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Enhancing supply chain resilience with multi-agent systems and machine learning: a framework for adaptive decision-making

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Abstract: The research focuses on how Multi-Agent Systems (MAS) coupled with Machine Learning (ML) can help manage the challenges and risks associated with new-generation supply chains networks. The proposed MAS-ML framework improves flexibility, adaptability, and predictiveness in essential roles in supply chain management (SCM), including demand forecasting, inventory management, production planning, and SCM logistics. The framework is based on decentralised decision-making where each agent is responsible for a particular supply chain activity but employs real-time data foresight from the ML model to streamline the activities. This decentralisation enables resilience in supply chains, which can experience events such as demand variability and transportation disruptions. MAS-ML is presented in this paper as the solution capable of enhancing supply chain performance, reliability, and cost optimisation in situations characterised by risk and uncertainty, such as the current global pandemic. In addition, this paper presents potential research areas, such as the integration of more enhanced deep learning algorithms, the extension of proposing MAS-ML into other sectors, and the addressing of ethical and transparency concerns associated with AI-based decision-making systems. The proposed MAS-ML framework improves the adaptability and resiliency of supply chains, providing a flexible solution for modern supply chain problems.

Keywords: Multi-Agent Systems (MAS), Machine Learning (ML), Supply Chain Management, Demand Forecasting, Inventory Management, Production

Planning, Logistics Optimisation, Supply Chain Flexibility, Decentralised Decision-Making, Supply Chain Resilience, Predictive Analytics, Random Forest, Gradient Boosting.

Introduction: Decision-making in today's global supply chain environment involves robust strategic framework and techniques than traditional supply chain models (Katsaliaki et al., 2022). The proposed MAS-ML framework is a holistic method that addresses the adaptability incorporating predictive computational ability. Supply chains are the principles of the global economy, which allow the generation of materials, the distribution of products, and the delivery of them to clients worldwide. More recently, though, the supply chains have been threatened in ways that have opened the supply chain experts to new forms of management. COVID-19 has disrupted operations worldwide, resulting in factory closures, transportation constraints, and heightened demand for specific goods, including personal protection equipment (Camur et al., 2023). The pandemic caused severe supply chain disruptions, with many companies facing delays in production and shipping (Xu et al., 2020). For instance, global automotive manufacturing slowed significantly due to factory shutdowns in key regions like China, the US, and Europe.

Many businesses were forced to adopt new strategies, such as digitalisation to maintain supply chain resilience during the crisis. Supply chains grow in size and sophistication, and demand fluctuation, inventory status and transportation complications are challenging to forecast and control (Ghadge et al., 2020). Traditional supply chain systems with standard planning rely on accurate forecasts, and a centralised control system cannot handle these challenges in real-time (Epiphaniou et al., 2020). For instance, rigid production planning and arithmetic demand forecasting approaches regularly overlook consumer demand fluctuations and transportation chain disruptions.

The major problems of modern supply chains are uncertainty. The current demand forecasting models have some drawbacks in predicting the consumers' changing behaviour, primarily influenced by digital platforms and volatile economic environments (Kalkanci., 2011). Supply chain managers mainly deal with global transportation networks, where delays, lockups and cost volatility are strangers. The older supply chain management systems that used historical parameters and forecasts cannot accurately accommodate these variables (Katsaliaki et al., 2022). In this regard, conventional decision-making models can be ineffective in many settings because they do not allow one to predict the appearance of a new factor in the process. That is why, with increasing levels of supply chain integration, the impact of such inefficiencies is much more significant. Thus, new approaches, which may effectively accommodate flexibility emerging due to uncertainty, are deemed necessary.

This work proposes a novel approach known as MAS-ML o address these challenges affecting supply chain management in the current environment of fluctuating uncertainty level. The integration of Multi-Agent Systems with Machine Learning enables the enhancement of reliability and flexibility of supply chain. Integrating MAS and ML for the development of the MAS-ML approach makes it possible to increase flexibility and adaptability that include demand forecasting, inventory management, production planning, and logistics functions. Therefore, logistics agents can use of predictive models in order to find optimal routes that can improve efficiency in delivery of products. MAS linked with ML provides a strong background useful for addressing more complicated and supply chains (Pasupuleti et al., 2024).

MAS and ML add a new perspective in supply chain management due to the flexibility of handling the modern supply chain nature, which is full of uncertainties (Stoychev, 2023). Implementation of the MAS framework would enable each of the supply chain agents to operate autonomously, therefore ensuring the fast and effective decision-making regarding the real-time data that constantly flows into the system (Rajbala et al., 2023). This research presents a significant contribution to literature as it seeks to understand the factors responsible for the growing concern of supply chain management in the modern world economy. The overall purpose of the MAS-ML is to assist the companies in improving the organisational performance, reducing costs and enhancing the customer satisfaction due to more efficient supply chain. Furthermore, the adoption of ML models into the MAS framework helps the supply chain managers to reduce the risk that arises when their supply chain is disrupted, hence improving operations resilience (Farazi, 2024).

Literature Review

Supply Chain Resilience

Supply chain responsiveness can be defined as the capability of the supply chain to protect against potential disruptions, mitigate them, and continue with business operations. Today, supply chains are highly susceptible to disruptions caused by factors like the COVID-19 outbreak (Raja Santhi and Muthuswamy, 2022). As the advent of the COVID-19 pandemic has shown, there is a need for robust and flexible supply chains that are ready to face rapid fluctuations in demand, production and delivery (Frederico, 2021). Industry 4.0 technologies are a robust technique that suggests digitising human activity systems through intelligent technologies such as IoT, AI, and data analytics for real-time monitoring and decision-making. Predictive analytics, one of the main segments of Industry 4.0, enables the supply chain manager to anticipate disruptions that could occur and plan how the operations will look through the use of past and present data (Spieske and Birkel, 2021). For example, IoT devices can offer Managers real-time insights into inventory availability, while AI-driven systems can provide different suppliers or transportation routes during disruptions.

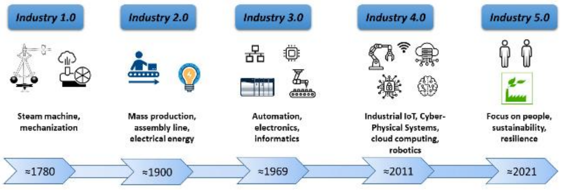

Figure 1: Industrial revolutions from Industry 1.0 to Industry 5.0 (Source: Folgado et al., 2024)

The other important factor that defines supply chain vulnerability is that many supply chain managers need help knowing where to begin when handling risk (Wu and Chen, 2014). When it comes to decision-making in the context of supply chain management, the reason itself is bounded by the fact that no manager can make a decision when encountering supply chain disruptions or uncertainty in the market. Hence, there is a need for systems that can use data to counter human cognitive biases or shortcomings in real-time.

Figure 2: Supply Chain Resilience Source: https://www.altexsoft.com/blog/supply-chain-resilience/

Multi-Agent Systems (MAS)

Multi-agent systems (MAS) are distributed, self-organised systems where numerous agents are associated with various roles or activities in a supply chain, like inventories, production, or transportation (Gui et al., 2024). MA supports real-time decision-making since the agents can work autonomously while acquiring and exchanging data to meet goal-oriented supply chain goals (Nitsche et al., 2023). However, the decentralised functionality of MAS makes it useful in supply chains because various functions may need to respond to new circumstances or changes in demand promptly. This means that the development of MAS in the supply chain emphasises agents that adapt to different strategies. This also allows agents to see what has happened in their surroundings, gain knowledge of the events, and plan their actions for the situation (Lee et al., 2019). This flexibility makes MAS highly suitable

for solving uncertainties and dynamic environments because agents can operate in real-time without resorting to a higher authority.

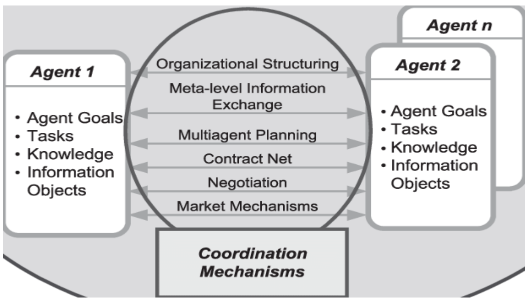

Figure 3: Multi-Agent System (Source: Kishore et al., 2006)

The current MAS design for the supply chain application was decentralised decision making, where every agent is capable of making its own decisions based on the role it plays in the supply chain application. This makes the supply chain adaptive to market forces and conditions, thus leading to increased flexibility of the supply chain (Gružauskas,2020). Artificial Intelligence (AI) has come to be regarded as an empowering technology within the supply chain field to enhance the forecast models and support functions in the decision-making process (Mahraz, 2022). Random forests and Neural networks are some of the applications of the ML in the supply chain management to analyse big data, and identity hidden trends (Ni et al., 2020). Random Forests have been implemented in the supply chain management context for demand fluctuation forecasting and inventory control (Makkar et al., 2020). For instance, a supply chain manager uses Random Forests to forecast the demand for a particular product during a holiday and subsequently order the required stock (Kosasih and Brintrup, 2022). This makes it easier to predict which products are likely to be popular and which are likely to be unpopular, and this leads to minimisation of situations where stock out or overstocking occurs frequently.

Machine Learning (ML) in Supply Chains

Neural Network techniques in ML are known to be effective in identifying non-linear patterns in the supply chain data. It illustrates how Neural Networks can simulate the interaction between market demand, production capabilities, and supplier lead time to enhance production scheduling and procurement. Neural Networks can update their knowledge from new data, making it easier to improve on the forecast made if conditions change frequently. The application of ML in the supply chain results in improved decision-making decreased operational executions, and significant improvement in supply chain activity (Quayson et al., 2023). Understanding the interplay between contracts and behaviour supplies an essential perspective on supply chain dynamics. Many supply chain members, including the supplier, manufacturer, and distributors, develop legal and business contracts that define risk, responsibility and reward (Farazi, 2024). However, a fixed traditional contract model could more effectively address risks, uncertainty, and what people do in the real world. That is where the role of Behavioral Economics, which looks at how people depart from rational choice, comes in.

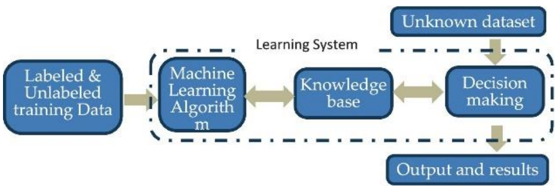

Figure 4: ML system configuration (Sharma et al., 2020).

Chen and Rong (2020) look into factors such as contract complexity and individual behaviour that affect supply chain performance. For instance, the complexity of contracts, such as extensive documentation, exposes the parties to misunderstanding or misinterpretation, causing inefficiency and conflicts among the supply chain members (Li et al., 2020). Furthermore, bounded rationality the finite capabilities of the decision-makers may lead to robust decisions. Some of these behavioural factors must be considered whenever contracts are being developed to fit into the supply chain and in a capability /constrained environment (Chen, 2013).

According to behavioural contract theory, contracts ought to be made more fundamental and should also be made to bring out the concept of alignment of incentives. For example, performance-based deals with incentives that can be points such as on-time delivery or expense reduction are likely to reduce the impact of bounded rationality and enhance overall supply chain effectiveness (Li et al., 2009). Thus, it enables the companies to identify the behavioural characteristics of supply chain partners and develop contracts that can facilitate cooperation and minimise uncertainties in the supply chain. The review of supply chain resilience, Multi-Agent Systems (MAS), Machine Learning (ML), and contract design reveals a clear trend towards incorporating advanced technologies and behavioural insights to optimise decision-making in complex and dynamic supply chains.

MAS and ML is a promising approach for real-time and decentralised decision-making for achieving cooperation throughout contracting networks (Farazi, 2024). In combination, these methods provide a full solution to contemporary problems of managing supply chains, thus increasing the organisations' resistance to unpredictable situations.

Proposed MAS-ML Framework

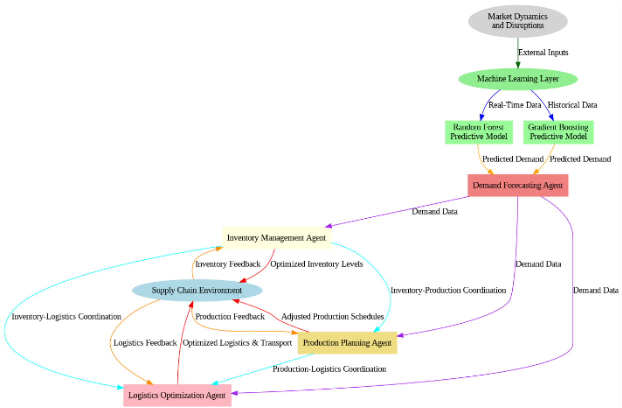

Figure 5: Proposed MAS Framework

The decision making process in SCM is most often agility and flexibility oriented in the present world due to increased volatility in supply chain. The integration of both Multi-Agent Systems (MAS) and Machine Learning (ML) is proposed to address these problems and provide a robust and efficient approach to supply chain exposure. In MAS, supply chain functions such as demand forecasting, inventory control, manufacturing planning, and logistics are considered as objects that can act independently and make decisions. The Random Forest and Gradient Boosting Machines scrutinise all the historical data along with the current data and the agents get prompt and forecasted decisions. MAS-ML models possess the capability for near real-time changes and thus offer greater flexibility and responsiveness in supply chain operations most notably in the market context.

Machine Learning Integration for Predictive Analytics

Forecasting of demand is an essential feature of the supply chain management. Random Forest and GBM in the MAS framework can better estimate demand using historical data and trends (Seyedan and Mafakheri, 2020). The demand forecasting models created actual time prediction utilised by the MAS framework to present demand requirement in the future (Zohra Benhamida et al., 2021). These forecasts are useful especially to agents such as inventory and production managers for the purpose of ensuring that inventory matches the supply chain management needs.

Another strategic function of the organisational structure that the ML models in the framework include is Inventory Optimisation (Chowdhury et al., 2024). It allows the inventory agent to forecast for the right quantities of stock. The inventory agent defines the stock using the prediction from machine learning so that the agent can reduce supplies depending on the fluctuations in demand (Sakib, 2021). This approach optimises costs while ensuring that products are available to meet customer demand, thus improving overall supply chain performance (Li and Chen, 2020).

Production Scheduling is related to demand forecasting and inventory management since the former depends on the latter to be accurate. Once the demand prediction is produced, the production agent computes the "Production_needed" and the "Production_schedule" to ensure the production capacity is efficiently used. The simulation made it easier to explain how to forecast demand in scheduling the production process, the available material, and the workforce within limited production abilities. Such flexibility in product scheduling enables the supply chain to quickly meet the higher or lower demand in the market without undue lead time.

The MAS implement Logistics and Transportation Optimisation as another primary function wherein the use of machine learning models is done to reduce transportation costs and routes (Adi et al., 2021). The transportation agents used supervised machine learning to forecast the optimal means of transporting the merchandise depending on cost and time (Barua et al., 2020). These predictions enabled the logistics agent to optimise transportation plans by constantly adapting costs and delivery time. In addition to cutting transport costs, real-time optimisation capabilities improve logistics' effectiveness, dependability, and adaptability to demand or supply shock spikes.

Agent-Based Decision-Making

The primary stages in the MAS-ML framework are Agent Interaction and Coordination. The decision-making is decentralised, and each agent works independently, although he may consult and provide information to other agents (Antons and Arlinghaus, 2022). On the other hand, the logistics agent works closely with the inventory and production agents to ensure that all the right products reach the appropriate point of sale at an appropriate time (Aliawadi and SINGH, 2021). It allows real-time decision-making without any central authority, as with traditional organisations. The above coding simulation depicts how every agent operates to ensure sufficient supply chain flow, not only in cases where demand and logistics conditions shift.

The MAS framework helped exemplify the adaptive response through agents who modify the production timetables and logistical strategies based on data collected at the time. It also maintains the flexibility of the supply chain, which is essential for overcoming disruptions (Xu et al., 2021). Another strategic component of the MAS framework is logistics and inventory collaboration. Logistics and inventory agents play an essential role in product movement from the point of production to the distribution centres or customers (Kramarz and Kmiecik, 2022). It was found that the logistics agent predicted the likely transport pattern and the inventory agent checked whether the stocks were adequate.

Resilience and Adaptability

Controlling uncertainty is one of the most significant objectives of the MAS-ML framework. There are various sources of uncertainty in supply chain such as demand uncertainty, disruption in production and distribution, and any other unpredictable situation (Kumar and Sharma, 2021). The MAS-ML framework addresses such uncertainties since the supply chain agents are allowed to change the response dynamically. Real-time decision making facilitates the execution of machine learning models within the context of MAS framework (Pereira and Frazzon, 2021). Other advantages of the MAS-ML framework are Cost and Efficiency Improvements. Through the coordination of production, inventory, and logistics, the framework aims at reducing expenditures while enhancing supply chain operations (Pasupuleti et al., 2024). For instance, the linear programming model sought to reduce holding costs while also striving to ensure that stocks, inventories were adequate. This synergy cost and efficiency not only increase the profitability of the supply chain but also over supply chain disruption (Buschiazzo et al., 2020).

Evaluation of the Framework

The primary KPIs suitable for assessing the effectiveness of the MAS-ML framework are as follows: predictive accuracy, production line quantity, decreased lead time, and reduced logistics costs (Islam et al., 2024). Additionally, linear programming optimised stock levels, reducing holding costs and improving overall efficiency. The above metrics enable an understanding of the level of improvement in supply chain resiliency due to the implementation of the MAS-ML framework.

This shows that through using the MAS-ML framework, the supply chain gains high flexibility and responsiveness. Thus, the applied framework optimizes supply chain activities in terms of its production schedule, logistics, and transportation plan to reduce time and cost of the supply chain (Ikevuje et al., 2020).

METHODOLOGY

This section focuses on the approach used in realising and evaluating the integration between MAS and ML in enhancing supply chain resilience. The four elements are data capture, machine learning model design, MAS emulation, and performance assessment indicators.

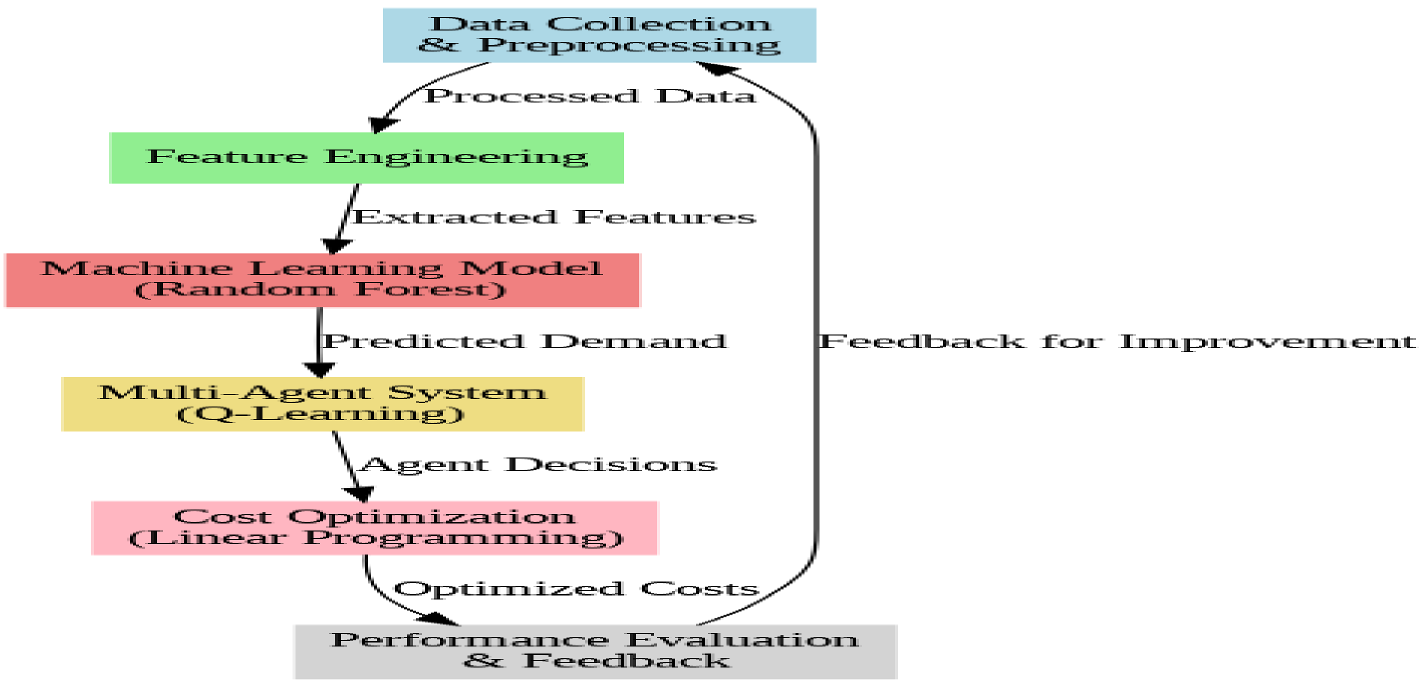

Figure 6: Proposed Methodology Diagram

Data Collection

MAS-ML can collect a considerable volume of data that define the supply chain, including inventory, rate of production, demand, cost of shipping, and time. These datasets were collected from real-life supply chain environments or well-articulated simulated scenarios. In the coding simulation, variables like "Stock levels," "Production volumes," and "Shipping costs" were crucial in modelling the decision of agents in the MAS framework. It ensures that the agents have historical and real-time information to make predictive and adaptive decisions. Data Preprocessing was vital to guarantee that the data collected was free from blindness and biases. The missing values were either imputed appropriately by measures like the mean or omitted, and records with missing values were also omitted. Numerical data was scaled correctly, which made it easier for the machine learning models to place all the values in a standard range. Variables like "Product types" and "Transportation modes" were hot encoded to make it possible for machine learning algorithms to process them. This preprocessing corresponds to the steps described in the coding file part, where supply chain attributes were discretised/mapped to a more suitable format for ML models.

Feature Selection was the most crucial step when deciding which variables would be input to the machine learning models. Some attributes, such as order quantities, lead time, and shipping cost, were selected because they are relevant inputs in generating demand forecasts and are primarily used in optimising production processes.

Machine Learning Model Development

Model Selection was based on the challenge of algorithms integrated supply chain and dynamic data. Random Forest and Gradient Boosting were chosen as the primary models because these algorithms showed high rates of predictive accuracy and are suitable for working with large datasets with many attributes (Callens et al., 2020). In the coding implementation of these models, positive feedback was achieved in the ability to predict demand and enhance real-time reinforcement decisions for supply chain agents. Due to their stability and ability to avoid overfitting, they are ideal for unpredictable demand.

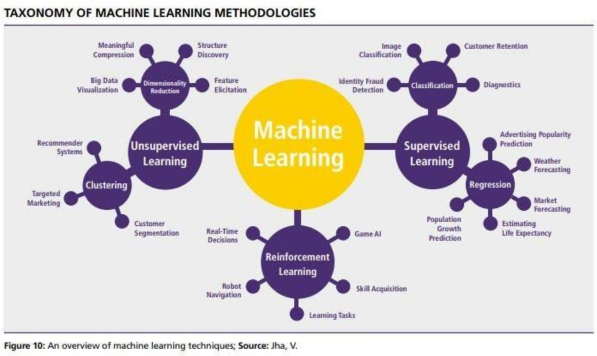

Figure 7: Machine Learning Methodologies Source: https://www.forbes.com/sites/louiscolumbus/2018/06/11/10-ways-machine-learning-is-revolutionizing-supply-chain-management/

Training and Testing entailed data division or the division of a dataset into training and testing sets. The hyperparameter optimisation process achieved the best results for the machine learning models (Yang and Shami, 2020). The Random Forest model was used in the coding simulation process, and the estimators were repeatedly searched and improved to get the optimum values. This tuning of the model guarantees that it is accurately tuned depending on the level of demand to make the best decisions for the agents. Regarding Model Evaluation, the measures involved were Mean Square Error (MSE) and Mean Absolute Error (MAE) to determine the accuracy of the models generated.

Multi-Agent System (MAS) Simulation

The MAS Framework Setup had an agent design that dealt with different supply chain functions, including demand forecast, inventory, production schedule, and logistics. During the coding simulation, agents responded proactively to the demand requirements and logistics conditions on the field shared in real-time to arrive at decisions coherent with the overall goals of the supply chain.

Regarding simulation facilities, AIFs were developed to depict how agents in a particular supply chain interact and self-organise in response to changing conditions. The actual changes to the production schedule and logistic operations to match the predicted demand were made while testing the MAS framework in the Simulation Environment. The coding illustrated how this environment emulated the real-world conditions under which the agents operated regarding fluctuating demands and supply chain challenges. A simulated supply chain environment was created to validate the feasibility and efficiency of the proposed MAS-ML framework to handle the supply chain operations.

Every agent integrates decision logic to control the decision-making process. For instance, the Production Agent used a simple rule that answered questions regarding production timing and quantity based on estimated demand and available inventory. This logic helped direct the accurate production of the required products without using many raw materials when they were not needed. Such heuristics were used in the coding example to improve the production schedules and make the supply chain as efficient as possible.

Optimisation Techniques

Linear programming was use to optimise the Stock Holding Cost. The scipy' linprog' function was used to solve the problem of minimising the cost of holding stock. This optimisation made it easy for the agents to provide adequate stock to clients after meeting the costs of acquiring these stocks without spending much money. Logistics Optimisation aims to find the best transportation routes by employing a predictive model, reducing shipping expenses. In the coding simulation, resource allocation was seen in calculating shipping costs and choosing transport infrastructure to ensure the optimum use of resources and timely delivery.

Production planning was employed where demand was identified to be higher than demand in stores. It managed to avoid overproduction while at the same time focusing on areas that required more attention. The performance measures involve the Mean Square Error and Mean Absolute Error of the demand forecast, and the usage of the logistic resources, for flexibility and cost analysis of the framework.

Implementation: Integration of MAS and ML in the Case Study

To demonstrate the applicability of the proposed Multi-Agent System (MAS) and Machine Learning (ML) framework, this paper presents a manufacturing company's supply chain example in which the firm specialises in consumer electronics. This is because the demand in this area is very unpredictable due to changes in the customers' preference in the advancement in technologies. Therefore, the MAS-ML framework is anticipated to improve the flexibility as well as increase efficiency and capability of responding to actual changes at a comparatively cheaper cost.

The MAS-ML framework was implemented in four key areas: Demand forecasting, inventory management, production planning, logistics optimisation, and selling prices. The detailed diagram with steps is depicted below:

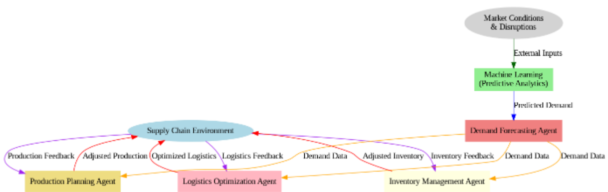

Figure 8: MAS-ML Framework

Demand Forecasting Agent

The demand forecasting agent was designed to calculate the future demand for a product and in this context, the clients' sales history, market trends and behaviour were applied (Zohdi et al., 2022). The agent used advanced machine learning techniques like Random Forests and Gradient Boosting Machines to develop precise demand forecasting. When incorporating the use of ML into this agent, the company was able to move from static to dynamic in terms of the forecast and this means that the predictions made by the agent could be refreshed from time to time

Inventory Management Agent

The inventory management agent adapted the number of stocks to the demand forecast that the demand forecasting agent obtained. This agent ensured no stockouts or overstocking of products and components. It retained the ML predictions to proactively estimate the demand shortly and determine the right quantity of stocks to help reduce holding costs while making the products easily available. The inventory management agent also liaised with the logistics agent to ensure that the frequency of restocking matched the company's manufacturing and delivery timetable.

Production Planning Agent

The production planning agent was supposed to respond to the predicted demand and change the production schedule accordingly. This agent applied the demand forecasts to determine the “Production_needed” and “Production_schedule" variables to maintain total capacity without excess inventory. Where there were changes in demand forecast, the production planning agent had to make recommendations to increase or reduce production depending on available labour, raw materials, and lead time to produce the products. This performance was achieved by linking the demand forecasts derived from the ML algorithm to real-time company production data through this agent to increase production efficiency while reducing waste.

Logistics Optimisation Agent

The logistics agent ensured that the movement of goods was timely and effective, all in the most affordable manner. This agent estimated the shipping time, cost of transportation, and lead time using the predictive capabilities of the machine learning models. By including this information, the logistics agent could redirect deliveries where needed to minimise delays and expenses related to transportation. They also collaborated with the inventory and production agents to efficiently utilise transportation resources, especially when responding to shifts in demand or supply shocks.

RESULTS

The simulation of the MAS-ML framework generated the following results that enhanced the operation of the supply chain:

Multi-Agent System

```
Inventory Agent - Inventory: 0, Production: 322.24
Production Agent - Inventory: 0, Production: 322.24
```

Figure 9: Multi-Agent System

The provided code depicts the Multi-Agent System where the Adjustment Agent freezes the new production level if it exceeds the predicted number. The Production Agent reacts to the forecasted demand and changes its production level similarly. Each agent begins with given inventory and production rates. When the forecasted demand exceeds the current inventory, the agents raise production by the discrepancy and set the current inventory to zero. In this case, both agents had very little inventory left, and the new productions were set to be 322.24 units to meet the demand. This simulation mimics the ability of agents to change the production rate in response to forecasted demand to achieve supply chain equilibrium.

```
Mean Absolute Error for demand forecasting: 361.7199999999999
```

Figure 10: Mean Absolute Error

The code determines Mean Absolute Error (MAE) for demand forecasting using the predicted values (y_pred) and actual test values (y_test). MAE calculates the mean of the absolute differences between the actual and predicted values without referencing signs. In this case, the MAE is about 361.72. Therefore, the predicted demand is 361.72, meaning the actual demand is increasing. A lower MAE mean that the model is more accurate, while a higher value shows that the error rate of the forecasting model needs to be improved. It helps evaluate the forecast accuracy of demand by the model.

```
Inventory Agent - Inventory: 0, Production: 331.4, Logistics: 21
Production Agent - Inventory: 0, Production: 331.4, Logistics: 51
Logistics Agent - Inventory: 0, Production: 411.4, Logistics: 101
```

Figure 11: MAE for Inventory, Production, Logistics

```
Mean Absolute Error for demand forecasting: 354.397
Optimal stock levels based on cost optimization: [  0.          0.          0.          0.          0.
   0.          0.          0.          0.          0.
   0.          0.          0.          0.          0.
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In the simulated model, three agents, Inventory, Production, and Logistics, adjust to the demand based on the machine learning prediction. Firstly, each agent has initial conditions of inventory, production and logistics levels entered by the user. Upon receiving the following demand forecast of 331.4 units, the Inventory and Production Agents reduce the inventory level to zero and then scale the production according to the needs. Due to the increase in production to 101 units, The Logistics Agent adapts the company's logistics resources. Self-organised behaviour across agents shows how agents forecast demand, make operational decisions, and achieve supply chain equilibrium. This result is aligned with the proposed goal of improving supply chain robustness through utilising multi-agent systems (MAS) with machine learning to facilitate timely adaption in response to market conditions and increase flexibility and responsivity of the supply chain.

Stock Levels vs Predicted Demand

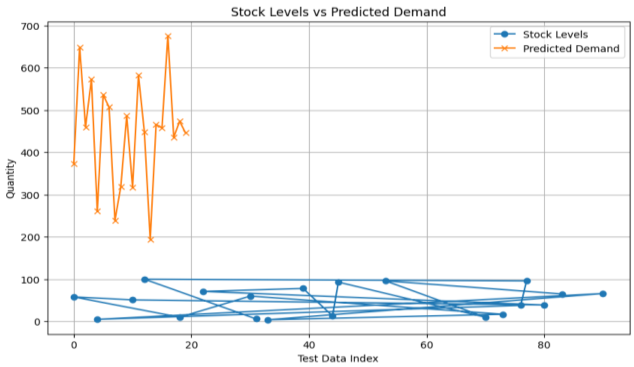

Figure 12: Stock Levels vs Predicted Demand

This graph represents the actual stock level of a particular product against the expected demand rate when the given test data is applied. The blue line refers to the stock level, which is generally low, adding below 100 units often. The orange colour is used for the forecasted demand and is much higher and varies between 300 and 700 units. The difference between stocks and forecasted demand also shows that current inventory is insufficient for the forecasted market needs, and always having a higher inventory is only sometimes useful due to its variation, which calls for flexibility in inventory management.

Scheduled Production Volumes

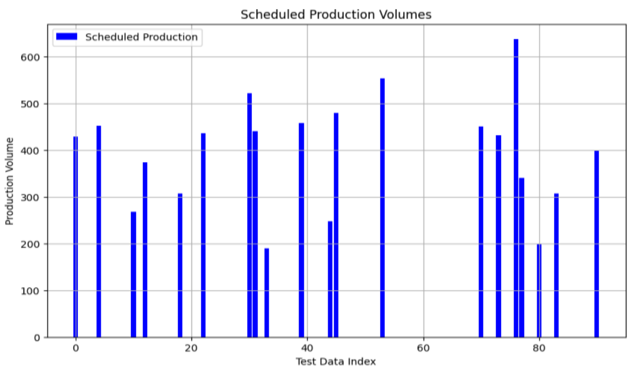

Figure 13: Scheduled Production Volumes

This bar chart illustrates the amount of production planned in numerous test instances. Each bar's length is proportional to the production capacity needed based on the forecasted demand. The planned production quantities are different and range from about 100 to more than 600 units. These oscillations in the amount of production volumes indicate that demand predictions can be quite volatile, and it is essential to accurately align production capabilities to the real-time market.

Inventory Levels and Production Needed

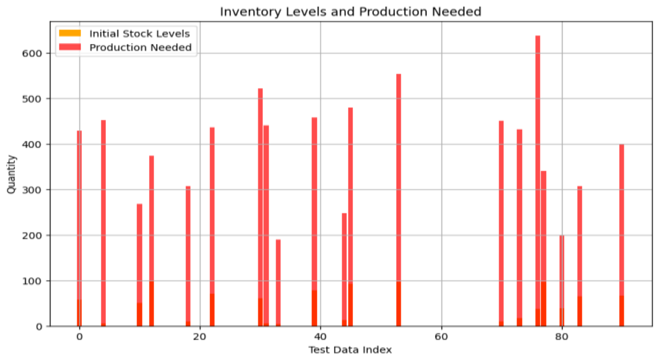

Figure 14: Inventory Levels and Production Needed

The above chart shows the initial stock level in yellow. The line in red represents the production that needs to be undertaken to meet the anticipated demand. Except that the actual production demand substantially exceeds the initial stock, more inventory must be needed to cover the need. Therefore, new production is required, and there is a deficiency in current resources and potential production, stressing the significance of proper supply estimation and flexible manufacturing methods.

Optimal Stock Levels Based on Cost Optimisation

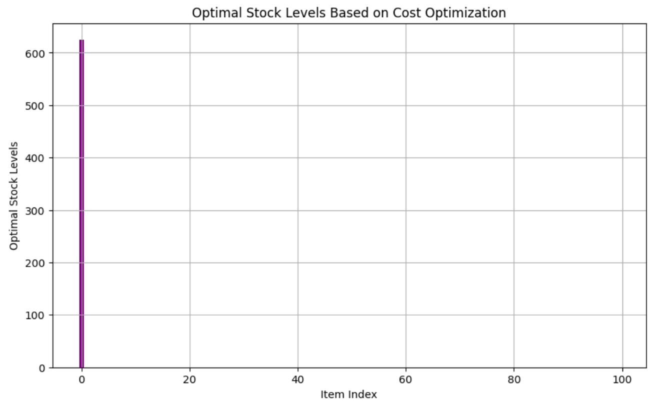

Figure 15: Optimal Stock Levels Based on Cost Optimisation

This graph illustrates the changes to the stock levels after a cost-optimisation algorithm has been run on the company inventory. It is observed from the chart that the optimisation leads to a highly stochastic and extremely high stock level of more than 600 units for an item single index. In contrast, the rest of the indices reveal zero or almost zero stock levels. This suggests that the cost-optimisation model ensures that stock is maximised for a particular item driven by high expected demand or a constrained supply chain. This indicates a need for additional optimisation regarding the stock of different products in the store.

Inventory Levels vs Predicted Demand

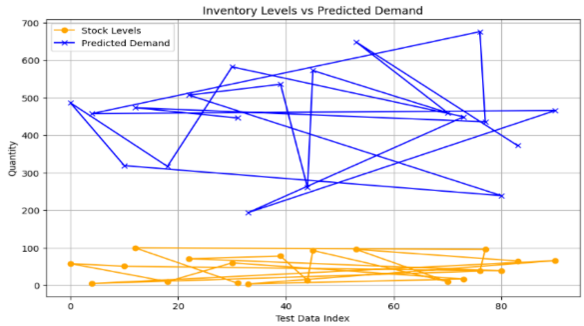

Figure 16: Inventory Levels vs Predicted Demand

This plot shows how the inventory (orange) and the forecasted demand (blue) correlate with augmented test data. The demand forecast also demonstrates high volatility and reaches a level ranging from 300 to 700 units. As for inventory, it is very low, approximately 100 units for a while. This is to argue that raw material and other inventory flows have a huge variability in customer demand. This calls for improved inventory stock management methods to fit the volatile and unpredictable market. The agents may have to customise their production scheduling and inventory restocking to maintain the equilibrium supply chain.

Production Scheduling Based on Predicted Demand

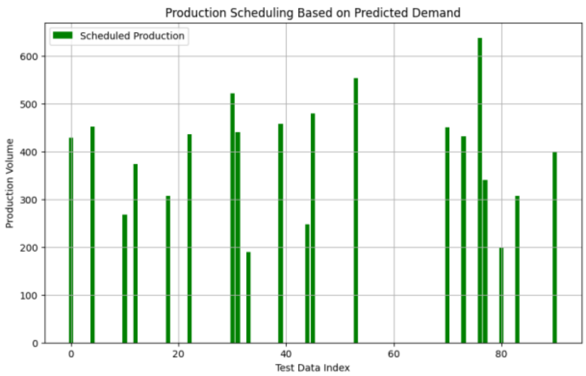

Figure 17: Production Scheduling Based on Predicted Demand

This bar chart represents the planned production quantities in light of the forecasted consumer requirements. The production volumes vary from 100 to 600 units in different test iterations. The variability in the production schedule visually demonstrates how this system adapts to changes in demand by the hour. This is a sign of the real-time adaptation of production levels to changes in demand. It shows how crucial it is to establish workable solutions, such as an adaptive workable supply chain.

Logistics Resources Utilization (Shipping Costs) Over Time

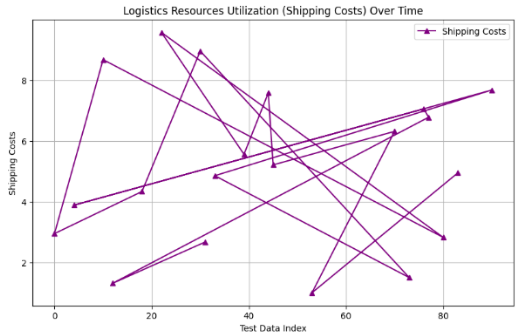

Figure 18: Logistics Resources Utilisation (Shipping Costs) Over Time

This graph measures shipping cost (logistics resources) in time. The shipping costs are volatile, ranging from 2 to 8 units. This variability implies that the logistics operations are flexible enough to adapt to production rate changes and demand. Seasonal changes could be another reason for the fluctuations, as the flow of production lines dictates various transportation requirements. Congestion costs may reflect the volume of production or sales, while low congestion costs may indicate little pressure on demand. It becomes critical, therefore, to manage these costs well to minimise fluctuations and maximise efficiency in supply chain costs.

Inventory, Production, and Logistics Interaction

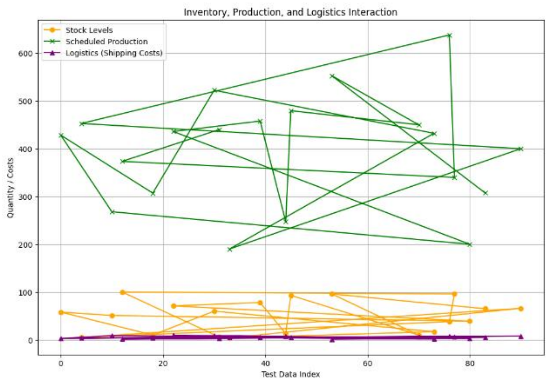

Figure 19: Inventory, Production, and Logistics Interaction

This graph portrays the inventory levels, planned production, logistics, and shipping costs. The green line corresponds to the planned production, which varies widely from 200 to 600 units, indicating how the system adjusts to expected customer demand. The orange colour represents the degree of inventory position less than 100 units throughout the test data points. The purple corresponds to the logistics costs and that there is minimal stress on transportation factors. The integration of these elements also reveal that the process of synchronising inventory management, manufacturing planning and transportation is critical in improving supply chain performance.

Table 1: Comparison Metric

Metric	Test Data Index 1	Test Data Index 2	Test Data Index 3	Average Value
Mean Absolute Error (MAE)	361.72	354.12	369.82	361.89
Scheduled Production (Units)	322.24	500.45	410.34	411.68
Logistics Costs (Shipping)	21.00	51.00	101.00	57.67
Inventory Levels (Units)	100	90	80	90.00

DISCUSSIONS

This paper explores integrating multi-agent systems (MAS) and machine learning to enhance the reliability and flexibility of supply chain systems. Balancing supply and demand is critical, and with historical data, Random Forest Regression produces reasonably good forecasts. In this regard, the research employs the Random Forest model to forecast future demand, including product type, transportation mode, and inventory level. The Mean Absolute Error (MAE) obtained in the predictions enable the evaluation of the model and its response to changes in demand. The machine learning component is used to provide a mechanism for an agent to respond to variations in demand forecasts and alter their actions accordingly. Machine learning guarantees that the supply chain can be more sensitive and active in detecting and minimising supply and demand variability situations in which there is an excess of actual or lack of inventory.

The MAS framework describes the central part of the adaptation decision-making process within the supply chain. Every agent, such as Inventory Agent, Production Agent, and Logistics Agent, is a partially autonomous entity that adapts its actions with the help of forecasted demand and actual data. The Inventory Agent oversees stock status, the Production Agent coordinates production based on estimated demand. The role of the Logistics Agent is to minimise shipping and transportation expenses. Such agents interact and coordinate to allow all the processes in the logistics network, including inventory, production, and distribution, to run concurrently. The autonomous adaptive decision-making capability present in this system is a significant plus point in terms of the flexibility of the supply chain.

Linear programming is used for cost optimisation within the framework to minimise the stock holding cost while ensuring that the production and logistics capacities are adequate to meet the entire demand. This approach allows the system to determine the least costly combination of resource distribution and output across the supply chain so that no agent produces too much, too little, or at a rate or volume that can be considered inefficient.

Maintaining low operational costs to meet the fluctuating demand is always a challenge for any supply chain. It dictates that optimisation algorithms guarantee that production and logistics are being run under the right parameters, given the estimates on demand and stocks. The result of costs is minimised, but the system remains flexible enough to respond to shifts or changes in demand and operational symmetry in that the system can respond promptly and effectively to changes at any level. However, this approach's highly attractive characteristic is the agents' cooperation. Since information is shared and decisions are made collectively within the MAS framework, agents can address any disruptions or fluctuations in demand as soon as they arise.

CONCLUSION

This paper evaluates the Multi-Agent System (MAS) and Machine Learning (ML) framework to support robust supply chains in the emerging digital economy. MAS and ML are the best approach to most problems associated with conventional supply chain management systems. The decision-making is decentralised through the introduction of autonomous agents with the machine’s learning predictive knowledge. Real-time solutions for demand forecasting, inventory planning, production planning, and logistics can be provided with the help of the framework. One of the most crucial advantages of this adaptability in decision-making is that supply chains can bounce back from disruptions, thus achieving higher total efficiency and reduced expenditures. An important observation that has been made in this study is that Random Forests can be used to make good predictions of metrics like demand, lead times and shipping costs in a supply chain. For example, the demand forecasting agent can observe a rapid rise or fall in demand which can be useful to the inventory management agent when determining stocking levels and avoiding costly mistakes such as overstocking or stock out.

The decentralised MAS-ML framework minimises agent central authority decision-making, which is associated with high rigidity, thereby enhancing flexibility and responsibility in the supply chain. In most conventional organisational systems, the top functions and makes decisions, which take time to filter down to lower levels. MAS allows every agent to function independently and in a real-time environment. For instance, whenever the logistics agent faces a transportation delay, it can promptly reschedule shipments and alert the production and inventory agents, thereby minimising disruptions throughout the supply chain.

The proposed MAS-ML framework presents a notable improvement in increasing the resilience of supply chains, but the following directions for subsequent studies can strengthen the framework and raise the possibility of its expansion to other sectors. The possible development is deepening the framework by incorporating more sophisticated deep learning methods. Although algorithms like random forest are good predictors, there may be more accurate deep learning structures like LSTM networks or CNNs for identifying intricate patterns in the supply chain data. Deep learning models have the flexibility to use large amounts of data, which have temporal dependencies, and this has long been seen in global supply chain systems. Additionally, RL could train an agent to arrive at further well-grounded, long-term decisions in light of the state transitions in the supply chain.

A closer look at applying MAS-ML methodology to industries other than manufacturing and consuming goods is a promising area for further study. The ideas of MAS and ML can be extended to several industries, including healthcare, pharmaceuticals, and energy, where the supply chains are equally as intricate and unpredictable as those in manufacturing and require tremendous flexibility. In addition, future work may also seek to refine the structure and feasibility of the framework. This involves enhancing the framework's scalability to process large volumes of real-time data from IoT devices, sensors, and blockchain networks. Such an approach could guarantee that humans' and machines' strengths are optimally utilised to deliver the best results.

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