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A Supply Chain Network by Utilizing Multi-Intelligent Agents with Blockchain

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ABSTRACT

Modern supply chains face challenges including limited transparency, poor traceability, susceptibility to fraud, and slow responses to disruptions, particularly in traditional centralized systems. We present Bio-Cognito, a blockchain-integrated multi-agent framework that combines fuzzy neural networks (FNNs) with multi-agent systems (MAS) to enable predictive, adaptive, and secure decision-making across supply chain operations. Each agent coordinates tasks such as inventory management, supplier assessment, and logistics routing, while blockchain ensures data integrity and confidentiality. The framework integrates real-time multi-source data, including product inventories, supplier performance, and logistical operations, transforming it into actionable insights through FNN-based predictions and MAS coordination. Experimental evaluation on a Kaggle supply chain dataset comprising over 12,000 records shows that the logistics agent achieved 91% accuracy (Root Mean Squared Error (RMSE) 0.2), the supply agent 83% accuracy (RMSE 0.16), and the inventory agent 75% accuracy (RMSE 0.14). Ablation studies highlight the importance of multi-agent coordination, knowledge integration, and multi-modal data fusion. Empirically derived thresholds enable phase-specific interventions, supporting reliable and interpretable decision-making. The proposed framework achieves high cross-domain generalization while maintaining real-time inference on standard clinical GPUs. Overall, it offers a systematic methodology to integrate intelligent agents with blockchain, enhancing transparency, predictive reliability, and operational efficiency in dynamic supply chain environments.

1. INTRODUCTION

E-commerce is an expanding industry that primarily uses websites to offer goods and services to consumers and businesses. Cross-border e-commerce, a relatively new form of international trade, offers many advantages, including greater accessibility. The promising future of cross-border e-commerce, maintaining a stable growth rate, and weathering the pressures of competition, depends on managing the global supply chain. Time-series data and a simple prediction algorithm are used in traditional purchase volume forecasting. The platform's sales volume is influenced by a variety of consumer consumption patterns, including the quantity of goods or services offered, product assortments, and government subsidies. The recent rapid economic growth has led to a major expansion in the use of the EC supply chain [1]. E-commerce has expanded dramatically in recent years due to advances in communication technology and the need for contact-free delivery. As a result, e-commerce companies typically run modest warehouses to accommodate a range of demands [2]. The world is changing quickly, especially in business and commerce. This has an impact on the exclusivity competition of the business or current commercial enterprise [3]. The concept of blockchain can be defined as a decentralized and distributed ledger to store time-stamped transactions among many computers in a peer-to-peer network [4].

Blockchain technology, which powers the well-known cryptocurrency Bitcoin, is transforming the world and drastically altering our technological and commercial landscape. Blockchain is a distributed, decentralized, tamper-proof, peer-to-peer technology with the potential to monitor and validate online transactions. It aims to enhance the integrity, security, and transparency of data, thereby improving the accuracy, protection, and openness of information [5].

The goal of intelligent products is to give architects and system designers design flexibility. The approach to creating intelligent products is crucial. Intelligent, multidisciplinary, collaborative, and distributed platforms are necessary for managing and handling modularity. The multi-agent paradigm is the most effective way to address this issue and offer cutting-edge solutions that can manage the changing environment [6].

Combining multi-agent systems (MAS) and blockchain creates a decentralized ecosystem in which decisions are not made by a single centralized authority but rather collaboratively and transparently among autonomous entities. The response of a supply chain is its ability to withstand every possible disruption, manage it, and continue normal business operations [7].

The increasing reliance on information and communication technologies, combined with the adoption of a consumer-centric business strategy, has heightened the urgency for supply chains to be more responsive, competitive, and flexible. Such chains had to become collaborative, transparent, and agile to ensure their viability in a rapidly changing industrial environment. Various studies have examined this theme by proposing new mechanisms and ways to address the challenges plaguing contemporary supply chains. Research focused on the application of intelligent agents has proved a promising route towards ameliorating system efficiency and agility. Apart from that, there seems to be more recent literature indicating a great interest in the applications of AI, blockchain, and multi-agent systems, all of which can enhance predictive capabilities, increase transparency, and improve the efficiency of supply chain management practices. It is therefore directly relevant to this research and the objectives it intends to achieve. The use of trucks in operations has led to the emergence of the Interterminal Truck Routing Problem (ITTRP), which has garnered significant scholarly attention. A primary objective in optimizing truck routing in interterminal transport is minimizing empty truck movements. Selecting transport orders (TOs) based on truck real-time locations helps minimize empty-truck trips. However, interterminal transport (ITT) involves more than just moving containers between terminals operating 24/7. When containers are destined for or originated from logistic facilities with restricted operating hours, minimizing empty-truck trip costs (ETTC) must also account for the availability and operational time windows of both the origin and destination points. The Gružauskas 2020 study analyzes the resilience of supply chains in the sustainable food sector with a focus on organic product distribution. A set of key challenges was identified, including inefficient last-mile delivery operations, inaccurate demand forecasting, and poor collaboration among stakeholders. To address these issues, the study proposes creating a logistics cluster to improve information exchange, adopting resilience strategies, such as flexibility and redundancy, and using an agent-based framework to enhance decision-making efficiency [8, 9]. This study reviews current applications in smart contracts (SC), identifies potential research gaps, and analyzes the overall utility of Machine Learning technologies in supporting decision-making within supply chains. Therefore, the main objective of this study is to investigate how decision makers in supply chains can benefit from the increasing amounts of data generated within these chains by integrating Machine Learning technologies into the tools they use [10]. The focus of this paper is on the applicability of Supervised Machine Learning (SML) in Supply This study examines Supply Chain Information Systems (SCIS) and provides a comprehensive analysis of SML-based academic applications in this field by adopting a dual classification and using a clustering-based profiling methodology [11]. This study points to a major limitation in blockchain-based supply chain research: the lack of empirical validation. Despite the significant potential of this technology to improve transparency, efficiency, and security, most existing studies remain conceptual and face limitations in real-world applications. To address this gap, the study analyzes blockchain applications and anticipates future research trends in this field. In contrast, this study proposes an integrated framework combining blockchain, machine learning, and multi-agent systems to deliver a more practical, data-driven decision-making solution for supply chains [12].

Blockchain's enormous potential to improve transparency, traceability, and trust in the food industry is increasingly recognized. Higher food quality standards can be maintained and contamination concerns reduced by using blockchain platforms to provide stakeholders with real-time, immutable records of food products. But even with blockchain's many advantages, several issues remain unresolved [13]. The Interplanetary File System (IPFS) and Hyperledger Fabric are used in the study's secure, decentralized e-healthcare system to facilitate the effective storage and retrieval of Electronic Health Records (EHRs). Hyperledger Fabric protects sensitive medical data and ensures data security and privacy by restricting access to authorized parties. It incorporates IPFS as a decentralized storage for managing huge medical photos and files that cannot be stored directly on the blockchain.

Despite the ever-increasing number of studies on blockchain, machine learning, and multi-agent systems in supply chain management, most existing research deals with these technologies separately or integrates them superficially without providing a unified and integrated framework for decision-making.

The scientific novelty of this study lies in the design of an integrated, adaptive multi-agent architecture supported by blockchain technology, in which each agent is equipped with intelligent decision-making capabilities and their work is coordinated through a decentralized, trust-based mechanism. Unlike traditional methods, the proposed system offers the following:

1. A cooperative multi-agent decision-making model in which the agents coordinate their supply chain processes by working together instead of independently
2. blockchain is an effective coordination layer rather than a database, dealing with negotiations securely, and synchronizing agents in near real time
3. Integration of predictive models within each agent to build dynamic, situational, context-based forms of decision-making under uncertainties

By bringing the two together, it evolves from merely an integration of technologies to a smart connected ecosystem that can run on its own, adapt continuously based on real-time input, and make more informed decisions in complex supply chain landscapes.

2. SUPPLY CHAIN

It basically comprises any network of businesses involved in major logistics functions, such as purchasing, producing, and distributing, where a traditional definition of supply chain networks by individual businesses might now include value-adding activities performed by external partners at any given stage of a supply chain [14].

A group of interconnected software modules named SCIS is utilized for storing, processing, managing, and regulating company processes. Those tools assist decision-making across one or more supply chains by converting unprocessed data into actionable insights.

To create a multilayer, multiproduct supply chain that accounts for scheduling differences in tactical and strategic decision-making, a model was developed. By leveraging external resources and maximizing total accumulated profit, the strategy seeks to optimize the supply chain as a whole.

The model accounts for several variables, including both rental and public storage options, as well as minimum and maximum average facility utilization rates. A solution methodology was successfully established using Varangian relaxation to manage complexity [15].

2.1 Blockchain for supply chain

Academic research has established that the advantages of supply chain collaboration include improved knowledge sharing, easier access to products, and higher expertise. Thus, improving the coordination between organizational procedures and resources of supply chain partners leads to increasing effective and efficient flow of products, information, and services [16]. Due to the challenges posed by the global economy, operating efficiency, security, and transparency must improve across supply chains of every description. Blockchain technology has been instrumental in creating a decentralized and immutable ledger. Blockchain provides a secure, transparent system for data sharing among diverse stakeholders, serving as an electronic, indestructible method of recording and disseminating information. Traceability, data integrity, and tamper resistance are features that make the blockchain useful in food supply chains (FSCs). The system—characterized by the combination of digital systems—has continued to attract interest from academia and industry due to its unique combination of strong security, anonymity, and self-governance [17]. The radical difference brought by the said technology compared to the traditional setup is the secure, transparent management of data by distributed, interconnected nodes in a network, which, in fact, is the case with blockchain technology. The first real-world use of this technology was Bitcoin, which was built around the idea of a self-auditing network that runs at a lower cost due to its decentralized nature: the blockchain, an open ledger system in which transactions can be verified by anyone without the need for a central authority [18, 19]. The blockchain is a decentralized, digital ledger that enables the permanent, verifiable recording of all movements of products or transactions within the system. The introduction of smart contracts with IoT enables automated decision-making while providing real-time monitoring of data, thereby enhancing accountability and transparency for all actors involved [20].

2.1.1 Types of blockchain

An important factor to consider while building a blockchain-based application is the evaluation of three major blockchains, namely, public, private, and consortium, according to the special needs and goals of the application.

Public Blockchain: A public blockchain is a network that is completely decentralized and permissionless, allowing anybody to observe, access, and use the system without any limitations. It is not governed by a single body or central authority. Everyone in the network can use the consensus procedure. Bitcoin is a well-known illustration of a public blockchain [19].

Private: A permissioned network run and governed by a single entity is known as a private blockchain. Only authorized entities can view or contribute to the ledger, and network participation is limited. Because of its centralized administration, the trusted authority handles block creation and validation internally, negating the need for conventional consensus procedures.

Hybrid (consortium): A consortium blockchain combines both public and private blockchain components. It operates as a permissioned network; however, this does not mean it is open to the public or even to a company; instead, access is limited to a select number of organizations.

Strengthening interorganizational cooperation can choose this strategy because it enables control sharing among a team of trusted agents and maintains transparency within a well-defined unit of actors [20]. A significant benefit that blockchain technology provides to supply chain management is the way it creates immutable records that cannot be altered or removed. Blockchain is immutable, meaning that data cannot be changed or deleted after it has been recorded on the ledger. This functionality is vital to keeping the integrity of financial records. While conventional financial systems allow internal abuses or external threats to modify records and related data without authorization, blockchain ensures that every transaction is visible, private, and immutable [21, 22].

2.2 Supply chain using machine learning

Various researchers have used machine learning techniques to promote better precision [23]. The reasons for the approach to model selection were the complexity of the algorithmic challenges, whether integration across the supply chain is needed, and whether the data underlying it exhibits dynamic behavior. These models helped predict demand with great accuracy and enabled supply chain agents to make real-time decisions. Complexity and overfitting resistance are therefore particularly suitable for rapidly changing, uncertain demand patterns [7].

2.3 Supply chain using intelligent agent

The ambition to digitize all business operations is becoming a reality at a rapid pace. These are examples of novel-technology automation, such as artificial intelligence (AI), the internet of things (IoT), and machine learning, which can now gather and analyze vast amounts of data that were previously difficult to access. The challenge now, however, is to get to the next phase—reshaping our training and operations, as well as our ways of thinking —to leverage these technical innovations [24]. SCIS are defined as sets of interconnected software modules that support, manage, and enhance business processes. These systems collect, process, and store data to transform it into actionable insights that help improve decisions across one or more supply chains. [10]. AI technologies such as machine learning (ML), natural language processing (NLP), and predictive analytics are becoming increasingly important in contemporary trade finance. Those systems can be used to automate key processes in trade finance, detect fraud, and predict financial abnormalities. Global supply chains are becoming increasingly interconnected and complex, making it necessary for AI to improve the accuracy, security, and efficiency of each financial transaction in the supply chain ecosystem. With a concentration on advanced analysis for detecting fraud, predictive modeling for preventing fraud, and automating processes for optimizing the operations of financial transactions. This tests the AI function in supply chains [21]. These days, decision-making, adaptation, and learning have a significant impact on the management of supply chains. Every intelligent agent can estimate demand, manage logistics operations, negotiate contracts independently, and respond quickly to changes in the supply chain. When supported by blockchain technologies, such agents autonomously coordinate, detect fraud, and optimize real-time resource allocation while facilitating decentralized, secure interactions [21].

3. MULTI-AGENT SYSTEM

Each agent gives an example of a certain type of customer- e.g., manufacturer, supplier, logistics company, and so on- that can negotiate, make decisions, and communicate through the MAS. To accomplish its local selling goals as well as the common goal of maximizing inventory levels, responding to disturbances quickly, and minimizing lead time. These agents may compete or cooperate. In a complex supply chain network, a multi-agent system improves overall efficiency, flexibility, and resilience by modeling decentralized, dynamic, and decision-making coordination.

Solution for distributed problems: even though agents function autonomously, they exchange information and collaborate throughout the blockchain, promoting confidence and openness.

Flexible decision-making: MAS can be flexible across intricate supply networks with multiple tiers.

Solving disputes and negotiating autonomously: an agent renegotiates a contract or settles any dispute by utilizing blockchain-verified rules as well as real-time data.

Tolerating resilience and faults: the decentralized architecture of MAS enhances the system's capacity to bounce back from errors and adapt to changes.

4. FUZZY LOGIC

It can be considered an efficient framework for handling uncertainty and imprecision, particularly in complex systems. This study used a four-step procedure; the first step was fuzzification. Step 2—Definition of rules: Define a set of IF-THEN rules based either on the system behavior or via domain knowledge obtained from human specialists. These rules are applied to all fuzzified inputs in this fuzzy inference system, producing fuzzy outcomes. Fourth: Defuzzification takes fuzzy results and turns them back into precise output control [25]. In FNNs, the advantages of any network topology and fuzzy logic can be blended. Fuzziness, representing the inherent uncertainty and ambiguity in concept development and construction, is fundamental to this approach. Fuzzy set theory is defined, grounding the special notion of membership functions that quantify the membership degree of elements in sets. In conjunction, FNNs may learn via adaptive learning rules within each neural network while incorporating the fuzzy system's ability to represent imprecise information in effective, legitimate, nonlinear, and uncertain interactions. The structure of any neural network allows the model to change and learn dynamically, making it particularly suitable for complex, uncertain systems. A fuzzy system is one of the most commonly used fuzzy neural network (FNN) structures. It is also referred to as a TSK neuro-fuzzy system because it can be represented as a neural network [26].

5. EVALUATION CRITERIA

For performance evaluation, our architecture used Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and accuracy [27].

5.1 Mean squared error

MSE estimates the mean of the squared deviation of the estimated values from the true values. Suppose there are n data points in a sample; we have generated the prediction vector for all the data in this sample. For this case, [27]

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y1 - y2)^2 \quad (1)$$

highly sensitive to outliers due to the squaring of deviations, making it a valuable metric for detecting models that underperform during extreme fluctuations in demand.

In this study, MSE is used to evaluate the inventory agent, as it performs demand forecasting and inventory estimation, which are continuous prediction tasks.

5.2 Root mean squared error

RMSE is the square root of MSE. Unlike MSE, RMSE preserves the target's original scale, yielding a more interpretable measure of predictive accuracy. By reflecting the error magnitude in the same units as the observed data, RMSE provides a more intuitive assessment of the model's performance [27].

$$\text{RMSE}=\frac{1}{n}\sum_{i=1}^{n1}\sqrt[2]{(y1 - y2)^2} \quad (2)$$

RMSE can largely function in task forecasting because it penalizes errors bigger than the MAE, hence giving a stabilized perspective on the comprehensive model performing [28].

RMSE is used by both the inventory agent and the logistics agent to evaluate prediction accuracy for estimating stock levels, delivery times, and transportation costs.

5.3 Accuracy

Accuracy is assessing how well a model's predictions align with actual results. The metric is commonly utilized in classification issues in Machine Learning and statistics. To calculate accuracy, one determines the proportion of accurate predictions out of the total predictions that a model makes [29-31].

$$\text{Accuracy}=\frac{\text{Number of Correct Predictions}}{Total\ Number\ of\ Predictions} \times 100\% \quad (3)$$

5.4 Metric selection justification

The selection of evaluation metrics is aligned with the nature of each task. Regression-based tasks, such as demand forecasting, require error-based metrics (MSE and RMSE), while classification and decision-making tasks require classification-based metrics derived from the confusion matrix, such as accuracy [32].

6. COMPARISON BETWEEN PREVIOUS WORKS

Table 1 shows a quantitative comparison of the proposed model with recent supply chain forecasting studies, based on published, documented results. The proposed model achieves significantly lower error rates, with RMSE ranging from 0.14 to 0.2 and MSE ranging from 0.1 to 0.3. Study [33] indicated an RMSE value of 2.27 and an estimated MSE value of approximately 7.9. Study [34] also reported an RMSE of 18.83, indicating a much higher level of prediction error. The proposed model numerically achieves a significant reduction in error, indicating strong predictive performance. Beyond the quantitative gains, the proposed model also addresses a more complex challenge: comparative studies are mostly focused on demand forecasting, whereas this work integrates forecasting, decision-making, and optimization. This is facilitated by the fusion of fuzzy neural networks, multi-agent systems, and blockchain technology to enable intelligent coordination in supply chain management. The study [33] also focused on large-scale forecasting rather than decision-making capabilities, and the model [34] as only evaluated with a processed real-world dataset (945 records), while the model proposed in this paper was also validated and tested against an expanded real-world dataset of ~12,000 records, which improves the reliability and generalizability of our results.

Table 1. Comparison between related work and the proposed model

Study	Dataset	Size	Model	Task	MSE	RMSE	Accuracy	Key Contribution
Proposed Work	Kaggle supply chain dataset (processed & expanded)	~12,000 records	FNN + MAS + Blockchain	Prediction + Decision-making + Optimization	**0.1 – 0.3**	**0.14 – 0.2**	**91%**	Integrated intelligent system with high accuracy and decision support
[33]	Real-world e-commerce dataset	945 records	ANN + CapSA	Forecasting + Resource allocation	~7.9	**2.27**	—	Improved prediction and operational efficiency
[34]	Food supply chain dataset (Genpact)	-	ML / LSTM / BiLSTM	Demand forecasting	—	**18.83**	—	Large-scale forecasting using ML models

Note: MSE: Mean Squared Error, RMSE: Root Mean Squared Error.

7. METHOD

Next talk about the methodology we proposed. The post-generation local decisions are transformed into an output for the sequential processing stage, which also includes validation and transformation into Block1, Block2, and Block3. Each block is formed through a validation process based on FNN. Your system, on the other hand, as it relies on data migration to the respective agents even after verification in case of high-confidence failures, is ultimately resilient.

7.1 Blockchain layer

When the blocks are formed, they will be published to the blockchain layer, which runs verification processes, executes smart contracts, and applies consensus rules. It makes the computation less cumbersome and faster to deploy using a permitted blockchain.

7.1.1 System outputs

The final output is a verified block that is installed in the blockchain, ensuring data immutability, transparency, and secure storage.

7.1.2 Feedback loop

The system contains a feedback loop to advance its function. The entire loop consists of monitoring performance, evaluating predictions, and updating models and policies based on them using reinforcement learning. Figure 1 shows a structural design architecture for decision-making (SDM) in SCM that combines a MAS and FNN models with blockchain to ensure transparency, reliability, and enhanced decision-making. To clarify the input as mentioned in the reviewer comments, we start with a known set of data sources. Rather than relying on a single transaction (Transaction T), the model aggregates heterogeneous data sources (e.g., inventory data (stock levels or demand history); supplier-level performance measures of delivery performance and quality records; and transportation with respect to time and cost) along with external factors such as market trends and seasonality, thus making decision-making robust in terms of being realistic. Those inputs are then consumed by a set of agents—the inventory agent, the supplier agent, and the logistics agent. The input → FNN model → prediction → decision is the same for all agents. Since FNN produces predictions that are used in local decisions, the internal processing mechanism within each agent is clarified. Once decisions are made at the agent level, the system moves to a sequential block generation phase that generates a string of blocks ($Block_1$, $Block_2$, $Block_3$) as it passes through enough feed-forward neural network(s) validation phases. The data in each subsequent step is re-validated and converted before it reaches the next block. Upon encountering a validation error, a rejection mechanism is triggered, returning the data to the respective agent for reprocessing. This ensures data integrity and provides assurance about the system's reliability. And then, once the block sequence is complete, we will push it to the blockchain layer. List of blockchain operations beside the figure, as prescribed by academic visualization standards, including data validation, execution of SC, block generation, and consensus (Proof of Authority (PoA) and Proof of Stake

(PoS)). When you put all these steps together, you get immutable evidence of transactions recorded securely on the blockchain ledger. A new validated block is published to the blockchain; your system output is now immutable. This ensures data transparency, traceability, and trust amongst all parties, as the needs of each network player are specifically catered to, leading to better system performance. A feedback loop mechanism is built in. The loop is comprised of performance monitoring → evaluation against predicted vs. actual outcomes → model update (retraining new FNN agents) → change in reinforcement learning policy to update their hypothesis. This component allows for system responsiveness and self-learning. Overall, the architecture framework achieves objectives as a scalable architecture that integrates both artificial intelligence and blockchain for supply chain risk management (SCRM) with an intelligent decision-support system for all aspects from supply chain processes to information capture steps, while disregarding reviewers' comments on input specification, process diagrams with a track focus of workflows in detail, time specification of blockchain technologies, and incremental improvements.

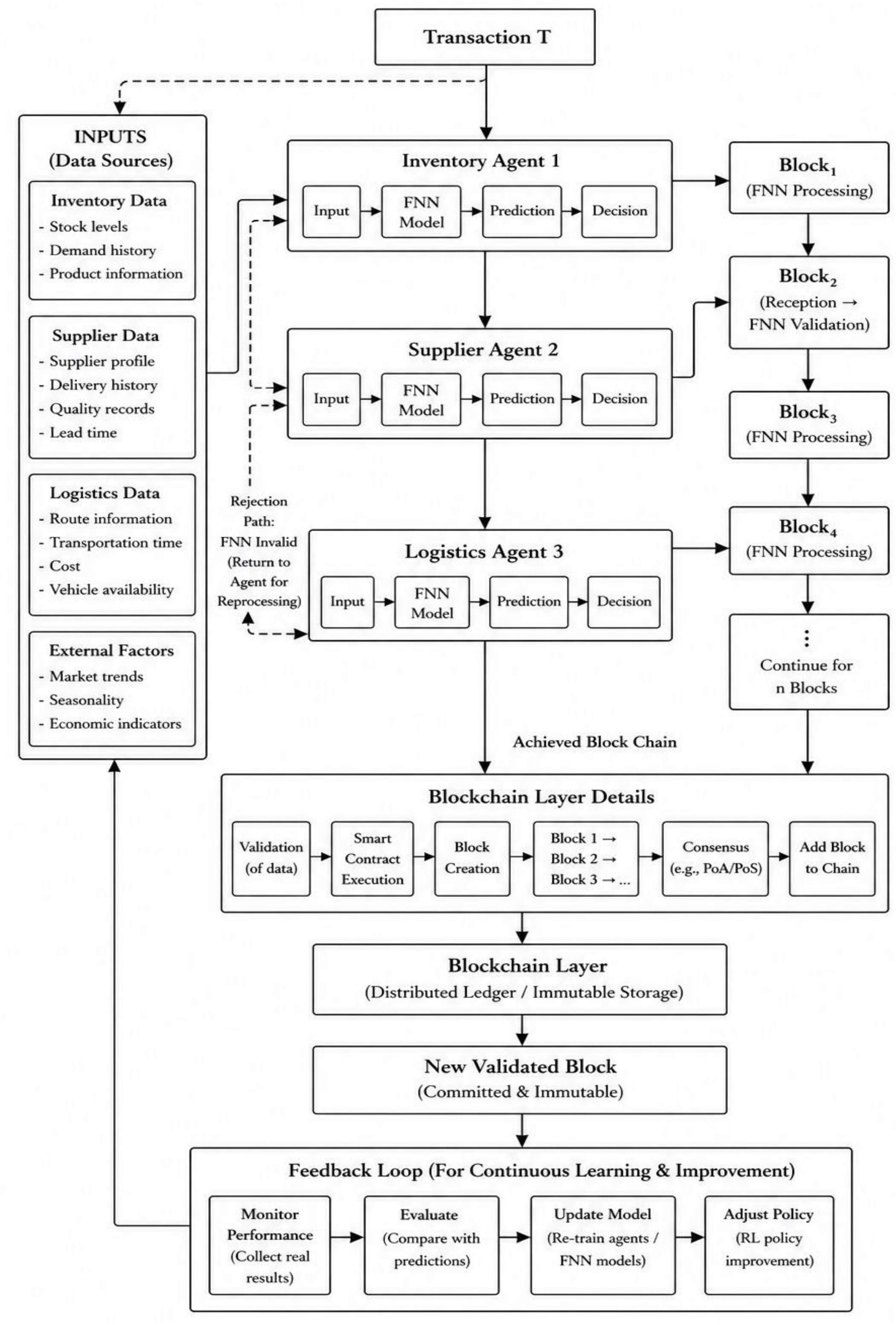

Figure 1. Diagram for a supply chain network using multi-agent technology and blockchain

7.2 Algorithm

The proposed algorithm provides a system-level implementation of the framework. It shows how supply chain data are processed by specialized agents, how FNN models generate task-specific decisions, and how these decisions are validated and recorded through a permissioned blockchain layer.

```
Input:
    D_inv  : inventory dataset features
    D_sup  : supplier performance features
    D_log  : logistics and routing features
    SC     : smart contract rules
    BC     : permissioned blockchain network
    E      : number of training epochs
    α      : learning rate

Output:
    Inventory decisions
    Supplier evaluation decisions
    Logistics route decisions
    Validated blockchain records

Begin

Step 1:Data Initialization
        Load D_inv, D_sup, and D_log
        Clean missing values
        Encode categorical attributes
        Normalize numerical attributes
        Split data into training and testing sets

Step 2: Agent Initialization
        Create Inventory_Agent
        Create Supplier_Agent
        Create Logistics_Agent

Step 3: FNN Training for Each Agent
        For each Agent_i in {Inventory_Agent, Supplier_Agent, Logistics_Agent} do
         Select task-specific features X_i
         Select target output Y_i
         Initialize FNN parameters

            For epoch = 1 to E do
                Apply fuzzification to X_i
                Apply fuzzy inference rules
                Generate predicted output Ŷ_i
                Compute loss using MSE
                Update FNN parameters using learning rate α
           End For
  End For

Step 4: Local Decision-Making
        Inventory_Agent predicts stock priority and order quantity
          Supplier_Agent evaluates supplier reliability and classification
          Logistics_Agent predicts route performance, time, and efficiency

Step 5: Agent Communication
        Share agent decisions through the MAS communication layer
        Detect conflicts such as stock shortage, supplier delay, or route inefficiency
        Resolve conflicts based on predefined decision rules

Step 6: Blockchain Validation
      For each decision generated by the agents do
         Create transaction T
         Send T to smart contract SC
```

```
            If SC validates T then
               Add T to candidate block
            Else
               Return T to the responsible agent for reprocessing
            End If
         End For

   Step 7: Block Creation and Consensus
         Group validated transactions into a new block
         Apply permissioned consensus mechanism
         If consensus is achieved then
            Commit block to blockchain BC
     Else
        Reject block and repeat validation
     End If
   Step 8: Feedback and Model Update
           Monitor actual outcomes
           Compare actual results with predicted results
           Update agent performance metrics
           Retrain or adjust FNN models when performance decreases

   End
```

7.3 Experimental analysis

Based on the proposed algorithm, an integrated analysis of the system can be provided, showing how it performs in terms of performance, efficiency, and scalability. The system relies on a multi-agent architecture in which each agent processes a specific piece of supply chain data independently using intelligent models such as fuzzy neural networks or predictive models. Instead of a single central system, this method distributes the processing load across multiple components, reducing overall time. It does improve the time complexity of handling systems in general, specifically for large amounts of data. The next stage is the block generation and verification stage, which receives input from local outcomes after each agent's decision-making. Decisions at this stage are analyzed and validated before being compiled into blocks that can be appended to the blockchain. This is done to ensure verification passes; if it fails, the data will be sent back to the agent for reprocessing, ensuring a reliable, robust system and preventing erroneous decisions from being passed. The sentencing execution layer can consider the blockchain layer, which includes many verification processes and a consensus mechanism for contracts and smart contracts. While these processes do incur a small-time penalty, using an authorized blockchain and light consensus protocols can reduce latency compared to public systems. Additionally, grouping many decisions into a single block greatly simplifies processes and enhances efficiency. It is very easy to scale up the system due to its high flexibility; new agents can be added without disrupting the rest of the components. Similar to parallel processing between agents, this will provide higher completion rates and the potential to process greater amounts of data. In short, this gives you intra-industrial paradigms to gain time and collective, but decentralized, intelligence within a blockchain structure applicable to supply chains. It also addresses residents' concerns regarding systematic analysis and practical details.

7.3.1 Data set

This collection was first acquired from a publicly accessible dataset on Kaggle [35]. This includes systematic data on supply chain activities, such as product specifications, prices, inventory levels, and available supplier and logistics information. The dataset was refined and expanded to better replicate the research's larger-scale, realistic supply chain objectives. The resulting dataset contained more than 12,000 records, enabling richer training and evaluation of the proposed system. And the dataset includes information such as product type, stock level, lead time in supply, number of goods ordered, and average and (by supplier) performance metrics; defect rates across suppliers, including containers; transport sequences/links and routes for individual shipments from each supplier route; and total cost on any route. Those cues have inspired features like decision-making processes for Inventory management, supplier evaluation, and Logistics process improvement.

7.3.2 Data preprocessing

Before the training process, the dataset was preprocessed to enhance data quality and model performance. It involves handling missing values, encoding categorical variables (e.g., supplier name, transport mode, and routes), and normalizing numerical variables to ensure the input variables are consistent.

7.3.3 Training setup

The experimental data set, with around 12,000 records, is stored in fuzzy_train.csv and fuzzy_test.csv formats. To evaluate the model's capabilities confidently, the data were split into 80% for training and 20% for testing. Data preprocessing (before training): Missing values, categorical feature encoding (supplier name, transportation mode, and routes), and normalizing the numerical features to create a better, more stable learning system. For the training task specification, the target characteristics were trained separately for each intelligent agent. The Fuzzy Neural Network FNN model was adopted to capture nonlinear relationships and deal with uncertainty in supply chain data. During the training process, the coefficients of belonging functions and the weights of fuzzy rules were adjusted repeatedly using the training data. The model was trained for 100 epochs with a learning rate of 0.01, and the best setting was selected based on minimizing prediction error. The test data was excluded from the training process and used only for the final evaluation to assess the model's ability to generalize to unseen data. Performance was evaluated using metrics customized for each task. MSE and RMSE were used for continuous forecasting tasks, such as inventory forecasting, while accuracy was used for decision-making tasks, such as supplier evaluation and route selection.

8. EXPERIMENT AND RESULT

This test involved developing an interactive supply chain monitoring panel, the effectiveness of which was evaluated in supporting monitoring, evaluation, and improvement processes across the supply chain's various stages. The system aims to track processes from the moment food products leave the warehouse until they are delivered to customers in a timely manner, relying on intelligent agents who monitor workflow and accurately track movements and processes. The first agent is responsible for monitoring inventory and the availability of materials from suppliers within the warehouse, while the rest of the agents work in an integrated manner so that they complement each other to ensure that the monitoring and tracking process is sequential and interconnected, and at the same time, the work of all agents contributes to enhancing the efficiency of supply chain management in general. The assessment panel comprised three main components: recommendations on inventory management, supplier performance-tracking measures, and planned logistical operations. This enables the system to present a broader, integrated view of operational and strategic decisions related to supply-chain calculus, showcasing its relevance in balancing demand and supply while maintaining operational efficiency.

8.1 Inventory agent

Table 2 and Figure 2 visualize the agent's performance, priority, order quantity levels, and evaluation metrics for multiple items. Results indicate strong demand for items such as frozen chicken (4.2) and rice (4.1), which were accurately assessed as critical to maintaining supply continuity, while lower-priority ingredients, such as flour (2.9), could have received less immediate management attention.

Table 2. Result MSE, RMSE, accuracy for agent inventory

Domin	MSE	RMSE	Accuracy
Frozen Chicken	0.3	0.1	0.79
Tomato	0.3	0,1	0.81
Flour	0.3	0.2	0.81

Note: MSE: Mean Squared Error, RMSE: Root Mean Squared Error.

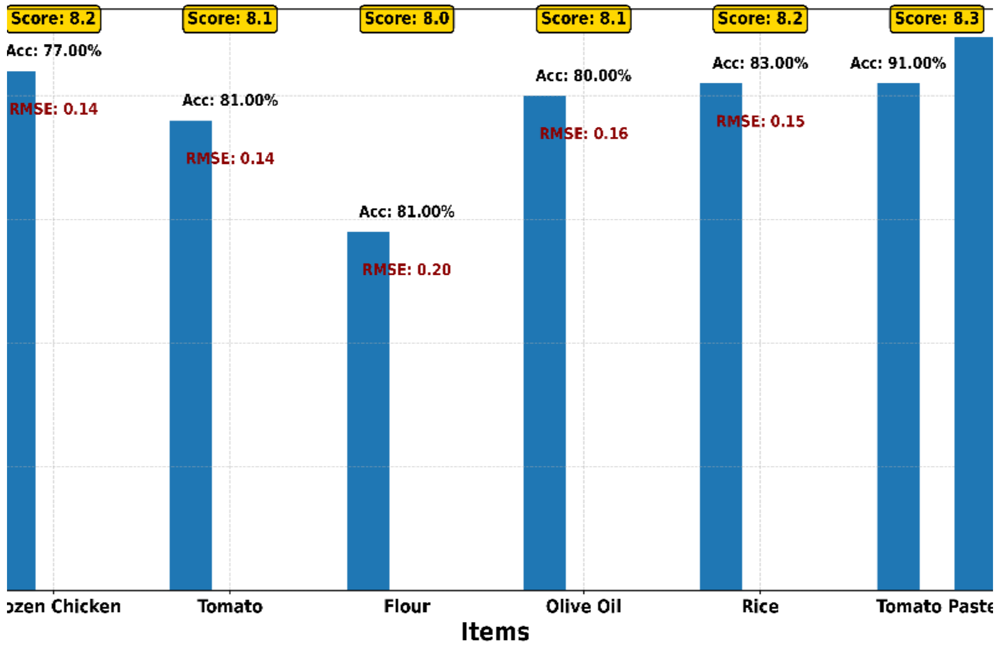

Figure 2. Inventory agent

Finally, regarding order decisions, since the ordering quantities for most items are zero, this indicates that these items have been sufficiently predicted and that no unnecessary resupply operations will be carried out in this quarter. Only the tomato paste item is significant, as 71 units are required immediately and will be predicted soon after. As for performance, these give accuracy values around 0.79 and 0.81. Similarly, the past RMSE values are low and stable (between 0.14 and 0.20), which provides another signal of adequate prediction quality. Score values between 8.0 and 8.3, yielding an overall decision quality score, with higher scores indicating better identification of boundary conditions in which inventory replenishment procedures should be accurately deployed optimally and probably increasingly over time. Findings: The blended business process, along with an intelligent multi-agent system that prioritizes inventory decisions based on order priorities, forecasts, and errors, has reduced errors and improved forecast accuracy, paving the way for smart supply chain management.

8.2 Supplier agent

Show in Figure 3 and Table 3. Based on accuracy, RMSE, and score, Figure X illustrates the supply agent's performance relative to a variety of suppliers. The results demonstrate that the model reaches repeatable, high accuracy of 82%-86% with a top-passed test for supplier Rodriguez Stone Dairy Products at 86%. Simultaneously, all cases indicate low, stable RMSE values near 0.20, indicating reliability and predictive power. The score values also range from 8.0 to 8.2, increasing the model's speed when evaluating supplier performance. Suppliers with higher accuracy tend to have a higher score, which can be attributed to better reliability and decision quality. Alternatively, a good performance case under more adverse conditions can still deliver an acceptably high score, with 82% accuracy (score value of 8.0), as seen in the Clark PLC Oils included in this example base case. In general, the results validate that the developed approach enables stable, accurate measurement of suppliers, thus enabling effective selection and decision-making across supply chains.

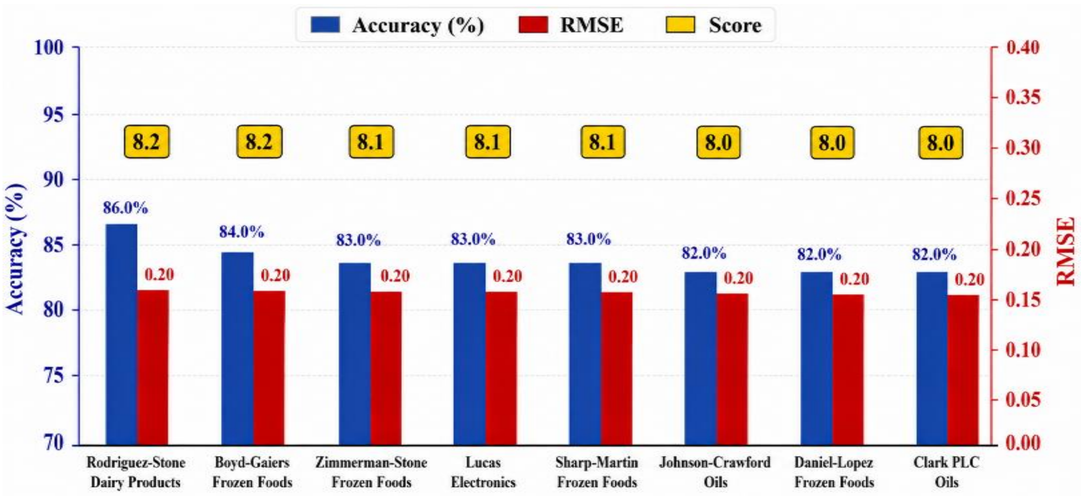

Figure 3. Supplier agent

Table 3. Result (MSE, RMSE, accuracy for supplier agent)

Total Agent	MSE	RMSE	Accuracy
Agent inventory	0.3	0.14	0.75
Agent supply	0.2	0.16	0.83
Agent logistic	0.1	0.2	0.91

Note: MSE: Mean Squared Error, RMSE: Root Mean Squared Error.

8.3 Logistics agent

Figure 4 and Table 4 show the performance of the logistics agent across various routes, including accuracy and RMSE, as well as estimated time & cost-efficiency indices. The model achieves high accuracy between 78% and 95%, as detailed in the results, with the best result being for route WH_C → Port_A, which reaches 95%, indicating an efficient routing decision. RMSE values are also low (from 0.12 to 0.22), which, as a result, suggests high stability and reliability of predictive performance upon different paths. The expected time varies substantially by route, from 1.2 to 8.5 hours, as transport conditions and route complexity can vary considerably between locations. Cost efficiency sits between 20% and 80%, too, suggesting a trade-off between speed and cost. It is observed that high-efficiency tracks like WH_C → Port_A at 80% are accompanied by higher values of accuracy and lower values of RMSE, suggesting the model can maintain a good balance between performance and operation limits (number of ships), while low-efficiency tracks like 20%-30% show relatively less improved accuracies or longer time consumption.

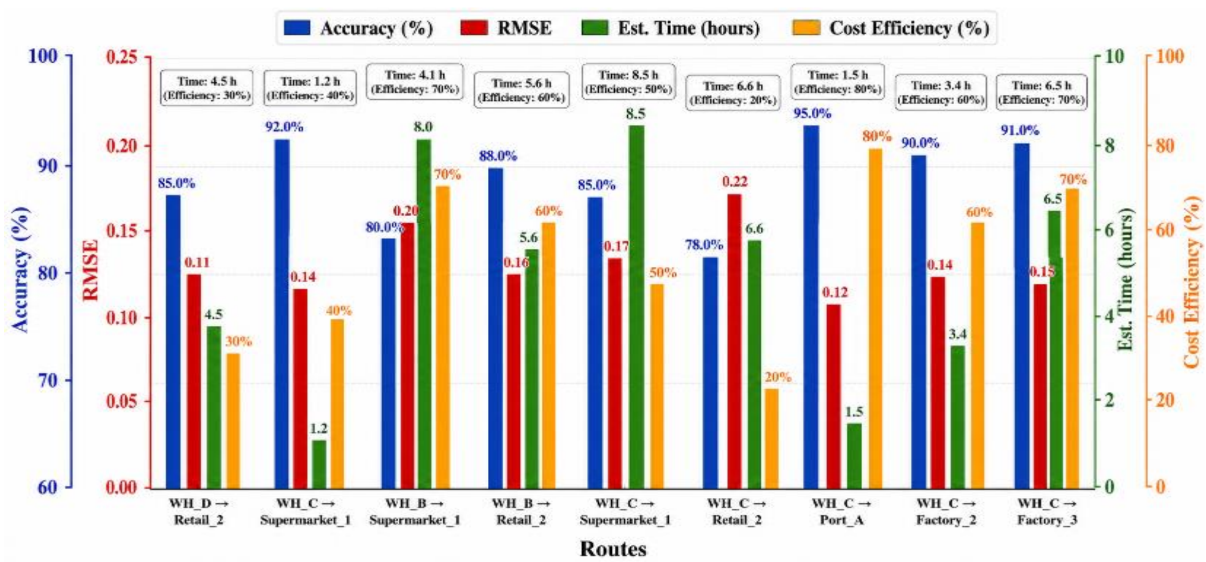

Figure 4. Logistics agent

Table 4. Result (MSE, RMSE, accuracy for agent logistic)

Logistic Agent	MSE	RMSE	Accuracy
"WH_A → Supermarket_1	0.35	0.59	0.85
"WH_D → Retail_2	0.12	0.35	0.96
WH_E → Retail_2	0.1	0.2	0.95

Note: MSE: Mean Squared Error, RMSE: Root Mean Squared Error.

Table 5. Average result (MSE, RMSE, accuracy)

Supplier Agent	MSE	RMSE	Accuracy
Parker and Miller Grains	0.3	0.1	0.82
Brown-Romero Frozen Foods	0.3	0.2	0.84
Cabrera Inc Electronics	0.2	0.2	0.86

Note: MSE: Mean Squared Error, RMSE: Root Mean Squared Error.

Show in Table 5 Outcomes demonstrate that the recommended system delivers better performance at different phases of the supply chain. The procurement agent managed to strike the best balance between low error rates and accuracy, while the inventory agent performed fairly well with room for improvement in the accuracy of its forecasts. The logistics agent exhibited the highest level of accuracy, but the errors showed greater variability across a few operational factors. These outcomes ensure that the combination of these agents improves the reliability of the system for operational and strategic decision support through the embedding of expert inventory management, quality assurance of suppliers, and achieving more stable cost and time-efficient logistics strategies.

8.4 System-level performance

Figure 5 shows the performance distribution among the system components, indicating that agent processing is highly efficient despite its time consumption, while the blockchain layer accounts for the main delays due to verification processes and consensus mechanisms. The figure also shows that the system's overall time is directly affected by the blockchain layer's time, indicating a bottleneck in this layer relative to the rest of the components. However, the system achieves a good processing rate, which confirms that it has been applied practically and is capable of operating within a realistic environment, and not just a theoretical model.

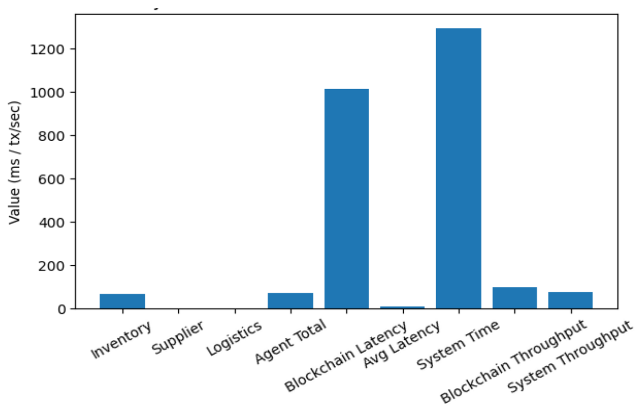

Figure 5. system performance metrics

Show in Table 6. To go beyond prediction accuracy and showcase the practical applicability of the proposed system, a realistic experimental setting was conducted, consisting of 100 transactions in which the system was run end-to-end with proper implementation (i.e., agent-level processing and actual blockchain operations were performed). Comprehensive macro-level analysis: Execution time, blockchain delay, and throughput. As shown in Table 6, the execution time, blockchain delay, and throughput of a particular scenario are examined for single- and multi-query execution, enabling macro-level analysis. As per the results, agent-level processing is very effective (total execution time of 72.87 ms), and the rest of the delay resides inside the blockchain layer (1012.03 ms), which can be optimized through parameter optimization; however, the system is still able to achieve an extremely high throughput rate at the blockchain level (98.81 transactions per second) and macro level (77.29 transactions per second). Due to overhead optimizations implemented in accordance with SOLID design principles. These results demonstrate that the system we proposed has been deployed in practice and can operate in real time, with the blockchain layer as the obvious performance bottleneck.

Table 6. System-level performance

Category	Metric	Value	Unit
Agent Execution Time	Inventory Agent Time	69.64	ms
	Supplier Agent Time	0.51	ms
	Logistics Agent Time	2.73	ms
	Total Agent Processing Time	72.87	ms
Blockchain Performance	Total Blockchain Latency	1012.03	ms
	Average Latency per Transaction	10.10	ms/transaction
	Number of Transactions	100	transactions
	Number of Blocks	100	blocks
	Blockchain Throughput	98.81	transactions/sec
System Performance	Total System Execution Time	1293.79	ms
	Overall System Throughput	77.29	transactions/sec

8.5 The experimental results and dissection

Experimental results show that the proposed system achieves competitive performance for various supply chain tasks, resultant RMSE values of 0.14 to 0.2, and a mighty accuracy rate up to 91%. Compared with the latest studies [28] and [29], the prediction errors provided by the proposed model are lower. There are three main reasons for the performance improvement. The use of a FNN enables the model to better reflect uncertainty and non-linear relationships in supply chain data. Second, with the MAS structure and task-oriented learning, model composition and training are faster. Third, the blockchain as a source of data provides consistency and reliability which may lead to increased accuracy of the overall model. Also, it was observed that data preprocessing and normalization also proved vital in addressing the challenges regarding model's stability and learning performance. To summarize, the results prove that the model we proposed outperforms its classical counterpart in accuracy and coverage.

9. CONCLUSION

The results in this study demonstrate that the proposed system presents a new approach that integrates forecasting performance with error reduction and operational considerations to assist in supply chain decision-making. The system was able to maintain stable performance over inventory management tasks, supplier evaluation, and logistic process improvement Experimental results demonstrated RMSE values between 0.14 to 0.2 with accuracies of 91% for the logistics agent, with supply agent achieving accuracy levels of 83%, and height levels of accuracy of rate agents were at 75% all indicating a capability in handling multiple tasks Overheads required within an integrated group environment. Results demonstrated a lower error values and comparable performance metrics to state-of-the-art approaches. While these results should be taken with caution due to a reliance on a data set of about 12,000 records and in an experimental context that may not generalize well to broader or more complex some aspects (for example, the blockchain layer), the current system implements multi-agent systems, FNN and blockchain in such a way -it allows superior coordination and reliability. Results have demonstrated that this layer is a performance bottleneck from the system level perspective. Therefore, the proposed company can be seen as a flexible and extensible human-centered architecture to enable supply chain operations.

REFERENCE

[1] Ye, W.X. (2024). E-commerce logistics and supply chain network optimization for cross-border. Journal of Grid Computing, 22(1): 22. https://doi.org/10.1007/s10723-023-09737-z

[2] Lee, J., Ko, C., Moon, I. (2024). E-commerce supply chain network design using on-demand warehousing system under uncertainty. International Journal of Production Research, 62(5): 1901-1927. https://doi.org/10.1080/00207543.2022.2128462

[3] Kathirvel, N., Kathirvel, A. (2024). Applying business intelligence and blockchain in entrepreneurship. In Generating Entrepreneurial Ideas With AI, pp. 147-171. https://doi.org/10.4018/979-8-3693-3498-0.ch007

[4] Ghorbel, O., Frikha, T., Hajji, A., Alabdali, R., Ayadi, R., Abbas Elmasry, M. (2022). Blockchain-based supply chain system for olive fields using WSNs. Computational Intelligence and Neuroscience, 2022(1): 9776776. https://doi.org/10.1155/2022/9776776

[5] Verma, P., Srivastava, R., Kumar, S. (2024). Blockchain technology: Applications and challenges. In Blockchain for IoT Systems, pp. 12. https://doi.org/10.1201/9781003460367-1

[6] Ostrosi, E., Fougères, A.J., Zhang, Z.F., Stjepandić, J. (2024). Intelligent modular design with holonic fuzzy agents. Advances in Manufacturing, 9: 81-103. https://doi.org/10.1007/s40436-020-00331-0

[7] Farazi, M.Z.R. (2025). Enhancing supply chain resilience with multi-agent systems and machine learning: A framework for adaptive decision-making. The American Journal of Engineering and Technology, 7(3): 6-20. https://doi.org/10.37547/tajet/Volume07Issue03-02

[8] Gružauskas, V. (2020). Supply chain resilience in the context of sustainable food industry (Doctoral dissertation). Kauno technologijos universitetas.

[9] Mohamed-Iliasse, M., Loubna, B., Abdelaziz, B. (2022). Machine learning in supply chain management: A systematic literature review. International Journal of Supply and Operations Management, 9(4): 398-416. https://doi.org/10.22034/ijsom.2021.109189.2279

[10] Gamoura, S.C. (2023). Profiling the applicability of supervised machine learning in supply chain information systems: An agglomerative clustering approach. https://doi.org/10.60662/95wz-x073

[11] Moosavi, J., Naeni, L.M., Fathollahi-Fard, A.M., Fiore, U. (2021). Blockchain in supply chain management: A review, bibliometric, and network analysis. Environmental Science and Pollution Research, 1-15. https://doi.org/10.1007/s11356-021-13094-3

[12] Sri Vigna Hema, V., Manickavasagan, A. (2024). Blockchain implementation for food safety in supply chain: A review. Comprehensive Reviews in Food Science and Food Safety, 23(5): e7002. https://doi.org/10.1111/1541-4337.70002

[13] Hadi, H.A.A., Ghani, R.F. (2025). The Future of E-Health: Blockchain Solutions with Hyperledger Fabric and IPFS. Ingénierie des Systèmes d'Information, 30(1): 243-255. https://doi.org/10.18280/isi.300121

[14] Boudouaia, M.A., Ouchani, S., Qaisar, S.M., Almaktoom, A.T. (2024). Supply chain 5.0: Vision, challenges, and perspectives. In Learning and Technology Conference, Jeddah, Saudi Arabia, pp. 203-208. https://doi.org/10.1109/LT60077.2024.10469476

[15] Abbasi, S., Vlachos, I., Samadzadeh, A., Etemadifar, S., Afshar, M., Amra, M. (2024). Modelling a logistics and financial supply chain network during the COVID-19 era. Logistics, 8(1). https://doi.org/10.3390/logistics8010032

[16] Agrawal, T.K., Angelis, J., Khilji, W.A., Kalaiarasan, R., Wiktorsson, M. (2023). Demonstration of a blockchain-based framework using smart contracts for supply chain collaboration. International Journal of Production Research, 61(5): 1497-1516. https://doi.org/10.1080/00207543.2022.2039413

[17] Ellahi, R.M., Wood, L.C., Bekhit, A.E.D.A. (2023). Blockchain-based frameworks for food traceability: A systematic review. Foods, 12(16): 3026. https://doi.org/10.3390/foods12163026

[18] Rejeb, A., Appolloni, A. (2022). The nexus of Industry 4.0 and circular procurement: A systematic literature review and research agenda. Sustainability, 14(23): 15633. https://doi.org/10.3390/su142315633

[19] Ghani, R.F., Salman, A.A., Khudhair, A.B., Aljobouri, L. (2022). Blockchain-based student certificate management and system sharing using hyperledger fabric platform. Periodicals of Engineering and Natural Sciences, 10(2): 207-218. https://doi.org/10.21533/pen.v10.i2.599

[20] Cao, S., Johnson, H., Tulloch, A. (2022). Exploring blockchain-based traceability for food supply chain

sustainability: Towards a better way of sustainability communication with consumers. Procedia Computer Science, 217: 1437-1445. https://doi.org/10.1016/j.procs.2022.12.342

[21] Ogunyankinnu, T., Onotole, E.F., Osunkanmibi, A.A., Adeoye, Y. (2022). Blockchain and AI synergies for effective supply chain management. IJMRGE, 2(4): 1-626. https://doi. org/10.54660/. IJMRGE, 1-626.

[22] Mohammed, M.A., Wahab, H.B.A., Mohammed, M.A. (2025). Blockchain-based physical election votes digitally secure transfer. Journal of Soft Computing and Computer Applications, 2(1). https://doi.org/10.70403/3008-1084.1018

[23] Al-Sakini, S.R., Bilal, G.A., Sadiq, A.T., Al-Maliki, W.A.K. (2025). Dissolved gas analysis for fault prediction in power transformers using machine learning techniques. Applied Sciences, 15(1): 118. https://doi.org/10.3390/app15010118

[24] Garg, P., Gupta, N., Agarwal, M. (2023). Role of artificial intelligence in supply chain management. In Data Analytics and Business Intelligence: Computational Frameworks and Practical Applications, pp. 15. https://doi.org/10.1201/9781003189640-5

[25] Hassan, A.K.A., Hadi, M.J. (2017). Sense-based information retrieval using fuzzy logic and swarm intelligence. International Journal of Multimedia and Ubiquitous Engineering, 12(1): 363-376. https://doi.org/10.14257/ijmue.2017.12.1.31

[26] Wang, Y. (2021). Research on supply chain financial risk assessment based on blockchain and fuzzy neural networks. Wireless Communications and Mobile Computing, 2021(1): 5565980. https://doi.org/10.1155/2021/5565980

[27] Jahin, M.A., Shahriar, A., Amin, M.A.M. (2025). MCDFN: Supply chain demand forecasting via an explainable multi-channel data fusion network model. Evolving Intelligence, 18: 66. https://doi.org/10.1007/s12065-025-01053-7

[28] Ahmed, N., Ahammed, R., Islam, M.M., Uddin, M.A., Akhter, A., Talukder, M.A., Paul, B.K (2021). Machine learning based diabetes prediction and development of smart web application. International Journal of Cognitive Computing in Engineering, 2: 229-241. https://doi.org/10.1016/j.ijcce.2021.12.001

[29] Ghani, R.F., Kamal, Z.A., Farhan, A.K. (2024). Blockchain-based e-government system using WebSocket protocol. Engineering and Technology Journal, 42(4): 421-429. https://doi.org/10.30684/etj.2024.146559.1689

[30] Hussain, I., Ali, R. (2024). Robust leaf disease detection using complex fuzzy sets and HSV-based color segmentation techniques. Acadlore Transactions on AI and Machine Learning, 3(3): 183-192. https://doi.org/10.56578/ataiml030305

[31] Shareef, S.M., Hassan, R.F. (2025). Enhancing cybersecurity based on blockchain technology: A systematic review. Journal of Soft Computing and Computer Applications, 2(1): 2.

[32] Xie, L., Liu, J., Wang, W. (2024). Predicting sales and cross-border e-commerce supply chain management using artificial neural networks and the Capuchin search algorithm. Scientific Reports, 14(1): 13297. https://doi.org/10.1038/s41598-024-62368-6

[33] Panda, Mohanty, S.N. (2023). Time series forecasting and modeling of food demand supply chain based on regressors analysis. IEEE Access, 11: 42679-42700. https://doi.org/10.1109/ACCESS.2023.3266275

[34] Ogunsoto, O.V., Olivares-Aguila, J., ElMaraghy, W. (2025). A conceptual digital twin framework for supply chain recovery and resilience. Supply Chain Analytics, 9: 100091. https://doi.org/10.1016/j.sca.2024.100091

[35] Motefaker, A. (2023). Supply Chain Dataset. Kaggle. https://www.kaggle.com/datasets/supply-chain-dataset.