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Hiba Hamdi Hassan

Rana Fareed Ghani

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ORIGINAL STUDY

Supply Chain Network Based on Blockchain and Intelligent Agent

Hiba Hamdi Hassan [a,*], **Rana Fareed Ghani** [b]

[a] University of Technology – Iraq, College of Computer Science, Al-Sina'a St., Al-Wehda District, 10066 Baghdad, Iraq
[b] University of Technology – Iraq, College of Computer Science, Department of Computer Networks and Web Development, Al-Sina'a St., Al-Wehda District, 10066 Baghdad, Iraq

ABSTRACT

In agricultural supply chains, the complexity and indeterminacy pose serious challenges to traceability, reliability and confidence today. This challenge is especially acute in the olive oil industry where adulteration, wrong labeling, and uneven chemical quality threaten the actual well-being of producers and consumers. The project aims to design a blockchain-based hybrid architecture with intelligent agents (FNNs) to enhance transparency, reliability and responsiveness in the olive oil supply chain. The Blockchain component enables a completely open, tamper-proof ledger to be built in a very decentralized way and preserved as an archive of every account of its transactions. The intelligent agents contribute to automated decision making, quality control and logistical optimization. The system leverages a real dataset of chemical olive oil with 572 samples with nine fatty acid statistics by being trained, and the system consists of four intelligent agents who work with a specific FNN-based FNN model. The system was validated using agent-based simulations that can reach accuracy levels of 82%, with low error rates, minimum Mean Squared Error (MSE) equal to 0.0157, low execution delay, and no real-world use was possible, the experiments were conducted as controlled simulations, and the feasibility of this model into real supply chain was assessed based on future studies. Results indicated that the computational overhead of the agents is uniform, and the performance is better than that of the ordinary or independent method. This system validates the system real-time and provides reliable information throughout the supply chain, creating an ability to establish real value from a single supplier and in achieving the goal of the SCM in the process of sustainable SCM for the other perishable goods sections.

Keywords: Supply chain, Intelligent agent, Blockchain, Decision automation, Fuzzy neural network, Agricultural sector

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* Corresponding author.
E-mail addresses: cs.19.05@grad.uotechnology.edu.iq (H. H. Hassan), rana.f.ghani@uotechnology.edu.iq (R. F. Ghani).

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1. Introduction

Today's supply chains are complex multi-level networks that include numerous contributors and involve varying methods, computing instruments and systems. For the olive oil industry, such complexity presents a genuine supply chain challenge because of the perishable decentralized form of agriculture and it results in traceability issues where it is challenging to determine the source and quality of each batch produced for farmers, distributors, and retailers. A problem in the supply chain network arises when suppliers, manufacturers, warehouses, distributors, retail stores, and customers are all part of a system. Disruptions due to lack of logistics, operational, financial or external factors, such as disruption of flow of products, information, capital and fluctuating demand or season, unreliable exchange of data means higher quality problems and incorrect information for the consumers, which will delay the service. Blockchain has introduced itself as a potential technological method for enhancing global trade and Supply Chain Management (SCM) [1]. This is compounded in agriculture as goods are perishable, demand varies, and production is decentralized. Challenges related to this have helped to ensure transparency, traceability and trust at every stage in the supply chain from suppliers to end consumers [2]. Nevertheless, despite this growth of worldwide trade, application of the world average of Most-Favoured-Nation (MFN) tariffs at around 9% (currently) suggest continued high demands for trade liberalization [3, 4]. A centralized model is unable to maintain the same level of data integrity and real-time coordination due to the inherent inefficiencies, delays and unaccountability associated with this. Novel blockchain technology has shown remarkable potential to overcome these limitations by allowing for a decentralized, tamper-proof ledger to track transactions and confirm their authenticity [5, 6]. Through consumer empowerment, platform switching, and market transparency, e-commerce has transformed competition dramatically [7]. The increasing application of information and communications technology and on customer-centric business solutions is creating an increasing demand for flexible, responsive, and competitive supply chain systems. Today's supply chains call for flexibility, cooperation, integrity and agility. Thus, there are a number of existing researches that suggest new strategies and methods for these reasons. Blockchain allows participants trust to be established amongst themselves by virtue of data immutability; verifiable traceability through transparency, verifiable traceability and distributed consensus, which obviates intermediaries [8]. However, as of now, no one would dispute that blockchain can't provide smart decision making or predictive analysis itself yet. This is necessary in the context of modern day supply chain optimisations processes, especially in high-velocity scenarios such as agricultural logistics, where rapid agility and responsiveness are vital [9]. To address these potential shortcomings, we present an integrated intelligent method by merging blockchain and Fuzzy Neural Networks (FNN) in an artificial intelligent agent for self-thinking agent. The agents autonomously verify ongoing supply chain activity, predict the state of the system, support real-time and adaptive decision support, and all those other tasks. The reliance on FNN-based reasoning allows for better handling of uncertainty, incomplete information, and often active operating conditions in agriculture supply chains. In particular, it is the olive oil supply chain which is a key element of agricultural network, in particular because the perishability and traceability (quality and traceability of its product) of the olive oil supply chain are key for them. So in this way, the introduced framework seeks to increase operational transparency, automate the information validation and optimize the supplier validation with hybrid intelligence. The research framework is further tested with agent-based simulation experiments to measure predictive accuracy, Mean Squared Error (MSE), and computational performance. The above results indicate that the system proposed here performs better than simple centralised models in dealing with supply chain uncertainty and improving the overall resilience.

This study aims to:

(1) Develop a blockchain-based smart framework supporting transparency, integrity and end-to-end traceability within the olive oil supply chain,
(2) Create an intelligent multi-agent architecture to enrich automated network management on account of human perception, in precision, effectiveness and deterministic control;
(3) Develop the two stage learning and validation approach to build reliable decision rules, thereby enhancing system flexibility in the presence of uncertain and imperfect data.

This study is divided into sections: the first part is the literature review, presented in Section Two. Section 3 provides the theoretical background for the relevant subject of this research. This integrated intelligent system is presented in Section 4. Sections 5 and 6 illustrate the experimental results and the conclusion.

2. Literature review

In practice, different implementations of blockchain, artificial intelligence (AI), and multi-agent systems have been studied in the literature to improve SCM practices. Recent works offer several solutions to improve SCM practices. Here they include:

Ghorbel et al. [1] provide a secure environment for production security and monitoring on blockchain. This platform also collects and stores data from Internet of Things (IoT) sensors. Emmanuel et al. [4] investigate the theoretical foundations for artificial intelligence and their applications to improve the efficiency, responsiveness, and robustness of supply chains. Bager and Dodder [10] developed a highly realistic event-driven solution for tamper-proof traceability, which they subsequently verified in the coffee supply chain. Wang [11] designed an AI and blockchain approach to supply chain resource management to build secure systems, leading to improvement in employee contentment, economic security, and user satisfaction. Ghani et al. [12] developed a blockchain system to enhance the security and functionality of university e-certificate operations on campus. Moya, Chica, and Cordon [13] propose that we consider multi-objective performance indicators and attainment surfaces for performance evaluations of different evolutionary multi-objective optimization strategies. The analysis will be supplemented with statistical techniques to test the significance of the indicator values and to benchmark the algorithms' performance against a traditional mathematical framework. Experimental results reveal that, in most cases, decomposition-style algorithms outperform the other methods. [14] proposed agri-food supply chains. However, IoT technologies can be applied across agricultural fields, and without accurate predictions of crop demand, their effectiveness cannot be utilized. This study aims to overcome this shortcoming by using intelligent agents as a strategic model with the aim of enhancing the operational efficiency and transparency in the supply chain. The findings contribute toward the intelligent agent-based SCM, by incorporating smart agents in line with the dynamic needs of the new dynamic characteristics of contemporary supply chains and by focusing on its role within SCM. Forecasting is necessary to optimize the performance of all components of the supply chain such as OFD, and agricultural operations. Zheng et al. [15] suggested an iterated greedy algorithm, for food preparation time analysis by decomposing food preparation time into OFD units of processing and time to enhance the scheduling of foods and better performance. Zhang et al. [16] have applied ensemble learning methods for a national scale prediction of wheat production. It highlights the dire need for data-driven strategies for enhancing agricultural predictions and forecasting yield. Furthermore, for domains like the manufacturing of food and food distribution centers which may have significant energy consumption, as well as power consumption in restaurants, where the electricity consumption can be extremely varying, forecasting demand for electricity sources is even more important. Venkatramulu et al. [17] suggest a novel approach based on blockchain technology for the issuance, administration and validation of academic certificates for student programs in a decentralized and secure way. They illustrate the three-pronged nature of this work: showing reliable, trustworthy academic certificates, a secure way to exchange these certificates over a decentralized Application (dApp) and information sharing with responsible parties involved in certificate verification and exchanging only the required documents. The system guarantees that the academic records are tamper-proof, easy to share, and verifiable without a central authority through these elements. [18] introduced a new method to retrieve data more securely. It depends on generating a Quick Response (QR) code for the signature of the hash algorithms generated after the participants are proposed to do a transaction. Luo et al. [19] aim to review current risk assessment methods in import and export companies, focusing on integrating fuzzy logic and neural networks as a model better equipped to handle data ambiguity, multiple influencing factors, incomplete or inaccurate data, and nonlinear relationships between variables. The authors also highlight the Adaptive Neuro-Fuzzy Inference System (ANFIS) model as a suitable system for risk assessment in this field. Rita et al. [20] proposed a holistic approach to analyzing the applications and benefits of blockchain technology in SCM and to help researchers and practitioners understand the managerial impact, benefits, challenges, and limitations of this technology within each process in the supply chain. Abrar et al. [21] aim to develop an advanced, understandable deep learning-based model, the Multi-Channel Data Fusion Network (MCDFN), to improve the accuracy of demand forecasting in supply chains. The model aims to increase accuracy by integrating several types of neural networks, such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM), and Gated Recurrent Units (GRUs), while providing clear explanations of the forecasts using explainable AI (XAI) techniques.

A comparison between the current research and related work is presented in Table 1.

3. Theoretical background

3.1. Supply chain network

The complexity of worldwide supply chains builds from multiple business actors who handle operations under different administrative authorities with separate legal guidelines. In the olive oil field this complexity is especially challenging because companies often struggle to track product origin, ensure consistent quality and verify proper handling, which can result in delays, quality variations and reduced consumer trust. National variations in social values, environmental controls and work standards cause moral challenges throughout the entire supply chain. In the real olive oil market, issues like mislabeling and adulteration hurt both suppliers and consumers. Constraints on income and market demand for cheap offerings are essential, but people are increasingly mindful of ethical considerations [22]. SCND seeks to determine the best ways to source, produce, distribute, and store by evaluating the combined efficiency of operations and finance [23]. The strategy acknowledges that in some cases, retailers will prefer to pay higher unit prices to other retailers to achieve cost optimization. This strategic approach minimizes

Table 1. Comparison between the proposed system and related work.

Ref.	Method	Problem Addressed	Datasets	Results	Limitations
[1]	Blockchain + IoT platform for olive fields	Need for secure monitoring and real-time production tracking	IoT sensor data	Secure data storage and traceability for olive farms	Limited to Wireless Sensor Network (WSN-based) environments, scalability concerns
[4]	Theoretical AI approaches for SCM	clarity on how AI improves efficiency, adaptability, and resilience		Identified pathways to integrate AI in SCM	Limited to experimental validation
[10]	Event-driven blockchain traceability	Ensuring tamper-proof traceability in coffee supply chains	Coffee supply-chain events	Successful event-based traceability validation	Domain-specific, not generalized across industries
[11]	AI + blockchain for supply-chain resource security	Improving economic and production security	Enterprise operational data	Enhanced employee satisfaction and resource security	Limited evaluation, focuses on economic security only
[12]	Blockchain-based e-certificate system	Need for secure digital certification		High security and performance for student certificates	Not SCM focused, limited domain applicability
[13]	Evolutionary optimization for agent-based model calibration	Improving the accuracy of ABSM models	Synthetic and simulation datasets	Decomposition-based algorithms outperform others	Computationally expensive, not SCM-specific
[14]	IoT + agents for agri-food forecasting	Inaccurate food-demand forecasting	Agricultural data	Improved forecasting using intelligent agents	Depends heavily on high-quality IoT data
[15]	Iterated greedy algorithm for OFD scheduling	Stochastic online food delivery scheduling	OFD time data	Better scheduling and operational efficiency	Limited to the OFD domain, not suitable for multi-sector SCM
[16]	Ensemble learning for wheat production forecasting	Need for accurate national-level crop forecasting	National wheat statistics	High prediction accuracy for wheat yields	Focuses solely on agriculture, not SCM-wide
[17]	Blockchain for student certificate generation	Need for secure academic certificate verification	Academic records	Tamper-proof, decentralized verification	No relation to supply chains, limited scalability
[18]	Smart-contract–based data retrieval using QR	Secure data retrieval process	Cryptographic hash datasets	Improved data retrieval security	Narrow application, not applied to SCM processes

(Continued)

Table 1. Continued

Ref.	Method	Problem Addressed	Datasets	Results	Limitations
[19]	Fuzzy logic + neural network risk assessment	enigmatic uncertain import/export risks	Risk assessment datasets	ANFIS improves handling of unclear data	No real-world deployment, conceptual model
[20]	Holistic blockchain analysis for SCM	Fragmented understanding of blockchain in SCM	Secondary case-study data	System for blockchain benefits, challenges, and impact	No experimental system, only qualitative
[21]	MCDFN deep-learning forecasting	Low demand-forecasting accuracy in SCM	Retailer sales dataset	MSE = 23.57, Root Mean Square Error (RMSE) = 4.85, improved forecasting	High computational complexity, limited explainability
Proposed system	Blockchain + Intelligent Agents + FNN	Lack of transparency, traceability, and intelligent validation in the olive oil supply chain	Olive oil chemical dataset	Accuracy = 82%, MSE = 0.0157, low latency, real-time validation,	real-world deployment, integrating IoT-based sensory data for live tracking

inventory management costs effectively protects perishable goods from spoilage and creates improved supply chain performance and better customer satisfaction [24]. Modern economic conditions transform global markets causing significant modifications to the supply chain structure throughout every industrial sector. Modern organizations encounter strong demands to reshape their supply networks because they must handle production process adaptations together with input sourcing and distribution of customer orders. The sequence of supply chain modifications stems from changes in market performance cost fluctuations and innovations and instability in government rules and market value movements. Global supply chains become more difficult to manage because governments implement protectionist measures and trade-war policies aimed at boosting their domestic economic activities. Organizations have started to enhance their cross-border supply chain operations since they manage operations through extensive international material and financial movements within multiple regulatory areas [22]. Fig. 1 shows the visual representation of SCM [25].

3.2. Blockchain in supply chain management

Blockchain is one of the most beneficial technologies in SCM due to its decentralized, immutable ledger that records all operations and events on the network [9]. This decentralized traceability targets contemporary supply chain issues, not least demands for more transparency and traceability. One important benefit of blockchain is that it encourages ethical and sustainable behaviours by helping trace companies back to their origins and throughout their lifecycle for ethical sourcing and compliance with labour regulations. This transparency reduces counterfeiting and labour exploitation, ultimately strengthening trust among all parties involved in the supply chain [8]. Originally known as a decentralized, secure accounting system for cryptocurrencies, blockchain is a system of records that timestamps transactions on a peer-to-peer network. In addition, in blockchain systems,

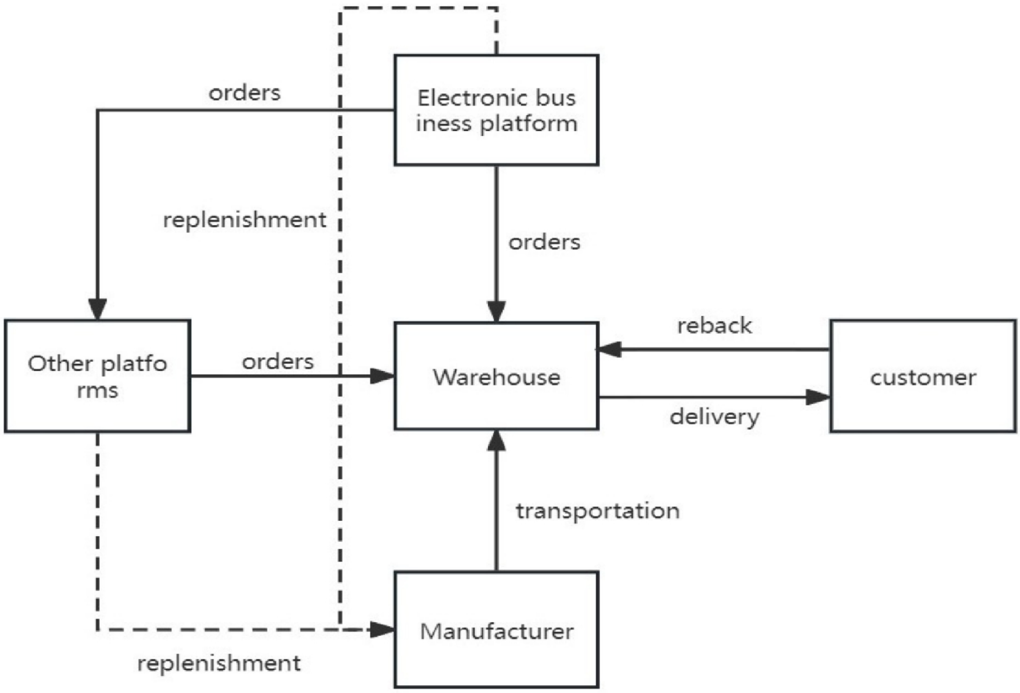

Fig. 1. Distribution process in cloud SCM.

data is distributed across multiple nodes, enhancing security and durability. Blockchain analytics has begun to rise as a new method of information analytics.

Nevertheless, organizations need to overcome certain limitations to leverage the advantages of blockchain analytics [2] effectively. Smart contracts, a widespread use of blockchain technology, are based on pre-defined code that automatically executes agreements according to predetermined terms. First widely used in the financial industry, the implementation of standardized templates is providing a gateway for the widespread use of smart contracts in other industries [8]. Real-world examples of effective blockchain applications in agricultural supply chains have been demonstrated; for example, olive oil monitoring systems implemented using blockchain and Wireless Sensor Networks (WSNs) achieved secure traceability and real-time data validation [1]. The results of a parallel experimental analysis of coffee supply chains showed that it was still feasible to establish blockchain event tracking to successfully identify anomalies and prevent tampering in operational systems [10].

3.3. Structure of blockchain

There are five main components of a block in a blockchain [26]:

a. Main Data: The information, which depends on the type of transaction the block captures.
b. Previous Block Hash: A unique identifier that identifies the current block as related to the previous block. Once a transaction has occurred, a hash is created and sent to the network. Merkle tree hashing algorithms are commonly used for efficient and secure transaction verification.

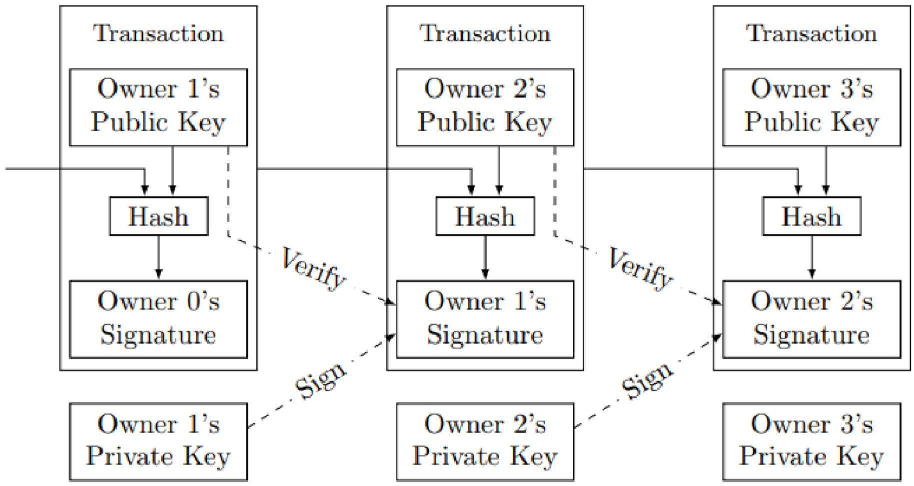

Fig. 2. Structure of the Blockchain.

c. Current Block Hash: Hashed on the header for the block (and the actual block information in the body), it provides the security of the data and integrity.
d. Timestamp: The precise date and time of the block's creation.
e. Nonce & Other Data: A nonce is a random value obtained during the mining process. Other information, such as a block's signature, adds to the uniqueness and security of the block.

Blockchain technology is also able to address inefficiencies and ethical concerns concerning SCMs because of its characteristic transparency, security, and traceability. It can enable secure connections of all actors in a process, reduce fraud, enhance the efficiency of processes, and revolutionize supply chains internationally. Exemplary on-the-ground efforts, including that of monitoring olive oil over the agricultural supply chain, demonstrate that the blockchain architecture allows for product origin to be validated and tampering to be identified in the field, with gains in tangible ways in real contexts that exceed those theoretical benefits. Fig. 2 [27] depicts the architecture of the blockchain.

3.4. Automation and optimization in supply chain management

Artificial intelligence (AI) is re-orienting SCM, moving the current theoretical and professional perspectives on AI from a passive decision-making mechanism to an active one. AI and supply chain models emphasize the notion of complexity and interdependence in supply chains that are relevant considering worldwide changes [3]. AI converging with SCM is a leap forward in both. The recent development of AI has transformed supply chains to be more resilient, efficient and optimized [10]. What AI does — basically streamlining the normal functions of order processing, inventory management and warehouse management, for example — saves the company money and dramatically increases the process efficiency. It allows human beings to focus on strategic decision making [23]. Supply markets which nowadays are undergoing complexity and uncertainty are also facing firms. AI practices like machine learning, evolutionary algorithms, reinforcement learning and ensemble learning present firms tremendous optimization opportunities to contend with the complexities and uncertainties of today's supply networks. They alleviate demand forecasting, production planning, inventory control and logistics planning. Low quality data, integration problems, and shortage of experts are some of the obstacles facing enterprises in pursuing AI to a complete level [4]. In real agricultural supply chains which utilize AI based technology, such as that used for olive oil production, quality variability detection, prediction of harvest outputs, and reduction of distribution delays are achieved, which can resolve manufacturing issues such as inconsistent quality of product, poor traceability and variability in delivery performance [14]. Machine learning is a part of a recent wave of AI where machine learning is a powerful enabler for demand forecasting, inventory optimization and risk avoidance. With machine learning, machine learning has a mechanism that analyzes historical data to spot trends in patterns for analysis and inventory optimization and forecasting, preventing the imbalance of supply and demand from falling. Neural networks, support vector machines, and decision trees can be incorporated to develop prediction methods based on them to produce prediction, which will be a well-suited method of market trend generation to predict the trends in pre-run scenarios, as risks should further increase.

3.5. Multi-agent systems in supply chain management

Multi-Agent Systems (MAS) provide a decentralized method for modeling and optimizing complex SCM. Independent agents in MAS interact with their environment and with each other to achieve individual and collective objectives. With the scalability and flexibility of MAS, supply chain stakeholders (suppliers, manufacturers, distributors, retailers, and customers) can be well and truly simulated with significant diversity and heterogeneity [7]. Agent-Based Simulation and Modelling (ABSM) uses extensive modelling of supply chain entities as independent agents to optimize the performance of aggregated systems through disaggregate analysis. The recording of stakeholder-specific goals together with their restrictions enables MAS systems to drive inter-agent interaction as well as supply chain optimization [4]. Practical examples of algorithmic applications in MAS include the use of evolutionary multi objective optimization methods which demonstrated significant performance improvements in agent based model calibration through experimental comparative studies [13].

3.6. Fuzzy logic

A useful approach for handling complexity and uncertainty is fuzzy logic, which models systems by mimicking human thought processes without depending on quantitative and qualitative data for calculations. It is difficult to evaluate import and export companies using sustainable decision-making processes due to the imprecise and complex nature of the metrics involved. Traditional mathematics finds it challenging to characterize the risks due to a lack of knowledge and a significant degree of uncertainty regarding domain difficulties. Simple risk assessment, rating, and prioritization based on expertise, experience, and user opinions are made possible by fuzzy logic-based techniques. Finding suitable fuzzy rules is the key to fuzzy logic. Fuzzy IF-THEN rules, for instance, are IF-THEN statements. The number of rules needed varies based on the particulars of the problem, and membership functions are used to specify specific linguistic labels in a problem [19].

3.7. Fuzzy neural networks in supply chain management

Fuzzy Neural Networks (FNN) combine neural network learning with the fuzzy decision-making capabilities of SCM to support decision-making in uncertain circumstances better. In two important aspects vital for achieving market success, such systems are characterized by adaptability and rapid response. Agents adopted fuzzy-based strategies for SCM by handling both sales forecasts and customer booking adjustments [28]. Predictive accuracy improves significantly when an adaptive learning algorithm is incorporated into an FNN [29]. The way of performing implementation can further lead to reduction of prediction error and better decision making of that method. The introduction of FNN in SCM has two advantages: greater system stability and improved operational transparency which causes highly stable supply chain relations [28]. Fuzzy inference based on the Takagi-Sugeno-Kang (TSK) method has been widely employed in everyday systems for control, forecasting, and decision making. The two rules given below are instances of fuzzy inference rules in an FNN model. FNNs marry artificial neural networks and fuzzy logic to create intelligent learning models capable of dealing with uncertain and imprecise data. Both these rules show how an FNN fuses fuzzy conditions with a simple linear equation to generate an output [19].

Rule 1: If x is A_1, and y is B_1, then $f_1 = p_1 \times x + q_1 \times y + r_1$
Rule 2: If x is A_2, and y is B_2, then $f_2 = p_2 \times x + q_2 \times y + r_2$

FNN include three layers, fuzzification layer, rule layer, normalization layer, defuzzification layer, and summation layer [19]. These layers are explained in following:

Layer 1 is the fuzzification layer, which uses membership functions to convert the input variables to the appropriate fuzzy sets. The bell-shaped membership function is frequently utilized, and its shape is determined by the parameters. Eq. (1) calculates the degree of membership of the input variable x to the fuzzy set A [19].

$$O_i^1 = m_A(\mathrm{x}) \tag{1}$$

where i is the node and x is the input value of i. Ai is the linguistic label that describes the characteristics or properties of node functions. Oi is the membership function of Ai; the superscript represents the sequential number of layers. Eq. (2) is typically a bell-shaped or other type of membership function, which defines how strongly the input belongs to a specific linguistic category (e.g., “Low”, “Medium”, “High”). This transformation is essential for enabling the fuzzy inference process in the following layers [19].

$$\frac{\mu \mathrm{A}(\mathrm{x})}{\mathrm{mu}_{\mathrm{A}(\mathrm{x})\mu \mathrm{A}(\mathrm{x})}} \tag{2}$$

Eq. (3) is used to compute the degree of membership of a given input x to a fuzzy set A. It serves as part of the fuzzification process, in which precise (crisp) numerical inputs are transformed into fuzzy values [19].

$$M_A(x) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i}\right)^2\right]^{b_i}} \tag{3}$$

where $M_A(x)$ is the bell-shaped function that ranges from 0 to 1, and a_i, b_i, c_i is the parameter set.

These fuzzy values are then used in subsequent stages of the inference system to evaluate fuzzy rules. The generalised bell function is highly flexible in modelling different membership shapes, which can be helpful for instance in the setting of pattern learning and approximation for adaptive systems, such as the ANFIS [19]. The second layer is the rule layer. The firing power of each rule is determined by multiplying each feature’s membership values. Eq. (4) tests how strongly the current input pair (x, y) satisfies the fuzzy condition defined by the i^{th} rule. The firing strength ωi, the magnitude of which, indicates how forcefully the rule is triggered and affects the rule's weighted contribution in subsequent layers of the system. This mechanism guarantees that rules more suited to the inputs influence the final outputs [19].

$$O_i^2 = \omega_i = \mu_{Ai}(x) \times \mu_{Bi}(y) \quad (4)$$

where ω_{i} is the firing strength and i = 1, 2.

Layer 3 is the normalization layer used to determine the weights assigned to each rule. This layer performs normalization of the firing strengths calculated in the previous layer. Its primary function is to determine the relative weight of each rule in relation to the total activation of all rules. The normalization is expressed by the following equation [19]:

$$\bar{w}_i = \frac{\omega \mathrm{i}}{\omega_1 + w_2} \quad (5)$$

where i = 1, 2.

Layer 4 is the defuzzification layer, and it is used to compute the outcomes of the rules. Its primary role is to compute the individual output of each fuzzy rule, combining the normalized firing strength from layer 3 with the rule's consequent function. The computation is described by the following equation [19]:

$$O_i^4 = \bar{\omega}_i x f_i = \bar{\omega}_i \times (p_i \times x + q_i \times y + r_i) \quad (6)$$

Layer 5 is the summation layer. This layer plays a crucial role in defuzzification by aggregating the contributions from all the rules, based on their weighted outputs. The equation for this layer is [19]:

$$O^5 = \sum_i \omega_i \times f_i = \frac{\sum_i \omega_{i \times f_i}}{\sum_i \omega_i} \quad (7)$$

where pi, qi, and ri are the parameters set.

4. The proposed system

This section presents the core findings of the presented framework. It demonstrates the role of blockchain technologies and smart agent platforms in improving supply chain transparency, data accuracy, and security of oversight. This platform is an internet-based application for managing the supply chain for olive oil sales, overseeing supervision and control activities. With the aid of secure blockchain operations and agent software platforms that securely integrate SCM, the system supports the transportation of goods from farms to end consumers. A complete block diagram is also included to illustrate the system's architecture, showing the interactions among the blockchain layer, the four intelligent agents, and the end-to-end dataflow from transaction submission to validation and block creation. This diagram illustrates precisely how data moves across system components and how agents collaborate with the blockchain during the validation process.

Fig. 3 shows the diagram of the proposed hybrid system where the FNN performs learning and fuzzification and then sends its output toward both the blockchain layer and the group of agents the agents carry out validation and decision functions while the blockchain layer

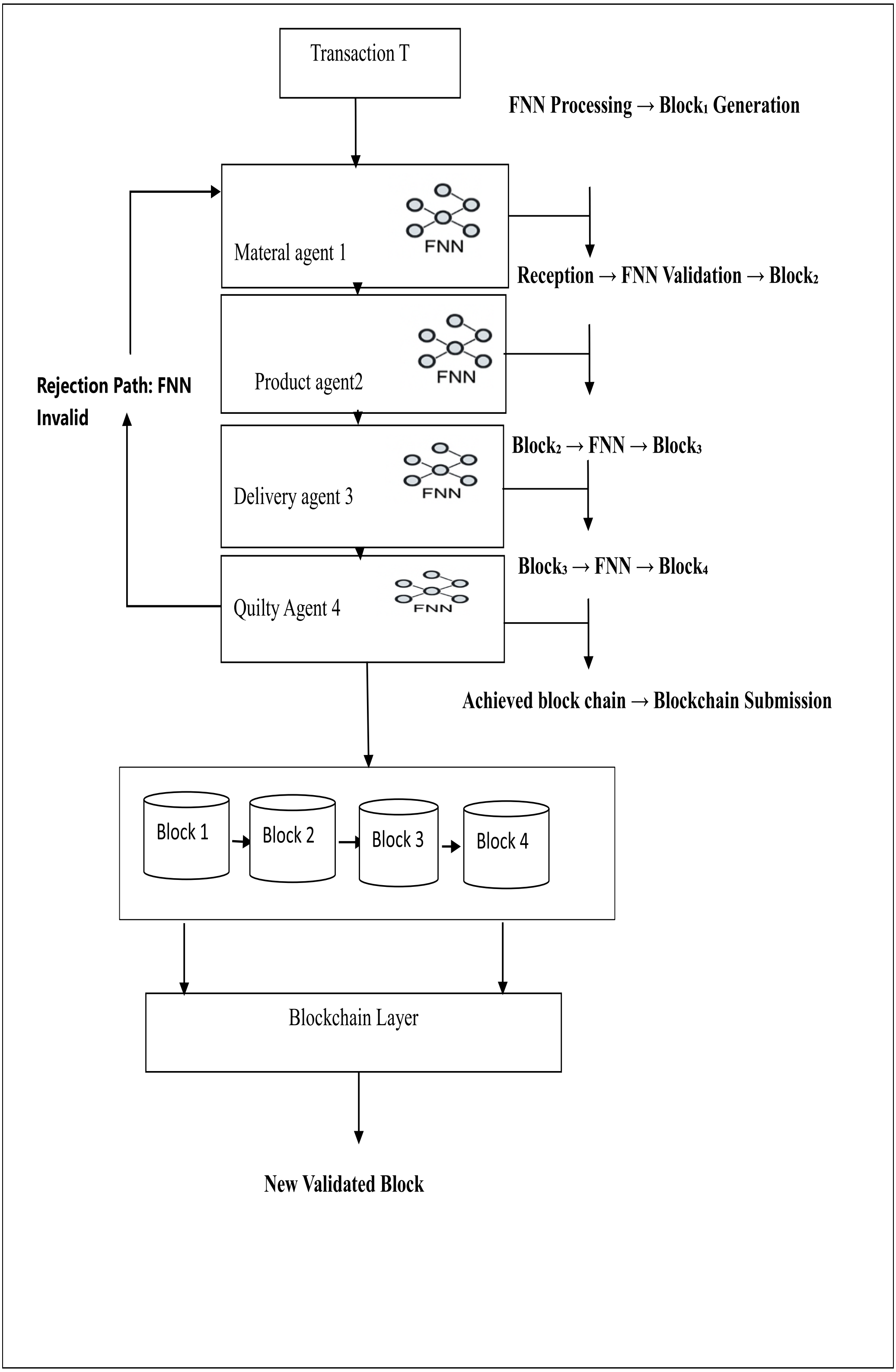

Fig. 3. Shows the diagram of the proposed hybrid system.

manages hashing and block formation and the outputs from these components merge to produce a new validated block that is added to the ledger.

4.1. Mathematical evaluation

Gaussian fuzzy membership has been used to computes the degree of membership of crisp input value x (chemical concentration j) to fuzzy set k (low/medium/high level). It models natural data distribution using bell-shaped curve with peak value = 1 at center $c_{k,j}$. Gaussian fuzzy membership is compute as following [30]:

$$\mu_{j,\ k}(x) = \exp\left(0\frac{(x - c_{j,k})^2}{2\,\sigma_{j,k}^2}\right) \tag{8}$$

where $k \in \{\text{low},\ \text{med},\ \text{high}\}$, $j = 1,\ 2, \ldots,\ 9$, $\mu_{j,k}(x)$ is membership degree, $c_{j,k}$ is center (mean), $c_{j,k}$ is standard deviation.

The firing strength of fuzzy rule r for input sample n, denoted $w_r(n)$, is computed as the product t-norm aggregation of membership degrees across all antecedent fuzzy sets. The firing strength $w_r(n)$ for rule r and sample n uses product t-norm is compute as following [30]:

$$w_r(n) = \prod_{j=1}^{9} \mu_{r,j}\left(x_j(n)\right) \tag{9}$$

where $w_r(n)$ quantifies the degree of activation of the r, the fuzzy rule when presented with an input vector $x(n) = [x_1(n), x_2(n), \ldots, x_9(n)] \in \mathbb{R}^9$ it employs the product t-norm operator, which multiplies the membership degrees $\mu_{r,j}(x_j(n))$ of each input feature $x_j(n)$ in the corresponding fuzzy set $A_{r,j}$ of the rule antecedent.

The fuzzy rule r for input sample n, denoted $\bar{w}_r(n)$, is obtained by dividing the raw firing strength by the sum of all rules' firing strengths. Normalizing firing strength ensures obtaining probabilistic weights ($\sum \bar{w}_r(n) = 1$) [30].

$$\bar{w}_r(n) = \frac{w_r(n)}{\sum_{s=1}^{27} w_s(n)} \tag{10}$$

The normalization ensures that each rule's contribution to the final output is proportional to its relative activation strength among all activated rules. This normalized weighting scheme enables proportional rule contribution in the TSK defuzzification layer. Furthermore, $\mathrm{R} = 27$denotes the number of fuzzy membership features obtained by applying three membership functions to each of the nine input variables, rather than employing a full combinatorial fuzzy rule base.

The predicted quality score $\hat{y}_i(n)$ is compute according to Eq. (11). The defuzzied output of the TSK FNN computed as a combination of local linear models weighted by their normalized firing strengths [30].

$$\hat{y}_i(n) = \sum_{r=1}^{27} \bar{w}_r(n)\left(p_r^T x(n) + b_r\right) \tag{11}$$

where $p_r \in \mathbb{R}^9$ and b_r is the scalar.

The output of the TSK FNN architecture, implementing weighted average defuzzification. Each of the 27 fuzzy rules contributes a local linear approximation $\mathrm{p_r}^{\mathrm{T}}\ \mathrm{x(n)} + \mathrm{b_r}$ of the quality function within its region of competence, defined by the antecedent fuzzy partition.

The normalized firing strength *wrn* for layer 3 becomes the interpolation weight to create a smooth transition between nearby local models. This construct facilitates universal approximation of continuous nonlinear functions by piecewise linear interpolation and results in a quality surface of global scale that is a continuous mixture of 27 specialized linear experts. The Mean Squared Error (MSE), is a very important indicator of prediction accuracy, whose significance lies in the average squared difference between the predicted values and the actual observed values. We compute the MSE as [31]:

$$\mathrm{MSE}_{\mathrm{train},i} = \frac{1}{N_{\mathrm{train}}} \sum_{n=1}^{N_{\mathrm{train}}} \left(y(n) - \hat{y}_i(n)\right)^2 \tag{12}$$

The MSE is the expected value of the squared L2-norm loss between the actual observations and the model's predicted values. It acts as a risk function for decision-making and an optimality target for machine learning. The MSE is the mathematical estimate of the arithmetic mean of the squared residuals; each residual represents the deviation of a predictive estimate y $\hat{i}$ (n) from its real value y(n). The quadratic transformation is non-negative and differentiable, and the averaging one gives scale-invariance relative to the size of the data given. MSE $= 0$ indicates perfect prediction; practical convergence targets MSE < 0.05 mean predictions will stand within $\pm 22.4\%$ RMSE of ground truth for normalized quality Algorithm 1.

Algorithm 1 represents the working of the blockchain-based hybrid intelligent agent model, a framework that combines blockchain technologies, fuzzy logic, neural networks, and security in supply chain operations by using intelligent agents that verify and learn in real time, ensuring accurate and data-driven decisions.

5. Experimental results

5.1. Experimental setup

The experimental design was conducted to validate the proposed blockchain-based, integrated hybrid system with FNN-based intelligent agents for the olive oil supply chain. Chemical olive oil data (572 samples, 9 numerical features) were preprocessed, and a quality score was calculated as the regression target. The training and testing data were split randomly into 70/30 for each dataset. In this case, all input variables have been fuzzified using Gaussian membership functions, with three linguistic levels (low, medium, high). The Adam optimizer trained an FNN for the 9–10–1 specification. Training continued until the MSE dropped below 0.05 or reached the maximum number of epochs. Four intelligent agents (material, production, delivery, compliance) then verified the FNN output and recorded transactions to the blockchain using the generated hash function. Decision reliability and supply chain service performance were analyzed using MSE, RMSE, and prediction accuracy. The Python programming language has also been employed. Many libraries are used in a data analysis environment, such as Pandas, NumPy, and Scikit-learn. These libraries are used for cleaning and analysis, as well as for developing statistical and intelligence models. All of these experiments were conducted on a well-specified personal computer with an Intel Core i9 processor and ample RAM, which enabled fast processing and the execution of various algorithms without performance issues.

Algorithm 1 Fuzzy Neural Supply Chain Validator.

```
Input:
    T = {x_T1, x_T2, . . ., x_T9                  // New transaction (9 chemical inputs)
    D = Historical dataset (N samples)
    MSE_thr = MSE threshold (0.05)
    train_ratio = Train/test split (0.70)
    max_epoch = Max training epoch
Output:
    Status ∈ {SUCCESS, FAILED}
Begin
Step 1: Initialize Blockchain and Agents
    ledger ← LoadBlockchainLedger()
    previous_block_hash ← ReadLastBlockHash(ledger)
Step 2: Dataset Preparation
    X ← ExtractFeatures(D)
    y ← ExtractTarget(D)
    N ← length(D)
    N_train ← [train_ratio × N]
    [Training_Set, Testing_Set] ← RandomSplit(D, N_train)
Step 3: Gaussian Membership Functions                //Using Eq. (1) FNN Agent Training
    For j = 1 To 9 Do                   //FNN Agent Training
      [c_k,j, σ_k,j] ← EstimateParams(Training_Set[:, j], k ∈{low,med,high})          //Using
Eq. (8)
    End For
Step 4: Fuzzification (Training Data)
    For n = 1 To N_train Do                    //Generate fuzzy
      Generate input vector z(n) using Eq. (8) membership degrees
      z(n) ← [μ_k, j(x_j(n)) ∀ j = 1 : 9, k ∈ {low, med, high}]
    End For
Step 5: FNN Training Loop
    R ← 27; Agents ← {1: Material, 2: Production, 3: Delivery, 4: Quality}
      For i = 1 To 4 Do                   //4 Agents (Material, Production, Delivery, Quality)
      Initialize
      FNN_i: 27→10(tanh)→1(linear)                  //Network Architecture
      θ_i ← {p_r ∈ ℝ^9, b_r ∀ r = 1, . . ., R}             //Initialize TSK Parameters Using Eq. (11)
      epoch ← 0; MSE_train,i ← ∞                  //Training Initialization
      While (MSE_train,i > MSE_thr) and (epoch < max_epoch) Do
         For n = 1 To N_train Do
            Compute Firing Strength (w_r(n)) Using Eq. (9)
            w_r(n) ← ComputeFiringStrength(r, n)
            Compute Normalized Firing Strength (w_r(n)) Using Eq. (10)
            w_r(n) ← NormalizeFiringStrength()
            Compute FNN output (ŷ_i(n)) using TSK Model by using Eq. (11)
            ŷ_i(n) ← ComputeFNNOutput(w,θ_i,x(n))
         End For
         Compute Loss (MSE_train,i) Using Eq. (12)
         MSE_train,i ← ComputeMSE(y,ŷ_i)
         Update Parameters using Adam Optimization
         θ_i ← AdamUpdate(θ_i, ∇_θ MSE_train,i)
         epoch ← epoch + 1
```

Algorithm 1 Continued.

```
            End While
            [MSE_test,i, Accuracy_i] ← Evaluate(FNN_i, Testing_Set)
        End For
Step 6: Transaction Validation and Consensus
        Transaction Validation (T)
        x_T ← ExtractFeatures(T)
        Fuzzify the new transaction input using trained functions using Eq. (8)
        z_T ← [μ_k,j(x_T[j]) ∀ j=1:9, k∈{low, med, high}]
        Obtain validation decisions from each agent
        v1 ← Validate_Material(z_T, ledger, FNN_1)
        v2 ← Validate_Production(z_T, ledger, FNN_2)
        v3 ← Validate_Delivery(z_T, ledger, FNN_3)
        v4 ← Validate_Quality(z_T, ledger, FNN_4)
Step 7: Blockchain Consensus
        If (v1 ∧ v2 ∧ v3 ∧ v4) Then                    //Consensus Check
            Transaction_Packet ← {T, {v1,v2,v3,v4}, scores, CurrentTime()}
            Compute the block hash using SHA256
            New_Block ← {. . ., SHA256(Packet||prev_hash), "APPROVED"}
            Append (New_Block, ledger); Broadcast(New_Block)
            Status ← SUCCESS
        Else
            failed_agents ← DetectFailedAgents({v1, v2, v3, v4})
            RecordException({T, failed_agents, "FNN validation failed"})
            Status ← FAILED
        End If
Return Status
End
```

5.2. Dataset description

We have utilized the olive oil dataset for this study. This dataset comprises olive oil samples with chemical parameters of various fatty acids. These indices evaluate the quality of oil and its region of origin. The dataset is primarily used to classify olives and to perform chemical analyses across different regions of olive production [32]. On the one hand, the proposed FNN–blockchain multi-agent validation is developed and evaluated by using the dataset. This dataset includes 572 olive oil samples, each with 9 chemical composition attributes (palmitic, palmitoleic, stearic, oleic, linoleic, linolenic, arachidic, eicosenoic, and other components). To serve as the regression target, a computed quality_score and its normalized version were produced. Chemical variables were cleaned and normalized, and the dataset was split into 70% for training and 30% for testing.

5.3. Results analysis

By integrating blockchain and AI, the proposed system introduces an independent supply chain model for transaction authentication and compatibility checks. Of all those previous techniques, the FNN algorithm performed better for maneuverability and error margins. In experiments, the system reached 82% accuracy, with an error rate of 0.02, indicating its efficiency. Hence, the autonomous system enables agents to improve and optimize the

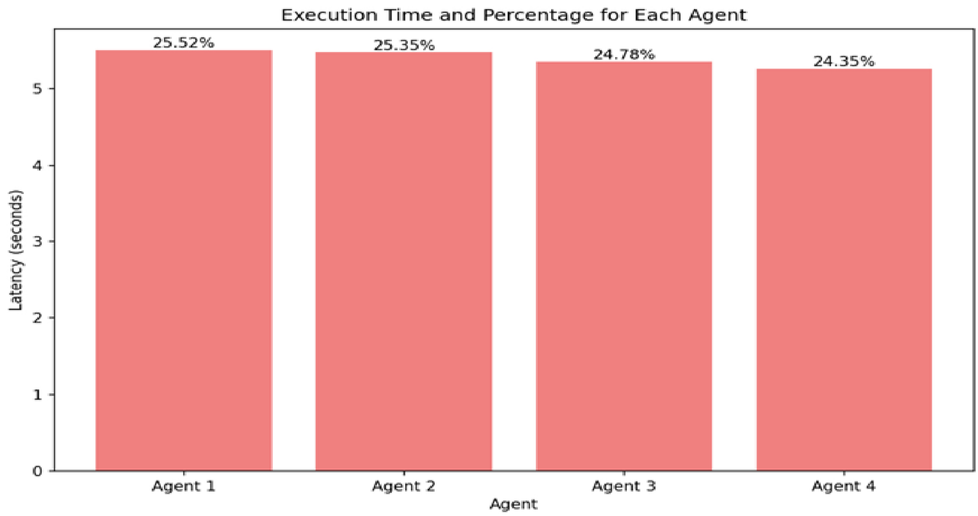

Fig. 4. Each agent's contribution to the total execution time.

decision parameters leading to reduction of lead time and increase operational efficiency, thereby minimizing procurement and inventory decision times, whilst ensuring reliable and traceable outcomes. It enables practitioners to model relationships among supply chain inputs by simulating the interactions of a variety of parameters, which offers a better understanding and optimization of the supply chain network through agent-based simulation and manages the complexity of supply chain interactions successfully. The FNN, trained on divided training and test datasets, interprets and tunes its decision-making through learning and classification. The results include enhanced, faster decision-making through intelligent agents and blockchain, significant time savings and accurate results in operations and validation, and flexibility through adjustments to user input while maintaining high precision and allowing for error rates. and based the system uses nine chemical input parameters consisting of palmitic palmitoleic stearic oleic linoleic linolenic arachidic, eicosenoic and other, with a 70% training, 30% testing split to ensure clarity in model configuration and dataset usage

Fig. 4 represents the execution latency (in seconds) and percentages of total execution time for four intelligent agents (Agent 1 to Agent 4) in the blockchain-enabled supply chain model. The first agent has the highest execution time at around 5.31 seconds (25.52%), followed by the second agent at 5.27 seconds (25.35%). The execution times for the third and fourth agents are 5.14 and 5.01 seconds (24.78% and 24.35%, respectively). On average, the times are quite close for all of the agents, with the biggest difference not exceeding 1%, suggesting a precise balance in performance. This shows the efficiency of delegation of computationally demanding tasks, and is also supported by agent-level design such that no one agent becomes a bottleneck. Such symmetry validates the balanced scalable architecture essential for real-time execution in a decentralized supply chain system.

The training and validation MSE curves of four intelligent agents (Agents 1–4) trained for 1500 epochs in this blockchain-based supply chain system show efficient learning and convergence, with a consistent decrease in both the training and validation MSE curves for all agents (see Fig. 5). Agent 1 stabilizes at 0.02 with a slight increase in overfitting. In contrast, Agent 2 achieves the fastest drop in MSE at approximately 0.01, representing stronger generalization capability. Like Agent 1, Agent 3 achieves an error rate of ~0.03,

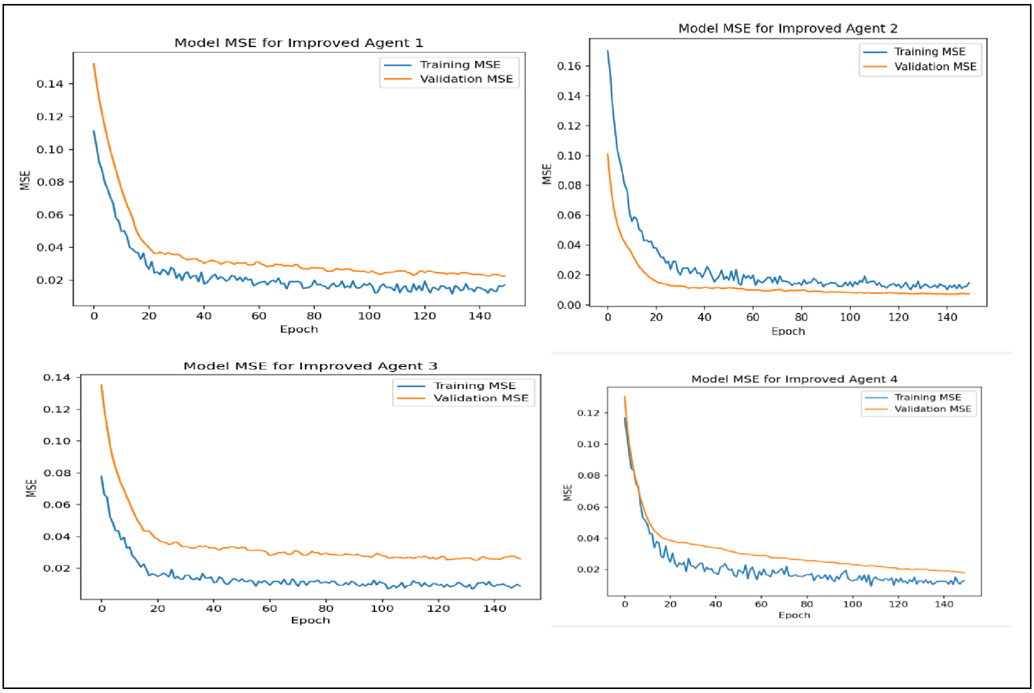

Fig. 5. MSE results for each agent.

and Agent 4 shows smooth convergence, with a final MSE around 0.02, close to the training value, ensuring a reliable balance between bias and variance and no significant overfitting or underfitting across all agents. All of them achieve stable convergence, indicating they received sufficient training time.

An analytical method for Table 2, comparing the performance of 4 intelligent agents in a blockchain-based supply chain system across error rate, accuracy, total latency, MSE, and execution time. Agent 2 obtains the highest accuracy of 82% with a low error rate of 1.0, while Agent 4 gets the highest accuracy with 82% accuracy at the highest error tolerance: 1.7. Agent 1 possesses the least error rate (0.5) and the least accuracy (78%). Agent 2 also has the lowest overall latency, 5.0670 seconds, and the best execution time, 25.39 seconds, while Agent 4 has a balanced latency of 5.1434 seconds and an execution time of 24.31 seconds. Agent 4 had the minimum MSE of 0.0157, and Agent 3 had the maximum MSE of 0.0265. Overall, Agent 4 is best at combining balance and precision. On the other hand, Agent 2 is able to do the real-time task accurately because of low latency, but requires balanced optimization due to its low error and relatively poor accuracy. This comparison demonstrates how effectively the system is performing at workload scheduling and assigning agents to a number of performance expectations, allowing for reliable and responsible SCM decision-making.

The Table 3 gives comparison of the proposed system with several of more recently related systems. This is also represented in the comparison showing that the accuracy has increased significantly and error has reduced. It has been demonstrated that the hybrid system by blockchain is linked as intelligent agents by FNNs, with a predictive accuracy of 82%, and a very low MSE of 0.0157 and RMSE of 0.1. These results have resulted not only in superior results compared to 2021, 2022, and 2024 studies, but also demonstrate with concrete evidence the robustness, scalability, and predictive capability of the system. The

Table 2. MSE results.

Multi agent	Errored Rate	Accuracy	Total Latency	MSE	Time (Seconds)
Agent 1	0.5	78%	5.3097	0.0230	25.53
Agent 2	1	82%	5.0670	0.0211	25.39
Agent 3	1.5	81%	5.1434	0.0571	24.77
Agent 4	1.7	82%	5.1434	0.0157	24.31

Table 3. Comparison results.

Ref.	Data Set / Domain	Task	Main Model(s)	Accuracy	MSE	RMSE
[21]	Retailer sales time-series	Demand forecasting	MCDFN (CNN + LSTM + GRU + XAI)	20%	23.57	4.85
[33]	Italian olive-oil dataset, Fatty Acids (FA)	Origin classification	Naïve Bayes (NB), k-Nearest Neighbors (kNN), Linear Discriminant Analysis (LDA), Decision Tree (DT), Artificial Neural Network (ANN), Support Vector Machine (SVM)	2.71%	–	–
[34]	Wholesale food price time-series	Price forecasting	ARIMA, Prophet, LSTM, CNN-LSTM	72.5%	–	0.50
[35]	Olive-oil dataset (572, 8 FA)	Region classification	k-means, Hierarchical Clustering (Hclust), Expectation–Maximization Gaussian Mixture Model *(EM-GMM), Factorial Mixture Analysis (FMA)*	76.6%, 61.4%, 65.2%, 50.5%	–	–
The Proposed System	Olive-oil dataset (572, 9 vars + quality_score)	Quality scoring and validation	Blockchain + Multi-Agent FNN	82%	0.0157	0.125

negligible error rates underscore the system's capacity to provide reliable, transparent, and efficient decision support to today's SCM.

6. Conclusions

The study aims, for one, to design and validate a Hybrid intelligent system integrating blockchain technology and agents, supported and verified by FNNs to enable traceability, fraud prevention, and enhanced decision-making efficiency for the olive oil supply chain. The technical aims of this work have been successfully met with the construction of well-scaled, secure, and transparent blockchain infrastructure, with self-driven agents for adaptive learning and real-time analysis. Our system was verified empirically: with high accuracy (up to 82%), low error (MSE = 0.0157) and optimal execution time (24.31 sec.), suggesting equitable workload distribution, stable performance, and avoiding overfitting. The hybrid model enhanced the computational efficiency, data transparency, and adaptability of traditional models, thus providing an integrated framework for modern SCM. The olive oil sector application in the system is valid, supporting its use in logistics coordination, product traceability, consumer trust, as well as in sustainability. Exploring future research topics, e.g., deployment in the real world, IoT sensory data used for real-time tracking with the next generation of models; scaling the system up to alternative agricultural supply chains with perishable goods; and tuning the model's flexibility using real-time feed-forward loops and dynamic pricing optimization.

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None.

Authors contributions

Hiba Hamdi Hassan: Responsible for writing, review, and analytical editing; also contributed to outlining future research directions. Rana Fareed Ghani: Review and editorial process.

Conflict of interest

Regarding the publishing of this paper, the authors state that they have no conflicts of interest.

Data availability

The data that support the findings of this study are openly available at https://www.kaggle.com/datasets.

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