Optimization of Emergency Material Logistics Supply Chain Path Based on Improved Ant Colony Algorithm

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Path selection is a critical challenge in emergency logistics management, particularly under realistic disaster-related conditions. This study addresses the problem of optimizing logistics transportation during major epidemics, considering constraints such as vehicle load, volume, and maximum travel distance per delivery. The goal is to minimize costs related to distribution trips, time, early/late penalties, and fixed vehicle expenses. By framing the problem as a generalized Traveling Salesman Problem, we developed an Improved Ant Colony Algorithm (IACA) to reduce the longest distribution path. Simulation data from Pudong, Shanghai lockdown zones revealed that IACA outperformed the traditional ACO algorithm, achieving a 30% cost reduction and higher accuracy (R^2 = 0.98). Additionally, experiments on gate assignment and TSP demonstrated the algorithm's superior optimization ability and stability. Overall, IACA enhances delivery route efficiency, lowers costs and energy consumption, and improves emergency logistics performance, proving to be a robust and reliable solution.

Povzetek: Avtor je razvil izboljšan algoritem kolonije mravelj (IACA), ki optimizira poti v logistični oskrbovalni verigi za nujne materiale.

1 Introduction

The logistics industry's use in many different industries is growing more and more common as the global economy develop. Researchers are becoming more aware of the crucial role emergency logistics (EL) plays in delivering supplies to disaster zones as a result of the exponential rise in emergency response operations and the rising frequency of disasters, both man-made and natural [1]. In particular, since 1980, catastrophes caused by nature have claimed the lives of over 2.4 million people globally, and their economic toll has grown by more than 800%, reaching $210 billion in year 2020 alone.137 million people in China were directly impacted by different disasters by natural in the same year, resulting in 19,956.7 hectares of crops being damaged, 370.15 billion yuan in direct economic losses, and 591 fatalities [2].

The National Disaster Reduction Commission and the China National Ministry of Emergency Management both state, China experienced 130 million individuals impacted by various disasters by natural in 2018, 588 fatalities, and 264.46 billion RMB in direct economic losses. Using earthquakes as an example, in 2018, earthquakes of magnitude 6.0 or higher killed 3068 people worldwide and wounded over 16,000 more. In order to reduce the number of casualties and property damage following a disruption, emergency materials must be delivered to the disaster zones promptly, precisely, and efficiently [3]. Emergency rescue is usually quite urgent because most disruptions are unpredictable and emergency material elements are very complicated.

In order to effectively provide goods while minimizing losses, emergency logistics was first established in 2004 to address the logistical challenges resulting from disasters. With its emphasis on facility placement and material delivery, it is essential to emergency decision-making. Supply channels are frequently disrupted by disasters, resulting in large losses. 15% to 20% of all disaster losses may be attributable to inefficient distribution [4]. The focus of humanitarian logistic modeling services, which account for 80–90% of rescue expenses, is on rapid reaction deployment, which is essential for successful rescue operations. The ideas under discussion centre on maximizing the distribution, transportation, and positioning of emergency supplies to rescue locations. For disaster response to be successful, emergency logistics efficiency must be increased [5].

For emergency rescue and relief efforts to be successful, the emergency supply chain must run smoothly. It is quite challenging to gather comprehensive information to support emergency operations during large-scale calamities since they are frequently unanticipated and exceedingly destructive. The victims' livelihoods and security may be negatively impacted by ineffective or even halted emergency material operations brought on by a shortage of supplies and knowledge [6]. Therefore, while reacting to large-scale emergencies, it is essential to solve the fundamental concerns of rapid acquisition and integration of comprehensive emergency supply chain materials and information flow.

The planning, coordinating, and carrying out of logistics theory expert operations during emergencies, disasters, and crises are guided by the framework and set of principles known as emergency logistics theory. It includes a variety of ideas, tactics, and procedures meant to guarantee the smooth and efficient movement of information, products, services, and resources in order to meet the demands of impacted communities and lessen the effects of the crisis. The study uses a hybrid technique of simulated annealing and ant colony optimization to offer a low-carbon vehicle route optimization model for logistics and distribution. For increased efficiency, it uses an adaptive elite individual reproduction strategy and adds a multifactor operator and carbon emission factor [7]. Researchers are becoming more interested in emergency logistics. Nonetheless, the majority of recent studies address the location of facilities. This study focusses on the supply chain for emergency material logistics following a disaster. After a disaster strikes, it seeks to create the best plans possible for moving emergency supplies from one-to-many supply depots to disaster depots. Fig. 1 depicts the emergency management domain. In order to demands victims and finish rebuilding the disastrous event region after a disaster occurs, EM is a specific type of problem with vehicle routing that examines how to transport relief materials from depots for supply to depots for demand (disaster areas). EMS is typically separated into many-to-many scenarios based on the quantity of supply depots, as seen in Fig. 2

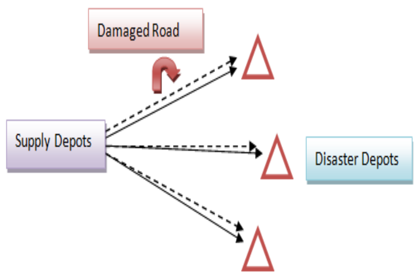

Figure 1: Supply depots to demand depots

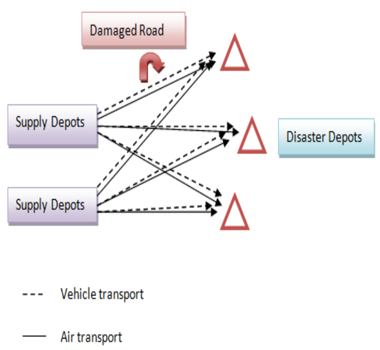

Figure 2: Quantity of supply depots in many to many scenario

The most important thing should be the timeline. Only if the emergency supplies are delivered to the Disaster Supply Depots accurately and on time will the damage be reduced. The fastest delivery time is therefore practically the most crucial factor in the improved ant colony model. We suggested an Improved ACA-based approach to solving the routing emergency material path problem. To get the best answer, the process determined the shortest path between nodes using a travelling salesman shortest path tree structure [8]. According to research findings, the suggested approach performed admirably in various disaster networks. In conclusion, even though ACO has been researched extensively and shown to perform effectively in organising routes, it is incredibly uncommon to utilise Ant Colony to optimise the supply chain route for emergency material logistics in disaster areas.

The study's primary contributions fall under the following categories.

- First, this study identifies and measures the variables that have been discovered to affect ACA's efficacy from both an internal and external standpoint. This includes the IACA's shortest route while taking into account the supply chain's external environment, funding for materials and equipment, complex emergency decision-making, and material transportation deployment. This is a definite step in filling the knowledge gap in the body of existing literature.
- Second, according to research methodologies, the majority of models in use today use traditional algorithms including precise, heuristic, and meta-heuristic algorithms.
- Third, in order to show the validity of the results, we contrasted the outcomes of the IACA method with those of the conventional ACA strategy. Furthermore, these findings will help emergency managers better pinpoint the sources and means of important elements, as well as the causal and hierarchical connections among them, and they will be able to contribute to the development of a robust and effective path.

This study is organized as the literature review for this topic is presented in Chapter 2. The research strategy and methodology are described in-depth in Chapter 3. The application of the proposed Improved-ACO Algorithm is shown in Section 4, followed by the application's outcomes and the discussion these finding, Section 5 summarises the findings, study shortcomings, and future research directions.

2 Literature review

These days, the transportation sector is growing quickly, and its main concentration is on the logistical distribution of perishable agricultural goods. The Emergency material logistics supply chain path finding path optimization method's application usefulness is recognised by experts. The supply chain for perishables has been examined by several academics.

For the uncertainty of unanticipated events in roadways in cities during shipping, a GA-based path optimisation model was introduced [9]. As part of the endeavour to reduce transportation costs, the logistics path optimisation model with a challenging window was developed to address the path dynamic. The outcomes of the experiments showed that this path optimisation model performed successfully. In order to address the sustainable food supply chain optimisation issue, this study presented a mixed integer linear programming model. In the purpose to reduce fuel costs, transportation expenses and carbon emissions were integrated, and Norwegian salmon exporters were used to conduct a suitability analysis [10].

For the prompt delivery of disaster relief materials after natural catastrophes, [11] and his team proposed an algorithm based on meta-heuristics. in hybrid Three optimisation improvement approaches were presented, the urgency coefficient of each demand point was evaluated, and Harris eagle optimisation and random PSO were integrated. The outcome of the study shows that the suggested approach had a maximum degree of computational correctness.

This Study developed a path optimisation technique based on enhanced GA to meet the cost and efficiency criteria of distributing fresh food. The procedure implemented a linear adaptive cross-variance technique and designated certain elements as penalty factors. The finding of the study shows that the approach could successfully reduce delivery path length and had a higher path optimisation efficiency [12].

A two-objective optimisation model was presented by this author for the adaptable perishable supply chain design commodities [13]. During the process, product and route disruption deterioration were thoroughly examined, utility role GA was added to optimise the method, and dynamic pricing was employed to handle crises. The experimental results demonstrated the good flexibility of the suggested approach. Using Ant Colony Optimization (ACO) or other technologies related to computers has been researched by several academics.

An ACO-based optimisation technique was put forth by researchers to address the issue of UAV scheduling routes. The procedure was solved for DSP and optimised for hierarchical “pheromone”-based processing. According to the testing results, the suggested approach has outstanding path planning speed and good path planning quality [14].

To solve the path routing problem of the fourth- party logistics, a method based on the ant colony system and the improved grey wolf algorithm was proposed. During the process, which included a carrying capacity and reputation constraint from the beginning node to the node of destination, known as the transit range, the ratio utility theory was used to determine the customer's risk appetite. The results of the study demonstrated that the recommended strategy could effectively finish path optimisation planning [15].

For the planning of the return path challenge of logistics networks in reverse, author suggested an ACO-based path technique. The procedure created a MINLP model, evaluated costs using a closed-loop, multi-stage logistics network, and tested using thirty instances. Results from experiments showed that the suggested approach could produce return pathways of excellent quality [16].

An ACO-based approach to solving the routing nodal path problem. To get the best answer, the process determined the shortest path between nodes using a rooted shortest path tree structure. According on research findings, the suggested approach performed effectively in networks of various sizes. In conclusion, despite extensive research and demonstrated effectiveness in route planning, ACO is currently rarely used to optimisethe route taken by cold chain logistics to distribute perishable agricultural goods. Given the pressing need for additional technical references to support the growth of the cold chain logistics distribution industry, the Improved ACO-based optimisation model was put forth, and the technical features of ACO were applied to optimise the cold chain logistics distribution path for perishable agricultural products [17].

Table 1: Summary on existing and suggested method compared with computational accuracy, time efficiency and cost reduction

Algorithm	**Computational Accuracy**	**Time efficiency**	**Cost reduction**
TGWO	TGWO algorithm as a decision support tool to boost supply chain performance, cut expenses, and improve cold chain logistics operations.	When compared to the TS and GWO algorithms, the TGWO method reduced the overall journey distance by 50.34% and 30.66%, respectively.	In terms of the overall cost of distribution, it saved 14.34 percent and 9.03 percent.

IPSO	The algorithm and emergency logistics vehicle route optimization model for severe epidemics that are suggested in this research work well.	If every demand's delivery priority is met, an enhanced vehicle routing optimization algorithm that takes delivery urgency into account can save a specific amount of time;	According to the sensitivity analysis, when the time cost is at its lowest, there should be three vehicles in the distribution center. The whole expense was lowered by 20.09%.
NN	The prediction findings demonstrate that the prediction can yield increased accuracy and better route matching.	Choose the route for material delivery that has the quickest speed and the lowest distance.	Reduce the percentage of transportation expenses as much as you can, and save money on supplies and automobiles.
IACA	the suggested model achieved the best solution accuracy with 98.5%	this study uses travelling salesman problem to find the shortest route and efficient in time travelling distance for emergency	cost reduction based on transportation, inventory, labor, minimize distance, avoid traffic and harzards by 30.2%

3 Methodology

Inspiration:

The process of optimising ant colonies is iterative. Several fictitious ants are considered at each cycle. With the restriction that ant not go to any vertices that already made it to during the ant walk, each of them constructs a solution by moving from vertices to vertices on the graph. An ant uses a stochastic mechanism biassed by the "pheromone" to choose the next vertex to visit at each stage of the solution building process. For instance, the next vertex in vertex I is selected at random from among those that haven't been visited yet. More specifically, k can be chosen with a probability proportional to the "pheromone" connected to edge (m, n) if it has never been visited before. The calibre of the answers the ants have created will depend on, the "pheromone" values are modified at the end of an iteration. By doing this, the ants are skewed to create solutions that are similar to the greatest ones they have created in previous cycles. The basic concept underlying the AC method is inspired by the way ant colonies behave when they are looking for food. Ants usually start by aimlessly looking around for food, bringing some of what they find back to their colony. They also leave a "pheromone" on the track they found. The worth of "pheromones" left in their wake, which gradually dissipates, depends on the quantity and calibre of the food supply. The "pheromone" that remain on a trail may persuade other ants to follow it. The strongest "pheromone" indicates a shorter path, which most ants can eventually follow.

3.1 Improved ant colony algorithm

This study uses the improved ant colony algorithm's high adaptability, multi-concurrency, resilience, and global search capabilities to handle the logistics supply chain's emergency material problem. Consequently, the enhanced ant colony method is presented to solve the model since it is highly parallel, offers the benefits of high fault tolerance and self-adaptation, and allows for heuristic improvement to enhance the algorithm's convergence. The ant colony method is a Traveling salesman algorithm that finds the shortest path by simulating ant populations' foraging behavior. Individuals of the ant colony will evaluate and choose the optimal foraging path based on the concentration of "pheromones" left by ants as they pass through nodes along the route. Rich customer and order data are challenging for traditional logistics to manage. Therefore, in the event of a natural disaster, the logistics automation path finder now incorporates an improved ACA. The drawbacks of conventional ACA are addressed with certain enhancements, which successfully resolve issues like resource scheduling and route planning in the logistical process. Figure 3 explained about the flow of emergency material path supplying method.

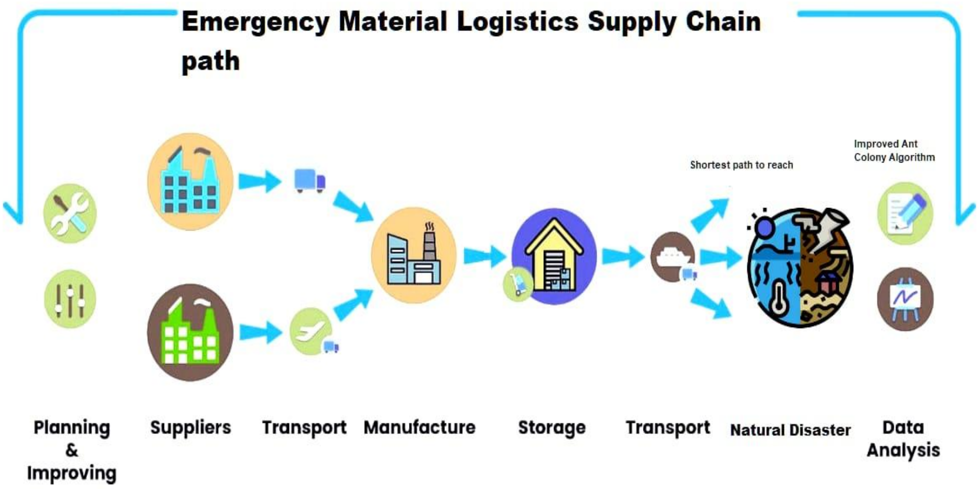

Figure 3: Block diagram of the method

3.2 Improved ant colony algorithm optimization strategy for emergency logistics material

Several production process connections are becoming more specialized due to the escalating market competitiveness. As a result of this tendency, logistics and commercial flow are now separated, progressively emphasising the significance of logistics. Conventional logistics models are inefficient and do not provide intelligent assistance. A lot of management and operations involve manual labor, which is ineffective and prone to mistakes. At the same time, businesses find it challenging to forecast and decide on logistical procedures when they lack intelligent help. Additionally, this hinders the rapid optimization and modification of logistical plans. The emergency logistics model has been developed based on this. The material logistics supply chain is a complete system that controls and optimizes the logistics process using a variety of automation technologies and tools. Logistics transportation costs are a significant part of the logistics chain, and they can be managed and controlled to increase the efficiency of logistical processes.
The cost of logistics transportation is shown in eq. (1).

$$C_1 = \sum_{k=1}^{k} s_k \sum_{i=1}^{m}. f_{\mathrm{i}} \quad (1)$$

$s_k$is the variable in **eq. (1).** The vehicle number is v. The number of articles, including all transportation expenses, is denoted by m. $f$is the cost of driving eq.(2) displays the associated transportation cost.

$$C_2 = \sum_{j=1}^{n} \sum_{j=0}^{n} i \sum_{v=1}^{n} C_{ijk}{}^{x_{ijk}{}'} \quad (2)$$

The set of transportation between places $i$and$j$ is represented by C_{ijk} in eq. (2). The variable between transportation points is called C_{ijk}. One constant is n. IACO puts ants at the first dispersion site in Fig. 4. After creating a tabu table, the cycle is initiated. The experimental random selection technique determines the next transfer node based on the chance of ants travelling to various nodes. The transfer node is added to the tabu table once it satisfies the constraint constraints. The ants' relevant journey length and delivery cost are determined once the transfer is completed constantly until the tabu-table is full. The worldwide ""pheromone"" is adjusted and the path optimisation is finished based on the computed results. After the maximum number of cycles has been reached, the outcome is the optimal path solution. In the real-world application, the starting point and associated fundamental path of dispersion parameters are input. The research method is then used to develop the path solution, and the best solution is chosen to finish the path generating process.

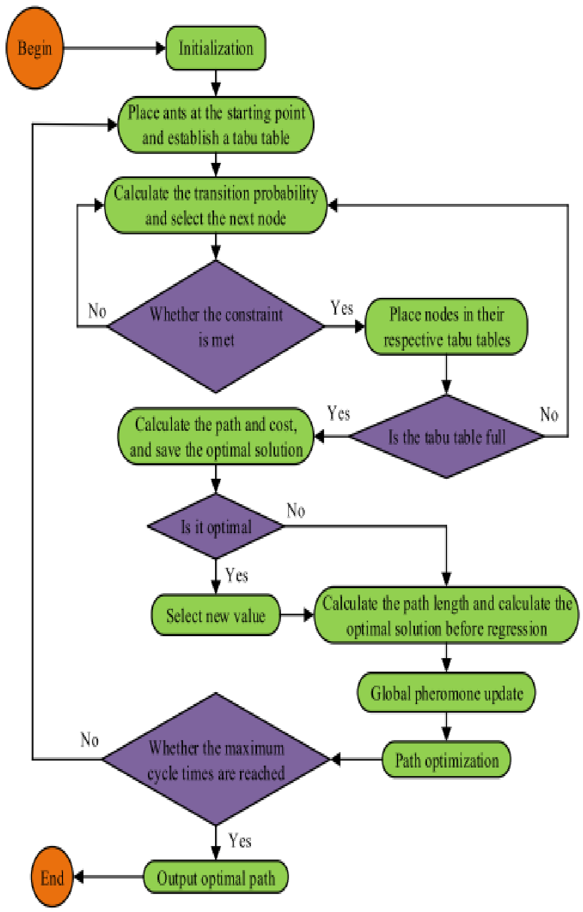

Figure 4: IACA flowchart

The logistics supply chain system consists of a server, front-end work, mechanical arm, three-dimensional warehouse management, AGV monitoring, PLC monitoring, sorting system, and commodities warehouse, among other components. The primary the sorting system's objective is to determine and categorise products. They are dispersed throughout various locations or forms of conveyance based on their type or destination. A commodities warehouse, which includes both automated and conventional warehouses, is a facility used for the storage of products. PLC and AGV monitoring are the two primary components of logistics system monitoring. Several components of the logistics system can be monitored and controlled using PLC monitoring, which functions as a programmable logic controller. Transporting items within or between warehouses requires AGV monitoring, which keeps track of the equipment's position and operational state. To guarantee precise storage and retrieval of items, the logistics system as a whole uses three-dimensional warehouse management, tracking, and computer-based management. Order processing, inventory queries, and other front-end tasks are the key tasks. The system uses a robotic arm to operate in order to accomplish a variety of activities, including grabbing, moving, assembling, etc. The management level of conventional autonomous logistics systems is rather low, despite the growing need for logistics technology. It is necessary to enhance the capacity to develop transportation networks, manage the supply chain, and optimise warehouse operations. An optimisation algorithm called ACA mimics how ants might forage for food in the wild. By mimicking the ant's ""pheromone"" transmission mechanism, it facilitates cooperation and information exchange throughout the optimisation process. Thus, adding ACA to the logistics control model can improve the management level of autonomous logistics control by successfully resolving issues like resource scheduling and path planning in the logistics process. Eq. (3) shows the node selection probability in ACA.

$$P_{ij}^{k}(t) = \begin{cases} \frac{[\pi_{ij}(s)]^{\alpha}\,[\eta_{ij}(s)]^{\beta}}{\sum[[\pi_{is}(s)]^{\alpha}\,[\eta_{ij}(s)]^{\beta\,\alpha}]}, \text{j}\in \textit{without passed} \end{cases} \quad (3)$$

In eq. (3), τij is the data concentration. $ij\eta$ is the path visibility of path. $\alpha$is the trade-off factor in ""pheromone"". β is the "heuristic factor" for expected values

. The $ij\eta$ is shown in eq. (4)

$$\eta_{ij} = \frac{1}{d_{ij}} \quad (4)$$

In eq. (4), d_{ij} is denotes the point i and point j distance. After complete ant colony cycle, its ""pheromones" will also be updated accordingly. The expression for "pheromone" update is shown in eq.(5)

$$\tau_{ij}(t+n)=(1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}$$

(5)

The "pheromone" evaporation coefficient is represented by eq. (5). The time point is t. The next node is typically chosen at random by conventional ACA, though. While random selection facilitates the exploration of broader problem areas, the early stage's convergence speed is slower due to the lengthy application of positive feedback. If the complete supply chain is not coordinated and optimised, the logistics chain as a whole may operate inefficiently, which may increase time costs. In order to achieve this, the study presents logistic chaotic mapping with the goal of leveraging its features to increase the precision of knowledge accumulation. Then, during the optimisation phase, some randomness is introduced into the basic ACA's routes.

In IACA, at the conclusion of every iteration, a logistics who possesses the best solution for that the optimal answer or iteration because the methods inception changes the disaster distanceas per eq.(6).Additionally, each instruction updates the amounts of "pheromones" on the final Communication, as illustrated in eq.(7), where $\tau i,j$ is the updated Schedule on the last feedback, denoted by $Ri,j,\tau i,j*$ is the updated location, τ0 is the initial warehouse, $\Delta\tau i,j$ is represented as $\frac{1}{L_{best}}$for the duration of the optimal route $Lbest$, and p and q are variables in (0,1) that correspond to the "pheromone" and its decay coefficient feedback rate, respectively. Based on the likelihood pi,jk, which is computed as shown in Equation (7) where η, each ant k chooses its new path.$I,J$is the inverse of the route's length.The locations that have not yet been visited are shown by the letters i, j, and l, while The respective impacts of “pheromone”s concentrations and heuristic data are indicated by the control parameters α and β, respectively.

$\tau i,j *= 1 - r\tau i,j + r \cdot \Delta\tau i,j, if Ri,j$ (6)
is in the best path $\tau i,j$, otherwise
$\tau i,j *= 1 - q\tau i,j +$
$q\tau 0$ (7)

As the process runs, FC first generate a variety of randomly generated solutions. “pheromone” s are then updated based on the problem type and IAC Algorithm, with “pheromone” s placed on the graph's edges or vertices, to improve the solutions. The probability of the edge, which is computed as follows, determines whether or not to traverse the edge between two nodes, i and j in eq(8).

$$P^k ji = \frac{\pi(t)_{ij}^{\alpha} n_{\mathrm{ij}}^{\beta}}{\sum_{j\in N^{\mathrm{k}(\mathrm{i})}} \pi(t)_{ij}^{\alpha} n_{\mathrm{ij}}^{\beta}} \text{isFeasible0}, \quad (8)$$

where, $P^k ji$ is chances for the understanding of instruction from nodes I and J, $\pi(t)_{ij}^{a}$denotes the value of the location range, n_{ij}^{β} is the materials, and $N^{\mathrm{k}^{(\mathrm{i})}}$is the establishment of nodes that can be visited by comments P^k. To get better results, it is advised to run a local search before upgrading the “pheromone” s. Nonetheless, the following approach is recommended for upgrading the eq. (9):

$$\pi_{ij}(t+1) = (1-\rho) \cdot \pi_{ij}(t) + \Delta\pi_{ij}(t) \quad (9)$$

Researchers and supply chain can learn more about the efficacy and customer communication as well as pinpoint areas for development by utilizing the IAC Algorithm to analyze emergency location from warehouse.

3.3 IACAmethod with traveling salesmen problem

Mathematicians and computer scientists in particular have focused a lot of attention on the travelling salesman problem (TSP) because it is both straightforward to explain and challenging to solve. Looking for the shortest restricted path to the target. A full directional graph $G = (N, A)$, can be used to represent the TSP, where A is a collection of arches and $D = d_{ij}$ is the price (a distance) vector for every arc $(i,j) \in A$.. Often referred to as cities, N is a collection of n nodes, or vertices. The cost of matrix D could be either symmetrical or asymmetrical. Finding the shortest closed tour that visits each of the $n = |N|$ nodes of G precisely once is known as the TSP. The distances between the cities in symmetric TSP are irrespective of the path in which they traverse arcs, therefore $d_{ij} = d_{ji}$for any pair of nodes. In the asymmetric TSP, for at least one pair of nodes (i, j), asymmetric TSP for at least one pair of nodes (i, j).

Define the variables in eq. 10:

$x\_(i,j) =$
$(1\ if\ the\ arc(i,j)\ is\ in\ the\ tour\ 0\ otherwise$ (10)

The TSP can be formulated as a generalisation of a well-known integer program formulation.

The constraints are written as:

$Xn\ c = 1\ xij\ =\ 1, d\ =\ 1,2,3,\cdots,n$ (11)
$Xn\ d = 1\ xij\ =\ 1, c\ =\ 1,2,3,\cdots,n$ (12)
$xij\ \in \{0,1\}, c, d\ =\ 1,2,3,\cdots$
$,n$ (13)
$Xn\ c,d \in S\ xij\ \le\ |S|\ -\ 1, 2\ \le\ |S|\ \le\ N\ -$ (14)

The overall cost that needs to be reduced is represented by the objective function (11) in these formulations. While constraint (13) ensures that each town has a single position allotted to it, restriction (12) ensures that each place is occupied by a single city j. The zero-one variables' integrality constraints xij $(xij \ge 0)$ are represented by constraint as follows. Constraint (14) guarantees that no detours will be created and that every city on the final itinerary will be visited once.

Algorithm 1: Pseudocode for IACA

1. Build an environment model
2. Intialising thne count of ants $Pmax, M, S\ E, \alpha, \beta, a, b, c, R0, \pi_{ij}, \eta_{ij}$
3. For $P = 1$ to $Pmax$ do
4. Calculate β according to the equation (3);
5. Calculate ρaccording to the equation (8);
6. For $k = 1\ to\ M$ do
7. Ant K into S;
8. While ant K does not reach E and Optional node>0 do
9. Determine the next emergency logistics from Equation 4,5,9;
10. While ant K in a deadlock do
11. Use deadlock handing route mechanism
12. Set the deadlock points as an obstacle point;
13. End while
14. End while
15. Save ant K taking path;
16. Calculate ant K length path;
17. End for
18. Calculate the shortest path for the iteration;
19. Divide the subpart by partitioning method;
20. Update pheromones for each subpart by Equation 10,11,12,13;
21. Set upper and lower pheromone limits by Equation 14;
22. End for
23. Output the optimal path;

4 Results and discussion

Ants make better initial decisions and spend less time pursuing fruitless avenues when they are given more insightful instruction. The enhanced algorithms minimize the number of iterations required by directing ants toward promising areas of the search space right away. *Experimental Setup:*
The technique is programmed and solved in this work using MATLAB 2017a, and it was evaluated on an Intel notebook running 64-bit software with a CPU speed of 2.20 GHz and 4 GB of RAM.

4.1 Dataset

The emergency supply mechanism was promptly put into place to provide the basic necessities of life for inhabitants in Shanghai lockdown zones. In order to store and distribute supplies, ten ESWs were quickly established all the way through the city, utilising logistics supply, district emergency food enterprises' distribution centres, and other locations [18] Therefore, if the emergency material logistics is considered the point as central, the largest geographic area a disaster can potentially cover is approximately 633 km2, since the area of administration of Shanghai is 63401 km2. Caolu Modern Agricultural Park was chosen as the Emergency material supply, and the relevant data came from the lock-down zones created on April 16, 2022, in accordance with Shanghai's distinct preventative and control needs. Within the ESWFootnote1's coverage area were 50 lockout zones, including Magnolia Fragrance Garden Phase II, Sunshine Flower City, and FengchenLeyuan. The ESW is represented by the number 1 (shown in Fig 5(b) with a dot in green), and the 50 lockdown zones are represented by the numbers 2–51. Figure 6 displays the regional geographic information's distribution map. The ESW and part of the lockdown zones in Shanghai's Pudong New Area are shown by the red area in Figure 5. The overall distribution data is displayed in Figure 5(b). The red circle indicates the ESW zone, while the red and green dots indicate the lockdown and ESW zones, respectively.

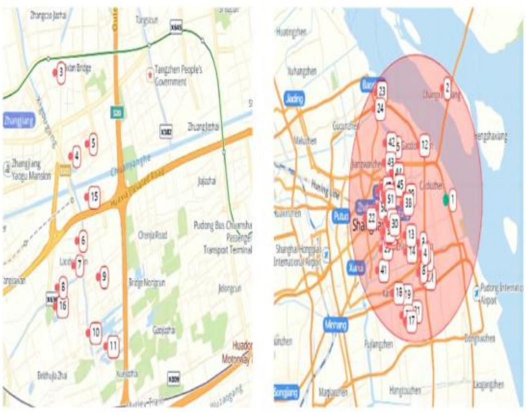

Figure 5: Lockdown zone for dataset

4.2 Experimental analysis

After improving ACA through performance analysis of the emergency logistics supply chain in Travelling Salesman, a logistics automation system is built. First, the suggested Improved Ant Colony algorithm is used to verify its performance. For system simulation, the experiment is carried out in MATLAB. Through table 2 establishment of appropriate parameters and limitations, the IACA algorithm's performance is monitored.

Table 2: the experimental model parameters

Parameters & units	Values
Fixed Cost (Yuan)	261
transport cost (Yuan)	4
Vehicle speed (Km/h)	60
Maximum Vehicle limit of mileage (Km)	14w
heavy load (Kg)	4250
pallet sizes(mm)	465*455

4.3 Data preprocessing

Min-max normalization

Min-max normalization is a technique for normalizing that involves linearly transforming the initial data to create an equilibrium of value comparisons before and after the process. This approach could use the following Equation.

$$Y_{new} = \frac{Y - min\,(Y)}{max\,(Y) - min\,(Y)}$$

Where,
Y-Old value,
Y_{new}- The new value obtained from the normalized outcome,
$min\,(Y)$–Minimum value in the collection,
$max\,(Y)$–Maximum value in the collection.

Outlier Detection and Removal

Outliers can degrade the efficiency of machine learning models by distorting statistical relationships among features. To eliminate outliers, we employ Z-score evaluation, which determines how far each data point deviates from the mean in standard deviations. A Z-score greater than 3 or less than -3 denotes an outlier that should be eliminated. The Z-score is determined as equation. below.

$$Z = \frac{X - \mu}{\sigma}$$

where X is the data point, μ is the mean of the attribute, and σ is the standard deviation.

Comparing Traditional and proposed method

ACO's initial total cost function value in **Figure 6** was above 3600, and after 132 iterations, it dropped to its lowest value of 339. The initial value of IACO's total cost function was less than 3243, and after 19 iterations, it dropped to its lowest value of 3208. The study approach outperformed the conventional ACO in terms ofthe convergence speed as well as the initial value of the total cost function speed when comparing the convergence function images of the ACO and IACO models. A region with little Testing was done on the passenger flows when the traffic flow was nearly nothing in order to confirm the efficacy of the study approach in real-world application. Litchi was chosen for transportation because it is perishable and must be stored at a low temperature while being transported. Fuel trucks were used by transport vehicles, and for testing the application, 31 locations as targets were chosen.

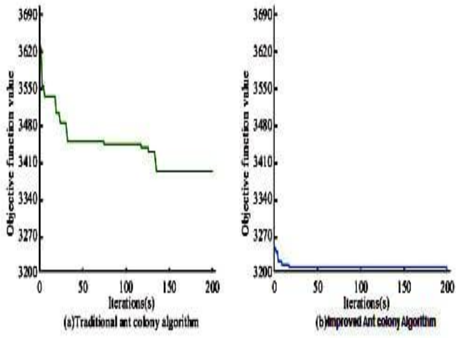

Figure 6: Total cost value of traditional and proposed

The prediction accuracy of four distinct logistics models is contrasted in Figure 7. The automated logistics control model developed for this study's prediction accuracy results are displayed in Figure 7(a). With an R2 of 0.98, the results demonstrated that the designed model had the highest prediction accuracy. This was 0.27, 0.30, and 0.17 higher than the prediction accuracy of the following algorithms: Tabu-Grey Wolf Optimisation (TGWO)[19], Improved Ant Colony Algorithm (IACA)[Proposed], Improved Particle Swarm Optimisation Algorithm (IPSO)[20], and neural network (NN)[21]. In conclusion, the model has a high prediction accuracy and can optimise logistics routes while lowering energy consumption in logistics distribution. Compared to other models, the fitting effect is superior. The suggested model is tested using real-world data to further confirm its scalability and dependability. The suggested model's accuracy and solution time are contrasted with those of the existing and proposed approaches.

A statistical metric called R-squared is used to assess how well a regression model fits data. R-squared values range from 0 to 1. When the model fits the data exactly and the anticipated and actual values are identical, we have an R-square of 1. However, when the model fails to learn any association between the dependent and independent variables and does not predict any variability, we obtain R-square equals 0. In conclusion, the model has a high prediction accuracy and can optimize logistics routes while lowering energy consumption in logistics distribution. Compared to other models, the fitting effect is superior. In order to confirm the suggested model's scalability and dependability.

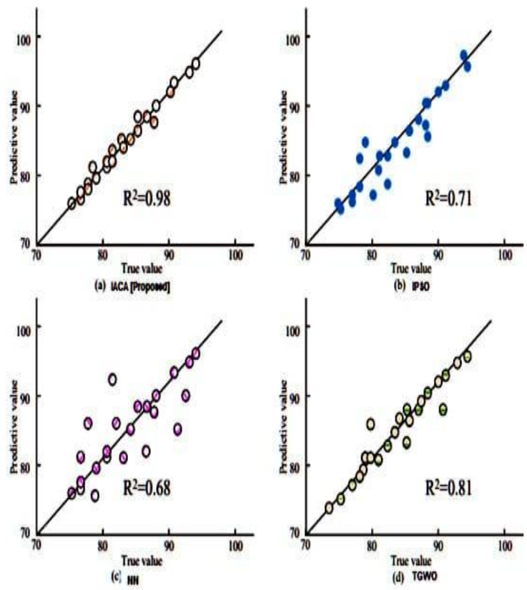

Figure 7: Comparison of model prediction accuracy

The accuracy and solution time of four distinct logistics models are contrasted in Fig 8. The accuracy comparison results are displayed in Fig 8(a). At 98.58%, the suggested model achieved the best solution accuracy. The contrast of solution times is displayed in Figure 8(b). Although it was greater than the other three models, the suggested model's solution time of 44.64 seconds was still within a reasonable range.

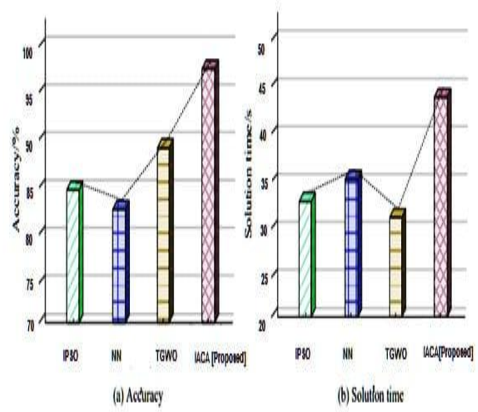

Figure 8: Accuracy and solution time of models

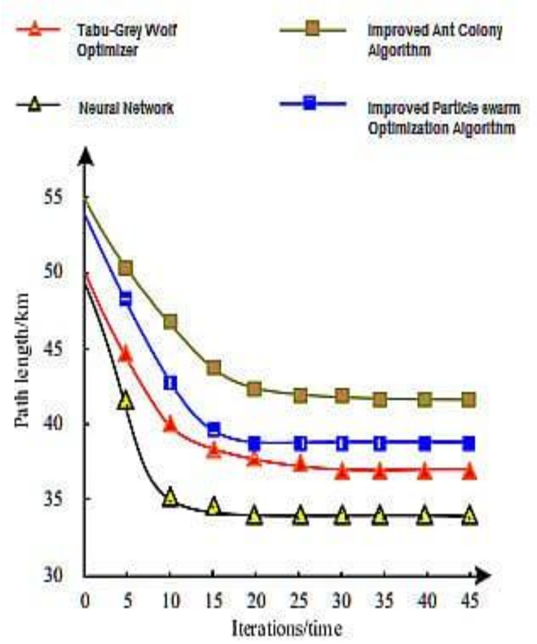

Figure 9: Finding Ideal path length finding

In Figure 9 it is clear that the improved ant colony algorithm requires less iterations to finding the ideal path than the current approaches. Additionally, the optimal path length is shorter, allowing for faster convergence.

Performance Analysis

For this paper, the method was run 55 times, and for the three algorithms in the literature, the average_time (t), inaccuracy (ξ) in %, and robustness (r) in % of every approach were noted. The following are the equations:

$$\xi = ave - best / best ;$$

$r = m/n$;

whereaverage is the overall mileage in average, Highestis the ideal overall mileage, **n** is the number of tests, and **m** is the number of counts at which the optimal solution is found. The information for each one of the four methods findings is shown in Table 3 and show that the algorithm generated the highest overall mileage, average overall mileage, inaccuracy value, robust r, and algorithm time expenditure when compared to the other examined methods. These findings suggest that the method performs well in terms of computing complexity and robustness. This implies that the method employed in this study surpasses the single ant colony algorithm and yields an ideal result with minimum error, high precision, and consistent robustness.

Table 3: Robustness analysis of the four algorithms.

Techniques	Highest	Average	inaccuracy(ξ)	robustness(r)	t(s)
IPSO	383.52	384.57	2.70	2.10	12.10
TGWO	377.82	388.79	2.38	5.30	9.56
NN	374.38	377.16	2.64	10.09	6.69
IACA [Proposed]	371.17	374.03	0.74	20.20	1.44

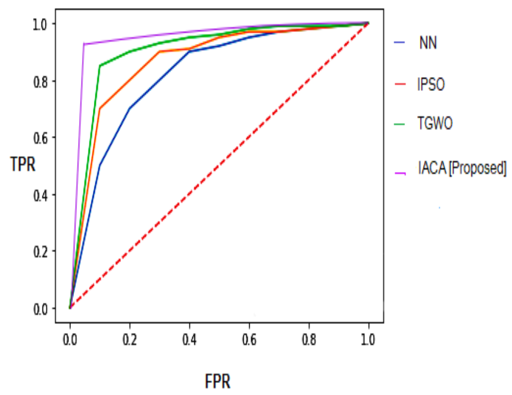

Figure 10: ROC Curve

Figure 10 shows a visual depiction of the model's performance over all thresholds is the ROC curve. The true positive rate (TPR) and false positive rate (FPR) are computed at each threshold (practically, at predetermined intervals), and the TPR is then graphed over the FPR to create the ROC curve. In the event that all other thresholds are disregarded, a perfect model, which at some threshold has a TPR of 1.0 and an FPR of 0.0, can be represented by either a point at (0, 1) The ROC is a helpful metric for evaluating the performance of distinct models, provided that the dataset is fairly balanced. In general, the better model is the one with a larger area under the curve. The suggested model [IACA] shows ROC curve has highest accuracy with 0.95. A confidence interval is a range of numbers that can be believe contains a population parameter. For any normal distribution approximately 95% of the values are within two standard deviations of the mean. From the following formula determine a 95% confidence interval:

$$95\% \text{ confidenceinterval} = \bar{x} \pm 1.96 \frac{s}{\sqrt{n}}$$

4.3 Discussion

IACA has been included to the emergency logistics supply chain path in order to increase logistics efficiency. The enhanced ACA served as the foundation for the building of the emergency logistics system model. The IACA algorithm demonstrated great optimization capabilities based on test results on the dataset. It was able to locate the ideal solution after 132 iterations, lowering the cost reduction value to be more than 30% below the average cost. Additionally, the suggested model's delivery distance was greater, its average power consumption per logistics node was lower, its emergency material for disasters was higher, and its prediction accuracy—which had an R2 of 0.98—was higher than that of the NN, TGWO, and IPSO. This suggests that the suggested approach has some practical application value and good optimization capabilities that can successfully increase delivery efficiency and lower fuel costs. While this study enhanced the program's performance, it also made the method more complex, which reduced its computing efficiency. Therefore, in order to maintain performance, it will be necessary to significantly lower the algorithm's complexity in the future.

Benefits of the proposed approach include: Lower operating costs due to the algorithm's optimization of routes and vehicle usage, which lowers labor, fuel, and maintenance expenses. When essential materials are delivered on time, penalties or reputational harm from delays are avoided; alternate routes are promptly found to avoid stopped highways; and time and expense are balanced to supply essential supplies effectively.

5 Conclusion

The logistics sector is changing dramatically as a result of its ongoing expansion. The IAC Algorithm was developed to reduce the amount of time it takes to distribute supplies from an Emergency Support Area (ESA) to Shanghai's 50 lockdown zones. Using data from Pudong, Shanghai, the system was evaluated and contrasted with three other intelligent optimisation techniques. The findings demonstrated that the algorithm's accuracy was enhanced by its local optimisation operation and that its relative error value was lower than that of other algorithms. In addition to being applicable to discrete optimisation issues, this method can serve as a general algorithmic framework for a number of scenarios, including rescue supplies, resource allocation during wildfires, emergency rescue during floods, and the transportation of hazardous items. However, the impact of road networks on transportation and supply distribution, lockdown zone configuration, and population density are not taken into account in this article.But existing logistics systems frequently lack the necessary flexibility and insight. In order to do this, the study modified the logistics supply chain system by integrating TSP into IACA. Simulation experiments were used to confirm the model's superiority. Future research can produce predictions with more accuracy and fewer iterations as the forecast results. which enhances scalability, adaptability, and real-time capabilities while integrating developing technologies with IOT. This achieves so by reflecting the precision and flexibility of the data in the optimization model.

Limitations of IACA:

• Enhanced features like dynamic pheromone updates, hybridization, and real-time data integration add computing overhead;

• Even with improvements, ACO may not be able to handle the exponential expansion in the number of paths as the network size increases.

• The effectiveness of the enhanced ant colony is highly dependent on sensitive parameters, including the number of vehicles, heuristic weighting, and pheromone evaporation rate.

• If dynamic data is imprecise or delayed, offer less-than-ideal routes.

There is a trouble striking a balance between time and money when shipping products to several high-priority sites.

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