

Logistic Analytics Management in the Service Supply Chain Market Using Swarm Intelligence Modelling

Congcong Wang, Henan Polytechnic Institute, China*

ABSTRACT

The industry sustainability in today's globalization relies on cost-effective supply chain management of diverse markets and logistics. Supply chain risks typically limit profits over the overall expense of the supply chain. In the supply chain design practices, the volatility of demand and limitations of levels are essential concerns. In this paper, a swarm intelligence-assisted supply chain management framework (SISCMF) has been proposed to increase profit and improve logistics performance. Due to the simplicity of design and rapid convergence, swarm intelligence (SI) algorithms are widely used in most supply network design fields and efficiently solve large-dimensional problems. A significant increase in resolving these problems has been seen in particle swarm optimization and ant colony algorithm. The simulation result suggested the operational cost (92.7%), demand prediction ratio (95.2%), order delivery ratio (96.9%), customer feedback ratio (98.2%), and product quality ratio (97.2%).

KEYWORDS

Ant Colony Algorithm, Logistics Management, Supply Chain Market, Supply Chain Optimization, Swarm Intelligence

INTRODUCTION

The Supply Chain is a present organization to buy products from other companies instead of domestically produced (Li, et al., 2017). Logistics can be well-defined as a Subsidiary of a Supply chain, focusing on inventory control, marketing strategy, management and inspection of production and consumption points regarding maintaining a flexible and cost-efficient storage system and delivering products (or order) time (Manogaran, et al., 2020). The algorithm for scheduling is then needed to determine which items are sent to consumers (Arntzen, et al., 1995). One approach to accomplish this aim is to delegate orders to individual agents and allow the agent population to identify an optimal schedule solution interactively (Kumar, et al., 2020). The exchange of quantity, starting, and arrival information between management will contribute to managers' interaction (Kadavevaramath, et al., 2012). These logistical challenges are complicated, and effective processes of optimization are required (Das, et al., 2020). Natural processes operate very well with self coordinating structures to overcome complicated problems (Guide Jr, et al., 2000). The idea is to imitate these processes of the ant colony algorithm (Pham, et al., 2020).

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*Corresponding Author

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Ant algorithms are multi-agents that simulate individual ants' actions and their interaction with each other through each agent's action (Aladwan, et al., 2020). If the ants go to a nutrition source from the nest and vice versa, they leave a compound pheromone along the way (Gao, et al., 2020). Other ants are headed and pursued, leaving the pheromones behind (Singh, et al., 2016). The shorter direction from nest to food supply is the dominant course of the oldest pheromones as it evaporates over time (Al-Turjman, et al., 2009). To solve many NP-hard classes, including dynamic scheduling, Dorigo introduced the ACO (Al-Turjman, et al., 2020). Ant Colony Optimization (ACO) is a system for optimizing pheromone paths to convey food's shortest routes (Tayal, et al., 2021). The core elements in ACO include artificial ants, basic computing agents that construct solutions to the problem individually and on an iterative process (Kumar, et al., 2021). Ants explore a visiting graph of nodes linked by boundaries (Li, et al., 2020). An ordered node sequence is a solution to the problem (Meade, et al., 1998, Boveiri, et al., 2019). The search is performed on multiple constructive computational threads in parallel (Karthikeyan, et al., 2020). The first ACO algorithm proposed is the Ant system (AS) (El-Shorbagy, et al. 2019).

This paper first explains the necessary improvements to the SISC MF and the impact on the ACO. These modifications are described in detail step-by-step to enable the Ant Colony Algorithm to combine the material demands on routes and send them to their paths. ACO based method to solve SISC MF problems more effectively in a short time to identify effective solutions and analyses the efficiency of heuristic approaches in detail.

The main contribution of this paper is,

- Design swarm intelligence assisted supply chain management framework has been proposed to increase profit and improve logistics performance.
- Determine the Ant Colony Algorithm (ACA) simulation analysis to find the shortest path to deliver the products.
- The numerical outcomes show that the suggested SISC MF improves the operational cost, demand prediction ratio, order delivery ratio, customer feedback ratio, and product quality ratio compared to other existing models.

The remainder of SISC MF can be arranged accordingly. In section 2 describe the related study of logistic analytics management in the service supply chain market. In section 3 summarize the proposed work that has been utilized in this study. The simulation outcomes and discussion are stated in section 4. Finally, section 5 conclude this paper with a detailed discussion of observation and results.

LITERATURE REVIEW

This analysis proved with a detailed literature review that evaluates localization methods that peers analyze for research. Google Scholars investigation is limited to journal papers to measure its accuracy.

Larson et al. (2004) recommended Supply chain management (SCM) is an essential concern for logistics administrators and educators. Based on these practitioners' experiences, the cluster study supports the presence of four logistics versus SCM perspectives—relabeling, Traditionalism, Unionism and cross-cutting. The paper ends by addressing the consequences for students and practitioners in all four viewpoints.

Darvazeh et al. (2020) modelled Big Data Analytics (BDA) is one of the best strategies to enable companies to solve their challenges is the big data processing capability. The supply chain professionals struggle with managing the enormous data to meet the organized, reliable, profitable and agile supply chain in the current competitive setting. As a result, exponential volume growth and multiple data forms have resulted in a need to develop technology that can quickly and intelligently analyze vast amounts of data.

Yadav et al. (2020) suggested Third-party logistics (3PL) service providers can play an essential role in agriculture supply chain management (ASCM) for customer satisfaction and cost savings. This research will increase the trend towards outsourcing logistics activities to improve IoT agriculture’s supply chain’s sustainability.

Brintrup et al. (2020) recommended a machine learning approach (MLA) is the growing popularity of the AI model in the industry for supply-chain data analytics. There is a substantial shortage of case studies that illustrate its applicability from a realistic point of view. MLA predict supply shortage is a contribution to this initiative. Finally, they emphasize the importance of field awareness for technology features effectively.

Hackius et al. (2020) suggested that Supply Chain and Logistics Approach Blockchain (SC-LAB) companies promote digital transformation, shape new market models, and consortia unification of the industry. Lacking technology usability and ongoing uncertainties are the key obstacles to such solutions. The findings of our research demonstrate theoretical frameworks and guiding practise of managers.

Zhong et al, (2020) modelled logistics service supply chain (LSSC) can lead to optimal globally centralized decision-making scenario and then introduce contract coordination systems, including cost-sharing and unit price delivery contracts. Finally, the effectiveness and usefulness of the suggested coordination strategies are demonstrated with numerical illustrations. This research strengthens the LSSC coordination theory and provides LSSC decision-makers with a management perspective.

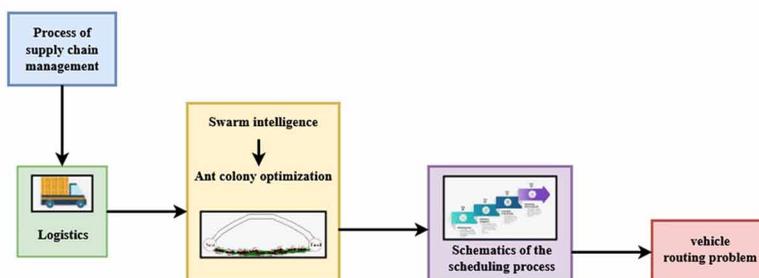
Swarm intelligence assisted supply chain management framework (SISCMF) has been proposed to improve logistics performance to overcome the existing model problems SCM, BDA, 3PL, MLA, SC-LAB and LSSC. SISCMF has been suggested to operational cost, demand prediction ratio, order delivery ratio, customer feedback ratio, and product quality ratio.

PROPOSED SWARM INTELLIGENCE ASSISTED SUPPLY CHAIN MANAGEMENT FRAMEWORK

Logistic management is the part of supply chain management that designs, implements and controls the efficient forward-looking process, reverses storage and flow between the origin and the consumption point of goods, services and associated information to meet customer requirements.

Fig 1 shows the proposed SISCMF. Supply chain management is a general concept that links several different processes for achieving a competitive advantage, whereas logistics refer to the movement, storage and flow of goods. Supply chain management discusses the manufacturing, delivery, and marketing processes for goods for the customer. Supply chain management has as far as possible the purpose of reducing waste. Control of the supply chain can be used to enhance consumer service. The saving-investment (SI) strategy has been provided to improve the SISCMF, which is based on the behavior of natural species, such as ant colony optimization (ACO) and particle swarm optimization

Figure 1. Proposed SISCMF

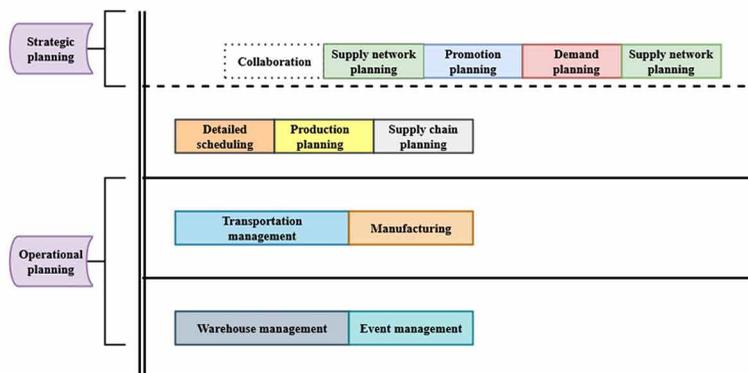


(PSO). Compared to EAs and other approaches, SI is a relatively young industry in meta-heuristics. To explore and exploit the quest space to find the ideal direction, SI approaches employ ad hoc and undefined strategies. Decentralization, self-organization, and collective behavior are three key SI attributes needed for SI actions. ACO is most often used in logistics to determine the most efficient path for clients' distribution.

Logistical scheduling refers to the problems that have been integrated within a single framework with decisions on work and transport. Such a coordinated scheduling situation can be modelled on the distributed systems of the transfers between the machines. Scheduling includes decisions to distribute the potential or services available overtime for jobs, tasks, activities, or customers. Path analysis helps managers generate the most effective route between the company's link with the supply chain (optimal route / short route). Alternative paths allow route supplies for difficulties (either people-made or naturally) where one route is challenging.

Fig 2 shows the process of supply chain management. Strategic planning, demand preparation, supply planning, manufacturing, warehouse management, order fulfilment and transportation business processes are the corner extensions of supply chain management.

Figure 2. Process of supply chain management



Strategic planning: Each aspect of the supply chain, including locations, transport, services and goods, is modelled on network-based planning. This allows a quick and effective response to new changes by alerts in the delivery network. Strategic sourcing helps to identify a reduced core supplier group, which can shape strategic connections. For the evaluation of potential suppliers, vendor analyses and sourcing data are used. Budget and contract compliance analytics for strategic sourcing execute quality control.

Demand planning: The forecast estimates forthcoming demand based on historic and assessment results. Lifecycle planning simulates the promotion, development, maturity and discontinuation stages of multiple goods based on forecast results. The Promotion Planning Mechanism allows promotions or other specific activities to be scheduled independently from the other forecasts.

Supply planning: The safety stock planning process provides a suitable level for all medium or finished goods at each location to achieve a level of objective operation. The supply network planning process calculates the quantity to be delivered to the locations to accommodate buyer demands and ensure the required service level.

Manufacturing: Production planning / Detailed scheduling facilitates issuing output orders within a particular time and sequence of resources.

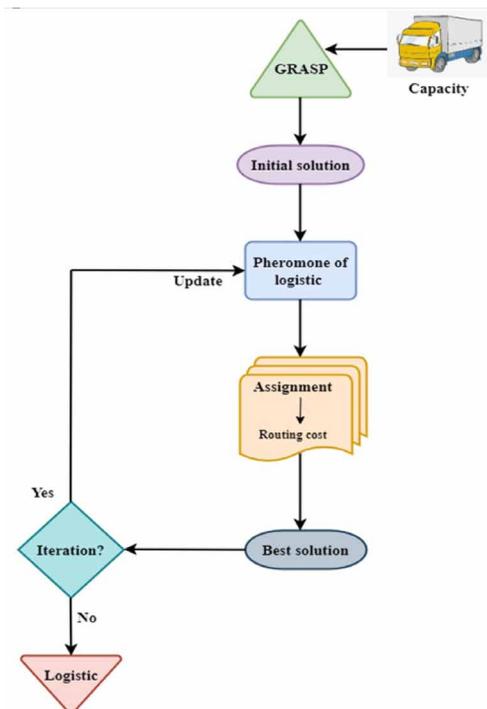
Warehouse:Storage and stocking processes internal factory movements and material storage.

Order fulfilment:The development of purchasing orders enables orders to be placed, costs and schedule. The billing process covers all activities from the invoicing to the payment received.

Transportation:The phase of transport planning creates for the company an optimized and implementable transport strategy.

Fig 3 shows a flow chart of the logistics process using ant colony optimization. A logistic environment is composed of a logistic GL graph representing the urban road network, the used factory for the sale of goods, and different consumer requirements for pick-up or delivery. The factory consists of collecting goods to be shipped to one customer and a small capacity vehicle. This study assumes that the high-quality final solution is optimal in the suggestion of an ACO approach. The GRASP approach is used to initialize the logistic route and logistic graph pheromones. This article uses ACO to find better solutions using the best strategy of the last decade. Both products are assigned to a suitable vehicle for any iteration according to the graphical pheromone and distance variables. In addition, all logistical routes generated by ACO are used for the optimization process. The only solution to far will be to change the logistic graph pheromone. After multiple pheromone modifications and iterative optimizations, the solutions will be stronger. ACO ends when the logistic pheromone is constant or the sum of iterations is generation-specific. As a final logistic route, the best option in the last route will be considered.

Figure 3. Flow chart of the logistic process using Ant colony optimization



In ACO, the solution provided in each logistic graph depends on the distribution of the pheromone. Better initial pheromone delivery would impact efficiency to find high-quality solutions in grasping Randomization then adaptive search procedures before ACO to construct the first logistic routes. This first solution is further used to produce the logistic graph's initial pheromone distribution. The

start from the restricted Candidate list (RCL) is structured to store the k of the goods known as the candidate that is not yet processed. Next, the following logistics items are randomly chosen for one of the goods in RCL. This paper check for other products not yet processed and add them to our RCL depending on the goods' location. Let's remember, GRASP must verify whether or not the logistic route generated meets the vehicle capacity limit. Replays the same method till all goods are treated. The order is used as the initial logistic routes.

Fig 4(a) shows the initial solution by GRASP. Route $\varphi = \langle a, G1, G2, \dots, Gn, a \rangle$ shall be provided by the vehicle that has not been overloaded, the $\mu(\varphi)$ routing costs denotes the overall transport distance shown in equation (1), while the $FC(s, t)$ function implies a Euclidean Distance between s and t .

$$\mu(\varphi) = FC(a, d_1) + \sum_{j=1}^{n-1} FC(d_j, d_{j+1}) + FC(d_n, a) \quad (1)$$

The best pair of vehicles and the best products will be considered the highest pheromone multiplied by a distance-based measure based on each vehicle's location and the unprocessed goods. Both items are allocated to an appropriate vehicle during any iteration based on the graphical pheromone and distance variables. In addition, the optimization procedure employs all logistical routes generated by ACO. Changing the logistic graph pheromone is a solution that goes too far. The solutions can become more powerful with several pheromone adjustments and iterative refinements. When the logistic pheromone remains constant, or the total of iterations is generation-specific, ACO comes to an end.

$$(l, m) = arg_{max} (pher(u_l, h_m)^\beta \times \omega(l, m)^\gamma) \quad (2)$$

As shown in equation (2), $pher(u_l, h_m)$ is a pheromone between the present place of vehicle and goods, β and γ indicates the impact of pheromone and distance-based factor. h_m is refers to goods and l^{th} is refers to the current location of vehicles.

$$\omega_{rout\ dis} = \frac{1}{Total\ Routing\ Distance_i} \quad (3)$$

As shown in equation (3) and (4), two types of distance-based factors are considered: 1) $ACO_{rout\ dis}$ defined reciprocally as the $\omega_{rout\ dis}$ cumulative routing distance of vehicle and 2) $ACO_{Euc\ dis}$ defined as the shared distance from Euclidean between two goods $\omega_{Euc\ dis} \cdot \omega_{rout\ dis}$ attempts to match each vehicle loading and $\omega_{Euc\ dis}$ tends to pick from one vehicle the closest unprocessed products.

$$\omega_{Euc\ dis}(l, m) = \frac{1}{Euclidean\ Distance(u_l, h_m)} \quad (4)$$

If a route between 2 locations produces slightly more pheromone and a greater value depending on distances, the route is preferable. As shown in equation (5), the selection probability can be calculated by normalizing a vehicle pair.

$$prob(l, m) = \frac{((pher(u_l, h_m))^2 \times \dot{E}(l, m)^s)}{\sum_{u_l \in U, g_n} ((pher(u'_l, h'_m))^2 \times \dot{E}(l', m')^s)} \quad (5)$$

Fig 4(b) shows the selection probability of vehicles. Transportation systems that join the different operations are the key feature of the logistics chain. Transportation from manufacture to supply for final customers and returns is important during production processes. The benefits can only be accomplished through good teamwork between each component.

Figure 4. (a) Initial solution by GRASP; (b) The selection probability of

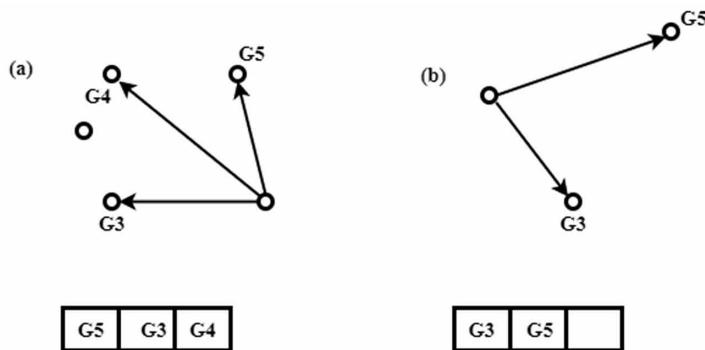
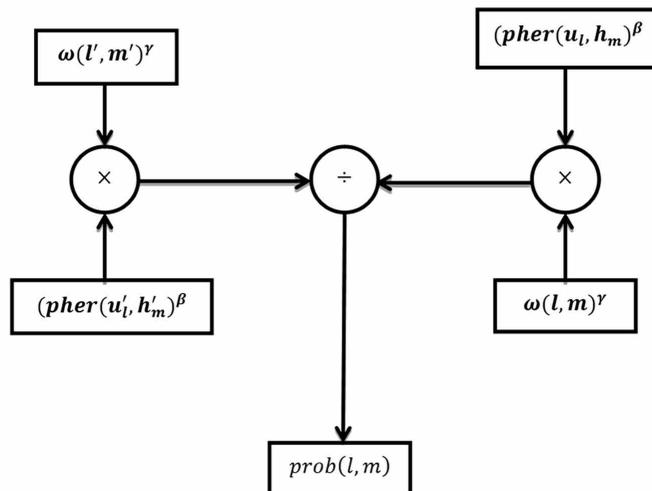


Fig 5 shows the scheduling process. Schematic view of the analyzed logistic process defined in terms of probabilism. The birth process (arrival in a new order for some time) and the death process can be explained in a classical queuing theory (command distribution per unit of time and time taken to process). This theory confirms the distribution of Poisson for the model of the birth process and the death process is modelled on an exponential distribution is shown in equation (6),

Figure 5. Scheduling process



$$q(a, \omega U) = \frac{(\omega U)^a}{a!} e^{-\omega U}, \quad q(U, \gamma) = \gamma e^{-\gamma U} \quad (6)$$

Table 1.

Parameter	Description
a	New of orders
ωU	Indicating the possibility of an event
U	Occur at a particular time
γ	Variable of death rate

The method can be divided into five levels: shipping of the order, product demands, arrival component and assignment of the component. Item assignment is an essential logistical issue because companies cannot monitor the supplier's entry or delay. When considering the order's collection of components, the only control variable is the arrival rate (death). Both orders are hopefully delivered in due course. To avoid large amounts and minimize delayed ordering, this programme assigns components for orders every day, not as part of their arrival orders in terms of volumes, specifications and delivery date.

The objective function is provided by equation (7),

$$g(U) = \frac{1}{\rho U + \frac{1}{\sum_{i=1}^m U_i}} \quad (7)$$

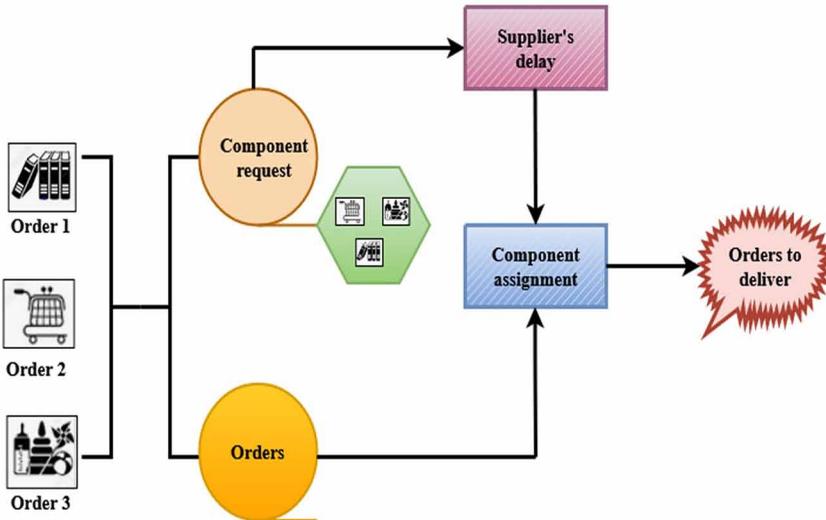
The most important goal is that the highest number of orders are delivered at the right time, though SI assumes it is important that the remaining orders have a small delay variance (ρU).

Fig 6 shows vehicle routing problems. One of the most discussed computational optimizations is the vehicle routing problem. It is based on the travelling salesmen problem (TSP) where a salesman has to go once in a few cities to reduce his total journey time. The problem of vehicle routing (VRP) involves even various customers that must be visited once. Consumer orders a certain quantity of goods. A specific time is spent on each customer for loading and unloading. The consumer can even request for several goods to be withdrawn in cases of special need. Except for the TSP, several vehicles start from the same location and share the load within themselves. Each vehicle has a limited capacity in the standard VRP variant, referred to as the capacitated vehicle routing problem (CVRP).

ACO for Vehicle Routing

In the first instance, ant colonies are extended to a traveller's problem and the quadratic assignment and other issues such as spatial planning, machine delay, multiple objective sequencing and product design. A classified ACO approach has indeed established, along with a multi-colony approach, other methods. ACO has discovered high-quality solutions to vehicle routing challenges through cost reductions, and is especially well-suited to changing tough roadblocks and impediments along the

Figure 6. Vehicle routing problems



route. Even though there are many other tactics and types of colony optimization, the algorithm’s main features include route building techniques, pheromones trail upgrades, and route improvement.

A single artificial ant simulates a vehicle using ACO, and routes are built to allow each ant to choose clients until they are all visited. Every ant starts at the depot, where there are no clients on tour. The ant selects the next client from a list of potential destinations, and the vehicle’s storage space can be adjusted before it goes to a new place. The ant returns to the depot when a vehicle’s capacity limit is reached. After all, the ant visits, the clients return to the depot, and the total distance traveled for the complete ant path is statistically measured. The VRP includes several clients who should have been visited just once. A customer places an order for a specific number of items. For loading and unloading, each client is given a set amount of time.

Using this method, a predefined number of ants, m , produces complete individual routes sequentially. In addition, each ant needs to build a route for any customer. The ant uses the following equation (8) for selecting the next consumer location.

Table 2.

Parameter	Description
μ_{ax}	Amount of pheromone on the route between the current spot.
a	Current location.
x	Potential locations
ϑ_{ax}	Inverse distance between the two customer location.
α	Importance of distance in the selection algorithm as compared to pheromone quantity.
L_m	The Ant working memory tracks already visited locations that are no longer selected.

$$p = \arg \max\{(\mu_{ax})(\vartheta_{ax})^\alpha\} \text{ for } x \notin L_m, \quad \text{if } r \leq r_0; \text{ otherwise } Y \quad (8)$$

The value r is a uniform $[0,1]$ random variable, and a value r_0 parameter. The highest value of equation (8) is selected when an ant selects a new position to go until r is greater than r_0 .

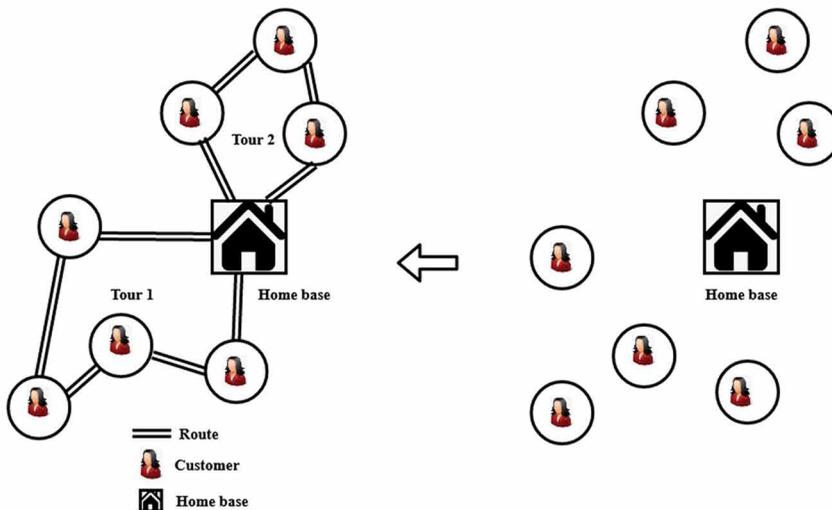
In that case, ant prefers to be the next random variable (Y), which promotes high levels of pheromones and short pathways, depending on the probability distribution:

$$Q_{an} = \frac{(\mu_{an})(\vartheta_{an})^\alpha}{\sum_{x \notin L_m} (\mu_{ax})(\vartheta_{ax})^\alpha} \quad \text{if } n \notin L_m \text{ otherwise } 0 \quad (9)$$

Each ant takes the most favourable path by using the equation (8) and (9) or selects a path arbitrarily to follow based on the distribution of the probability of distance and the pheromone accumulation.

Fig 7 shows dynamic vehicle routing problems. ACS-DVRP depends on the breakdown of the DVRP into the static VRP sequence. The algorithm design has three key elements: event management, new orders collection and the trace of already-served orders, the location and the residual capacity of each vehicle. The sequence of VRP-similar instances is constructed using this information. In the “ACS for SVRP” section, the Ant Colony system algorithm for solving static instances is described. The retention of pheromones provides details about the good solutions to these problems after a static problem has been overcome. Because each static problem is very close to the next, this information is moved to the following issues: new orders.

Figure 7. Dynamic Vehicle Routing Problems (DVRP)



The tours’ performance relies on the Event Manager’s strategy for breaking up the day into periods. The resulting tour should be designed myopically as the algorithm starts until a new order is reached since a new (still unknown) order is available on tour. On the other hand, a delay too long leads to a significant decline in customer satisfaction when ordering and delivery are too long. Transport costs

for vehicles depend on the consumption of petrol, maintenance, and other factors and are proportional to the distance between vehicles. The model transportation costs are as shown in equation (10):

$$\sum_{m=0}^M \sum_{n=0}^M D_{mn} \times A_{mn} A_{mn} = 0 \text{ or } mn = 1, 2, 3, \dots, M \quad (10)$$

Total export costs over time for M shipments is shown in equation (11).

$$K_d = \sum_{n=1}^M (q_n \times D(q_n)) \quad (11)$$

Table 3.

Parameter	Description
q_n	The size of n^{th} exports to the assembly.
$D(q_n)$	Exporting cost q_n shipment
K_d	Total export costs over the time shipment
A_{mn}	dependent on the consumption of petrol
D_{mn}	proportional to the distance between vehicles

In equation (11), the logistics network optimization evaluation through total export cost over the time shipment has been depicted. The above equation finds the optimized results by summing the exporting cost for every shipment for all shipments.

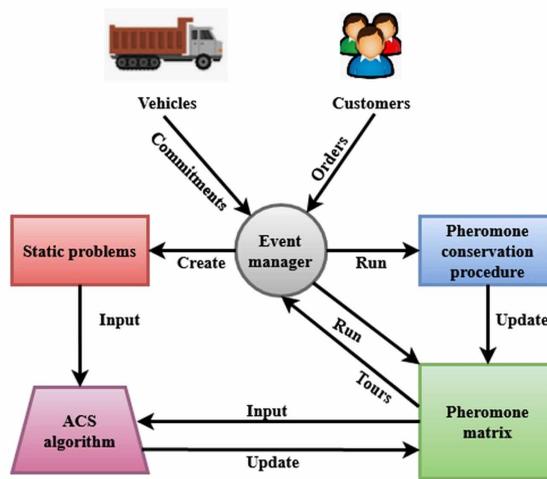
This research objective is set to save money on stocking expenses, setup expenses, total channel bill prices, and order export expenses by purchasing outsourced components. Assuming steady demand reduces the overall cost of the channel by decreasing startup expenditures. Operational cost, demand forecast ratio, order delivery ratio, customer feedback ratio, and product quality ratio are all achieved using the SISC MF model. The suggested model has been compared to the big data analytic (BDA) model offered by [22], and the machine learning method (MLA) proposed by [24].

SIMULATION RESULTS

The proposed SISC MF model’s experimental results have been performed. This paper analyzed operational cost, demand prediction ratio, order delivery ratio, customer feedback ratio, and product quality ratio.

Fig 8(a) and 8(b) shows the operational cost and customer satisfaction. The two primary categories of logistics costs include shipment and storage expenses. The customer has to pay a shipping firm for distribution until they find a source for goods or raw materials. The goods usually come to the customer house on a half lorry and must have a secure place to unload the truck and store it. The

Figure 8. Operational cost and customer satisfaction



number of deliveries receives every day is the facility’s size and the number of available docks, all of which impact leasing and service payments. It is necessary to satisfy consumers because it gives marketers and entrepreneurs a measure to manage and improve companies. Consumer satisfaction is a way to assess customer engagement to evaluate a company’s continuity or product life. If consumers are pleased and fulfilled, the consistency of sales will guarantee the continuity of the organization. Customer satisfaction has been based more on requirements, such as efficiency and durability, that decrease quality costs.

Table 4 shows the demand prediction ratio. Demand forecasting in supply chain management refers to planning or predicting material demand to ensure can deliver the correct goods and quantities without any excess to satisfy consumer demand. Demand forecasting is a predictive analysis that aims to assess and predict customer demand for supply chain management to make better market and supply choices. Quantitative methodologies, such as data mining and particular historical sales, and test market statistical techniques, are used to estimate demand. Demand projections are frequently

Table 4. Demand prediction ratio

Number of Orders	BDA	MLA	SISCMF
10	62	78	82
20	67	71	84
30	65	79	81
40	61	77	84.9
50	64.1	84	80.55
60	68.2	81	89.1
70	65	86	90
80	66	77	84.1
90	69	77.9	90.3
100	61	85	95.2

utilized in the evaluation and decision-making phases of projected capacity needs for new markets and industrial strategy and supply management. Compared to the existing models, the observed greatest demand forecast ratio aids supply chain managers in making decisions. These decisions by supply chain managers increase earnings by assisting in the management and reduces supply chain expenses, resulting in large increases in business profitability. To decrease fixed assets, supply chain managers can eliminate plants, warehouses, and passengers throughout the network with this efficient demand prediction.

Fig 9 shows the order delivery ratio. Product delivery is the set of activities, decisions and goods essential for producing and distributing new products to the global consumer. The key consumers of this process are the product delivery teams to deliver products by their requirements. The managers are responsible for purchasing orders and pick flexible manufacturing and distribution procedures to fulfil the order. The supplier takes the regular transport of the assembled materials and goods in smaller quantities for operating efficiency advantages.

Figure 9. Order delivery ratio

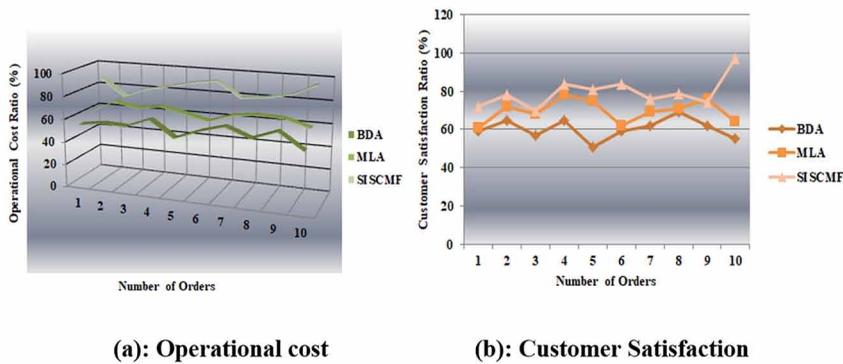


Table 5 shows the customer feedback ratio. For the logistics companies seeking a competitive advantage, customer satisfaction is increasingly critical when they know that other companies whose operations will rely more on customer demands will be taken over if they do not fulfil customer

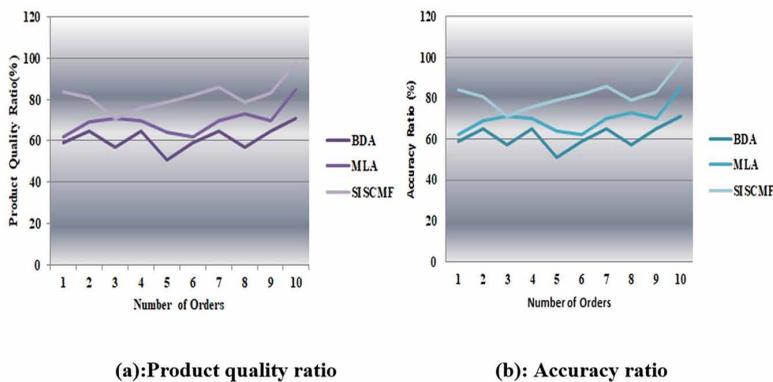
Table 5. Customer feedback ratio

Number of Orders	BDA	MLA	SISCMF
10	65	76	89
20	61	78	84
30	62	75	85
40	69	72.9	80
50	69	77.2	81
60	64	79.5	87
70	69	71	82
80	67	74	88
90	69	77	90
100	68	83	98

expectations. Logistics companies must ensure that all customer service elements, regardless of what they entail. A logistics company customer must ensure that the organization selected knows the specifications even though the SISC MF mentions customer satisfaction and quality report conclusions. Study results suggest that logistic factors, such as inventory, lead time, transport, and logistics, benefit consumers. To conclude, the findings have shown a significant customer satisfaction relationship with the product, lead time, transportation and logistics.

Fig 10(a) and 10(b) shows the product quality ratio and accuracy ratio. Supply chain management influences the consistency of the goods and the overall performance of a company. For these factors, quality control is vital to preserving a competitive market edge and reducing operating costs in the supply chain. Waste becomes prevalent above a modest amount without quality management. Quality is an essential aspect of the supply chain. Quality control evaluates when items reach the consumer or quality management when raw materials and products enter the plant during the production process. The core of ant food search behavior inspired the ant colony optimization (ACO) method, which solves large-scale issues. Using graphs, the ant colony optimization technique can reduce the time spent searching for pathways. A graph represents the food search type's direction. This swarm intelligence approach is part of a metaheuristic optimization mechanism with other ant-colony optimization techniques. As an improved strategy, the "dynamic adaptive strategy" has been used to optimize the ant colony. This approach's value is the high rates of convergence and the search for a global optimization solution. The new strategy can deliver more accurate results compared to traditional ACO.

Figure 10. Product quality ratio and Accuracy ratio



CONCLUSION

The swarm intelligence assisted supply chain management framework is proposed to increase profitability and logistics efficiency. Swarm Intelligence (SI) algorithms are typically used in the majority of the fields of network architecture. They can overcome large-scale problems efficiently due to their simple design and fast convergence. In refining the ant colony algorithm, there had been a major improvement in these problems' solution. Advanced Logistic Systems require high-performance algorithms for optimization. The Ant Colony Optimization algorithm is one of the most successful and most influential in vehicle routing. The classic VRP problem, where the order is known, has been discussed in advance before optimization starts and extend to on-line (dynamic VRP) planning where orders come during the delivery process. An ACO based new heuristic was briefly defined for the DVRP solution. The simulation result shows the Operational cost (92.7%), Demand prediction ratio (95.2%), Oder delivery ratio (96.9%), Customer feedback ratio (98.2%), and Product quality ratio (97.2%).

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