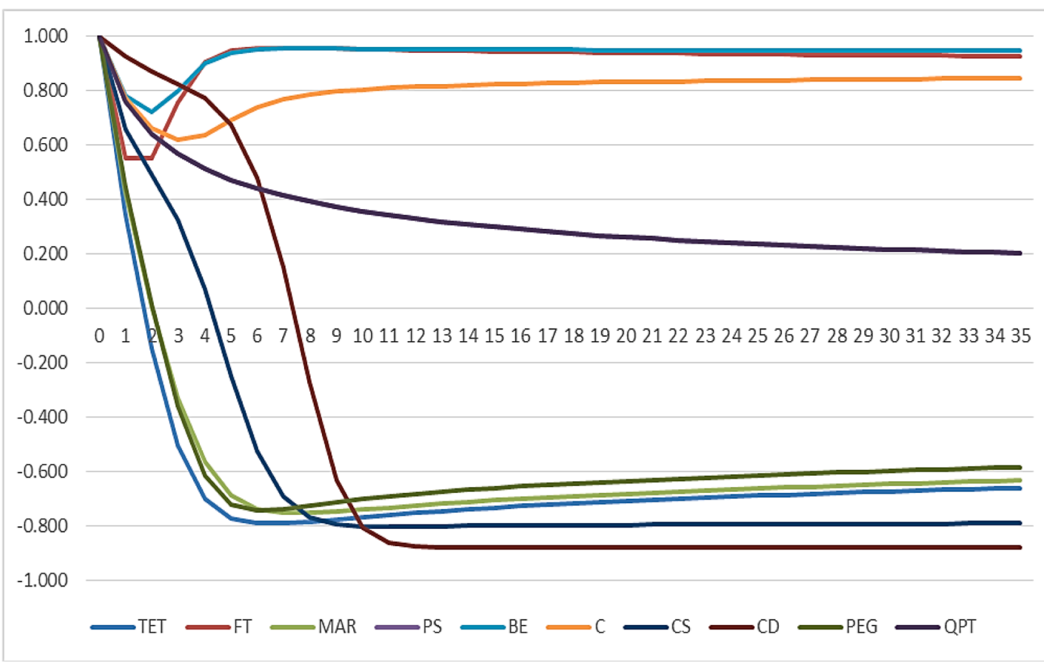


Fig. 22. PL-FCM simulation result for Scenario 5.

The effects of BCT on the supply chain are identified by factors, and the causal relationships between factors are evaluated by experts. Causal relationships involving uncertainty are evaluated by experts using HFLTS, PLTS and Rough-set assessment tools. In order to analyze this complex structure, cognitive mapping methods are developed. The experts' HFLTS, PLTS and Rough-set evaluations are aggregated to obtain weight matrices for use in HFCM, PFCM and RS-CM. PFCM is a novel model that is developed based on the PLTS evaluation scale and is used for the first time in this study. Weight matrices are simulated in HFCM, PFCM and RS-CM models according to the initial state scenarios, and converged values of factors are evaluated.

The purpose of this study is to evaluate the scenarios determined by the experts that arise with the integration of BCT into the supply. Five different scenarios are evaluated in terms of BCT impacts. As a result of the evaluations, it can be observed that the performance of supply chain management increased in Scenario 2 and 4. The reason for this is that, the value of customer satisfaction and customer demand is higher, as well as the bullwhip effect and cost decrease. It has been observed how

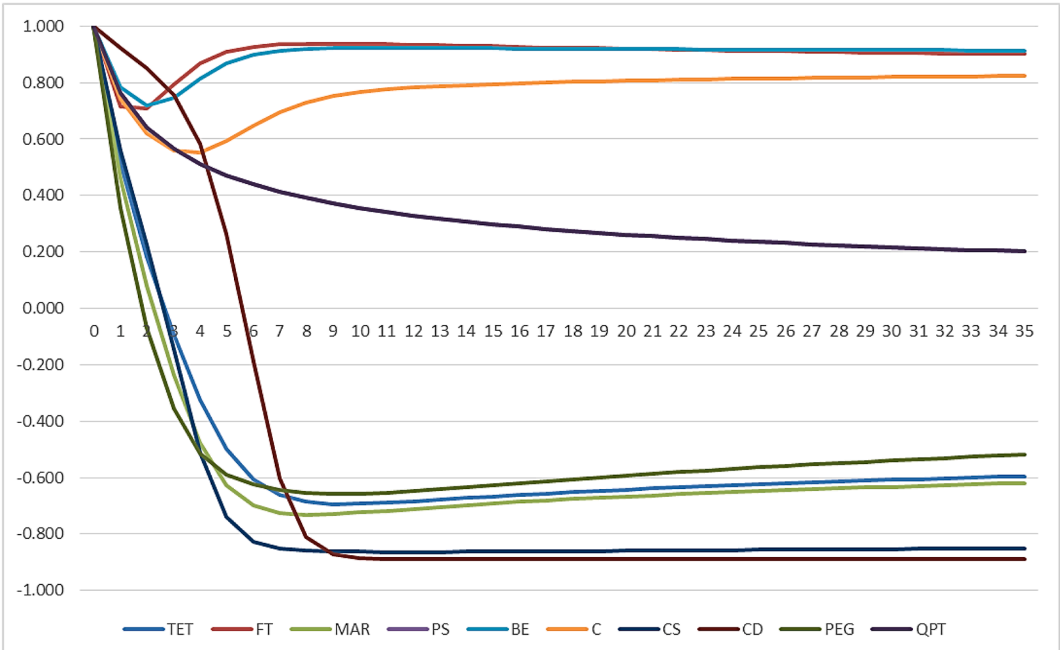
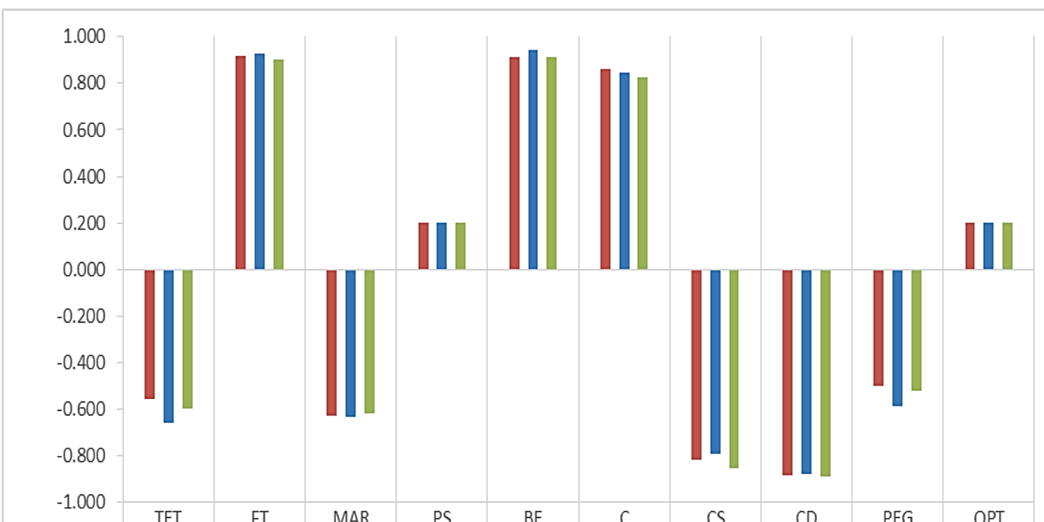


Fig. 23. RS-CM simulation result for Scenario 5.



	TET	FT	MAR	PS	BE	C	CS	CD	PEG	QPT
HFCM	-0.559	0.919	-0.626	0.201	0.914	0.861	-0.818	-0.884	-0.501	0.201
PL-FCM	-0.661	0.926	-0.634	0.201	0.945	0.845	-0.792	-0.878	-0.585	0.201
RS-CM	-0.595	0.901	-0.620	0.201	0.914	0.823	-0.851	-0.888	-0.519	0.201

Fig. 24. Steady states of factors in different CM models for Scenario 5.

supply chain performance improved after BCT integration. In addition, the situation of increasing expected risks in the system is evaluated. According to the results in scenarios 1 and 3, decrease in the performance of the supply chain is expected. In this case, cost and bullwhip effect factors are quite high, customer satisfaction and customer demand levels are low. It can be observed how the performance of the supply chain changes with increasing risks factors. Scenario 5 is developed to determine the dominant factors in the system. Sensitivity analysis is performed to observe the effects of the factors on other factors.

Cognitive map, which defines the effects of BCT on the supply chain, is an important source model for companies to make corporate evaluations. HFCM, PFCM and RS-CM methods are consistent in explaining causal relationships among factors. Managers will be able to analyze the possible effects that may occur after BCT integration.

Fig. 25. Cumulative influence of factors from initial state vectors.

CRediT authorship contribution statement

Ayşenur Budak: Conceptualization, Investigation, Methodology, Writing - original draft. **Veysel Çoban:** Software, Formal analysis, Visualization, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Abeyratne, S. A., & Monfared, R. P. (2016). Blockchain ready manufacturing supply chain using distributed ledger. *International Journal of Research in Engineering and Technology, 5*(9), 1–10.

Ahl, A., Yarime, M., Goto, M., Chopra, S. S., Kumar, N. M., Tanakã, K., & Sagawa, D. (2020). Exploring blockchain for the energy transition: Opportunities and challenges based on a case study in Japan. *Renewable and Sustainable Energy Reviews, 117*, Article 109488.

T. Ahram A. Sargolzaei S. Sargolzaei J. Daniels B. Amaba June). Blockchain technology innovations 2017 IEEE 137 141.

Apte, S., & Petrovsky, N. (2016). Will blockchain technology revolutionize excipient supply chain management? *Journal of Excipients and Food Chemicals, 7*(3), 910.

Ar, I. M., Erol, I., Peker, I., Ozdemir, A. I., Medeni, T. D., & Medeni, I. T. (2020). Evaluating the Feasibility of Blockchain in Logistics Operations: A Decision Framework. *Expert Systems with Applications, 158*, 113543. https://doi.org/10.1016/j.eswa.2020.113543

Awwad, M., Kalluru, S. R., Airpulli, V. K., Zambre, M. S., Marathe, A., & Jain, P. (2018). Blockchain Technology for Efficient Management of Supply Chain. *Proceedings of the International Conference on Industrial Engineering and Operations Management*.

Azzi, R., Chamoun, R. K., & Sokhn, M. (2019). The power of a blockchain-based supply chain. *Computers & industrial engineering, 135*, 582–592.

Bordogna, G., & Pasi, G. (1993). A fuzzy linguistic approach generalizing boolean information retrieval: A model and its evaluation. *Journal of the American Society for Information Science, 44*(2), 70–82.

Bozarth, C. C., Warsing, D. P., Flynn, B. B., & Flynn, E. J. (2009). The impact of supply chain complexity on manufacturing plant performance. *Journal of Operations Management, 27*(1), 78–93.

Chang, S. E., Chen, Y.-C., & Lu, M.-F. (2019). Supply chain re-engineering using blockchain technology: A case of smart contract based tracking process. *Technological Forecasting and Social Change, 144*, 1–11.

Challa, S., Das, A. K., Gope, P., Kumar, N., Wu, F., & Vasilakos, A. V. (2020). Design and analysis of authenticated key agreement scheme in cloud-assisted cyber–physical systems. *Future Generation Computer Systems, 108*, 1267–1286.

Chen, G., Xu, B., Lu, M., & Chen, N.-S. (2018). Exploring blockchain technology and its potential applications for education. *Smart Learning Environments, 5*(1), 1.

Chen, S., Shi, R., Ren, Z., Yan, J., Shi, Y., & Zhang, J. (2017). A blockchain-based supply chain quality management framework. *2017 IEEE 14th International Conference on e-Business Engineering (ICEBE)*.

Çolak, M., Kaya, İ., Özkan, B., Budak, A., Karaşan, A., & Kahraman, C. (2020). A multi-criteria evaluation model based on hesitant fuzzy sets for blockchain technology in supply chain management. *Journal of Intelligent & Fuzzy Systems, 38*(1), 935–946.

Dobrovnik, M., Herold, D. M., Fürst, E., & Kummer, S. (2018). Blockchain for and in Logistics: What to Adopt and Where to Start. *Logistics, 2*(3), 18.

Dorri, A., S. S. Kanhere and R. Jurdak (2016). "Blockchain in internet of things: challenges and solutions." arXiv preprint arXiv:1608.05187.

Fang, H., Li, J., & Song, W. (2018). Sustainable site selection for photovoltaic power plant: An integrated approach based on prospect theory. *Energy conversion and management, 174*, 755–768.

Fan, K., Bao, Z., Liu, M., Vasilakos, A. V., & Shi, W. (2020). Dredas: Decentralized, reliable and efficient remote outsourced data auditing scheme with blockchain smart contract for industrial IoT. *Future Generation Computer Systems, 110*, 665–674.

Filev, D., & Yager, R. R. (1998). On the issue of obtaining OWA operator weights. *Fuzzy sets and systems, 94*(2), 157–169.

Francisco, K., & Swanson, D. (2018). The supply chain has no clothes: Technology adoption of blockchain for supply chain transparency. *Logistics, 2*(1), 2.

Glykas, M. (2010). *Fuzzy cognitive maps: Advances in theory, methodologies, tools and applications*. Springer.

Gupta, S. S. (2017). *Blockchain*. John Wiley & Sons Inc.

Hackius, N., & Petersen, M. (2017). *Blockchain in logistics and supply chain: trick or treat? Digitalization in Supply Chain Management and Logistics: Smart and Digital Solutions for an Industry 4.0 Environment* (Vol. 23).

Heikkilä, J. (2002). From supply to demand chain management: Efficiency and customer satisfaction. *Journal of operations management, 20*(6), 747–767.

Helo, P., & Hao, Y. (2019). Blockchains in operations and supply chains: A model and reference implementation. *Computers & Industrial Engineering, 136*, 242–251.

Janssen, M., Weerakkody, V., Ismagilova, E., Sivarajah, U., & Irani, Z. (2020). A framework for analysing blockchain technology adoption: Integrating institutional, market and technical factors. *International Journal of Information Management, 50*, 302–309.

Kamble, S. S., Gunasekaran, A., & Sharma, R. (2020). Modeling the blockchain enabled traceability in agriculture supply chain. *International Journal of Information Management, 52*, Article 101967.

Kim, J.-S., & Shin, N. (2019). The impact of blockchain technology application on supply chain partnership and performance. *Sustainability, 11*(21), 6181.

Kosko, B. (1986). Fuzzy cognitive maps. *International journal of man-machine studies, 24*(1), 65–75.

Kshetri, N. (2018). 1 Blockchain's roles in meeting key supply chain management objectives. *International Journal of Information Management, 39*, 80–89.

Lin, C., He, D., Huang, X., Choo, K.-K., & Vasilakos, A. V. (2018). BSeIn: A blockchain-based secure mutual authentication with fine-grained access control system for industry 4.0. *Journal of Network and Computer Applications, 116*, 42–52.

Liu, H., & Rodríguez, R. M. (2014). A fuzzy envelope for hesitant fuzzy linguistic term set and its application to multicriteria decision making. *Information Sciences, 258*, 220–238.

Liu, Z., & Li, Z. (2019). A blockchain-based framework of cross-border e-commerce supply chain. *International Journal of Information Management, 102059*.

Longo, F., Nicoletti, L., Padovano, A., d'Atri, G., & Forte, M. (2019). Blockchain-enabled supply chain: An experimental study. *Computers & Industrial Engineering, 136*, 57–69.

Madhwal, Y., & Panfilov, P. B. (2017). BLOCKCHAIN AND SUPPLY CHAIN MANAGEMENT: AIRCRAFTS'PARTS'BUSINESS CASE. *Annals of DAAAM & Proceedings* ***28***.

Mougayar, W. (2016). *The business blockchain: Promise, practice, and application of the next Internet technology*. John Wiley & Sons.

Muhr, J., & Laurence, T. (2017). *Blockchain fur Dummies*. John Wiley & Sons Incorporated.

Pang, Q., Wang, H., & Xu, Z. (2016). Probabilistic linguistic term sets in multi-attribute group decision making. *Information Sciences, 369*, 128–143.

Papageorgiou, E. I. (2013). *Fuzzy cognitive maps for applied sciences and engineering: From fundamentals to extensions and learning algorithms*. Springer Science & Business Media.

Pawlak, Z. (2012). *Rough sets: Theoretical aspects of reasoning about data*. Springer Science & Business Media.

Pawlak, Z., & Skowron, A. (2007). Rudiments of rough sets. *Information sciences, 177*(1), 3–27.

Pettersson, A. I., & Segerstedt, A. (2013). Measuring supply chain cost. *International Journal of Production Economics, 143*(2), 357–363.

Queiroz, M. M., & Fosso Wamba, S. (2019). Blockchain adoption challenges in supply chain: An empirical investigation of the main drivers in India and the USA. *International Journal of Information Management, 46*, 70–82.

Rodriguez, R. M., Martinez, L., & Herrera, F. (2012). Hesitant Fuzzy Linguistic Term Sets for Decision Making. *IEEE Transactions on Fuzzy Systems, 20*(1), 109–119.

Saberi, S., Kouhizadeh, M., Sarkis, J., & Shen, L. (2019). Blockchain technology and its relationships to sustainable supply chain management. *International Journal of Production Research, 57*(7), 2117–2135.

Song, W., Xu, Z., & Liu, H.-C. (2017). Developing sustainable supplier selection criteria for solar air-conditioner manufacturer: An integrated approach. *Renewable and sustainable energy reviews, 79*, 1461–1471.

Swan, M. (2015). *Blockchain: Blueprint for a new economy*. ": O'Reilly Media, Inc.".

Tang, H., Shi, Y., & Dong, P. (2019). Public blockchain evaluation using entropy andTOPSIS. *Expert Systems with Application, 117*, 204–210.

Tian, F. (2016). An agri-food supply chain traceability system for China based on RFID & blockchain technology. *2016 13th international conference on service systems and service management (ICSSSM), IEEE*.

van Engelenburg, S., Janssen, M., & Klievink, B. (2018). *A Blockchain Architecture for Reducing the Bullwhip Effect*. Cham: Springer International Publishing.

Wang, Y., Han, J. H., & Beynon-Davies, P. (2019). *Understanding blockchain technology for future supply chains: A systematic literature review and research agenda*. Supply Chain Management: An International Journal.

Wang, Y., Singgih, M., Wang, J., & Rit, M. (2019). Making sense of blockchain technology: How will it transform supply chains? *International Journal of Production Economics, 211*, 221–236.

Xu, X., Lu, Q., Liu, Y., Zhu, L., Yao, H., & Vasilakos, A. V. (2019). Designing blockchain-based applications a case study for imported product traceability. *Future Generation Computer Systems, 92*, 399–406.

Yli-Huumo, J., Ko, D., Choi, S., Park, S., & Smolander, K. (2016). Where is current research on blockchain technology?—a systematic review. *PloS one, 11*(10), Article e0163477.

Zadeh, L. and R. A. Aliev Fuzzy Logic Theory and Applications.

Zhang, R., Xue, R., & Liu, L. (2019). Security and privacy on blockchain. *ACM Computing Surveys (CSUR), 52*(3), 1–34.