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RESEARCH ARTICLE

Di-ANFIS: an integrated blockchain–IoT–big data-enabled framework for evaluating service supply chain performance

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Abstract

Service supply chain management is a complex process because of its intangibility, high diversity of services, trustless settings, and uncertain conditions. However, the traditional evaluating models mostly consider the historical performance data and fail to predict and diagnose the problems' root. This paper proposes a distributed, trustworthy, tamper-proof, and learning framework for evaluating service supply chain performance based on blockchain and adaptive network-based fuzzy inference systems (ANFIS) techniques, named Di-ANFIS. The main objectives of this research are as follows: (1) presenting hierarchical criteria of service supply chain performance to cope with the diagnosis of the problems' root; (2) proposing a smart learning model to deal with the uncertainty conditions by a combination of neural network and fuzzy logic; and (3) introducing a distributed blockchain-based framework due to the dependence of ANFIS on big data and the lack of trust and security in the supply chain. Furthermore, the proposed six-layer conceptual framework consists of the data layer, connection layer, blockchain layer, smart layer, ANFIS layer, and application layer. This architecture creates a performance management system using the Internet of Things, smart contracts, and ANFIS based on the blockchain platform. The Di-ANFIS model provides a performance evaluation system without needing a third party and a reliable intermediary that provides an agile and diagnostic model in a smart and learning process. It also saves computing time and speeds up information flow.

Keywords: blockchain; industry 4.0; Internet of Things (IoT); big data; service supply chain; performance evaluation

1. Introduction

Over recent years, the world's economies have become more service oriented than before. The service economy is a driving force for developed countries and growing rapidly in developing countries, and this trend continues (Smith *et al.*, 2007). Due to the increase in competition of service organizations for survival and profitability, utilizing systematic thinking to improve their performance and provide more qualified services is inevitable. Hence, organizations focus more on supply chain management (SCM) to improve their performance (Dos Santos & Leite, 2016). The supply chain includes all processes from providing raw materials and required resources to product delivery and final ser-

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vice to consumers (Handfield & Nichols, 1999). Baltacioglu *et al.* (2007) define a service supply chain (SSC) system as "a network of suppliers, service providers, consumers, and other supporting units that performs the functions of transactions of resources required to produce services, transformation of these resources into supporting and core services, and the delivery of these services to customers." Because of intangibility and high diversity of services, performance evaluation in an SSC is a complex and complicated task (Cho *et al.*, 2012).

In SCM, many managerial processes are performing, including planning and controlling long-term relationships with partners, suppliers, and customers, managing information sharing throughout the supply chain, and receiving feedback to reduce resources and increase customer satisfaction (Chorfi *et al.*, 2018; Lima-Junior & Carpinetti, 2020). Therefore, it is crucial to evaluate the whole chain's performance and predict its performance for future supply chain planning. In this regard, many studies have evaluated supply chain performance (Cho *et al.*, 2012; Lakri *et al.*, 2015; Huang, 2018; Palang & Tippayawong, 2019; Lima-Junior & Carpinetti, 2020). These models often used multicriteria decision-making (MCDM) methods, artificial intelligence (AI) or statistical techniques, and quantitative and qualitative criteria to evaluate supply chain performance (Lima-Junior & Carpinetti, 2019). On the other hand, industry 4.0 and the emergence of new technologies have made it possible to share information in real time, and these developments have not only affected SCM but also changed its performance evaluation criteria. Because of the supply chain's big data and value-added data, performance evaluation systems' focus has shifted from control to learning and performance management (Helo & Shamsuzzoha, 2020). Hence, decision makers are forced to move toward smarter solutions for SCM. In today's complex world, traceability and integration are the basic needs of SCM (Witkowski, 2017). Furthermore, factors such as complex structures, the multiplicity of evaluation indicators, uncertainty, distrust, and ambiguity in decision making call for complex evaluation methods. However, because of the diversity of services, geographical extent, uncertainty, and distrust conditions, SSC performance evaluation is a challenging task. In a comprehensive study, Cho *et al.* (2012) introduced performance evaluation criteria in SSC. Besides, Xie *et al.* (2020) also suggested seven performance measurement indicators in the intelligent supply chain. However, there is a lack of comprehensive frameworks for the performance evaluation of smart SSC using new technologies.

Based on the aforementioned challenges, this research's main objective is to develop a trustworthy and self-learning theoretical model for performance evaluation of smart SSC named distributed adaptive network-based fuzzy inference system (Di-ANFIS). To diagnose the root problems, a hierarchical framework for SSCP criteria is introduced. Moreover, by integrating the Internet of Things (IoT) and blockchain technology in the proposed Di-ANFIS model, a smart and tamper-proof system has been designed to evaluate the performance of the SSC. The main contributions of this paper are as follows:

1. Providing a distributed and trustworthy framework for the SSC under the condition of uncertainty.
2. Presenting a hierarchical performance evaluation criterion for SSC enabled by blockchain technology.
3. Modeling a smart and self-learning SSC performance evaluation system by integrating blockchain, IoT, and big data named "Di-ANFIS."

The remainder of this paper is organized as follows. Section 2 includes a brief overview of related work about SSC performance evaluation and blockchain technology. In Sections 3 and 4, we describe the ANFIS model, blockchain technology, and its application in SC. The proposed framework is discussed in Section 5. This section presents a hierarchical framework of performance evaluation, and finally, we propose a Di-ANFIS model for SSC performance evaluation. In Section 6, we discuss the strengths and limitations of the proposed model and the possible challenges. Section 7 summarizes the results of this study and concludes the paper.

2. Related Work

Chopra *et al.* (2013) conceptualize supply chain performance as "the result of how the supply chain is managed and how well the logistical drivers (facility, inventory, and transportation) and cross-functional drivers (information, sourcing, and pricing) interact together to determine the level of performance in terms of supply chain's responsiveness and efficiency." The purpose of supply chain performance management is to identify gaps between actual and planned outcomes, understand the root causes, and obtain improvement plans (Melnyk *et al.*, 2014). So, performance forecasting systems to prevent correction instead of correction can be suitable and useful (Melnyk *et al.*, 2004). Past studies have shown that many reports have used MCDM techniques such as the Analytic Hierarchy Process or Data Envelopment Analysis for evaluating supply chain performance (Lima-Junior & Carpinetti, 2017; Guersola *et al.*, 2018). Rajab and Sharma (2018) discussed many studies using neuro-fuzzy systems in medical science, business planning, production, marketing, and traffic control. Guersola *et al.* (2018) studied 100 articles from 1999 to 2014, and Lima-Junior and Carpinetti (2017) analysed 84 studies between 2003 and 2014, including models of SCM measurement and shown that researchers in many studies use the MCDM method and its combination with fuzzy logic to evaluate supply chain performance. Among them, four models focus on predicting SC performance (Didehkhani *et al.*, 2009; Ganga & Carpinetti, 2011; Fan *et al.*, 2013). As stated by Lima-Junior and Carpinetti (2017), AI techniques were used in only 11 out of the 84 studies for SCM performance evaluation. Kar *et al.* (2014) stated that ANFIS is a well-adapted model for prediction and forecasting in most previous studies. Ganga and Carpinetti (2011), Lima-Junior and Carpinetti (2019), and Lima-Junior and Carpinetti (2020) developed fuzzy inference and neural fuzzy inference models to evaluate supply chain performance using supply chain operations reference (SCOR) criteria and provided predictive evaluation systems.

It should be noted that SCM has been emerged from production and operations management based on physical resources transport (Giannakis & Croom, 2004). Comparing production and service performance evaluation models has shown that criteria used in production processes are not appropriate for evaluating service processes (Pandari & Azar, 2017). Unlike production processes, few publications are available that discuss service processes' performance evaluation due to various and intangible aspects of services (Arnott *et al.*, 2007). Intangibility, simultaneity, and heterogeneity are the principal sources of complexity for service performance evaluation (Baltacioglu *et al.*, 2007). To tackle these challenges, Kathawala and Abdou (2003) evaluated the accounting SSC under cost reduction and quality improvement. Giannakis and Croom (2004) proposed a framework for service organizations based on the SCOR model. Fitzgerald *et al.* (1991) defined six service performance dimensions as competitiveness, flexibility, innovation, financial, quality of service, and resource utilization. The result obtained by Parasuraman *et al.* (1988) suggests tangibility, responsiveness, competence, reliability, and empathy as six dimensions of service quality called SERVQUAL. Baltacioglu *et al.* (2007) proposed the metrics and measures of SSC processes. The process was defined as capacity and resource management, supplier relationship management, service performance management, demand management, customer relationship management, order process management, and information and technology management. A most comprehensive approach to this problem has been proposed by Cho *et al.* (2012) based on the studies of Parasuraman *et al.* (1988), Fitzgerald *et al.* (1991), and the SCOR model. They provided a hierarchical framework for evaluating the SSC's operational, tactical, and strategic performance and defined its criteria and metrics. They reported SSC operation, customer service, and corporate management as assessment areas. Pandari and Azar (2017) developed a fuzzy cognitive mapping model in the insurance industry to evaluate SSC performance.

With the advent of industry 4.0, technologies such as AI, IoT, and blockchain have been integrated increasingly and consequently improved the supply chain performance evaluation. Xie *et al.* (2020) proposed a performance indicator framework of the intelligent supply chain under Industry 4.0. They classified indicators into leagility (the combination of lean and agile), visibility, personalization, supply chain warning, information governance, green and innovation, and learning. One of the most promising technologies is IoT that includes a set of virtual and physical objects for monitoring, sensing, or interaction on the network. It provides a framework for connecting objects to applications and can develop services (Čolaković & Hadžialić, 2018). This emerging technology can transform traditional SC into a smart one. IoT helps create a common operating picture by sharing integrated information (Gubbi *et al.*, 2013). It implies using actuators and sensors, machine-to-machine, control systems, and data analytics to get real-time data and share key information. IoT transforms data to big data in SC and empowers SC to adopt new data-driven strategies. Big data analytics constitute the basis for customization and individualization. The analysis of big data can enhance innovation performance, firm agility, and support decision making (Rouhani *et al.*, 2016; Ashrafi *et al.*, 2019).

Applying IoT improves agility and visibility and provides interconnected, intelligent, automated, and innovative SC (Abdel-Basset *et al.*, 2018). Although IoT generates big data and power for SC, trustworthiness, reliable security, and data privacy are still key challenges (Reyna *et al.*, 2018). Blockchain, as a distributed and decentralized platform, can guarantee security and trust. It uses a verification mechanism, p2p network, consensus algorithm, and immutable and auditable ledger to reduce the problems (Reyna *et al.*, 2018; Hald & Kinra, 2019). Blockchain has also provided a platform for the realization of smart contracts. Smart contracts are predefined programs that run automatically by establishing relationships. Blockchain provides a trusted environment without centralized control to execute smart contracts (Reyna *et al.*, 2018).

Several studies have been published in recent years demonstrating blockchain's effects on supply chain and its performance in different domains, including pharmaceutical, agricultural, aviation, construction, or digital supply chain (Bocek *et al.*, 2017; Korpela *et al.*, 2017; Madhwal & Panfilov, 2017; Leng *et al.*, 2018; Sivula *et al.*, 2018). Kshetri (2018) studied 11 cases and showed blockchain's positive effect on key SCM goals such as cost, quality, speed, reliability, risk reduction, sustainability, and flexibility. He indicated that using blockchain in the supply chain would increase transparency and accountability.

More recently, Wong *et al.* (2019) investigated the impact of blockchain on SCM of Malaysian small- and medium-sized enterprises. Saberi *et al.* (2019) proposed to decrease opportunistic behaviors based on blockchain technology and smart contracts applications in SCM. Yadav and Singh (2020) represented factors for achieving a sustainable supply chain. They modeled data safety and decentralization, accessibility, laws and policy, documentation, and data management using principal component analysis and fuzzy decision-making trial and evaluation laboratory (DEMATEL) to the integration of blockchain and supply chain. Wen *et al.* (2019) proposed a blockchain-based SC by industrial IoT and blockchain for real-time data recording. Also, smart contracts were defined as access policies for SC entities to access the transactions. Basnayake and Rajapakse (2019) suggested a public blockchain platform to verify the food quality and origin tracking of organic food SC. They designed smart contracts to control business logic. In another study, Salah *et al.* (2019) proposed a trust agricultural SC obtained from the integration of Ethereum blockchain and smart contracts. Chen *et al.* (2017) addressed a blockchain-based framework to improve the SC quality management consisting of four layers. Niya *et al.* (2019), employing smart contracts on Ethereum blockchain in SC, facilitated SC traceability. Kaid and Eljazzar (2018) discussed the integration of blockchain and enterprise resource planning and used smart contracts to automate transactions between distributors and retailers. Tsang *et al.* (2019) designed a blockchain-IoT-based and fuzzy logic food traceability system to improve SC's reliability, scalability, and information accuracy.

Although there have been many related studies focusing on SSCP, there is a lack of reliability, information accuracy, and trust in SSCP evaluation systems. To fill this gap, we have specifically addressed the issue of providing a distributed performance evaluation model based on the blockchain and ANFIS technique named Di-ANFIS.

3. Adaptive Network-Based Fuzzy Inference System

Zade (1978) introduced the fuzzy set theory to handle uncertainty and imprecision of linguistic terms in the decision-making process. Under fuzzy logic, the decision support system is a smart computational method to cope with nonlinear systems (Hamouda, 2017). The fuzzy logic system is applied in various applications and evaluation systems such as risk assessment or performance evaluation systems, interference management, self-organizing networks, irrigation systems, and mobile communication (Hamouda, 2017; Pourjavad & Shahin, 2018; Munir *et al.* 2019).

The ANFIS is proposed by Jang (1993) based on Takagi–Sugeno fuzzy inference system and supervised learning capability. It can extract appropriate rules by combining numeric and linguistic inputs. ANFIS is a feed-forward neural network composed of five layers, as presented in Fig. 1.

In each layer, the nodes do the same tasks, and square nodes are adaptive, meaning that their output depends on the parameters obtained using the learning process. In the first layer, the input values are converted into fuzzy sets. The membership functions such as Triangular, Trapezoidal, or Gaussian map crisp inputs into fuzzy inputs. First, this step's parameters are set as premise parameters, and then during the learning process, more suitable membership functions are set. In the second layer, rules are constructed in each node using the membership functions of layer one. The output of each node determines the firing power

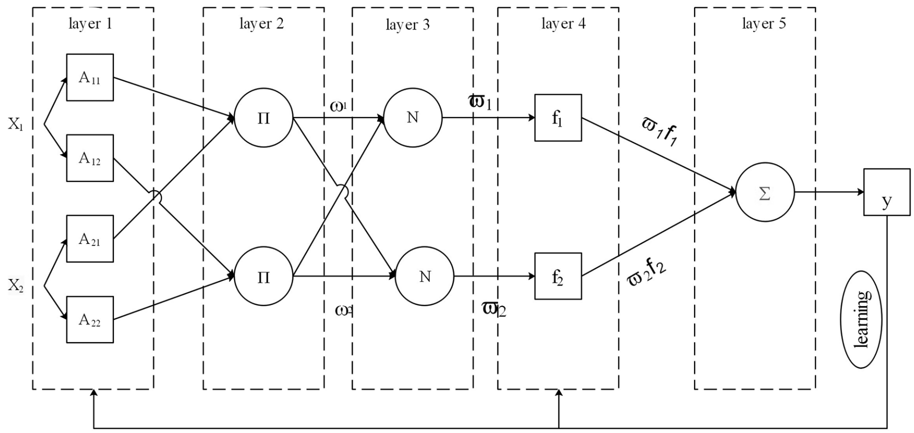

Figure 1: Structure of ANFIS technique.

(w_i) of each rule (Jang, 1993). In this layer, the T-norm operator is used to produce output equation (1). In the third layer, the previous layer's firing power is normalized, as given in equation (2). All nodes in layer two and three are fixed. In the fourth layer, using equation (3) we obtain some functions that their parameters are improved during the learning process. Finally, in the fifth layer, the total output is calculated by equation (4).

$$\text{Second layer outputs}: O_i(x) = \mu_{iA}(x) \cdot \mu_{iB}(x) \tag{1}$$

$$\text{Third layer outputs}: \varpi_i = \frac{\omega_i}{\omega_1 + \omega_2 + \ldots + \omega_n} \tag{2}$$

$$\text{Fourth layer outputs}: O_i = \varpi_i f_i = \varpi_i (a_i x + b_i y + c_i) \tag{3}$$

$$\text{Fifth layer output (total output)}: O = \sum \varpi_i f_i \tag{4}$$

To improve the ANFIS accuracy, it is needed to choose the appropriate network topology, such as the type and number of membership functions and operator of the inference rules. This process requires a set of output and input data samples. Then, the sample set is divided into two parts for training and validation. In the forward pass, using the least-squares method, we identify the consequent parameters and parameters updated by the gradient descent method in the backward pass. As a stop measure, the number of epochs indicates the frequency of the training process.

Supply chains face uncertainty, mass, and vagueness of datasets and complex conditions due to the expansion and existence of different layers. In such situations, the ANFIS model can provide efficient and flexible solutions by combining fuzzy logic and neural networks (Rajab & Sharma, 2018). The ANFIS is a powerful predicting technique used in many studies (Nayak *et al.*, 2005; Lin & Chang, 2008; Patil *et al.*, 2011). ANFIS usually works with big data due to its learner nature, and its integration with blockchain technology can provide a trusted platform for data collection across the supply chain (Salah *et al.*, 2019). The proposed decentralized ANFIS would receive, store, and analyse data in real time without trusted intermediaries.

4. Blockchain Technology

Blockchain has become one of the disruptive technologies. Although this technology was introduced in 1990, it was not widely used until 2008, when Nakomoto introduced Bitcoin. Blockchain is a peer-to-peer network in which all members can interact without intermediaries (Pundir *et al.*, 2019). As a "public ledger," blockchain includes a distributed digital ledger in which all transactions and data are collected and shared in a secure and trustless platform using cryptography and consensus algorithms (Di Vaio & Varriale, 2020). The blockchain contains a sequence of blocks, each containing a list of transactions and data, the hash block, and the previous block hash. The hash of each block is unique and identifies that block's authenticity. Therefore, blocks are connected in a chain, and a change in one block causes a change in the whole chain. If a user intends to manipulate or change data in a blockchain, it needs to make many costly changes that make it virtually impossible. Each member in the blockchain has a private key and a public key. Network transactions are digitally signed by private keys and shared across the network, and users can access these transactions using public keys (Zheng *et al.*, 2017).

Based on access to read and write information, blockchains are divided into three categories: public, private, and consortium (Zheng *et al.*, 2017). In a public blockchain, as a sort of permissionless blockchain (Bamakan *et al.*, 2020), information is available to all members, and everyone can be present in the consensus process. This sort of blockchain is fully decentralized and does not require a preestablished identity, and anyone can join the network as a node (Litke *et al.*, 2019). In the consortium blockchain (federated blockchains), although the information is available to all members, only the selected nodes can participate in the consensus process. Private blockchain (permissioned blockchains), like a centralized network (Zheng *et al.*, 2017), is only available to specific members, and an authorized group performs the consensus process. Permissioned blockchain requires a third party to manage identity and access to join the network (Litke *et al.*, 2019). In permissioned blockchain, the main goal is to maintain the security of transactions between groups of members who do not have complete trust in each other. In this category, the participants' identities are identified, and other members do not necessarily have access to other members' transactions. These features reduce the cost of consensus and increase efficiency and privacy (Carvalho, 2020).

Consensus algorithms are used to validate transactions in a decentralized network. The consensus algorithm is considered a blockchain core operator, and each block is added to the previous blocks if approved in the consensus algorithm (Bamakan *et al.*, 2020). Consensus algorithms are divided into two types (Nguyen & Kim, 2018). In proof-based algorithms, nodes must solve a cryptographic problem to verify and add a new block (Pahlajani *et al.*, 2019). The most important proof-based

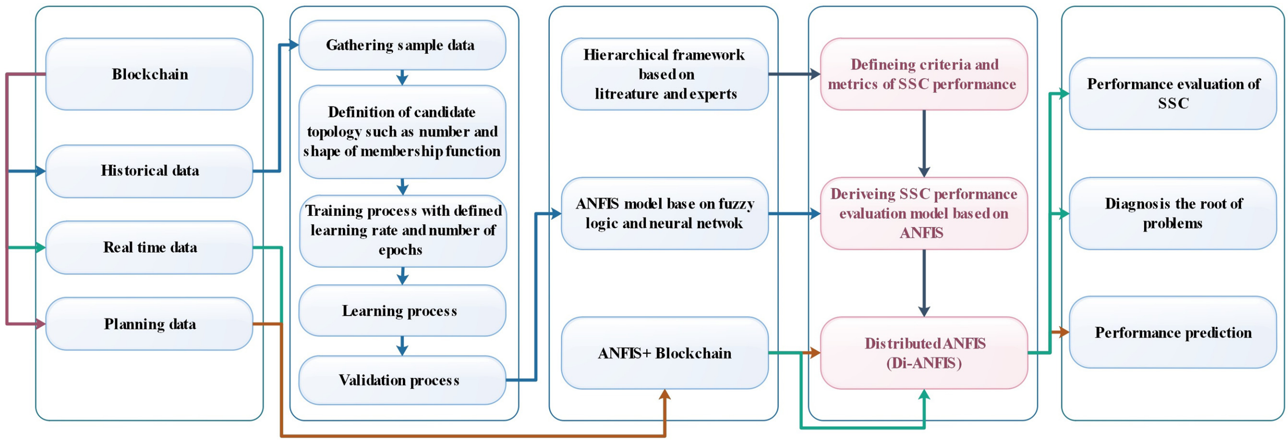

Figure 2: The steps of deriving the SSC performance evaluation system.

consensus algorithms used in blockchain are Proof of Work (PoW), Proof of Stake, and Proof of Burn. In PoW as the most popular algorithm, the nodes compete to reach an agreement, and finally, a miner or node calculates a mathematical cryptographic puzzle through the hash function. The PoW provides high trust and decentralization but requires expensive hardware and significant energy. In permissioned blockchains, voting algorithms are preferred. A new block is verified in these consensus types and joined to a network that at least *x* (threshold set) peers agree (Pahlajani *et al.*, 2019). Practical Byzantine Fault Tolerance (PBFT), Delegated Byzantine Fault Tolerance, and Federated Byzantine Agreement are samples of voting algorithms. For example, in the PBFT algorithm, all nodes must participate in the voting process, and when two-thirds of the nodes agree, the consensus is reached. PBFT does not have hardware dependence nor high energy consumption. These algorithms are used according to network conditions and various criteria such as speed, energy efficiency, decentralization levels, scalability and hardware dependence (Bamakan *et al.*, 2020). It should be noted that the permissioned blockchain and PBFT algorithm are the most common blockchain and consensus algorithm for supply chain.

Implementing smart contracts is one of the capabilities of blockchain. Smart contracts are computer programs that are executed automatically if the predetermined conditions are met. Blockchain platform allows them to run without the need for reliable intermediary approval. These contracts are stored in the blockchain as an immutable transaction, and their implementation depends on consensus protocols. Smart contracts can monitor the progress of planned processes and detect plan deviations (Dolgui *et al.*, 2020). IoT could benefit from smart contracts. For instance, device identities are registered and verified by smart contracts. Also, messages from devices can be stored in the form of transactions through smart contracts (Reyna *et al.*, 2018). Smart contracts reduce risk and increase real-time decision making and efficiency by saving negotiations cost, communication time, and setting rules and regulations (Wan *et al.*, 2020). Ethereum is one of the blockchain platforms for implementing smart contracts.

One of the major barriers to supply chain integration is the lack of trust, substantially addressed by blockchain features (Wan *et al.*, 2020). Besides, the integration of blockchain with smart contracts and IoT devices makes it able to collect, store, and share information in real time, which increases transparency and traceability. While in many cases, the third part is required to confirm transactions, blockchain would meet this need with its unique features. This capability can be significant, especially in SCM, which includes many individual and organizational relationships and the interconnected chain of planning, coordination, and control from suppliers to customers (Di Vaio & Varriale, 2020).

5. Proposed Model

In this study, to evaluate SSC's performance, a conceptual model based on ANFIS and blockchain is presented. The model includes the three main steps provided in Fig. 2. In the first step, according to the literature, key performance areas (KPAs), criteria, and metrics for performance evaluation in smart SSC are defined. In the second step, the SSC performance evaluation model based on ANFIS is derived that enables decision makers to design an up-to-date model for supply chain performance evaluation using big, historical, and trusted data in the learning process. By combining fuzzy logic and AI and using hierarchical criteria, the ANFIS model is not only able to evaluate performance with quantitative and qualitative inputs but also has the power to predict the performance. Finally, in the third step, based on blockchain, a distributed ANFIS named Di-ANFIS model is characterized. At this step, the blockchain, in combination with IoT and smart contracts, meets the data required by the ANFIS model. IoT empowers the ANFIS learning model by collecting big data. Besides, smart contracts prepare data and select the best models to evaluate performance and bring automation and privacy into the system. Di-ANFIS would evaluate SSCP and diagnose the root of problems through available real-time and trusted data. The proposed model is described in detail in the following subsections.

5.1. KPAs, criteria, and metrics of SSC

The SSC consists of three sections as basic units, namely the supplier, the service provider, and the customer, that work closely together (Baltacioglu *et al.*, 2007). SSC management includes activities on the whole chain under these basic units, and information flow as a critical factor has a wide impact on chain management.

In this study, based on the literature, a hierarchical framework for SSCP evaluation is proposed. Based on the criteria extracted from Cho *et al.* (2012) and Xie *et al.* (2020), and the SCOR model, we categorize them into three levels to develop the hierarchical structure. This division is derived with a broad

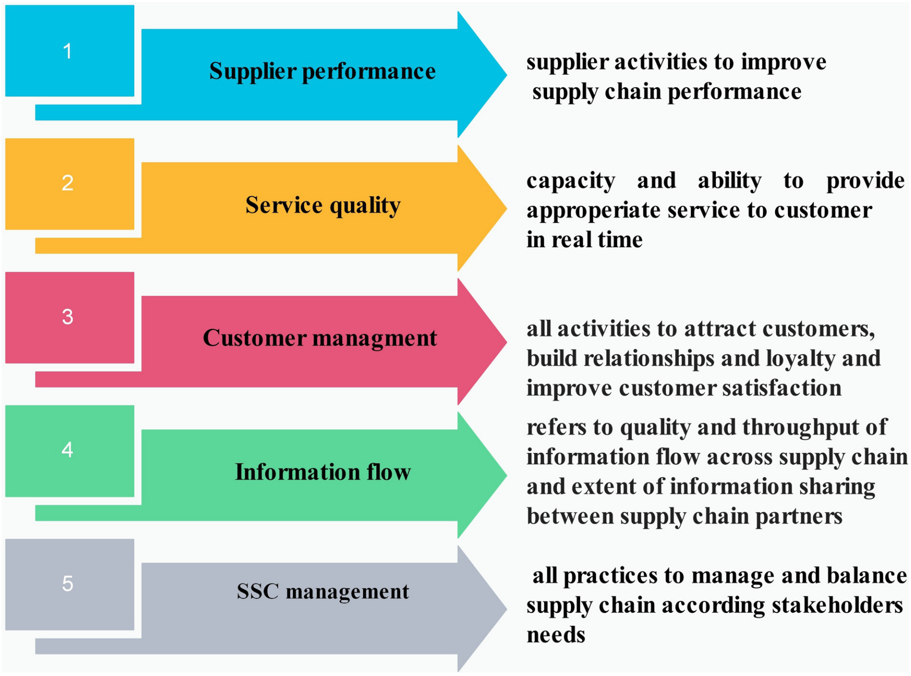

Figure 3: The KPA of the SSC.

perspective at SSC, the smart SC under Industry 4.0, and the SCOR reference model. KPAs of SSC emerged as the first-level criteria. These criteria include up and down streamside of supply chain and information flow across it. The KPAs are categorized into supplier performance, service quality, customer management, information flow, and SSC management, as shown in Fig. 3. Each of the first-level criteria is measured by submetrics, as shown at the second level. Additionally, to identify the root of the gaps in the second level, another submetric level is proposed as the third level. Table 1 illustrates the hierarchical framework of SSC performance evaluation criteria.

Supplier performance as one of the KPAs underlines the supplier activities to improve SSC performance, such as quality of supplier service, delivery speed, and supplier commitment. This area is broken down into two subcategories of suppliers' strategies and the quality of their services.

Service quality depends on the capacity and ability to provide appropriate service to customers in real time. Customer query time and variety of services are among the important criteria of this part. Service quality addresses the reliability, responsiveness, and tangibility of SSC.

An important area in the performance evaluation of SSC is the customer management, which means all activities to attract customers, build relationships and loyalty, and improve customer satisfaction. It includes planning for customer relationship management and providing unique customer services.

Information flow as a critical factor refers to the quality and throughput of information flow across the supply chain and the extent of information sharing between supply chain partners. In this area, accuracy and adequacy of information, visibility, and decentralization degree play important roles in SSC performance.

Finally, SSC management is considered another key area to maintain the whole chain's integrity, including effectively managing the demands according to stakeholders' needs. This area comprises seven criteria: leagility as the combination of lean and agile, sustainability, financial, effectiveness, profitability, governance, and intelligence.

The criteria presented in Table 1 have been extracted due to SSC's nature and new approaches to the supply chain, such as sustainability and supply chain 4.0. Under Industry 4.0, real-time information sharing and intelligent big data analysis transform SCM. Using smart contracts and trust models, decentralization, traceability, and transparency are important criteria that affect new supply chains' performance. Intelligent and learner SC is an approach that we also discuss in this study. In the next section, we address applying these criteria to evaluate the SSC performance.

5.2. ANFIS model for SSCP evaluation

ANFIS proposes a quantitative model for performance evaluation. ANFIS model by employing fuzzy logic and supervised learning algorithms would deal with uncertainty and simulate the human decision-making process (Kar *et al.*, 2014). According to the hierarchical framework for SSC performance evaluation presented in Table 1, a set of 22 ANFIS models is designed to model the causal relationships between criteria (Figs 4 and 5). This causal structure makes it able to diagnose the root cause of weak performance. Besides, it would help managers to predict the supply chain performance and improve it.

The proposed model's inputs include quantitative and qualitative data gathered across the supply chain parts. The results of the 1st to 16th ANFIS model construct the second level of criteria. In the case of the fourth ANFIS model, "customer query time" and "order time" as inputs are used to estimate the value of "responsiveness" as the input of the second level. The output value of responsiveness and two other variables, including reliability and tangibility, are used as the input value of the 18th ANFIS. Finally, the 22nd ANFIS measures SSC's overall performance value using KPA scores as the input variables.

All ANFIS models from 1st to 22nd are generated in the process that is shown in Fig. 2. For this purpose, at first, a sample

Table 1: The hierarchical framework for SSC performance evaluation.

KPAs	Criteria	Metrics	Source
Supplier performance	Supplier strategies	Long-term partnership	(Gunasekaran *et al.*, 2004; Council, 2005; Cho *et al.*, 2012; Pandari & Azar, 2017)
	Supplier service quality	Supplier cost reduction plans Supplier commitment Quality of supplier service Pricing against market Delivery speed	
Service quality	Reliability Responsiveness Tangibility	Service order lead time Rate of orders full delivered Accurate forecasting Customer query time Order time Variety of service The capacity of offering service	(Cho *et al.*, 2012) (Council, 2005)
Customer management	Customer relationship	Customer order network Customer satisfaction Customer retention Attracting new customer plan personalized needs of customers	(Cho *et al.*, 2012; Xie *et al.*, 2020)
Information flow	Information throughput	Latency	(Li *et al.*, 2005; Debabrata & Albert, 2018; Xie *et al.*, 2020)
	Information quality Information sharing	Verification time Information accuracy Information adequacy Transparency Traceability Complaints management	
SSC management	Leagility	Flexibility	(Gunasekaran *et al.*, 2004; Council, 2005; Cho *et al.*, 2012; Pandari & Azar, 2017; Xie *et al.*, 2020)
	Financial Sustainability Effectiveness Profitability Governance Intelligence	Cross-selling Market share Overall value at risk Cost optimization Rate of return on Investment Total cash flow time Cost reduction Human productivity Energy productivity Environmental pollution Recyclability Total cycle time Actual-to-the planned working ratio Average customer spend per visit Degree of decentralization Trust model Permission model Innovation ability Adoption ability Risk management Smart contracts	

of historical data is collected from the measured criteria. Candidate topologies such as membership functions are selected, and the if-then rules are made. Then, the sample set is divided into two subsets of training and evaluation sets. By choosing values such as learning rate and training epoch, the learning and validating process is run. Finally, the ANFIS model with the best accuracy value is selected.

5.3. Di-ANFIS model for SSC performance evaluation

In this section, the Di-ANFIS model is designed for SSC performance evaluation by taking advantage of blockchain technology. Geographical extent, dynamic conditions, multistakeholders, and cultural differences are important factors influencing SSC. Hence, efficient and dynamic technologies are required to manage SSC. Motivated by this reality, a fuzzy inference system

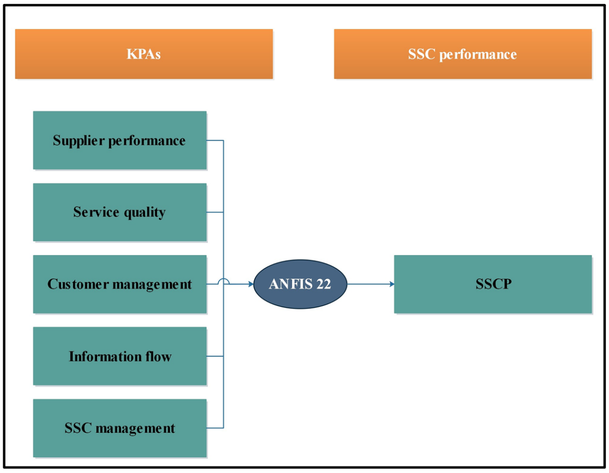

Figure 4: An overview of the ANFIS model for SSC performance.

and neural network were selected to deal with the uncertainty and complex nature of SSC. Besides, we have utilized new technologies such as blockchain, smart contracts, and IoT to guarantee SSC's agility, trust, and security. Blockchain-based IoT by cryptography, consensus algorithms, and distributed ledger provides decentralized and trustworthy data across the entire SSC and builds a smart SC.

As big data are being generated with great velocity, volume, and variety in SC, extracting useful information from them empowers managers to make decisions, optimize, and improve performance. However, this process requires a reliable information technology infrastructure to collect, record, share, and analyse data. To achieve this goal, the Di-ANFIS model is proposed encompassing six layers, as shown in Fig. 6. The first layer is the data layer representing the system's data input sources, including suppliers, service providers, and customers. The big data generation takes place through organizational and inter-organizational activities, communication, and supply chain partners' cooperation. Devices in SC entities act as nodes, and each node contains a copy of the blockchain. The components of this layer are connected as a network, and the next layer supports these connections.

The second layer is a connection layer that contains the necessary infrastructure to receive real-time information. IoT technology, as a dynamic global network infrastructure (Readiy *et al.*, 2015), supports big data collection and transmission. IoT consists of three main layers: sensor layer, communication layer, and application layer (Chettri & Bera, 2019). In the first layer, it collects data from all over the supply chain, and the second layer is responsible for communicating and storing information. The third layer would enable the system to exploit data in conjunction with the ANFIS model.

IoT improves data collection accuracy and paperwork management by the automation process. The standards and protocols applied in IoT devices facilitate organizational and inter-organizational communication, leading to the agile sharing of operational and planning data across the supply chain. It accelerates timely information sharing by wireless components and networks such as Wi-Fi, local area network, or wide area network. Among the benefits of enhancing information sharing are reducing paperwork and human errors and mistakes, besides increasing visibility and integration of processes.

IoT devices gather and record suppliers, service providers, and customer information. Nevertheless, the reliability and trustworthiness of data are an important issue. Blockchain would enrich IoT by a secure distributed ledger and sharing nonmanipulative information for all participants. The real-time data across the SSC are formatted and stored as transactions. By doing each transaction, a Cryptographic Digital Signature is created by using the private key. Each transaction includes the section ID, timestamps, and related notes. New transactions are placed in a distributed ledger in the network. For verifying and distributed storage, they are transferred to the next layer.

In the third layer, those transactions that passed the verification process by the mining operations and consensus algorithm append to the blockchain as a new block. Verification is usually done by one of the SSC stakeholders or through electronic voting due to consensus algorithms. Blockchain uses the Merkle tree function to generate a unique hash for each block. Merkel tree as a data structure stores the transactions separately. Each block must contain at least one transaction and can contain thousands of transactions. Each block contains the current hash block and the previous hash block, making it immutable. Therefore, the distributed database shares a tamper-proof ledger of data across the entire SSC.

In the smart layer, there are smart contracts as predefined programs on the blockchain platform. They are usually stored on a blockchain platform with special access. Privacy is another important issue in information sharing. Due to competitive advantage, some information in supply chain sectors should be kept confidential. Smart contracts would protect the privacy and enhance trust in SC by controlling access authority. They are applied to improve process management and process automation.

On the other hand, some smart contracts sample historical data for the learning process to derive the appropriate evaluation model. Some others collect data according to the metrics mentioned in Table 1. In particular, some smart contracts quantify and prepare data to use in the next layer as the ANFIS inputs. The other smart contracts choose the best model for performance evaluation from available models. So, many of them do the process of preparing big data for analysis.

The task of the fifth layer is evaluating SSC performance. The ANFIS model, using sample data in the training and verification process, derives the evaluation model. One of the limitations of the ANFIS model is the necessity of big data collections for the learning process. It should be noted that in real-work problems, decision makers face difficulties accessing trustable data across the supply chain, and even some of these data are manipulated.

The Di-ANFIS model architecture explains how we can employ blockchain and IoT to deal with this challenge. In the proposed model, IoT is used to collect, control, and manage all supply chain data, and blockchain provides a trustworthy platform. Learning models can be tested with smart contracts, and search paths can be saved in blockchain for future applications. This layer receives all the necessary trust data to measure SSC performance. It would enable decision makers to address the deviations from expected performance and identify the root causes of problems. Decision makers predict the performance and simulate strategies with different goals through the available planning data.

Performance management of SSC is the final goal of our model. Analysing data by business intelligence manual or software tools leads to specific plans for each performance area. Secure and traceable knowledge from the application layer is shared with the stakeholders in the blockchain platform. Therefore, partners receive trust feedback from their performance to motivate partners and lead to a positive experience.

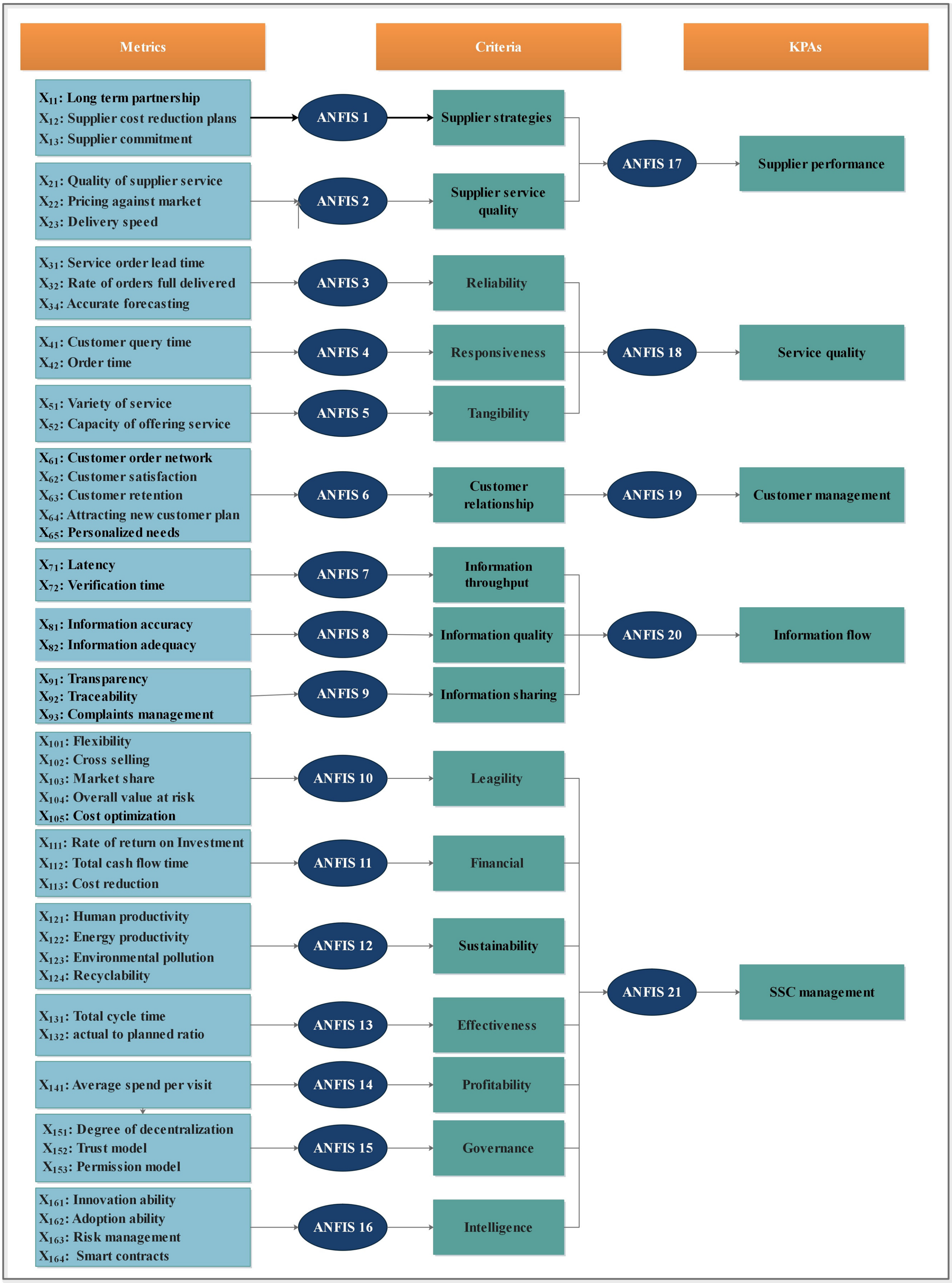

Figure 5: The hierarchical structure of the ANFIS model based on identified KPAs.

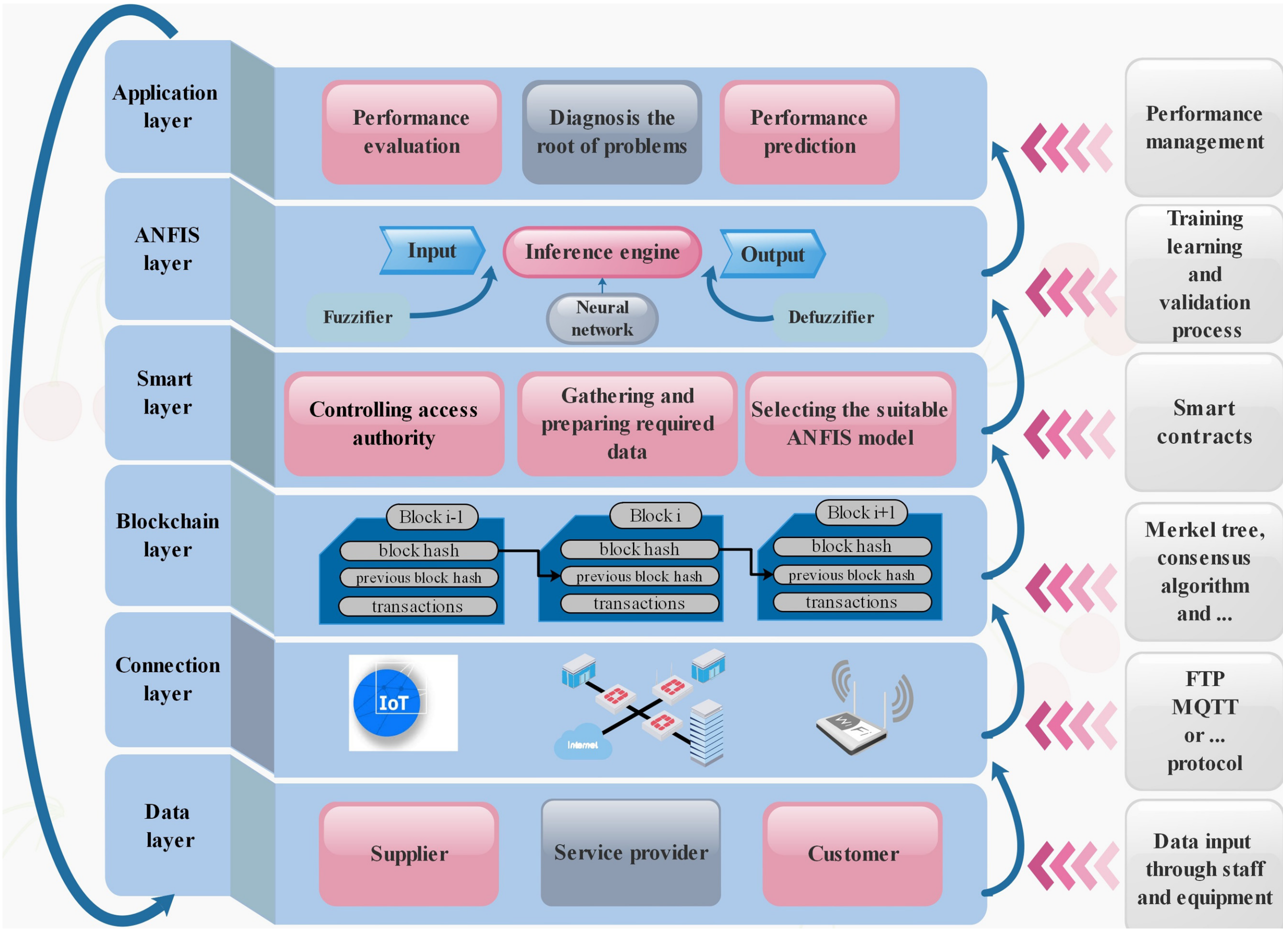

Figure 6: The Di-ANFIS model for SSC performance evaluation.

In this system, all performance evaluation processes, including collecting, transferring, managing, analysing, storing data, and reporting results, are performed in a safe, reliable, transparent, and traceable manner with the least manipulation. Besides, the Di-ANFIS model can continuously update the learning process, using trusted historical data. As a result, this system is considered an agile learning model that constantly adapts using reliable data. Decision makers in different parts of the chain can compare real performances with planned ones to achieve the root causes of poor performance and monitor their decisions. In such a system, the competition between the members of the chain would increase to perform efficiently.

6. Discussion and Challenges

In the last decade, blockchain and AI have developed rapidly. On the other hand, with the expansion of SSC, the use of new technologies in SCM has become an attractive research area. This paper's main purpose was to draw attention to the integration of blockchain and AI for SSC performance evaluation. We first proposed a hierarchical framework of the SSC performance criteria according to the literature review. Moreover, a predictive and diagnostic distributed ANFIS model was proposed. To turn this model into a secure, transparent, and traceable system, the Di-ANFIS model is integrated by blockchain, IoT, and smart contracts. However, some main concepts and challenges need to be addressed.

6.1. Traditional toward smart performance evaluation

Performance evaluation is a way to measure supply chain efficiency and plays an important role in SCM. Due to the dynamic nature of the supply chain, timely evaluation and even performance prediction before implementing strategies can play an important role in supply chain planning and management. Traditional methods and models are often based on past data and static models (Lapide, 2010). Traditional models usually evaluate the past performance of units to allocate funds and implement a reward and punishment system. Lack of trust and resistance is another challenge of traditional performance appraisal systems.

Under Industry 4.0 and the advent of new technologies, SCM also shifted to a smart system. These smart systems reduce risk and improve supply chain planning. Trust, distributed learning, and self-thinking supply chain are concepts that have changed or recently emerged through these technologies.

6.1.1. *Trust model*

Supply chains usually consist of a large number of components that have complex relations between themselves. These components have to interact with each other to share data, products, services, information, and infrastructure. One of the major factors to coordination, cooperation, risk management, and time and cost reduction is building trust between them (Esmaeili *et al.*, 2014; Mathew *et al.*, 2020). Trust is often considered the core of risk management and SC partners' long-term relationships (Laeequddin *et al.*, 2012). In this regard, many studies have explored trust factor identification, trust evaluation, and trust model construction. Handfield and Bechtel (2002) discussed the effect of trust on supply chain performance by proposing a relationship model to improve supplier responsiveness. Besides, Lin *et al.* (2005) proposed a trust model for network-enabled organizations and evaluated the SC performance. They stated the consequences of SC's trust mechanism, including in-time order fulfillment, reducing cycle time, and increasing unit cost of materials. Mukherjee and Nath (2003) proposed a trust model for online banking and indicated that shared value is the most critical factor in developing trust among involved parties. Xiong and Liu (2002) have demonstrated three critical parameters to evaluate the trustworthiness of peers. They suggested a peer-trust model for decentralized peer-to-peer electronic systems. Özer and Zheng (2017) proposed business infrastructure, personal values and norms, business process design, and market environment as four building blocks of trust in SC. They recommended information sharing as a major factor in risk reduction and increased coordination. In addition, some studies have used fuzzy logic, probability theory, or game theory to build models of trust. Nafi *et al.* (2012) presented a trust model for e-commerce systems based on fuzzy logic and probabilistic logic. Esmaeili *et al.* (2014) introduced a mathematical trust model in two-echelon SC by the Stackelberg game concept. They used the beta model to verify the trust of the proposed model.

Recently, with the integration of blockchain and IoT, the concept of trust in SC has been changed. In fact, by introducing Industry 4.0, information sharing and big data analysis have transformed the SCM. As a result, blockchain has great potential in information sharing and trust provision. A decentralized system consisting of blockchain and IoT eliminates the need for centralized trust and introduces a new approach to trust between partners in SC (Wingreen & Sharma, 2019). Due to peer-to-peer networks, distributed data sharing and storage, consensus algorithms, and authenticity verification, blockchain would support transparency and traceability in SC. Moreover, blockchain can reduce risk by deploying smart contracts to facilitating process automation. Jahanbin *et al.* (2019) improved trust in agricultural SC based on the integration of blockchain and IoT, using decentralized technology to support quality, safety, and sustainability. Lizcano *et al.* (2020) evaluated distributed ledger technology to create a trust model in higher education. In this study, blockchain is employed to remove the gap between the academic world and the working world. Reviewing recent studies illustrates the growth in the development of blockchain in SCM. To provide a secure and trusted SSC performance evaluation framework, this study proposed the Di-ANFIS model as presented in Fig. 6. At first, an ANFIS model was designed. Then, the final six-layer model was introduced, in order to provide a secure and trusted platform by using IoT, blockchain, and smart contracts.

6.1.2. *Distributed learning*

Blockchain-based SC encourages partners to share data on the network. Blockchain technology uses secure data sharing mechanisms to make decisions more reliable and trustable. The integration of blockchain, IoT, and big data facilitates the process of obtaining sufficient and appropriate data for training models. Data-driven analysing techniques such as ANFIS require a huge amount of data and high computing power. Although cloud computing can process big data, some challenges remain, such as visibility, trust, and privacy (McMahan & Ramage, 2017).

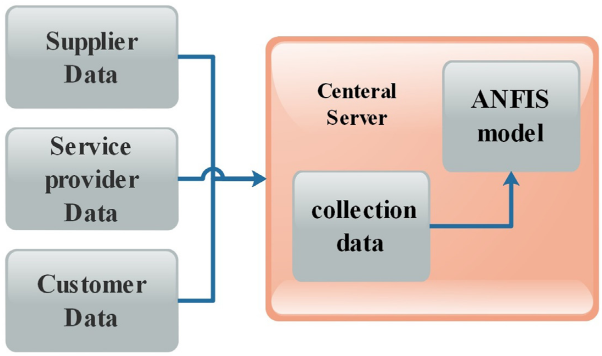

Figure 7: Centralized learning framework of Di-ANFIS (Mendis *et al.*, 2020).

Hence, blockchain technology would empower learning methods by leveraging decentralized data and distributed computing power (Mendis *et al.*, 2020).

The conventional models are designed as a centralized learning framework that required a central server with high storage capacity for collecting distributed data from SSC (Fig. 7). As a common challenge in such systems, SC entities are often reluctant to share data due to the privacy and high value of their data.

In recent studies, distributed computing models were proposed to solve the problem of sharing private data. McMahan and Ramage (2017) developed a distributed machine learning approach as federated learning. Strom (2015) proposed a new deep neural network by distributed stochastic gradient descent training. In such architecture, data providers reserve private data. After the local training process, a data provider only shares the private learning model. In this model, learning occurs in distributed servers. However, a central controlling agent is required, as shown in Fig. 8.

Mendis *et al.* (2020) introduced a distributed and autonomous learning model by adopting blockchain technology. To remove the central server, they presented a distributed learning model by homomorphic encryption techniques via sharing data and increased confidence. According to them, a distributed and autonomous learning framework of the proposed Di-ANFIS model is illustrated in Fig. 9.

6.1.3. *Self-thinking SC*

The self-thinking supply chain is introduced as a new concept in the field of SCM. Calatayud *et al.* (2019) proposed a new autonomous and predictive SC model by a combination of IoT and AI. With the advent of new technologies under Industry 4.0, a major transformation in data collection, data analysis, and process automation has emerged. Based on this revolution, SC is enabled by big data analysis in a real-time and accurate manner. Agility, autonomous learning, and self-awareness are the main objectives of SC's self-thinking perspective (Calatayud *et al.*, 2019). By adopting the concept of self-thinking, it can be stated that this study proposed a self-thinking SSC model, wherein data are collected across the SSC in real time at the communication layer and then exported to the Di-ANFIS model for further analysis. ANFIS layer leads to agility and flexibility with its prediction and learning power. In addition, blockchain-based self-thinking SC not only reduces risks of agility and flexibility, but also provides a secure and trusted environment for data sharing.

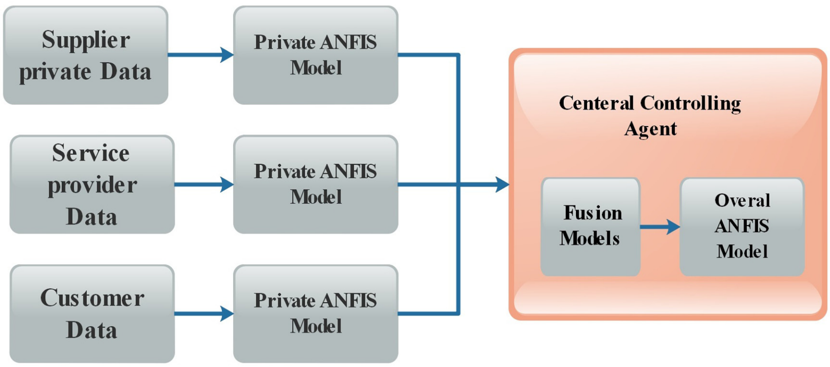

Figure 8: Distributed learning framework of ANFIS (Mendis *et al.*, 2020).

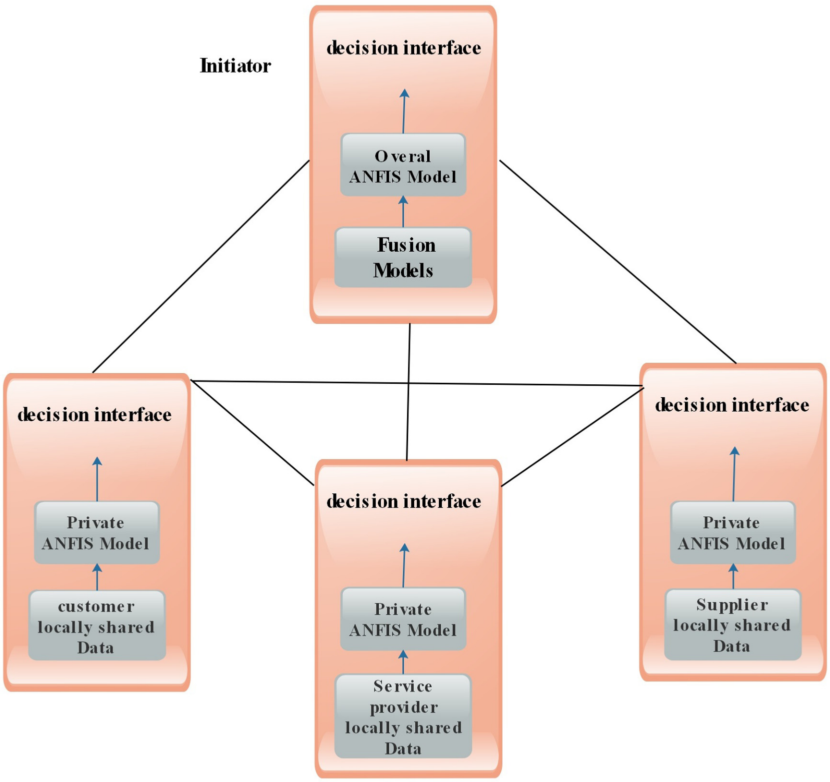

Figure 9: Distributed and autonomous learning framework of ANFIS (Mendis *et al.*, 2020).

Despite recent advances in blockchain's application in SC, several other issues remain as open challenges and future trends.

6.2. Challenges

6.2.1. *Technical and operational challenges*

Scalability is one of the main challenges of large-scale networks, causing high computational complexity and high cost (Patel *et al.*, 2017). The distributed nature of blockchain can be challenging for supply chain governance. Therefore, a set of rules for how members communicate and contribute must be specified (Wang *et al.*, 2019), and all actors must abide by these rules and policies. However, it should be noted that because of different degrees of computerization in organizations involved in the supply chain, the full realization of blockchain in the supply chain is difficult (Kshetri, 2018). Further, although blockchain protects the system from tampering, it is also difficult to correct when a mistake occurs (Patel *et al.*, 2017). Eventually, despite all the precautions, conflicts of interest, accidental errors, and malicious attacks may happen (Kshetri, 2018).

6.2.1. *Managerial and social challenges*

Although moving from traditional management to smart management has many benefits, it may face cultural resistance. Therefore, accepting new distributed and open systems and their full implementation take a long time. Besides, due to the technical complexity and high costs, raising capital and expert human resources are other challenges. Accurate perception and individual skills are other needs for using new technologies (Janssen *et al.*, 2020).

7. Conclusion

Evaluating supply chain performance is a challenging task in SCM. In addition, because of services' inherent characteristics, performance evaluation in this area faces more challenges. The main purpose of this paper was to design a performance evaluation system for the SSCs. At first, to diagnose the root of problems, a hierarchical framework for SSC performance evaluation criteria was presented. This framework consists of three levels: metrics, criteria, and KPAs. The ANFIS model was proposed as a learning and predictive model for performance evaluation in the next step. Finally, we proposed Di-ANFIS architecture by integrating blockchain technology, IoT, and smart contracts to achieve a secure, trustable, and intelligent performance evaluation system. The proposed Di-ANFIS architecture contains six layers: the data layer, connection layer, blockchain layer, smart layer, ANFIS layer, and application layer. This architecture can track and transfer information and collected data in a secure and tamper-proof environment across the supply chain. In this study, we presented a conceptual model that provides a foundation to develop a supply chain performance evaluation system, but this requires that the model be explored in the real world and practice. In addition, smart models of blockchain, IoT, and smart contracts can be developed in other supply chain areas such as risk management, innovation management, and product management.

Conflict of interest statement

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