sustainability

MDPI

Article

A New Version of African Vulture Optimizer for Apparel Supply Chain Management Based on Reorder Decision-Making

Shayan Bahadoran Baghbadorani [1], Seyed Abdolhassan Johari [2], Zahra Fakhri [3], Esmaeil Khaksar Shahmirzadi [4], Shavkatov Navruzbek Shavkatovich [5] and Sangkeum Lee [6,*]

1 Department of Industrial Engineering & Management, Shanghai Jiao Tong University (SJTU), Shanghai 200240, China
2 Management Faculty, Tehran University, Tehran 1417935840, Iran
3 Department of Marketing, Haslam College of Business, University of Tennessee, Knoxville, TN 37916, USA
4 Faculty of Tourism, Near East University (NEU), Nicosia 99138, Turkish Republic of North Cyprus, Turkey
5 The Department of Corporate Finance and Securities, Tashkent Institute of Finance, Tashkent 100000, Uzbekistan
6 Environment ICT Research Section, Electronics and Telecommunications Research Institute (ETRI), Daejeon 34129, Republic of Korea
* Correspondence: sangkeum@etri.re.kr; Tel.: +82-42-860-5716

Abstract: Supply chains may serve as an effective platform for the development of sustainability by encouraging responsible conduct throughout all chain members and stages. Agent technology may greatly aid in decision-making during supply chain management. Due to recent changes in the seasons, fashion trends, and the requirements of various religions, particularly with regard to the ordering procedure, the supply chain for clothing has become one of the most difficult duties in this area. Because of this, it is crucial to enhance process coordination throughout the whole clothing supply chain and develop a decision-making strategy that functions best in a fluid environment. The Unified Modeling Language (UML) is used in this work to define the relationship between agents and simulate the supply chain process. This research incorporates enhanced African vulture optimizer, a modified bio-inspired approach, and fuzzy inference theory to assist the supply chain agent in determining the appropriate replenishment quantity and reorder point to lower the inventory cost. According to test results, the suggested AAVO-based technique may be successful in determining a target demand ordering amount while reducing the overall cost of the supply chain due to a lowered convergence trend and algorithm accuracy.

Keywords: apparel supply chain; reorder decision-making; agent; improved African vulture optimizer

check for updates

Citation: Bahadoran Baghbadorani, S.; Johari, S.A.; Fakhri, Z.; Khaksar Shahmirzadi, E.; Navruzbek Shavkatovich, S.; Lee, S. A New Version of African Vulture Optimizer for Apparel Supply Chain Management Based on Reorder Decision-Making. *Sustainability* **2023**, *15*, 400. https://doi.org/10.3390/su15010400

Academic Editors: Gerhard-Wilhelm Weber, Alireza Goli, Erfan Babaee Tirkolaee and Mark A. Bonn

Received: 29 August 2022
Revised: 20 November 2022
Accepted: 25 November 2022
Published: 26 December 2022

1. Introduction

Economic and production enterprises have found themselves in need of managing and overseeing resources and aspects connected to outside the organization in the current competitive market, in addition to dealing with the organization and internal resources [1]. Accordingly, managing the supply chain is now observed as one of the technical foundations for the global adoption of businesses in the last decade. A supply chain consists of a network of companies, workers, and vendors, whose job it is to make, ship, and deliver products to customers; this infrastructure includes resources such as people, companies, data, activities, and technologies, and, as a result, the final products reach the buyers. The supply chain consists of several stages in order to deliver the product or service to the customer, and it refers to concrete and specific products but can also include things like digital products or other services, depending on how the products are delivered. These steps include considerations such as converting raw materials into products and moving products from the warehouse to the customer's home. Making these steps a reality is up to the people who work in industries, such as warehousing, shipping, manufacturing, assembly and manufacturing, and transportation personnel. Supply chains are considered a mechanism to reduce the final cost of product production for the customer, and its management is the supply chain regulation that optimizes a company's manufacturing processes for overall operational efficiency [2]. Managers' perspectives on the supply chain have changed in the modern era, and information technology is being used more frequently in this industry. The development of business intelligence, however, is one of information technology's greatest successes [3]. As a result, supply chain management may be improved through the employment of intelligent software agents [4].

In order to successfully compete in any production field, companies must be oriented according to market needs. This coordination with the market requires balancing production activities and supply chain management. The category of customer reorders system point is nowadays a significant input in the design and management of production and supply chain activities; it is considered a strategic position in the design and management of production processes from the most basic supplier to the final customer.

In order to achieve shared objectives—including reducing delivery delays, storage requirements, and transportation expenses—apparel producers must collaborate in today's fiercely competitive global apparel industry [5]. A supply chain includes storage facilities, producers, wholesalers, and retailers, all of which facilitate the acquisition, transformation, and distribution of commodities and goods to market customers. Increasingly, apparel firms are adopting and investigating improved supply chain management (SCM).

Moving away from managing discrete tasks toward taking part in activities crucial to supply chain procedures is necessary to provide effective supply chain management [6]. The supply chain in the apparel sector is extremely complicated and unpredictable, making it difficult for a typical centralized decision-making system to effectively handle all information activities and flows. In order to improve performance and make the administration of the apparel supply chain easier, the agent technology is examined in this study using a more dispersed approach.

Agents are often steady, active software components with the capacities for comprehension, communication, and action [7]. A user-predefined set of rules may be followed by the agent before being applied, and when it comes to user demands and the resources that are available, the intelligent agent learns and may acclimatize to the environment. Independence and the capacity to reason and act in the agent's environment, along with the ability to interact with other agents in order to solve complicated issues, are important characteristics of the agents. The ability to function independently of humans or other agents while maintaining control over their behavior is referred to as "autonomy".

To take the orders and give results, an agent has to interconnect with the user or other agents; the level of educated behavior and aptitude for probabilistic reasoning that an agent exhibit is a crucial characteristic. Due to lack of information and inaccurate information, the supply chain member typically cannot make an immediate choice, which is because of the wide variety of market demands and the quick updating of fashion. Delays in decision-making in the supply chain increase time intervals and reduce the competency of companies. Members of the supply chain must react quickly to minimize this delay [8].

Through information and material flows, which are managed and coordinated by supply chain management activities, various parts of the network are linked with each other. The supply chain features a characteristic distributed decision scenario since there are several decision makers involved, and the apparel industries are quite advanced, using digital transformation in various areas, such as manufacturing, industry 4.0, marketing 4.0 [9], fashion 4.0 [10], forecasting, etc. However, the seasonal apparel supply chain is particularly concerned with seasonal fluctuation, market variation, and other uncertainties. Research is established on the vendor-managed inventory (VMI) replenishment approach of key clothing goods, which is not enough consideration; inventory and order levels are also closely tied [11]. By increasing additional orders, shortages and higher holding costs have occurred, which degrade customer service levels.

Backs et al. analyzed and compared traditional supply chains with fast fashion supply chains in clothing manufacturing [12]. They used the agent-based approach (ABA). By comparing two supply chain tactics (rapid fashion versus the time-honored trend) with several products and intercommunicate policies (advertising and product features) in a number of market scenarios, the paper illustrated the capabilities of that agent-based market simulation. Wilson proposed another method to evaluate the global apparel supply chain system using an ABA [13]. He explained the system as it now exists before comparing it to a hypothetical system using POSIWID analysis and characterizing the system's agents using Complex Adaptive Systems analysis. The paper then utilized these analysis techniques to show where changes can be made to the supply chain system to convert it from a linear to a circular model.

Ma et al. developed a sustainable model of a make-to-order apparel supply chain using a collaborative cloud service platform [14]. In the proposed platform, a supplier selection heuristic was created to choose the best vendors for each demand that was received. The suggested platform was created using multi-agent simulation technology, which was also used to assess the new sustainable supply chain model. To compare a novel model to conventional apparel, make-to-order models, and models with subcontracting mechanisms, an experiment was run in the simulation. Results showed that the suggested platform and associated supply chain model had significantly improved sustainability. Pan et al. simulated the supply chain activities and describes the connections between the agents using unified modeling language [15]. To get help, the supply chain agent decides on the best replenishment amount and reorder point to reduce the cost of inventory. This research also integrates fuzzy inference theory and genetic algorithms with the dynamic reorder strategy.

Although the study is conducted on the vendor-managed inventory (VMI) replacement plan of basic clothing goods, the seasonal apparel supply chain, which is more concerned with season variation, market shift, and other uncertainties, has received little attention. Furthermore, inventory level is closely tied to orders. Excessive orders increase holding costs, whereas insufficient orders produce shortages and, hence, degrade customer service levels. In order to achieve customer service standards, we suggest an agency-based reordering system for seasonal apparel goods in this paper. We do this by taking into account sales data, seasonal distribution, and fashion trends. To increase ordering accuracy, fuzzy logic is used to take fashion and seasonality trends into account. For decreasing the overall cost of the inventory, a modified bio-inspired algorithm based on an improved version of African vulture optimizer is utilized in inventory management and reordering choices.

2. Methodology

2.1. Adaptive African Vulture Optimizer

One of the strategies that produce effective outcomes for these types of challenges is Metaheuristics [16]. Metaheuristic strategies are typically motivated by physical phenomena, natural occurrences, and even mathematical rules [17]. To give a more efficient solution, many forms of metaheuristics have been presented; for instance, Abdollahzadeh et al. [18] define the AVO Algorithm as a newly proposed bio-inspired algorithm. The AVO optimizer is inspired by vultures' quest for food and competition with one another. Despite the fact that these creatures are predatory, they also fertilize feeble animals.

Individuals that are unable to rip the carcasses stay for their friends to feed and slash on the carcasses, and afterward, when they are full, the weaker vultures attack the leftovers. The AVO algorithm begins with several random individuals (considered vultures in this context) and then determines their aptitude after analyzing their cost values. The finest vultures from 2 clusters have been identified and saved, that is:

$$R_i = \begin{cases} Best\ vulture\ 1, & if\ p_i = L_1 \\ Best\ vulture\ 2, & if\ p_i = L_2 \end{cases} \tag{1}$$

$$L_1 + L_2 = 1 \tag{2}$$

where, L_1 and L_2 represent, in turn, two parameters that are ranged between 0 and 1 and are attained before optimization. The Roulette wheel mechanism is used to choose the best individual in each group, such that:

$$p_i = \frac{F_i}{\sum_{j=1}^{m} F_i} \tag{3}$$

where F denotes the vulture's level of contentment. The starvation ratio for vultures is then calculated. The vultures soar upward in search of food and when the individual runs out of energy, the adjacent stronger vultures will compete for the meal, which may be represented as follows:

$$t = k \times \left(sin^w \left(\frac{\pi}{2} \times \frac{it_i}{max_{it}} \right) + cos \left(\frac{\pi}{2} \times \frac{it_i}{max_{it}} \right) - 1 \right) \tag{4}$$

$$F = (2 \times \delta_1 + 1) \times y \times \left(1 - \frac{it_i}{max_{it}} \right) + t \tag{5}$$

where it_i indicates the current iteration, w signifies a constant value to define the optimization operation, δ_1 signifies a random integer between 0 and 1, max_{it} represents the total quantity of iterations, y specifies a random quantity between -1 and 1, and k represents a random digit between -2 and 2. If $y < 0$, the vulture becomes hungry; else, it changes to one. Then, in order to accomplish algorithm exploration, a random mechanism with 2 strategies is proposed. The following individuals in the environment use the model of seeking food sources:

If $P_1 < rand\ (P_1)$,

$$P(i+1) = R_i - F + \delta_2 \times ((U - L) \times \delta_3 + lb) \tag{6}$$

If $P_1 > rand\ (P_1)$,

$$P(i+1) = R_i - D(i) \times F \tag{7}$$

where

$$D(i) = |X \times R(i) - P(i)| \tag{8}$$

where the best vultures are characterized by R, X denotes the random changing of the vulture to keep food taken from other vultures by $X = 2 \times \delta_{i|i=1,2,3}$, and L and U denote the variables' lower and upper limits. Also, to conduct algorithm exploitation, we should have $|H| < 1$. This comprises 2 pieces with 2 strategies of siege-fight and rotational flight, specified by P_2 and P_3 as 2 parameters in the range [0, 1]. If it is between 0.5 and 1, the first term of the exploitation starts. Vultures will be happy if $|H| \geq 1$. The frailer vultures seek to obtain nourishment from the strong ones using the strategy described as follows:

$$P(i+1) = D(i) \times (F + \delta_4) - d(t) \tag{9}$$

$$d(t) = R_i - P(i) \tag{10}$$

where δ_4 describes a number in the range [0, 1]. In addition, the mathematical description of the vulture's spiral movement is as follows:

$$S_1 = R(i) \times \left(\frac{\delta_5 \times P(i)}{2\pi} \right) \times cos(P(i)) \tag{11}$$

$$S_2 = R(i) \times \left(\frac{\delta_6 \times P(i)}{2\pi} \right) \times sin(P(i)) \tag{12}$$

$$P(i+1) = R_i - (S_1 + S_2) \tag{13}$$

where δ_5 and δ_6 represent two random numbers ranging from 0 to 1.

If $|H| < 0.5$, the migration of vultures is based on siege and hostile fighting; they will go to other sites to acquire food. Most vultures will battle to gain food if δ_{P_3}, as a random value between 0 and 1, is equal to (larger than) the P_3. When δ_{P_3} is less than P_3, the violent siege-fight policy is used. In rare situations, vultures are famished, resulting in a massive rivalry among them to locate food, which is accomplished as follows:

$$A_1 = BestVilture_1(i) - \frac{BestVilture_1(i) \times P(i)}{BestVilture_1(i) - P(i)^2} \times F \tag{14}$$

$$A_2 = BestVilture_2(i) - \frac{BestVilture_2(i) \times P(i)}{BestVilture_2(i) - P(i)^2} \times F \tag{15}$$

where $BestVilture_1(i)$ and $BestVilture_2(i)$ indicate the best of 2 sets of vultures, and $P(i)$ represents the current vector position, which is attained by the following equation:

$$P(i+1) = 0.5 \times (A_1 + A_2) \tag{16}$$

If $|F|$ less than 0.5, the previously healthy vultures lose energy and capacity to stand against the others. At that point, they fly to an unfamiliar location to achieve nourishment, that is:

$$P(i+1) = R(i) - |d(t)| \times F \times LF(d) \tag{17}$$

where LF (Levy flight) is achieved as follows:

$$LF(x) = \frac{u \times \sigma}{100 \times |v|^2} \tag{18}$$

$$\sigma = \left(\frac{\Gamma(1+\rho) \times sin\left(\frac{\pi\rho}{2}\right)}{\Gamma(1+\rho_2) \times \rho \times 2\left(\frac{\rho-1}{2}\right)} \right)^{\frac{1}{\rho}} \tag{19}$$

where u and v represent, in turn, random values between 0 and 1, and ρ describes a determined integer.

Adaptive AVO

As previously stated, the AVO algorithm is a novel, well-organized, bio-inspired approach for solving optimization issues [19]. The solution candidates have randomly distributed values in the search space. When a candidate has no neighbors, a random walk policy was used based on the suggested adaptive mechanism, and the aforementioned technique decreases the convergence trend and algorithm correctness. As a result, the adaptive learning factor (ALF) is required to tackle this problem. This is accomplished as follows:

$$v = \frac{\left| f\left(P_i^j\right) - f\left(P_g^j\right) \right|}{f\left(P_g^j\right) + \varepsilon} \tag{20}$$

where $f\left(P_i^j\right)$ represents the ith vulture's cost amount at iteration j, ε signifies the minimal constant to avoid zero-division-error, $f\left(P_g^j\right)$ specifies the vulture's ideal cost value at iteration j. Vulture's ALF in this incarnation is as follows:

$$d_i^t = \frac{1}{1+e^{-g}} \tag{21}$$

where g is in the range between 0 and 2. Consequently, the new satisfaction ratio has been updated by the following:

$$F = \left(2 \times d_i^t + 1\right) \times y \times \left(1 - \frac{it_i}{max_{it}}\right) + t \tag{22}$$

In addition, opposition-based Learning (OBL) has been employed to improve algorithm efficiency. Opposition-based Learning is a technique that allows metaheuristic algorithms to be adjusted. OBL serves as an alternative place for the vultures to do a certain duty [20]. The vultures' new placement may produce better results for the objective function. The fundamental concept is to instantaneously reveal a new amendment for solution assessment and connect related conflicting solutions by picking the best results. The opposite solution ($P_i\prime$) has been derived for an individual solution, P_i, such as:

$$\begin{array}{c} P_i' = L + U - P_i \\ P_i \in [L, U] \end{array} \quad (23)$$

where L and U denote, in turn, the lower and the upper bounds of the search space. This is applied from the 2nd iteration to 50% of the candidates.

In this study, the proposed Adaptive AVO Algorithm is used in the ordering process, particularly in the fashion supply chain's reorder cycle, in a dynamic environment while taking uncertainties into account. The agents in the apparel supply chain will be determined in the parts that follow. The supply chain operations will then be presented in unified modeling language, and the apparel reorder strategy will be optimized using the Adaptive African Vulture Optimization Algorithm. The flowchart of the proposed African Vultures Optimization Algorithm is shown in Figure 1.

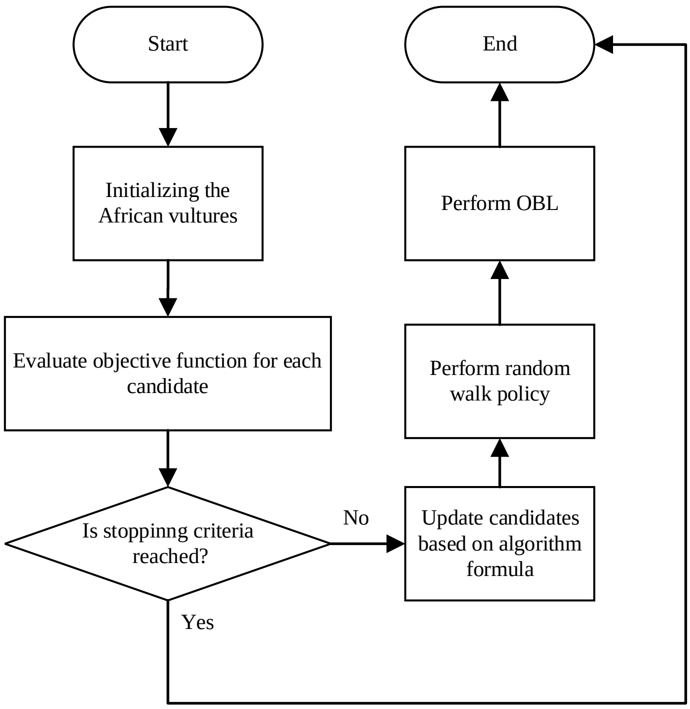

Figure 1. The flowchart of the proposed African Vultures Optimization Algorithm.

AVOA offers a more distinct exploration mechanism and exploitation mechanism than other metaheuristic optimization algorithms. However, AVOA still has certain drawbacks, including the ease with which it might adopt a locally optimum solution and the imbalance between its capacity for exploration and exploitation. The two explained methods also are included in the suggested AAVO algorithm in this research to increase the adoption of AVOA and improve its impact.

2.2. Supply Chain Modeling

Supply chain management is used in order to strengthen companies to obtain the necessary resources to make a service or product and deliver it to the customer. Managing the supply chain is the procedure of providing raw resources or organizational elements that a company requires for making a product/service and providing it to customers. The purpose of supply chain management is to progress supply chain performance. In other words, precise and opportune supply chain data permits producers to make and ship only saleable products. Operative supply chain systems assist retailers and manufacturers in decreasing redundant activity. This decreases the production cost, transportation, insurance, and storage of goods that cannot be sold.

2.2.1. Usecase Diagram

Usecase is a tool for defining the interactions required by the user in the system; in fact, it is a set of actions that define the step-by-step interactions between the user and the system to reach a specific goal (which is the completion of the case). A case can be considered a task that needs to be completed. The roles of the supply chain agents are depicted in Figure 2, which also primarily includes the Usecase diagrams for the production and merchandiser scheduler agents.

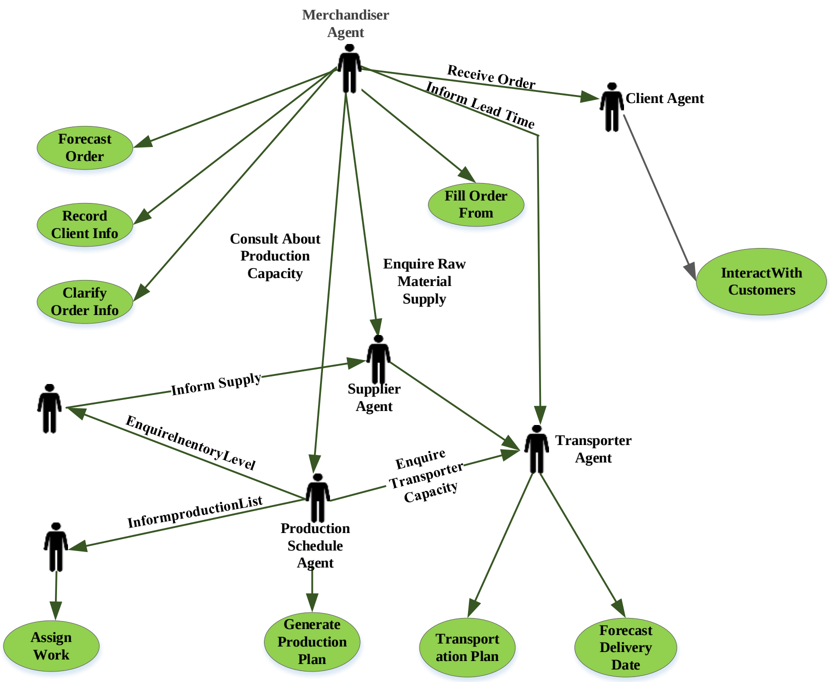

Figure 2. Usecase diagram for the supply chain agents.

In addition, the merchandiser agent collects the orders of clients, logs their data, fills their orders, and makes projections using client guidelines. Instead, the merchandiser agent interacts with the production scheduler agent about production capacity and queries the supplier agent about the raw material supply. The manufacturing scheduler agent also notifies the dispatcher agent to allocate production jobs, and inquiries about inventory levels from the inventory management agent.

The Usecase diagram incorporates explicit data of forecasts and judgments, as well as implicit knowledge of order information. The merchandiser agent bargains with the consumer and primarily decides whether to accept the order during the merchandising process. The production scheduler decides primarily on the orders' production allocation and creates a production plan based on the information obtained from the merchandiser and other agents.

2.2.2. Class Diagram

This diagram determines the central modeling that is implemented in almost all object-oriented techniques. The class diagram labels the system divergent objects in the system and the different types of affairs that exist between them. There are three important basic relationship types:

- Association: Represents associations between cases of types (one person works for one company, and one company has multiple offices).
- Aggregation: This is a procedure for object composition in designing object-orient.
- Inheritance: The most understandable addition to ER diagrams for utilization in object orientation. It has a direct correspondence with inheritance in object-oriented design.

The execution level and the conceptual level are the two levels we take into account. Figure 3 shows the concept level of supply chain management.

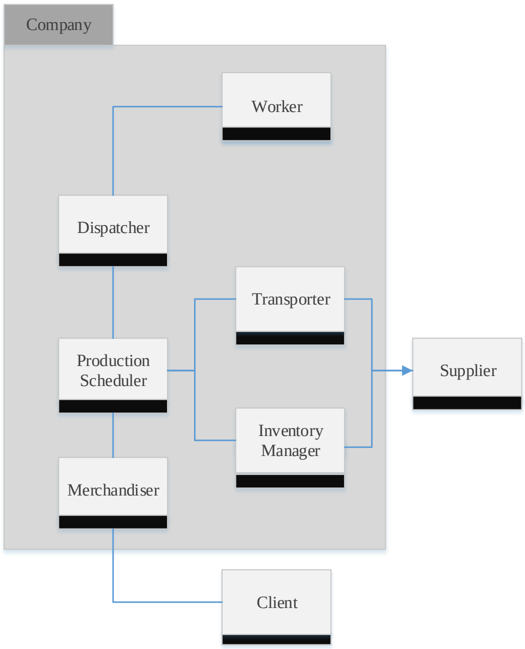

Figure 3. The supply chain management: concept level.

The theoretical level defines a sophisticated perspective that omits specifics such as the implementation of agents. Figure 4 shows the merchandising process management implementation level.

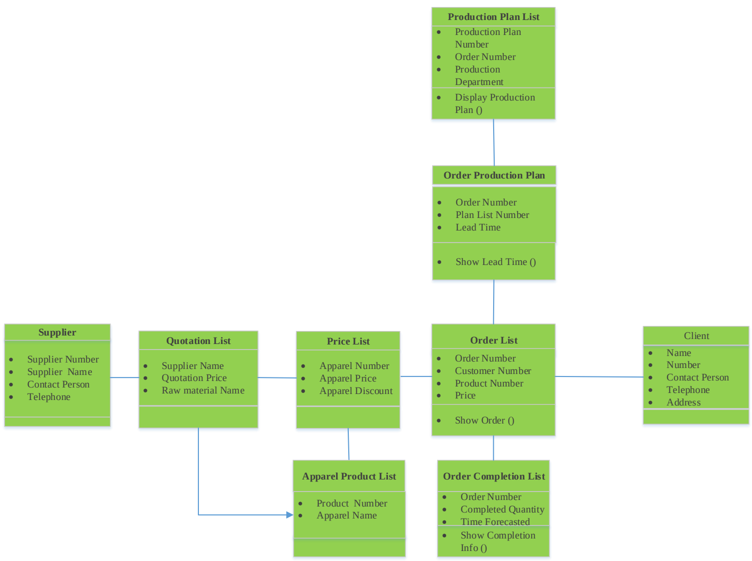

Figure 4. The merchandising process management: Implementation level.

The perspective of the system is defined by the level of implementation of the system that includes all the data. The data in the information is helpful and may be viewed as plain information for ordering.

2.2.3. Statechart Diagram

The name of the state chart indicates its applications. As its name suggests, this diagram models the different states in which an object is placed. In fact, this diagram shows an image of the object's life cycle. These situations are specific to a specific component/object of the desired system. A state chart describes a state machine, which is used to represent different states of an object in the system, and also to represent transitions between states. The mentioned situations are managed and controlled by internal or external events. In this work, the merchandiser agent's statechart diagram is taken into account, and it is shown in Figure 5.

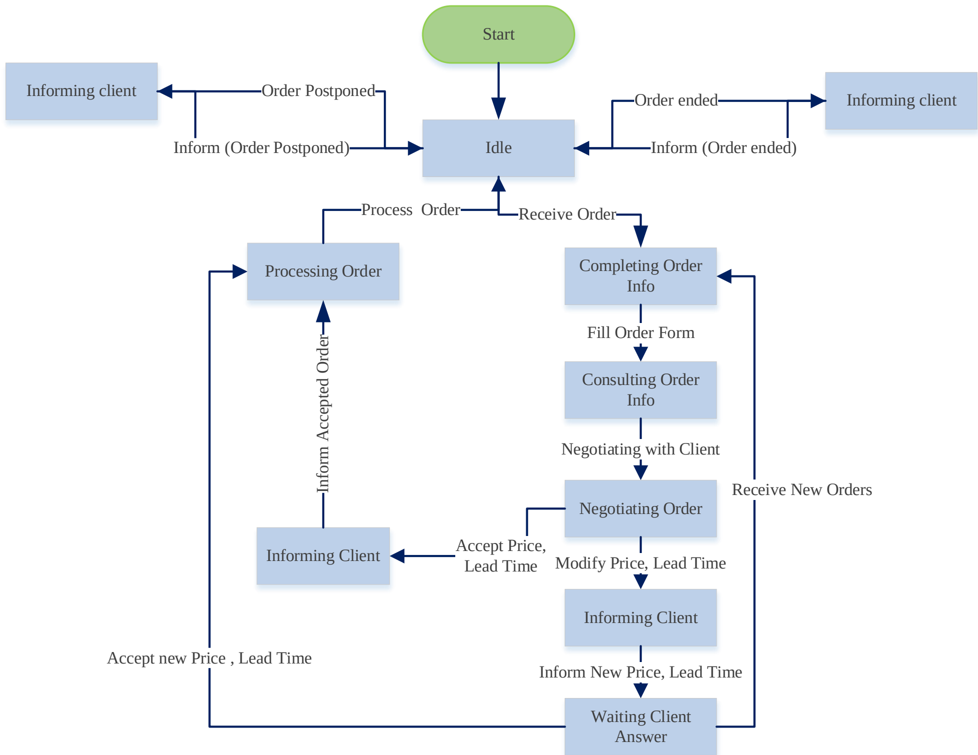

Figure 5. Merchandiser agent's statechart diagram.

Agent stations are shown as rounded rectangles. The relationships between two states can be categorized as either actions or events. The idle state is the starting point. The merchandise representative must fill out the order form and complete the order details when the order is delivered. If something is unclear, he will speak to other agents. He will also bargain with the customer about things like pricing and delivery date. Until the two parties concur on the outcome, the order cannot be processed.

2.2.4. Protocol Diagram

This diagram displays the roles, inputs, resources, outputs, and choices connected to the tasks/processes. The protocol diagram shows details on when and how particular activities and roles are carried out. The agent-related responsibilities and processes in unified modeling language are shown in Figure 6.

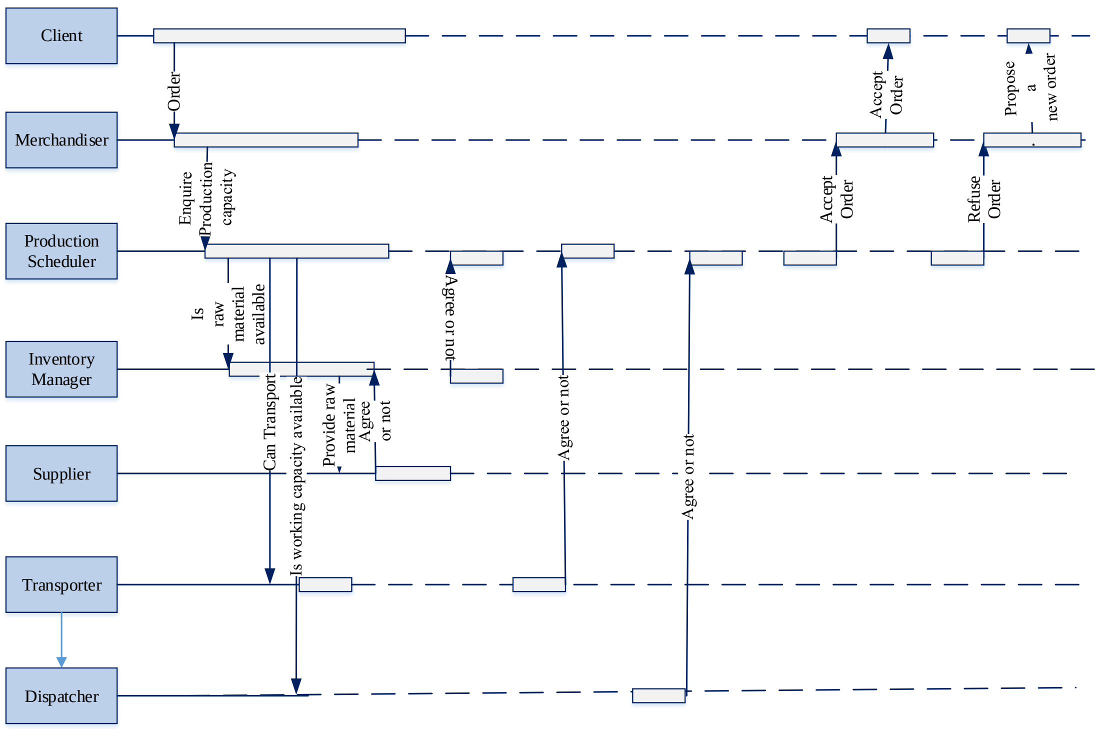

Figure 6. Agent-related responsibilities in unified modeling language.

Diagrams of the protocol explain how messages go between agents. These signals include both implicit and explicit information, such as order details and decisions about rejecting/accepting consumer orders. In our supply chain management example, there are several interactions. The set of interaction procedures for situations is as follows:

- Place an order for a product in which every agent in the multi-agent system participates.
- Alter the sequence in which all of the multi-agent system's agents can act.
- Withdraw an order in cases when the dispatcher, supplier, transporter, inventory manager, or merchandiser have intervened.
- Handle a delivery where the carrier and merchandiser are involved.
- If the production scheduler interferes with the transporter, or merchandiser, and postpones the product delivery.

Here, the order of a certain type of apparel goods is the main topic. The multi-agent system's primary protocol interaction involves all agents. An order is given by the client. The merchandiser agent gets the order and talks to the customer and the transporter agent to agree on a price and a delivery date. The transporter agent chooses the optimum route for the delivery of products and determines the cost and time of transportation in line with the information obtained from the scheduler agent. The supplier agent is called if the inventory management agent does not have the required raw materials (such as fiber, fabric, or cotton) for the order. The relevant protocol diagram is shown in Figure 5.

2.3. Agents' Formulation

The abstract concept of agents is simple to codify. At the first step, the environment is assumed to be in any one of a finite set F of instantaneous, discrete states, where $F = [f, f', \ldots]$. Then, it is believed that agents have a range of potential actions at their disposal that can change the environment. By considering $AA = [\beta, \beta', \ldots]$ as the agents' action, $A_{gent} : R^D \rightarrow AA$ can be used to define the agents. The multi-agents in the supply chain for apparel may thus be characterized as

$$A_{gent} = \begin{bmatrix} a_{merchandiser}, \ a_{client}, \ a_{production\ scheduler}, \\ a_{manufacturing\ dispatcher}, \ a_{inventory\ manager}, \ a_{supplier} \end{bmatrix} \tag{24}$$

They will play out the part and carry out the associated task in the apparel supply chain. They mostly record undocumented information, such as the supply chain organization's skill, human experience, and know-how, as well as explicit valuable data, procedures, and reports in the supply chain operations. The agents effectively interact with one another, make the best choices, and create a more well-coordinated environment based on the information. Taking into account the system's past, an agent decides what action to take.

The agents in the apparel supply chain cooperate, bargain, and even engage in conflict. All of the agents are considered to have two alternative actions it might do in order to simplify the analysis. Here, we refer to these two behaviors as "D" for "Defect" and "C" for "Cooperate". The collection of these acts is assumed as AA, where $AA = [C, D]$. The environment's behavior is then controlled by the function $\tau : AA \times AA \rightarrow \Omega$. The situation is sensitive to the activities that agents in the clothing supply chain do if it associates each set of behaviors with a particular consequence. The two agents will decide which action to do in the environment, and the acts they decide to take will have an effect on Ω.

What will really happen depends on the specific acts taken in combination. As a result, both agents have the potential to affect the result, which implies that any agent's activities in A_{gent} will have an impact on how well the apparel supply chain functions.

Agents can make deductions in accordance with the guidelines for making deductions. For instance, the inventory manager manages the inventory level in an agent-based apparel supply chain in the event of unforeseen orders and stock outs. Fuzzy rules, which may be viewed as inference rules to guide the go-between's comportment, can aid in the decision-making process for replenishing. Consider F to be the collection of fuzzy logic membership functions. Let $D = F(\beta)$ represent the collection of an agent's internal states. A collection of deduction rules may be used to simulate the decision-making process of the inventory manager agent. At first, the agent's perceptive function, "see", i.e., $see : S \rightarrow Per$c. It indicates that the agent perceives based on what it observes. The formal definition of the agent's next function is $Next : D \times Per \rightarrow D$.

Thus, it creates a new database by mapping a database and a percept. The action function of the inventory management agent, $Action : D \rightarrow AA$, may be described in terms of fuzzy rules, however. The optimal action to do is indicated by the fuzzy member function $F(\beta)$, which may be formed from terms that describe actions and which can be used to encode the deduction rules.

2.4. Reorder and Inventory Management Decision-Making Models

Inventory control is a key component of good supply chain management. It is a widely held belief that supply chain management results in cost savings, mostly over inventory drops. Inventory costs are reduced by around 60%, while transportation costs are reduced by 20%. Many have pursued inventory-reduction measures in the supply chain as a result of these cost reductions. This section defines several agents, which have been combined to imitate the inventory control. Seasonal demand and on-time delivery are important factors to consider in apparel marketing. Products for seasonal apparel are soon sold out, followed by reorders.

The role of the inventory manager plays a crucial part in maintaining inventory levels by selecting the right degree of price, reorganize point, and order quantity. The client agent gathers sales data from various locations during the selling season, projects future client demand, and provides input to the inventory manager agent.

In other words, the customer informs the inventory manager agent of the selling information. As a result, the inventory manager agent evaluates the demand data and chooses the appropriate amount of reorder. The apparel business should maintain a specific quantity of clothing on hand to quickly satisfy consumer requests and reduce lead times.

Nevertheless, if the amount is not adjusted appropriately, the overstock will raise the cost of storage, driving up the supply chain's overall cost. The choice of quantity must be carefully considered if delivery times are to be shortened and inventory levels are to be maintained. Conventional prediction techniques, such as simple moving averages, Winter's exponential, and the moving average model, are based on a huge amount of historical data and estimate the demand for the time $t+1$ with no taking the complete supply chain cost into account at time t. This study uses fuzzy knowledge to determine the reorder point, while taking market variation and fashion trends into account. It also suggests using an Improved African vulture optimization algorithm to predict the number of reorders in order to reduce overall costs.

If the buyer puts the demand while the inventory spreads the reorder point, the new items will reach before the company runs out of inventory to trade. The reorder level is always greater than zero. The order point problem, or how small would the inventory be reduced before it is reordered, is hence the term used to describe the choice of how much stock to keep. The procuring or delivery time stock—that is, the inventory required throughout the lead time—and the safety stock—that is the bare least of inventory retained as a safeguard against deficiencies—are the two elements that define the optimal order point. The supply chain's cycle for apparel inventory performance is depicted in Figure 7.

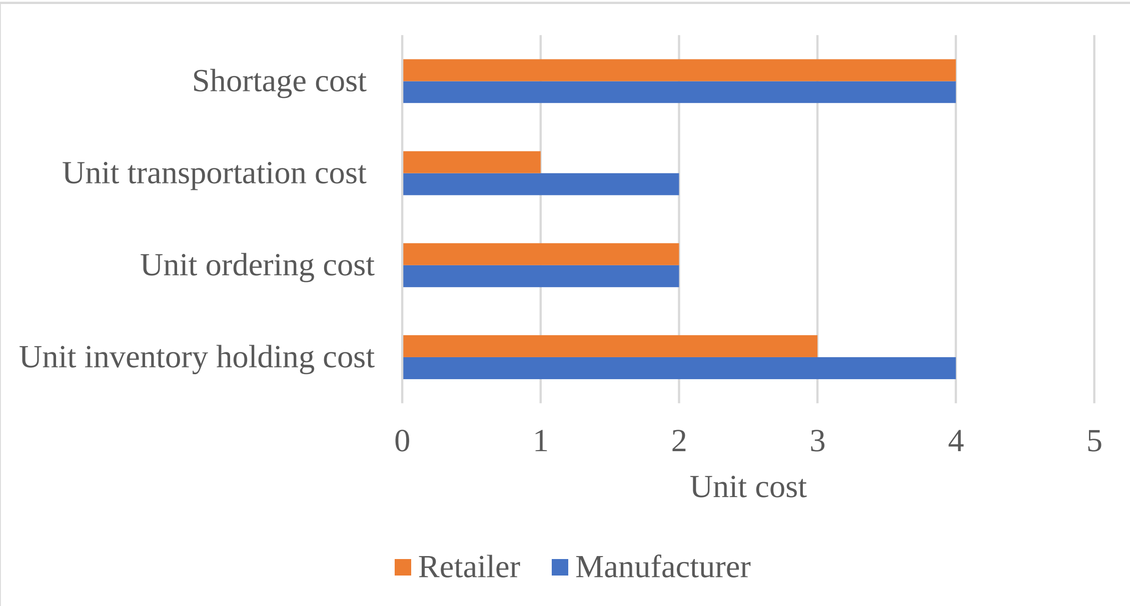

Figure 7. Unit costs of ordering cost, transportation cost, shortage cost, inventory holding cost.

Where the retailer's and manufacturer's order volume are the input. The cost of all inventory serves as the fitness function. Inventory holding costs, order costs, and transportation costs are all unit costs. Due to several unpredictable causes, the inventory curve may not changing linearly. Inventory is depleted by customers until the stock level is at its lowest. A reorder is started before the stock level falls to the minimum, so inventory will return before the out-of-stock situation arises. The refill order typically begins on day $t2$ of the figure and is delivered on day $t0$, although an unanticipated surge in client orders may occur sometime ($t1$), causing the inventory to unexpectedly fall to an extremely low level and leaving it unable to fulfill incoming requests.

The inventory management agent periodically checks and controls the inventory. A replenishment order is started once the level of available clothes drops below the boundary inventory. The client agent gathers consumer purchase data and uses fuzzy inference to predict market trends in order to determine more precise reorder quantities. We should address unpredictable elements in the garment sector, such as seasonality in the rag trade or market fluctuation. As a result, the reorder process is optimized using a genetic algorithm and fuzzy logic to use less inventory and provide better customer service.

The inventory management agent keeps track of the inventory for a certain amount of time and contrasts the boundary inventory (I_B) with the current inventory (I_C). When I_C falls below I_B, a reorder is started. As a result, the ordering point depends on the degree of I_B. The replenishment happens early when I_B is more. The incident often occurs at the beginning of the trade season. Alternatively, the reorder happens later when I_B is small. A circumstance like this occurs practically at the conclusion of the selling season. I_B will no longer require replenishing once it reaches a specific low point since fewer people will be using it. In contrast to the fixed border inventory, the boundary inventory used in this technique is dynamic.

The agent tunes the border inventory level as said by the sales of the preceding week based on last week's sales; the agent will change the border inventory level.

$$I_B = \overline{T} \times \overline{d} + Z \times \sigma_d \tag{25}$$

$$I_C = I_H + I_r - I_{tr} \tag{26}$$

$$Q_0 = \begin{cases} I_B - I_C, & I_C < I_B \\ 0, & I_C \geq I_B \end{cases} \tag{27}$$

where Q_0 describes the resupply value, $\overline{T}$ describes the typical replenishment cycle duration, I_H specifies the inventory that is currently on hand, $\overline{d}$ represents the typical customer demand throughout the cycles, I_r signifies the inventory already reserved, Z describes the safety stock's impact factor, I_{tr} defines the in-transit inventory, and σ_d signifies the standard deviation of demand throughout the replenishment cycle.

Although inventory changes in response to sales, the time to place an order should be sooner when the inventory drops suddenly from time to time. In order to respond to the shifting market, a more dynamic replenishment approach is thus suggested. Four elements are taken into account while calculating the dynamic replenishment: seasonal distribution, fashion trend, sales history, and point of sale (POS). The stores in various locations will get the final apparel goods. Since various regions have diverse purchasing habits, so do their sales. The merchandiser should speak with the merchant to obtain the data in order to connect the replenishment with fashion trends and market changes.

The client agent obtains the data from the merchants, transforms it into knowledge, and interacts with the marketer agent. To determine if a specific kind or color is preferred or not, fuzzy logic is applied. Each store will comment on how well a certain color or style of seasonal clothes has sold. The agent determines the degree of popularity using five criteria: "in", "less in", "average", "bit out", and "out". If there are n designers, we have:

$$Color : [x_1, x_2, x_3, x_4, x_5] \tag{28}$$

$$Style : \ [y_1, y_2, y_3, y_4, y_5] \tag{29}$$

$$Criteria\ matrix : C = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 & x_5 \\ y_1 & y_2 & y_3 & y_4 & y_5 \end{bmatrix} \tag{30}$$

The retailer's score for a certain color and size of apparel is represented by the percentages x_i and y_i.

Weight: $W = \begin{bmatrix} w_1 & w_2 \end{bmatrix}_{1\times 2}$, Therefore, the outcome would be:

$$R = WC = \begin{bmatrix} r_1 & r_2 & r_3 & r_4 & r_5 \end{bmatrix} \tag{31}$$

$$\beta = max\left(r_{i|i=1,2,\ldots,5}\right) \tag{32}$$

An aspect that influences replenishment is anticipated seasonal distribution, since specific types or colors of the material may be in demand during the selling season. The α coefficient is presented. The meaning of α is:

$$\alpha = \frac{The\ predicted\ seasonality\ distribution\ for\ the\ upcoming\ week}{Number\ of\ remaining\ sales\ weeks/sales\ season\ length} \tag{33}$$

The real sales record is another element added to producing responsive replenishment. We may discover the actual sales situation for a certain kind of material by using the POS data. We can use that information to analyze how well these items will sell in the future. To connect the real sales record to the replenishment, coefficient γ is used.

$$\gamma = \frac{point\ of\ sale\ info\ in\ week\ w}{Predicted\ sales\ in\ week\ w} \tag{34}$$

where w describes the earlier week before the replenishment quantity is achieved by the retailer.

Because apparel items with varying sizes, colors, and styles may sell differently, the agent keeps an eye on the inventory and replenishes it as necessary, such that

$$Z = \alpha \times \beta \times \gamma \tag{35}$$

The three variables α, β, and γ will influence the safety stock and, consequently, the reorder amount, i.e.,

$$I_B = \overline{T} \times \overline{d} + \alpha \times \beta \times \gamma \times \sigma_d \tag{36}$$

3. Objective Function

The best vulture candidate in each iteration and the timing of the end of progress are decided by an objective function in the Adaptive African vulture optimization algorithm. The objective function is used by the suggested objective function. All entities have ordering costs, transportation costs, and inventory holding costs [21]. Following N intervals (e.g., weeks), the total cost of supply chain has been evaluated by the following:

$$C_i^h = \overline{I}_i \times c_i^h = \left(S_i^s + \frac{Q_i}{2}\right) \times c_i^h \tag{37}$$

$$C_i^O = A_i \tag{38}$$

$$C_i^S = B_i \times Q_i^{BO} \tag{39}$$

$$C_i^t = C_i^{tr} \times Q_R \tag{40}$$

$$C_T = \sum C_i(t) = \sum\left(C_i^h + C_i^O + C_i^S + C_i^t\right) \tag{41}$$

where Q_i describes the turnover value of the cycles, c_i^h represents the holding cost per unit of the ith entity, C_i^h specifies the holding cost of the ith entity, S_i^s represents the safety stock of the ith entity, A_i describes the ordering cost per unit of the ith entity, C_i^O specifies the ordering cost of the ith entity, B_i signifies the shortage cost per unit, C_i^S defines the shortage cost of the ith entity, Q_i^{BO} represents the inventory of the backorder, C_i^t defines the transportation cost of the ith entity, C_i^{tr} describes the transportation cost per unit of the ith entity, Q_R defines the inventory value that will be received, C describes the total cost.

Afterward, the objective of the ith entity in time t is achieved as follows:

$$C_i(T) = \left(S_i^s + \frac{Q_i(t)}{2}\right) \times c_i^h + \sum_{0}^{N} A_i + B_i \times Q_i^{BO}(t) + C_i^{tr} \times Q_R(t) \tag{42}$$

$$Q_i(t) = \begin{cases} Q_i^R, & Q_i^{BO}(t) = 0 \\ Q_i^R(t) - Q_{BOI}(t), & Q_i^{BO}(t) > 0 \end{cases} \tag{43}$$

$$Q_i^{BO}(t) = \begin{cases} \left|Q_i^R + Q_i^H(t-1) - Q_i^D(t)\right|, & Q_i^R(t) + Q_i^H(t-1) - Q_i^D(t) < 0 \\ 0, & Q_i^R(t) + Q_i^H(t-1) - Q_i^D(t) \geq 0 \end{cases} \quad (44)$$

$$Q_i^{H}(t) = \begin{cases} \left|Q_i^R + Q_i^H(t-1) - Q_i^D(t)\right|, & Q_i^R(t) + Q_i^H(t-1) - Q_i^D(t) > 0 \\ 0, & Q_i^R(t) + Q_i^H(t-1) - Q_i^D(t) \leq 0 \end{cases} \quad (45)$$

$$Q_{i-1}^D(t) = Q_i^O(t) \quad (46)$$

$$Q_i^R(t) \leq Q_{i-1}^D(t-1) + Q_{i-1}^{BO}(t-1) \quad (47)$$

$$\text{If } Q_i^{BO}(t-1) = 0 \to Q_i^R(t) = Q_{i-1}^D(t-1) \quad (48)$$

where Q_i^H describes the on-hand inventory, Q_i^D represents the demand of the ith entity, and Q_i^O describes the ordering value of the ith entity.

It is supposed that each echelon's demand originates from the number of orders placed by the echelon above. The formula for the random distribution of customer demand is

$$u_D + M\left(0, \sigma^2\right) \quad (49)$$

where u_D and σ represent the mean demand and a random integer that may be determined based on market fluctuations, respectively.

As a result, it is possible to think of the client demand as a normal distribution of $M(\mu_D, \sigma^2)$. One week is the lead time. Since backorders are not permitted, there is no fee associated with them. Inventory numbers are usually positive. The costs associated with shortages, holding, transportation, and orders depend on the corresponding amounts.

4. Simulation Results

As mentioned before, the present study uses the Adaptive AVO algorithm to solve reorder process optimization. However, different types of metaheuristics are introduced before the proposed Adaptive AVO algorithm, which is a newly introduced algorithm that is improved here, providing better efficiency in solving this problem.

An inventory manager agent uses an Adaptive African vulture optimization algorithm to anticipate and choose the appropriate reorder volume in order to balance the cost of the inventory with the degree of customer service. The strategy indicated above, however, is reliant on the manager's knowledge and a substantial quantity of prior data. The Adaptive AVO creates the vulture candidates with the goal of generating low total covariance and does not rely on significant sales data.

Two agents are utilized during the optimization process that includes the inventory management agent, which determines the ideal ordering amount via the proposed Adaptive AVO Algorithm, and the other is the demand forecast agent, which provides outcomes for managers and agent controlling.

As a result of the Adaptive AVO's stochastic character, the outcomes may change each time it is used. As a result, we conducted each experiment 25 times. All algorithms were run with a cap of 200 iterations to ensure fair comparison (5000 function evaluations). The algorithms were written in MATLAB 2018b, 64-bit version, and ran on a 2.5 GHz Intel i5 processor and 4 GB memory computer. Figure 7 shows the unit costs of ordering cost, shortage cost, inventory holding cost, and transportation cost. Figure 8 shows the overall cost comparison with and without agent.

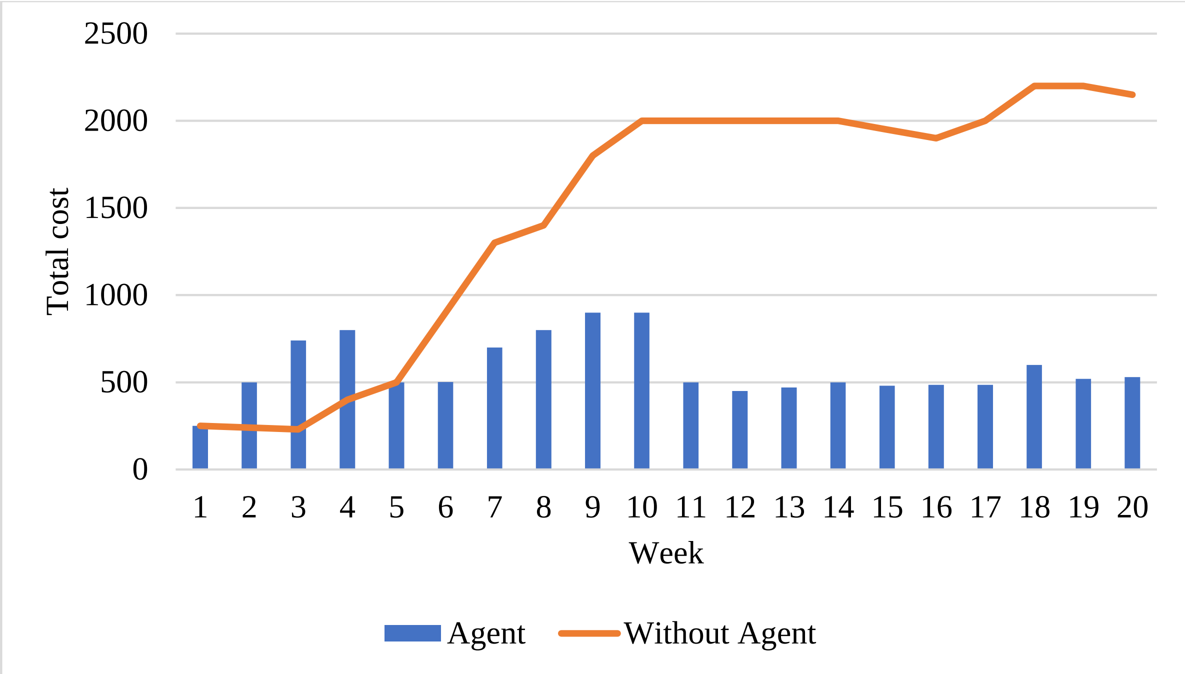

Figure 8. Over-all cost comparison with and without agent.

According to Figure 8, the overall cost increases rapidly to a high level before agent optimization, but only changes within a narrow range thereafter. This indicates that supplier cost may be decreased by optimization using fuzzy logic and Adaptive AVO algorithm. The difference in order variation using the AVO and the Adaptive AVO algorithm is seen in Figures 9 and 10.

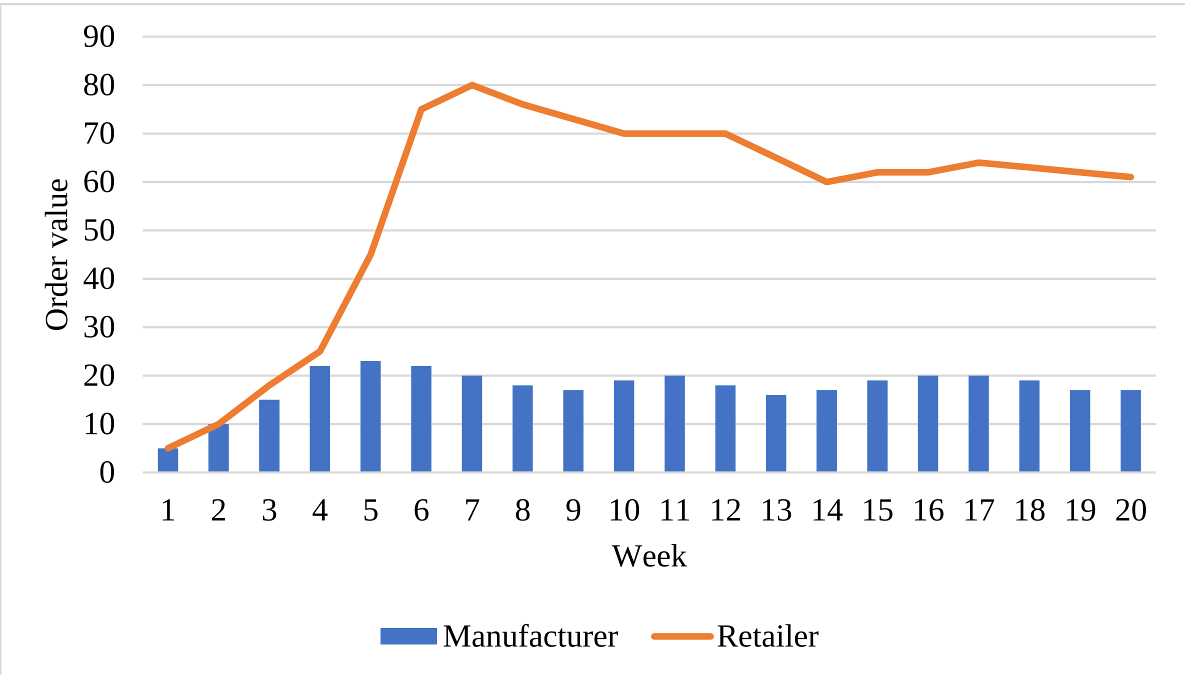

Figure 9. Ordering variation using African vulture optimization algorithm.

Figure 10. Ordering variation based on adaptive African vulture optimization algorithm.

We may conclude from the comparison that the proposed Adaptive AVO algorithm can successfully decrease order variation and, as a result, the bullwhip effect.

5. Conclusions

The aim of the current research was to provide a novel optimal methodology to achieve the replenishment amount and reorder point between the manufacturer and retailer, while taking into account a number of unpredictable variables, including fashion diversity and market change. To organize the supply chain technique, a supply chain network with agent technologies and unified modeling language diagrams was developed. To provide better choices about the ordering value and dynamically adjust to environmental changes, an agent-based system was employed. Also, an improved design of the African vulture optimization algorithm (AAVO) was used for optimal reorder decision making of the studied case. Experimental outcomes indicated that using the suggested AAVO-based method potentially holds promise for locating a target demand ordering amount, while reducing the supply chain's overall cost. For validation of the proposed AAVO, it was also compared with the original AVO, and the comparison showed that the proposed Adaptive AVO algorithm can better decrease order variation than the original AVO, which has the bullwhip effect. Future studies may concentrate on the issue when suppliers have a restricted supply capacity due to their skill, experience, and unequal obligations. Furthermore, we believe that customer demand is steady and predictable. Another future study might give a mathematical model for demand with stochastic characteristics. MCDM approaches, in addition to the one suggested in this paper, may be applied in a fuzzy environment. Greenhouse gas emissions and carbon footprints have recently become key environmental factors. Future study might look at this type of environmental topic in order to produce a more realistic method for green supplier selection.

Author Contributions: Data curation, S.B.B.; Investigation, S.A.J., Z.F., E.K.S., S.N.S. and S.L.; Project administration, S.L.; Supervision, S.L.; Writing—original draft, E.K.S.; Writing—review & editing, S.N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: There is no available data for this study.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wang, C.-N.; Pham, T.-D.T.; Nhieu, N.-L. Multi-layer fuzzy sustainable decision approach for outsourcing manufacturer selection in apparel and textile supply chain. *Axioms* **2021**, *10*, 262. [CrossRef]
2. Majumdar, A.; Sinha, S.K.; Govindan, K. Prioritising risk mitigation strategies for environmentally sustainable clothing supply chains: Insights from selected organisational theories. *Sustain. Prod. Consum.* **2021**, *28*, 543–555. [CrossRef] [PubMed]
3. Garcia-Torres, S.; Rey-Garcia, M.; Sáenz, J.; Seuring, S. Traceability and transparency for sustainable fashion-apparel supply chains. *J. Fash. Mark. Manag. Int. J.* **2021**, *26*, 344–364. [CrossRef]
4. Choi, T.-M.; Chen, Y. Circular supply chain management with large scale group decision making in the big data era: The macro-micro model. *Technol. Forecast. Soc. Chang.* **2021**, *169*, 120791. [CrossRef]
5. Liu, Z.; Lang, L.; Hu, B.; Shi, L.; Huang, B.; Zhao, Y. Emission reduction decision of agricultural supply chain considering carbon tax and investment cooperation. *J. Clean. Prod.* **2021**, *294*, 126305. [CrossRef]
6. Sumarliah, E.; Usmanova, K.; Fauziyah, F.; Mousa, K. Managing the risks in the clothing supply chain considering the coronavirus pandemic. *Oper. Supply Chain. Manag. Int. J.* **2021**, *14*, 576–587. [CrossRef]
7. Fontana, E.; Atif, M.; Gull, A.A. Corporate social responsibility decisions in apparel supply chains: The role of negative emotions in Bangladesh and Pakistan. *Corp. Soc. Responsib. Environ. Manag.* **2021**, *28*, 1700–1714. [CrossRef]
8. Rafi-Ul-Shan, P.M.; Grant, D.B.; Perry, P. Are fashion supply chains capable of coopetition? An exploratory study in the UK. *Int. J. Logist. Res. Appl.* **2022**, *25*, 278–295. [CrossRef]
9. Mavrotas, G. *Generation of Efficient Solutions in Multiobjective Mathematical Programming Problems Using GAMS. Effective Implementation of the ε-Constraint Method*; National Technical University of Athens: Athens, Greece, 2007.
10. Bertola, P.; Teunissen, J. Fashion 4.0. Innovating fashion industry through digital transformation. *Res. J. Text. Appar.* **2018**, *22*, 352–369. [CrossRef]
11. Shah, S.M.; Lütjen, M.; Freitag, M. Text Mining for Supply Chain Risk Management in the Apparel Industry. *Appl. Sci.* **2021**, *11*, 2323. [CrossRef]
12. Backs, S.; Jahnke, H.; Lüpke, L.; Stücken, M.; Stummer, C. Traditional versus fast fashion supply chains in the apparel industry: An agent-based simulation approach. *Ann. Oper. Res.* **2021**, *305*, 487–512. [CrossRef]
13. Wilson, O. Circular Economy in Global Apparel Supply Chains: Restructuring the Fashion System using Agent Based Approach (ABA). *J. Syst. Think. Prepr.* **2022**. [CrossRef]
14. Ma, K.; Wang, L.; Chen, Y. A collaborative cloud service platform for realizing sustainable make-to-order apparel supply chain. *Sustainability* **2017**, *10*, 11. [CrossRef]
15. Pan, A.; Leung, S.Y.-S.; Moon, K.; Yeung, K. Optimal reorder decision-making in the agent-based apparel supply chain. *Expert Syst. Appl.* **2009**, *36*, 8571–8581. [CrossRef]
16. Ramezani, M.; Bahmanyar, D.; Razmjooy, N. A New Improved Model of Marine Predator Algorithm for Optimization Problems. *Arab. J. Sci. Eng.* **2021**, *46*, 8803–8826. [CrossRef]
17. Razmjooy, N.; Khalilpour, M.; Estrela, V.V.; Loschi, H.J. World Cup Optimization Algorithm: An Application for Optimal Control of Pitch Angle in Hybrid Renewable PV/Wind Energy System. In *Metaheuristics and Optimization in Computer and Electrical Engineering*; Springer: Cham, Switzerland, 2021; pp. 25–47.
18. Abdollahzadeh, B.; Gharehchopogh, F.S.; Mirjalili, S. African vultures optimization algorithm: A new nature-inspired metaheuristic algorithm for global optimization problems. *Comput. Ind. Eng.* **2021**, *158*, 107408. [CrossRef]
19. Razmjooy, N.; Estrela, V.V.; Loschi, H.J.; Fanfan, W. *A Comprehensive Survey of New Meta-Heuristic Algorithms. Recent Advances in Hybrid Metaheuristics for Data Clustering*; Wiley Publishing: Hoboken, NJ, USA, 2019.
20. Razmjooy, N.; Ashourian, M.; Foroozandeh, Z. *Metaheuristics and Optimization in Computer and Electrical Engineering*; Springer: Berlin, Germany, 2020.
21. Kimbrough, S.O.; Wu, D.-J.; Zhong, F. Computers play the beer game: Can artificial agents manage supply chains? *Decis. Support Syst.* **2002**, *33*, 323–333. [CrossRef]