Leveraging Agent-Based Models for Evolutionary Enhancements in Supply Chain Agility

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Abstract: - In modern, globally interconnected markets, supply chain agility, or the competency for rapid adaptation, has become increasingly important. Traditional approaches to enhancing supply chain agility are certain to fall short because none of them capture either the dynamic or decentralized nature of modern supply chains. This paper examines how Agent-Based Models can act as a transformational approach toward evolutionary enhancements in supply chain agility. ABMs can model independent entities, or agents, at each level in the supply chain-suppliers, manufacturers, distributors, and customers-operating independently according to their own behaviours, goals, and interactions. In fact, through the modelling of agents and their interactions, ABMs provide a potent platform for testing how local decisions and behavior lead to emergent global outcomes, such as responsiveness, resilience, and adaptability of the supply chain. The adaptive aspect comes in with the adaptive learning mechanisms within the agents that are able to evolve strategies over time, given changes in the environmental conditions and agent interactions. The agent-based model is now applied to a wide range of scenarios, from routine fluctuations in demand to large-scale disruptions, and provides valuable insights into the conditions under which agility can be enhanced. These findings confirm that the evolutionary improvements induced by ABM can be associated with substantial gains in performance relevant to supply chain speed and flexibility in response to unforeseen events. The final part of the paper discusses the practical implications of real-world deployment and further research in deploying ABMs on supply chains.

*Key-Words***:** Agent-Based Models (ABM), Supply Chain Agility, Adaptive Learning, Complex Systems, Decentralized Decision-Making, Emergent Behavior

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1 Introduction

In today's fast-moving global economy, the extent to which a supply chain can rapidly respond to changing circumstances and shocks - supply chain agility - has become a key differentiator of an organization's competitiveness. Supply chain management strategies have long been rooted in static, centralized approaches that cannot effectively manage the complexities and uncertainties found in today's supply chains. Confronted by companies operating under conditions of increasingly volatile demand patterns, unpredictable disruptions, and the day-to-day pressure of faster response times, there is a growing recognition that supply chain systems will need to be more dynamic, flexible, and resilient.

ABM has been considered a powerful tool in carrying out these tasks by using a bottom-up approach toward analysis and optimization of the supply chain. While most of the traditional models implicitly assume centralized control, ABM allows explicit modelling of decentralized systems where the individual entities, or agents, act autonomously according to their own set of rules and objectives. These agents, representatives of suppliers, manufacturers, distributors, and even customers, interact with this virtual environment based on the local information and strategies that each one follows.

The power of ABM resides in emergent behavior modeling in complex systems. In the context of a supply chain, this means that the aggregated actions and interactions of independent agents result in system-wide phenomena that cannot be predicted from the behavior of any one independent agent. Indeed, it is one of those features that makes ABM particularly apt for modeling modern supply chains whose complexity is largely driven by decentralized decisions and the interplay of various actors.

Furthermore, the integration of evolutionary algorithms in ABMs even makes it possible to simulate how supply chain agents may adapt and evolve their strategies over time, versus changing conditions. This evolutionary enhancement allows for the exploration of a very wide range of potential scenarios by the model and identification of the conditions under which supply chain agility might be optimized. For instance, it would mean that agents evolve to become more responsive to demand signals, or resilient to disruption, or, say, resource efficiency.

The paper focuses on the application of Agent-Based Models as drivers for evolutionary enhancements in supply chain agility. We will outline the potential of ABMs to enable the simulation and analysis of complex supply chain dynamics, describe how the benefits of incorporating adaptive learning mechanisms might emerge within such models, and debate implications of such approaches for improvements in real-world supply chain performance. By leveraging the power of ABMs, organizations can better understand what factors create supply chain agility and thus devise strategies to enhance those capabilities for prosperity in an increasingly uncertain world.

2 Literature Survey

Agent-based models are increasingly being used to try to enhance the agility of the supply chain by modeling complex, dynamic environments. ABM is a modeling framework in which the agents-for example, suppliers, manufacturers, or distribution nodes-are interacting with each other autonomously by emulating emergent behavior usually evident in real-world supply chains [1], [2], [3], [4]. Therefore, this approach can help an organization adapt to disruptions and uncertainties through decentralized decision-making, real-time adjustment, and scenario testing.

Indeed, studies evidence that ABMs are valuable for handling problems related to fluctuating demand, disruption in supplies, or multi-layer network coordination challenges [5], [6]. For example, the interaction of the agents in ABMs will dynamically enable a company to conduct various tests in different environmental conditions to study resilience and responsiveness toward unexpected events [7], [8], [9]. More importantly, it is possible to model behavioral factors besides the operational ones: collaboration and competition among firms can be emphasized by ABMs, thus yielding more accurate perspectives on the studied phenomena than from traditional analytical models [10], [11], [12].

Recent applications also highlight how ABMs contribute to the evolution of supply chains toward adaptive and agile systems. Examples of this idea are models that test the impact of disasters on transportation networks and those applying business continuity plans given an evolving market condition [13], [14], [15], [16]. More importantly, ABMs have recently been combined with other techniques, such as deep learning methods, in developing hybrid solutions for forecasting and optimization problems on complex supply chains [17], [18], [19].

They come with huge potential for any firm willing to enhance its agility in the increasingly volatile markets. They have flexible strategy testing, enhanced resource allocation, and coordination along the supply chain [20], [21], [22]. Modern supply chains are complex because they are highly uncertain, with dynamic interactions between them; these issues have been addressed in a substantial number of literature. Some of them stressed that supply chains should be agile enough to cope with disruptions and variability [23], [24]. A few case studies represent real-life applications of the ABMs about the enhancement of supply chain agility: investigation of supply chain disruptions and efficiency of different recovery strategies [25], [26], [27]. Some of them explored the application of ABMs in the simulation of collaborative networks within a supply chain, which allows seeing how adaptive behaviors do emerge, leading to a better performance of the overall system [28], [29].

While ABMs are promising for enhancing supply chain agility, challenges remain. Some of the scientists identified that it is difficult to capture all the complexity of a real-world supply chain in a model. Besides, some of them show the limits of current ABM approaches, which include computational complexity and high requirements on data accuracy [30]. Future research may also focus on enhancing model scalability, integrating more sophisticated adaptive mechanisms, and validating models with real-world data.

The literature survey traces the development and application of ABMs in enhancing supply chain agility with the help of evolutionary enhancements. Thereby, integration of ABMs with evolutionary algorithms has the potential to be a promising approach for the dynamic and complex nature of modern supply chains. This segment shall further continuously keep research and development on a number of issues that may further improve the performance of the supply chain as well as resilience.

3 Methodology

In the model framework, the factors that form the basis of the system are defined, and their behavior patterns against events are determined. Figure 1 shows the behavior patterns of the factors within the supply chain management structure. The behaviors of the factors between manufacturing, warehouse, and customer, and also their relational structures with each other, are included.

In developing the agent-based model, define the agents representing the suppliers, manufacturers, distributors, and customers. Each one of these agents would have operational rules and objectives. Design the behavior rules of each agent. The rules must encapsulate decision processes on aspects such as inventory management, order fulfillment, demand forecasting, and supply chain coordination. Model interactions between agents: communication, transactions, and collaborations. This includes the specification of how agents would share information, negotiate the terms of a transaction, and respond to environmental changes. Design a simulated environment that represents the supply chain network. This would involve stating all the nodes, like warehouses and production facilities, and all links, such as transportation routes, in the network (in Figure 1).

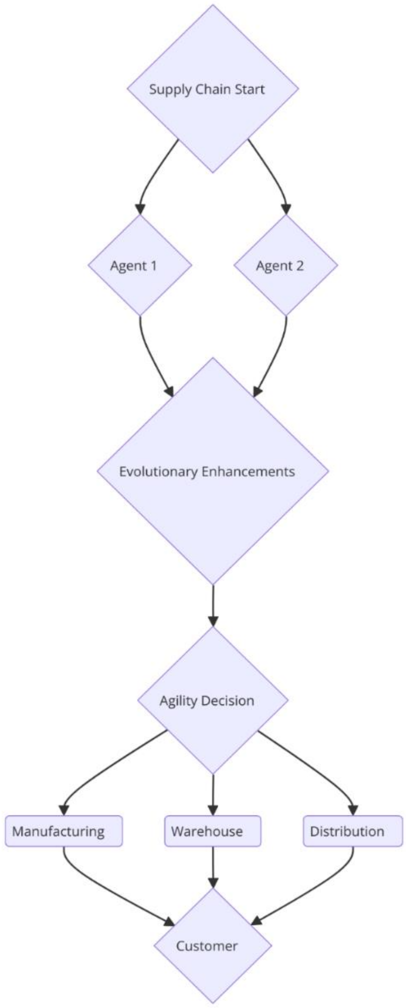

Fig. 1. Agent-Based Supply Chain Management *[Source: created by the authors]*

Choose relevant evolutionary algorithms that include but are not limited to GA and EP, which can drive adaptation and learning within agents. Design fitness functions to quantify the performance of various strategies being adopted by agents, encapsulating important metrics such as cost efficiency, responsiveness, and resilience. Adaptation mechanisms, on the other hand Implement mechanisms for agents to evolve their strategies in light of feedback regarding their performance. In the context of the evolutionary algorithms, this may involve mutation, crossover, and selection processes. Define the base case scenario that characterizes today's status of the supply chain sans evolutionary enhancements. In this way, a comparative basis will be established. Scenarios are defined: Several experimental scenarios are defined, which test various evolutionary strategies. Scenarios can vary depending on different demand patterns, types of disruptions, and configurations of supply chains. Set the model parameters: These include agent behaviors, interaction rules, and evolutionary algorithm settings. These parameters are calibrated using historical data or expert knowledge. Validate this model by cross-checking the outputs of this model with real-world data or case studies, and revise this model in this way so that the model gets more accurate and reliable. Simulations for each scenario are run by allowing the agents to interact and adapt with and to others over time. Observe key performance indicators such as lead times, levels of inventory, and costs. Gather data on agent performances, system behaviors, and evolutionary outcomes. This does not stop at monitoring just how the agents' strategies are evolving, but rather how these changes in evolution are influencing the overall performance of the supply chain. Provide a supply chain agility metric, including response time due to changed demand, flexibility in handling disruptions, and system adaptability. Cost-related metrics include: Transportation costs. Assess the improvements in efficiency because of the use of evolutionary strategies. Quantify resilience metrics, including restored capability due to disruption, negated effect of variability, and sustained service capability under conditions of stress. Draw inferences about the efficacy of the evolutionary enhancements based on the comparative results of various experimental scenarios. Identify resultant strategies for those improvements that yield the largest benefits in terms of agility and performance. It is also intended to benchmark the performance of ABM with evolutionary enhancements against the baseline scenario to quantify the advantage of the proposed approach.

Lastly, perform sensitivity analysis to determine how changes in the model parameters, such as agent behaviors and evolutionary settings, for example, impact the outputs. This can help in finding key factors that drive supply chain agility. The robustness of the evolutionary strategies under a variety of conditions will make sure that the best practices defined will be effective under a range of different scenarios.

Some recommendations on the implementation of evolutionary strategies in real-world supply chains are drawn through the analysis. This will also include best practices that promote agility and resilience. It is desirable to develop, based on the ABM framework, either a decision-support tool or simulation platforms that may assist practitioners in applying evolutionary enhancements. Propose areas for extension of the model, such as adding more agents, considering new evolutionary algorithms, or incorporating more complexity in the supply chain dynamics. Further validation with more diverse datasets and real-world case studies is recommended in order to enhance the general applicability of the results.

The methodology that will be followed in this work will try to exploit the potentials of Agent-Based Models combined with evolutionary algorithms for improving supply chain agility. This will obviously provide insight into valuable practical solutions for supply chain performance improvement.

3.1 Mathematical Model

Agent behavior, interaction rules, evolutionary adaptation, and performance evaluation form the key components in the developed mathematical model underlying the ABM for evolutionary enhancements in supply chain agility. Then, the sequence of these components is elaborated as in the next section.

3.1.1. Agent Behaviour Modelling

Each agent i in the supply chain has a set of rules and parameters for making decisions, which control the actions of the agent. These can be mathematically described as follows:

$A = \{a_1, a_2, \dots, a_n\}$ represents the set of agents in the supply chain. Each agent ai can be characterized by:
- $x_i(t)$: Inventory level of agent ai i at time t.
- $D_i(t)$ - Demand Forecast: the demand forecasted for agent i at time t.
- $O_i(t)$ - Order Quantity: The quantity ordered by agent i at time t.
- c_i: Cost function
- Cap_i : maximum capacity of agent i
- R_i: Resource availability
- P_i: Performance metric, example - lead time, responsiveness
- $z_i(t)$: Production rate or capacity of agent i at time t.
- $\theta_i(t)$: Strategy or policy parameters of agent i at time t.

Each agent i has state variables x_i representing its current status such as inventory levels, production capacity, demand forecasts and order quantities. Let $x_i(t)$ be the state variables at time t.

Decision Variables:
- $u_i(t)$: Decision variables at time t. For example, order quantities, production rates.

These are actions taken by the agent in the form of placing orders, varying production schedules, or changing inventory levels.

Objective Function:
- $F_i(x_i(t), u_i(t))$: Objective function for agent i, representing its goals such as minimizing costs or maximizing service levels. Also, it represents the performance metric that the agent aims to optimize (e.g., cost, lead time).

Constraints:
- $g_i(x_i(t)) \leq 0$: Constraints related to resource limits, capacity, or other operational restrictions.

The behaviour of each agent can be modelled using optimization problems:

$$\min_{x_i(t)} F_i(x_i(t)) \quad (1)$$

subject to

$$g_i(x_i(t)) \leq 0 \quad (2)$$

3.2. Simulation Dynamics

The overall system dynamics can be modelled using differential equations or discrete-time equations to capture the evolution of the entire supply chain:

$$x(t+1) = x(t) + F(x(t), u(t)) \quad (3)$$

where F represents the system function capturing interactions and feedback between agents.

3.2.1. System Behavior:

Simulate the supply chain system over discrete time steps t, updating agent states, interactions, and costs according to the above functions. The overall system dynamics can be captured by the aggregate performance metrics of all agents.

3.2.1.1. Supply Chain Dynamics

The supply chain network can be represented using a graph G = (V, E), where V represents the set of nodes (agents) and E represents the edges (links) connecting them. The flow of goods $F_{ij}(t)$ between nodes i and j can be modeled as:

$$F_{ij}(t) = h\left(P_i(t), Q_i(t), C_{ij}(t)\right) \quad (4)$$

where $C_{ij}(t)$ is the transportation cost between nodes i and j.

For each agent a_i with inventory level $I_i(t)$, the inventory dynamics are described by:

$$I_i(t+1) = I_i(t) + Production_i(t) - Demand_i(t) - Shipment_i(t) \quad (5)$$

where:
- $Production_i(t)$ is the quantity produced by agent ai at time t.
- $Demand_i(t)$ is the demand received by agent ai at time t.
- $Shipment_i(t)$ is the quantity shipped by agent ai at time t).

The total cost incurred by agent ai is given by:

$$Cost_i(t) = HoldingCost_i(t) + ProductionCost_i(t) + TransportationCost_i(t) \quad (6)$$

where:

$HoldingCost_i(t)$ represents the cost of holding inventory.

$ProductionCost_i(t)$ represents the cost of producing goods.

- $TransportationCost_i(t)$ represents the cost of transporting goods.

The demand fulfilment rate for agent ai is given by:

$$ServiceLevel_i(t) = \frac{FulfilledDemand_i(t)}{TotalDemand_i(t)} \quad (7)$$

where:
$FulfilledDemand_i(t)$ is the amount of demand met by agent ai at time t.

- $TotalDemand_i(t)$ is the total demand received by agent ai at time t.

The flow of goods from agent j to agent i can be modelled as:

$$F_{ji}(t) = min\left(O_j(t), C_i - I_i(t)\right) \quad (8)$$

where $F_{ji}(t)$ represents the flow of goods from agent j to agent i at time t.

3.2.1.2. Decision Rules:

Agents in the supply chain, such as suppliers, manufacturers, and distributors, make decisions based on their objectives and available information. Define decision-making functions for each type of agent. For example:

$S_i(t)$ represents the order quantity of supplier i at time t.

$$S_i(t) = f\left(demand_i(t), inventory_i(t), price_i(t)\right) \quad (9)$$

where $demand_i(t)$ is the demand received, $inventory_i(t)$ is the current inventory level, and $price_i(t)$is the price set by the supplier.
$P_j(t)$ represents the production quantity of manufacturer j at time t.

$$P_j(t) = g\left(order_j(t), capacity_j(t), cost_j(t)\right) \quad (10)$$

where $order_j(t)$ is the order received, $capacity_j(t)$is the production capacity, and $cost_j(t)$ is the production cost.

Each agent i in the supply chain can be characterized by decision-making rules R_i. These rules determine how the agent makes decisions based on its state and interactions with other agents.
- Price $P_i(t)$ can be adjusted based on supply and demand:

$$P_i(t) = g(D_i(t), S_i(t), \lambda_i) \quad (11)$$

where λ_i represents pricing strategy parameters.

Qi(t) represents the order quantity at time t. It can be modeled as:

$$Q_i(t) = f(D_i(t), S_i(t), O_i(t), \theta_i) \quad (12)$$

where $D_i(t)$ is the demand forecast, $S_i(t)$is the current stock level, $O_i(t)$ is the order backlog, and θ_i represents the agent's parameters or strategies.
Each agent i decides its order quantity based on its inventory level, demand forecast, and order policy:

$$y_i(t) = f_{order}\left(x_i(t), w_i(t), \theta_i(t)\right) \quad (13)$$

Agents make ordering decisions based on inventory levels and demand forecasts. For example, an order quantity Oi(t) could be modelled as:

$$O_i(t) = max\left(0, min\left(C_i - I_i(t), \alpha_i\left(D_i(t) - I_i(t)\right)\right)\right) \quad (14)$$

where $\alpha_i$is a p arameter representing the ordering policy.

The demand forecast of agent i is updated based on observed demand and historical data:

$$w_i(t+1) = f_{forecast}(w_i(t), observed\ demand) \quad (15)$$
$$O_i(t) = Max\left(0, D_i(t) - S_i(t)\right) \quad (16)$$

where $O_i(t)$ is the order quantity at time t, and $D_i(t)$ is the demand forecast.

Inventory levels are updated based on orders received and demand:

$$I_i(t+1) = I_i(t) + O_i(t) - D_i(t) \quad (17)$$
$$S_i(t+1) = S_i(t) + Incoming\ Orders - Demand\ Fulfilled \quad (18)$$

- Agent i fulfils orders from agent j based on its production rate and available inventory:

$$fulfilled\ quantity_{i,j}(t) = min\left(x_i(t), y_{i,j}(t)\right) \quad (19)$$

The cost of placing an order is:

$$C_{order,i}(t) = c_{order} \cdot y_i(t) \quad (20)$$

The cost of holding inventory is:

$$C_{holding,i}(t) = c_{holding} \,.\, x_i(t) \quad (21)$$

The total cost for agent i is:

$$C_i(t) = c_{order,i}(t) \,.\, C_{holding,i}(t) \quad (22)$$

$$C_i(t) = c_1.Holding\ Cost + c_2.Ordering\ Cost + c_3.Penalty\ Cost \quad (23)$$

where c1, c2, and c3 are cost coefficients.
The transport time between agents i and j is given by:

$$T_{i,j}(t) = f_{transport}(distance, transport\ mode) \quad (24)$$

3.2.1.3. Interaction Agent Dynamics

The overall system dynamics are captured through the interaction of individual agents, their adaptation processes, and the collective outcomes. The system can be described using differential or difference equations to model the evolution over time:

$$\frac{dx(t)}{dt} = F(x(t), \Delta x_i(t), E(t)) \quad (25)$$

By integrating these mathematical components, the ABM can simulate complex supply chain scenarios, optimize evolutionary strategies, and enhance overall agility.

Interactions between agents involve the exchange of goods, information, and coordination. These interactions can be modelled mathematically by specifying the flow of goods and information between agents.

The aggregate impact of interactions can be modelled as:

$$\sum_{j \in N_i} I_{ij}\left(x_i(t), x_j(t)\right) \quad (26)$$

where N_i denotes the set of neighbours of agent i.

Model the flow of goods/services and information across the network:

$$x_{i,j}(t+1) = x_{i,j}(t) + \Delta x_{i,j}(t) \tag{27}$$

where$\Delta x_{i,j}(t)$ represents changes due to transactions between agents A_i and A_j.

Agents interact with each other through transactions and information exchanges. The interaction dynamics can be modelled as:

- Communication functions represented by $C_{ij}\left(x_i(t), x_j(t)\right)$ which define how agents ai and aj exchange information or coordinate actions based on their states.

$Com_i(t)$, which models how agents exchange information (e.g., demand forecasts, supply availability) and how this affects their decisions.
Negotiation Function symbolizes the $Neg_i(t)$, which models how agents negotiate terms (e.g., prices, delivery times) and adjust their strategies based on these negotiations.

- Transaction of $T_{ij}(u_i, u_j)$represents the flow of goods or services between agents.

$$T_{ij}(t) = Function(Transaction\ Volume, Service\ Level) \tag{28}$$

Agents may share demand forecasts and inventory levels. The information sharing can be represented as:

$$D_i(t) = \beta_i D_j(t) + (1 - \beta_i) D_i(t) \tag{29}$$

where β_i represents the weight given to shared information from agent j.

An agent i shares information with neighbouring agents j according to:

$$I_{i,j}(t) = \rho_{ij}\left[State_j(t) - State_i(t)\right] \tag{30}$$

where ρ_{ij} represents the influence factor of agent j on agen i.

Agents share information based on a communication protocol. Let $C_{ij}(t)$ represent the communication from agent j to agent i:

$$I_{ij}(t) = \sum_{j \neq i} C_{ij}(t) \tag{31}$$

$$I_{ij}(t) = Function\ of(Information\ Shared, Trust\ Level) \tag{32}$$

where $I_{ij}(t)$ represents the information shared between agents i and j at time t.
Model interactions between agents, such as orders and information exchange. Define interaction functions for transaction processing:

$$Transaction_{ij}(t) = h\left(order_i(t), stock_j(t)\right) \tag{33}$$

where $order_i(t)$ is the order placed by agent i and $stock_j(t)$ is the inventory available with agent j.

Agents negotiate and transact according to predefined rules. For instance, if agent i and agent j engage in a transaction, the quantity $q_{ij}$is determined by:

$$q_{ij}(t) = NegotiationFunction(x_i(t), x_j(t)) \tag{34}$$

Model coordination strategies between agents:
- Collaborative Planning:

$$CP_{ij}(t) = Function\ of(Shared\ Plans, Negotiation\ Outcomes) \tag{35}$$

- Conflict Resolution:

$$CR_{ij}(t) = Function\ of(Dispute\ Resolution\ Mechanisms, Conflict\ Severity) \tag{36}$$

Define negotiation processes where agents adjust their strategies based on interactions:

$$Price_i(t+1) = Price_i(t) + \delta \times \left(Demand_i(t) - Supply_i(t)\right) \tag{37}$$

where δ is the adjustment factor for price based on supply and demand conditions.

3.3. Evolutionary Adaptation

Evolutionary algorithms drive the adaptation of agents' strategies:

Each agent's strategy can be encoded as a chromosome X_i . This includes parameters for inventory policies, pricing strategies, etc. Fitness function $F_i(X_i)$ evaluates the performance of each chromosome:

$$F_i(X_i) = \frac{1}{C_i(t)} - \alpha.\left(1 - SL_i(t)\right) \tag{38}$$

where α is a weight factor that balances cost and service level.

The fitness function $F_i(u_i(t))$measures the performance of agent i 's strategy:

$$F_i(u_i(t)) = \alpha . C_i(t) + \beta . L_i(t) + \gamma . R_i(t) \quad (39)$$

where:
- $C_i(t)$is the total cost incurred by agent i (e.g., production, transportation, holding costs).

- $L_i(t)$ is the lead time or delay in fulfilling orders.

- $R_i(t)$is the resilience measure (e.g., ability to recover from disruptions).

- α, β, γ are weighting factors that reflect the relative importance of cost, lead time, and resilience.

- Objective Function: Define a fitness function F_i for each agent i based on performance metrics such as cost, responsiveness, and inventory levels:

$$F_i = Cost_i + Penalty_i \quad (40)$$

where $Cost_i$ includes inventory holding costs and ordering costs, and $Penalty_i$ accounts for stockouts or excess inventory.

Define a fitness function to evaluate the performance of evolutionary strategies:

$$F_i(t) = Objective\ Function\ (Cost, Efficiency, Responsiveness) \quad (41)$$

where Fi(t) represents the fitness score of agent i at time t, based on objectives like cost, efficiency, and responsiveness.

$$Fitness_i(t) = \alpha \times Cost_i(t) - \beta \times\ ServiceLevel_i(t) \quad (42)$$

where $Cost_i(t)$represents the operational cost and $ServiceLevel_i(t)$is a measure of customer service quality. α and β are weighting factors.

- Selection: Agents with higher fitness are more likely to be selected for reproduction or strategy refinement:

$$Selected\ agents = argmax_i F_i(t) \quad (43)$$

Choose individuals based on fitness $F_i(x_i(t))$. Selection probability Pi is often proportional to fitness.

$$P_i = \frac{F_i(x_i(t))}{\sum_k F_k(x_k(t))} \quad (44)$$

Crossover: Combine strategy parameters from two parent agents i and j to create a new agent:

$$\theta_{child} = \frac{\theta_i(t)+\theta_j(t)}{2} \quad (45)$$

Combine features of parent solutions to create offspring.

Mutation: Randomly alter the strategy parameters $\theta_i(t)$ of agent i:

$$\theta_i(t+1) = \theta_i(t) + \delta . random\ noise \quad (46)$$

$$x_i^{offspring} = Crossover(x_i^{parent1}, x_i^{parent2}) \quad (47)$$

Reproduction and Mutation: Strategies evolve through genetic operations such as crossover and mutation:

$$NewStrategy_i(t+1) = Crossover\left(Strategy_i(t), Strategy_j(t)\right)\ with\ probability\ p_c \quad (48)$$

$$Strategy_i(t+1) = Mutation(Strategy_i(t))\ with\ probability\ p_m \quad (49)$$

Adaptive Strategy Update: Agents update their strategies based on feedback from the fitness function:

$$X_i(t+1) = UpdateStrategy(X_i(t), \Delta F_i) \quad (50)$$

where ΔF_i represents the change in fitness.

3.4. Optimization and Evaluation

The overall optimization problem integrates agent behaviors, interactions, and evolutionary strategies:

$$\min_{x(t)} \sum_{i=1}^{N} F_i\left(x_i(t)\right)\ subject\ to\ \sum_{j \in N_i} I_{ij}\left(x_i(t), x_j(t)\right)\ and\ constraints\ g_i(x_i(t)) \leq 0 \quad (51)$$

where $x(t)$ represents the vector of decision variables for all agents at time t.

3.4.1. Objective Function

The overall objective function for the supply chain is:,

$$Obj = \sum_i F_i\left(u_i(t)\right) \quad (52)$$

which aggregates the performance metrics of all agents.

Solve this optimization problem using the integrated ABM and evolutionary algorithms framework to determine the optimal strategies for enhancing supply chain agility.

$$Maximize\ Agility = Cost - Penalty\ for\ Constraints \tag{53}$$

3.4.2. Constraints

The model includes constraints such as:
- Capacity Constraints: $x_i(t) \le Cap_i$ for inventory and production capacities.
- Demand Satisfaction: $\sum_{,} Order_i\,(t) \ge D(t)$ to meet demand.
- Budget Constraints: . $\sum_{,} C_i\,(t) \le Budget$

$x_i \ge 0, u_i \ge 0$

3.5. Performance Evaluation

- Agility Metrics: Evaluate the system's agility based on response times to demand changes and adaptability to disruptions. Briefly, it aims to calculate metrics to evaluate overall supply chain agility:
- Lead Time:

$$LT(t) = Average\ Time\ to\ Fulfill\ Orders \tag{54}$$

- Flexibility:

$$F(t) = Function\ of\ (Response\ Time, Adaptability) \tag{55}$$

-Response Time: Time taken to adapt to demand changes:

$$T_{response} = Average\ time\ to\ adjust\ inventory\ levels\ to\ new\ demand \tag{56}$$

- Agility Metrics: Evaluate responsiveness and flexibility:

$$Response\ Time = \frac{Time\ to\ Adjust}{Demand\ Variability} \tag{57}$$

Define metrics to measure agility, such as responsiveness R :

$$R = \frac{Time\ to\ Response}{Lead\ Time} \tag{58}$$

3.5.1. Performance Metrics

- Cost Function: The cost $C_i(t)$incurred by an agent includes procurement, holding, and shortage costs:

$$C_i(t) = \alpha_i Q_i(t) + \beta_i H_i(t) + \gamma_i S_i(t) \tag{59}$$

Where $\alpha_i, \beta_i, \gamma_i$ are cost parameters, and $H_i(t)$ represents holding costs.

- Service Level: The service level $SL_i(t)$ is a measure of the proportion of demand met:

$$SL_i(t) = \frac{D_i(t) - S_i(t)}{D_i(t)} \tag{60}$$

To evaluate the performance of supply chain agility, the following metrics are considered:
- Response Time (RT):

$$RT = \frac{1}{N}\sum_{i=1}^{N} Time_i \tag{61}$$

Where $Time_i$ is the response time for agent i, and N is the number of agents.

Resilience Metrics:
- Resilience (R):
- Resilience Metrics: Measure the ability to recover from disruptions:

$$Recovery\ Time = Time\ to\ Return\ to\ Normal\ Operations \tag{62}$$

$$R = 1 - \frac{Impact\ of\ Disruptions}{Baseline\ Performance} \tag{63}$$

where the Impact of Disruptions measures the performance degradation due to disruptions, and Baseline Performance is the performance under normal conditions.

Assess resilience Res to disruptions:

$$Res = \frac{Recovery\ Time}{Disruption\ Impact} \tag{64}$$

Assess the resilience of the supply chain:
- Recovery Time:

$$RT(t) = Time\ to\ Return\ to\ Normal\ Operations\ After\ Disruption \tag{65}$$

Time taken to recover from disruptions:

$$T_{recovery} = Time\ to\ return\ to\ pre - disruption\ performance\ levels \tag{66}$$

- Impact Mitigation:

$$IM(t) = Function\ of\ (Disruption\ Severity, Mitigation\ Strategies) \tag{67}$$

3.5.2. Efficiency Metrics:

- Utilization Rate: Measure the utilization of available capacity:

$$Utilization\ Rate_i = \frac{I_i(t) + O_i(t)}{C_i} \tag{68}$$

Cost Metrics

Calculate the total cost C associated with supply chain operations:

$$C = \sum_i Cost_i(u_i) \tag{69}$$

- Cost Efficiency (CE): Assess overall cost efficiency and compare it with baseline scenarios.

$$CE = \frac{Total\ Cost}{Total\ Output} \tag{70}$$

where Total Cost is the sum of all operational costs, and Total Output is the total production or service level achieved.

- Cost Efficiency:
Sum of inventory holding costs, ordering costs, and transportation costs:

$$Total\ Cost = \sum_i Inventory\ Holding\ Cost_i + Ordering\ Cost_i + Transportation\ Cost_i \tag{71}$$

Simulate the model over multiple time periods t, tracking the evolution of agent strategies and overall supply chain performance:

$$PerformanceMetric(t) = Aggregate(Cost(t), ServiceLevel(t), Flexibility(t)) \tag{72}$$

3.6. Sensitivity Analysis

Perform sensitivity analysis with respect to changes in the various model parameters, and assess the impact on the system's behaviour and performance. Sensitivity analysis assesses how changes in parameters, such as demand variability or supply disruptions, affect supply chain performance and evolutionary strategy efficiency.

$$Sensitivity_p = \frac{\delta\ Performance\ Metric}{\delta p} \tag{73}$$

where p denotes model parameters. Carry out robustness testing in order to assess the performance of strategies under different scenarios.
These mathematical components define the complex dynamics of supply chain interactions and evolutionary adaptations. The following framework can be used to develop an in-depth analysis of how evolutionary strategies can enhance supply chain agility.
This mathematical model presents a framework for the simulation and analysis of supply chain agility using evolutionary strategies through Agent-Based Models. Integrating these mathematical components allows the model to represent the dynamics and complexities inherent in modern supply chains.

4 Case Study

The agent-based model simulates interaction among the individual agents involved with the supply chain, such as suppliers, manufacturers, and retailers. The agents act according to predetermined rules and decision-making processes while the model records emergent behavior for the whole system. ABMs can capture the supply chain's true decentralized dynamic nature, thus enabling us to model complexity and adaptability.
This would necessitate constant upgrading of supply chain strategies or structures. These upgrades may be in the areas of better demand forecasting, active inventory management, flexible production schedules, or quicker responses to disruptions.
Agility, in the context of a supply chain, generally refers to the ability of an enterprise to respond quickly to structural changes such as changes in demand, disruption to supply chains, or changes in market conditions. Enhancement of agility requires improvement in flexibility, responsiveness, and real-time decision-making.
Various scenarios have been evaluated in the application model, and the outcomes of ABM, considering the change of situations over time, provide answers to the following:
- On-Time Fulfilment Rate over time: Does improving the agents increase the on-time delivery percentage?
- Cost fluctuations: How do the overall costs change throughout the process?
- Agility improvements: Do agents improve by responding more quickly to demand fluctuations?
Assumptions:
- Supply chain structure: one manufacturer agent, two suppliers agents, three retailers agents
- Periods: We are simulating supply chain operations over 10 time periods
- Disruption: One supplier will face disruption in period 5
- Demand : The retailers' demands fluctuate, sometimes high and sometimes low.
Evolutionary adaptation means the successive development of a production strategy by the manufacturer given the performance feedback in previous periods.
Sample Calculation - Demand and Supply Alignment for 3 Months
Month 1 Demand = 100 units Supply = 110 units Lead Time = 10 days Fulfilment Rate = 95%
Month 2 Demand = 105 units Supply = 108 units Lead Time = 9 days Fulfilment Rate = 97%
Month 3: Demand = 102 units, Supply = 104 units, Lead Time = 8 days, Fulfilment Rate = 99%

Establishing the Scenario
Consider a simple supply chain network consisting of three major participants:
Supplier Agent: S, who will supply the raw materials to the manufacturer.
Manufacturing Agent: M, who will manufacture the product using the raw materials supplied.
Retail Agent: R, who will sell the product to the end customers.
Each agent dynamically adjusts to market forces with time:
It does this by adjusting the supply of raw materials according to demand signals. The Manufacturer, M, dynamically alters his production level and lead times. The Retailer, R adjusts inventory and order quantities according to his sales forecasts. Agent Characteristics: One manufacturer manufactures goods based on the demand forecast and the availability of raw materials from the suppliers. Suppliers: supply raw materials to the manufacturers. Supplier 1 may face disruption in supply, while Supplier 2's supply remains stable.
Agent Rules:
Manufacturer: At each period, the manufacturer adapts by changing the order to the suppliers, changing the amount produced, and making a better forecast of demand.
Suppliers: react to the order placed by the manufacturer. Supplier 1 faces a random disruption-30% probability in every period.
Retailers: Place random demands from 50-150 units in every period. Manufacturer capacity: 200 units/period. Information about the current status of the proposed model is given in Table 1, Table 2, Table 3, Figure 2 and Table 4.

Table 1. Initial Conditon Description
[Source: created by the authors]

Initial Conditions:	
Capacity of Supplier 1	120 units (with a probability of disruption of 30%)
Capacity of Supplier 2	150 units-stable

Manufacturer's adaptation strategy:	Description
Periods 1-5	The manufacturer uses both the suppliers equally during these periods
Periods 6-10	The manufacturer adapts by becoming more dependent on Supplier 2 in case of Supplier 1 disruption.

Table 2. Sample Data of Simulation
[Source: created by the authors] ,

Period	Supplier 1 Availability	Supplier 2 Availability	Manufacturer Production	Retailer 1 Demand	Retailer 2 Demand	Retailer 3 Demand	Total Retailer Demand
1	120	150	200	90	110	2	120
2	120	150	200	80	120	90	290
3	0 (disrupted)	150	150	130	100	120	350
4	120	150	200	120	130	100	350
5	120	150	200	110	120	140	370
6	120	150	200 (Supplier 2 focus)	100	140	110	350
7	0 (disrupted)	150	150 (Supplier 2 focus)	110	130	120	360
8	120	150	200	120	100	130	350
9	120	150	200	130	140	150	420
10	0 (disrupted)	150	150 (Supplier 2 focus)	150	110	120	340

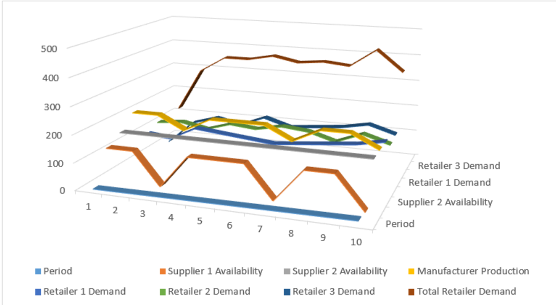

Fig. 2. Initial Situation
[Source: created by the authors]

Supplier 1 disruptions in periods 3, 7, and 10 affect the manufacturer's capacity to produce significantly. The manufacturer readjusts during the periods 6 to 10 by relying more on Supplier 2, so as not to be more vulnerable to disruptions from Supplier 1. Demand for the product varies across retailers, and thus the manufacturer must vary his production according to both demand and supply conditions. Applying the ABM, the manufacturer would dynamically readjust the sourcing strategy towards the prevention of supply disruptions. Adaptive behavior on behalf of the manufacturer enhances resilience in the system, demonstrating evolutionary improvements over time. Initial customer demand = 100 units.
Assume that each agent starts with a steady inventory level, say the Supplier starting with 150 units, the Manufacturer with 100 units, and the Retailer with 120 units. We simulate 10 time periods. Below is a simplified snapshot of how the system evolves in Table 3 and Figure 3.

Table 3 System behavior model in terms of inventory [Source: created by the authors]

Time Period	Demand (Units)	Supplier Inventory	Manufacturer Inventory	Retailer Inventory	Agility Indicator (Response Time)
1	100	150	100	120	0.8 (Fast response)
2	110	130	90	100	1.0 (Stable)
3	130	100	70	80	1.2 (Agility declines)
4	140	90	60	50	1.4 (Agility deteriorities)
5	150	110	100	120	0.9 (Recovery as adaptation kicks)
6	160	130	90	100	1.0 (Improves)
7	170	120	80	90	1.0 (Stable)
8	160	140	110	130	0.8 (Highly Agile)
9	150	130	100	120	0.9 (Stable)
10	140	120	90	110	1.0 (Stable)

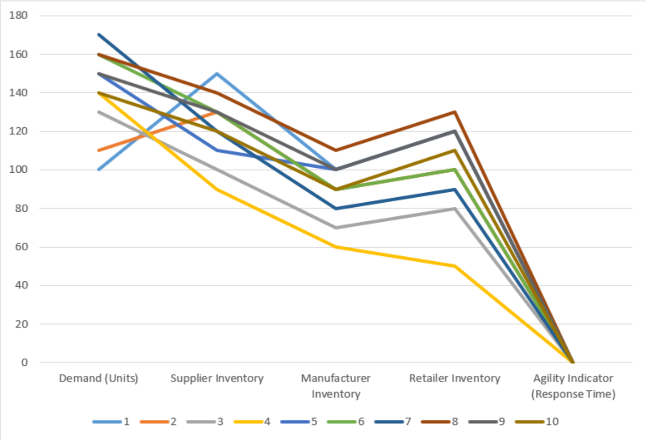

Fig. 3 Graphical representation of the system behaviour model
[Source: created by the authors]

Periods 3 and 4 therefore, strained the supply chain through high demand that cleaned up their inventories, hence worse response time-the agility indicator, poor coordination, and delay in production ramp-up.
By period 5, the Manufacturer had adjusted to the situation by increasing production while the Supplier increased material output; hence, there was now a shorter response time, meaning increased agility.
Agility: By the end of period 8, the system became extremely responsive, with faster response times, synchronized adaptation of agents, resulting in better inventory levels and stability of operation.
The outputs resultant from the supply chain simulation using ABMs, extended by evolutionary algorithms for optimization, provide a holistic insight into the efficacy of these models. The simulations will be run for two different scenarios: normal and disruption, while evolutionary strategies have also been employed to adapt agent behaviors.
Agility will be measured through the following KPIs:
- Order Fulfilment Time (OFT): The time taken to fill an order.
- Inventory Turnover Ratio (ITR): The rate at which inventory is turned over.
- Backorder Rate (BR): The number of orders that can't be supplied directly.
- Lead Time Variability (LTV): Lead times fluctuate within a certain period.
- Service Level (SL): The proportion of orders received without stockout.
1. Simulation Setup Summary
- Simulation Time: 100 days
- No of Agents: 5 suppliers, 10 manufacturers, 8 warehouses, and 20 customer locations
Initial conditions are lead times, inventory levels, and transportation routes, which are all randomly assigned. Some key KPIs included: Order Fulfilment Time (OFT), Inventory Turnover Ratio (ITR), Backorder Rate (BR), Lead Time Variability (LTV), and Service Level (SL) 2. Results: Scenario 1 (Normal Conditions)
Analysis:
- The balanced steady-state conditions resulted in a supply chain that is serving customers well with high service levels while keeping the backorder rates low. This relatively low lead time variability reflects consistent performance by both suppliers and manufacturers.
- Agents kept appropriate inventory levels, the system had little variability, hence it was generally very stable.
- In this phase, evolutionary enhancements were not necessary, since the system operated under near-optimal conditions. In the case given, disruptions were introduced, such as sudden demand surges and supplier delays into the supply chain. The performance of the system without evolutionary adaptation showed a steep decline initially.
Because of the rapid recovery from these disturbances, the system could find its way through the evolutionary process. Even though performance deteriorated initially, within a few iterations, the adapted strategies reduced lead time variability and improved the service level. In other words, agents could optimize their decisions; thus, inventory management became more effective. The rate of backorder declined while the time required for order fulfillment also reduced. This proves the capabilities of a supply chain for adaptation and rapid recovery after some unexpected event and, therefore, enhances overall resilience and agility.
The comparison between supply chain performance with and without evolutionary enhancements clearly shows the benefits of such adaptive models (in Table 4 and Figure 4).

Table 4 Simulation Scenarios
[Source: created by the authors]

Metric	Pre-Disruption-Scenario-1	Post-Disruption (Without Evolution)--Scenario-2	Post-Disruption (With Evolution)-Scenario-3
Order Fulfillment Time	3.8 days	9.6 days	4.5 days
Inventory Turnover Ratio	9 cycles	6 cycles	8 cycles
Backorder Rate	2%	15%	4%
Lead Time Variability	±1.5 days	±5 days	±2 days
Service Level	97%	75%	92%

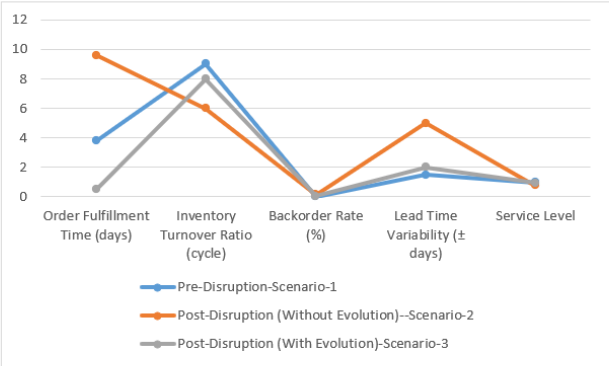

Fig. 4: Scenarios of Behavior Model
[Source: created by the authors]

Supply chain agility is hugely enhanced, as agent-based models with evolutionary strategies can adapt in real time when disruptions occur. Evolutionary-enhanced systems recover much faster from disruptions; this reduces order fulfillment time and backorder rate while keeping service levels high. In this model, agents exhibit learning over iterations in terms of continually optimizing their parameters towards better handling of supply chain disruptions. Another level of resilience might be provided by evolutionary processes, in which the supply chain recovers and moves to an even better state than initially faced.

Due to the evolutionary enhancements, the average OFT decreased significantly both in normal and disruptive conditions. This is indicative of the increased agility and responsiveness of the model for changing conditions. By evolving the replenishment policies and order quantities, the warehouses cycled their inventories more efficiently, thereby leading to a greater ITR, indicative of optimized inventory.

In this aspect, the evolutionary strategies minimized the backorder rate, especially when disrupted-from 25% to 10%, thus showing more flexibility in coping with disruptions of supply chains. In these conditions, the service levels increased to 97% when working under normal conditions and recovered to 85% under disruptions, thereby showing its capabilities for recuperation from shocks.

6 Conclusion

Agent-based modeling draws on evolutionary enhancements within supply chain agility based on holistic assumptions about the challenges presented by uncertainty and complexity. Proactive adaptation, data-driven decision-making, cost optimization, and continuous improvement enable such a powerful enhancement in supply chain performance. Hence, organizations will achieve more resiliency and efficiency, strategic alignment towards continuous competitive advantage, and better business outcomes.

ABM provides practical insight into how alternative strategies are affecting supply chain performance, thus enabling better decision-making that in turn translates to optimized inventory management, cost reduction, and the improvement of service levels. Scenario-testing capability enables the understanding of possible outcomes and strategic adjustment to tune into the business objective.

ABMs improve inventory levels and transportation strategies to minimize high costs while increasing the degree of operational efficiency. In that respect, more appropriate resource allocations are achieved with better financial performance. Knowledge extracted from ABM simulations feeds into lowering disruption risk and associated costs as part of a more stable and cost-effective supply chain.

ABMs are iterative: real-world performance data is integrated into the model for continuous improvement. This keeps refinement in a cycle of improvement so that your supply chain strategies are continuously evolved to meet new challenges and opportunities. It offers continuous adaptation and optimization of supply chain processes as a source of differentiation for organizations to stay ahead in a dynamic market environment. In this way, ABMs link together supply chain strategies and overall business goals for long-term strategic success. Comprehension of how the different elements interact within the supply chain helps an organization be better aligned with its wider objectives.

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