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Enhancing sustainability in logistics through stochastic network routing mechanism optimization using ant colony algorithm

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Abstract

Stochastic networks are one of the most prevalent types of networks these days. Therefore, many researchers directed to study them and summarize the essential points and challenges they face in developing these types of networks, especially optimal route path selection. In this paper, a solution to this problem was addressed using the evolutionary algorithm ACO (Ant Colony Optimization), where the path with the lowest cost was obtained according to several scenarios studied in the research, which consider the fact that, the traffic information in the network is available either in a static or in a dynamic form in real-time. The proposed method presented contributions for real networks that can be used in many applications. The results are essential in solving the problem of choosing the optimal route. Also, they can be applied to various scenarios of the stochastic networks that exist in real life. Optimization improves logistics efficiency, which contributes to sustainability by minimizing fuel consumption, reducing emissions, and conserving resources.

Keywords: Stochastic networks, Ant colony Optimization, Minimizing fuel consumption, Reducing emissions, Conserving resources

1. Introduction

Non-binary vertices in stochastic networks reflect a probability for a link between nodes, and the network itself changes with time. To examine the development, adaptation, or reaction of such networks requires statistical analysis or computer simulations. The dynamic nature of the network, which is employed in a wide variety of scientific and academic disciplines, makes it challenging to administer and guarantee a consistent level of service by always picking the best possible route between any two points in the network.

The optimum selection of the routing path helps to increase the efficiency and effectiveness of the network on one hand and to reduce the use of the available bandwidth in the network, which reduces network congestion and gives the ability to send a larger number of messages at the same time, thus improving the overall network throughput. The time and effort required to account for journey time variations negatively impact a traveler's quality of life. For businesses, this means lower worker productivity and higher freight transportation expenses. Transport networks should model all link transit times as dynamic random variables to account for unforeseen delays and adjust schedules accordingly.

Directing vehicles to receive parcels, services provided according to dynamic requests in a special area. Requests are determined dynamically within a specific and unspecified period, and due to working hours restrictions, the service is provided within a limited period of time, because of this many requests cannot be confirmed [1]. Provided proactive time extrapolation Exploratory budget anticipatory time budgeting heuristic (ATB) based on approximate dynamic programming methods. ATB often simulates the realization of the problem to approximate the values for each vector of a time point and space-time budget to achieve the approximation to an optimal decision policy.

The system traffic is accountable for it, seeks to manage it according to a specified plan, and influences the decision of travelers to travel or not during peak time. The authors of [2] suggested using Markov decision process (MDP) and some assumptions to ensure reaching the ideal state to achieve the Bellman equation.

Therefore, a method based on approximate dynamic programming has been reached to solve the implementation and computation problems to solve the control problem. In this study, we assume a network with certain levels of disruption due to factors beyond our control, such as an accident, severe weather, or terrorist attack. The researcher uses some of our analysis calculations to verify the validity of our final findings. The cost and revenue sections of this study were essential to the researcher. The other factor is time, which will be prioritized differently; therefore, who thinks time is more important? That depends on the work choice of the recipient. The equation's ratio will be 1 to 1. However, if the opposite happens, time will be given priority over money, and if the user wishes, the issue will be divided according to use.

Stochastic networks rely heavily on instantaneous calculations, making the time it takes to determine the distance between any two nodes a crucial metric. Once we reach the nodes, we have to quickly relocate to other nodes and stay there for a longer time, thus increasing the network's complexity. As network constraints worsen, the working colony will speed up calculations to alleviate the pressure on the system. As a bonus, I'll be able to finish my work sooner and avoid any unnecessary delays.

The increasing interest in modeling the uncertainty in the travel time, in some of transport networks, and improving the reliability of travel times at the level of the path and the network are among the important problems researchers turn to solve. The property of sub-path representation through naming correction is what was suggested by [3]. The quantitative estimation of travel time reliability at the link and path level increased in particular the determination of the travel time distribution of the proposed road network. The results indicate that the transformed logarithmic distribution of shifted log–normal (SLN) represents reasonable link travel time for all facilities. The relevant facility estimated distribution parameters.

Problems of optimal routing policy in time-dependent random networks. One of the most important problems is basic networking and optimization problems for a variety of applications (communication systems and networks). It is studied by searching for the shortest path in deterministic networks. The authors of [4] proposed a framework for optimal routing policy problems in time-dependent random networks, providing a comprehensive classification and in-depth discussion of the problem variables. By examining the details of a single closely related variable in traffic networks, considering random dependencies in terms of time travel times and correlations representing online information.

The problems of routing vehicles are the pure interest of researchers, and one of the most important things in them is to improve obtaining the best guidance for these vehicles. It was suggested [5] through the use of 20 ants in the algorithms of the ant colony and the alpha pheromone coefficient, whose quantity appears is the number of ants that took this route and the coefficient of evaporation. 05 Finding the best values for the control coefficients, which led to increasing the effectiveness of the ant colony algorithm in solving vehicle routing.

Traffic network disturbances lead to a significant increase in transportation costs. Networks that have venerable links have a longer travel time than usual, and the possibility of disruption links between cities will be possible. Suggested [6] to use new dynamic programming to calculate the time for the distances traveled and evaluate the online and offline routing policy using MDP. There are several disruptions spread over its 16 nodes, these disruptions render all protocols designed to control this network's operation useless. These Stochastic networks employ two distinct protocols, offline and online protocols. Sustainability has become a paramount concern in modern logistics operations. As supply chains grow more complex and interconnected, the need to optimize resource utilization, reduce environmental impact, and enhance overall efficiency has led to the integration of advanced technologies and optimization techniques. One such approach gaining prominence is the application of routing mechanism optimization in stochastic networks using the Ant Colony Algorithm. This innovative approach not only promises to improve logistics efficiency but also contributes significantly to sustainability by reducing fuel consumption, reducing emissions, and conserving resources.

2. Literature review

Since the arc lengths in a directed acyclic network are independent and lie within a defined range, the method provided by Etessami [7] for computing the distribution function of the longest (s, t) path can be simply modified for computing the shortest path in such a network. Puterman [8] posed the issue in the form of a stochastic linear program with undetermined values for the objective function coefficients. The likelihood that a given basis is optimal was calculated, hence a closed-form solution was offered by the study. In his study, Niknami [9] analyzed the maximum flow in networks with node capabilities that are both independent and uniformly distributed.

Several prior publications on route planning for (autonomous) cars characterize the problem as shortest path search on a graph with deterministic edge weights and focus on managing the potentially very large graph in a memory- and compute-constrained system [10,11]. Locating the best path through a network with uncertain edge weights is the subject of a different collection of papers. Uncertainty in travel times between road segments owing to traffic and congestion is modeled by the edge weights [13,14]. The routing problem is examined in some of these papers as finely as the lane level [9]. Although these studies are helpful, we are primarily concerned with a unique difficulty in vehicle routing. Considering stochastic outcomes of (lane change) actions as an alternative to stochastic edge weights. The motion planning module of an autonomous vehicle trying to carry out the route may encounter situations in which it is unable to switch lanes due to the presence of other cars.

It may only be possible to define travel times and route viability probabilistically. To accommodate more complex query semantics, such as maximizing the likelihood of arriving before a deadline [15] or finding the latest departure time and path to guarantee a certain likelihood of arriving before a deadline [3], stochastic routing algorithms [12] model travel times along network edges as random variables with given probability distributions. Since calculating journey time distributions along a path requires expensive convolutions of its edge distributions, stochastic routing is often many orders of magnitude slower than deterministic routing, despite recent advances [4].

The length of the routing path causes an increase in costs, both in terms of time and fuel consumption for vehicles. Relying only on static data does not give us a good impression of the network status; therefore, real-time data must be available. The construction of the optimization algorithm for the routing path better be simple, inexpensive, and not consume much time to find the path. The main objective of this work is to find the optimal Routing path in stochastic networks using Anti-colony Algorithm depending on online and offline data Network.

3. Network model

The network model consists of a number of nodes, that represent a number of existing cities. So that there is a cost to move from one city to another and that this cost is determined based on several factors, including the length of the road connecting two cities and the possibility of road disruption due to a traffic accident is show in red line between city as a congestion in addition to the data in the insured in real time. and which gives the driver information about the road status related to the node. and the numbers on the links between the nodes represent the static cost of travelling from one city to another. This cost takes into account not just the amount of fuel used but also the amount of time spent travelling. It is possible to formulate an expression for the cost function can be formulating using the following equation.

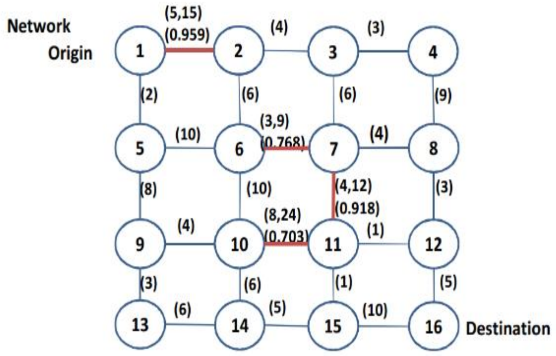

Figure 1. Network Model [6]

$$C_{total} = \lambda . C_{Time} + \gamma . C_{fuel} \qquad (1)$$

Where C_{total} represents the total cost, C_{Time} represents the cost of the time delay, C_{fuel} represents the cost of the fuel consumed, (λ) represents the weight factor of the cost of the time delay, and (γ) represents the weight factor of the fuel consumed. The variables (λ) and (γ) can change depending on the situation that is being studied; however, for the purpose of our investigation, we have chosen the values (0.7) and (0.3) for the amount of time delay and fuel usage, respectively. The numbers on the red links indicate the risk of the road failing, which is a figure between 0 and 1 for example, the link between node 1 and 2, at 0.9 the distance is 5 and 0.1 the distance 15that is regarded an additional cost that would be added to the cost of the road after multiplying the cost of the link by its percentage of the total cost of the road. The following operation indicate the cost ($C_{i,j}$) between the i_{th} and j_{th} of cities.

$$.C_{i,j} = (\rho + 1). C_{i,j} \qquad (2)$$

(ρ) is the probability of road failure. The above equation is used to describe the static status of road network, as for the dynamic status of the network, it is obtained through a communication system between the driver and the road management centre. To model the dynamic status of the network, we will assume that it is subject to a Gaussian probability distribution function as shown in figure 2.

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} \qquad (3)$$

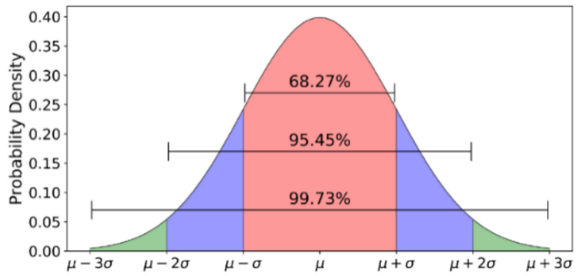

Figure 2. Gaussian probability distribution

Where (σ) is the standard deviation, (μ) is the mean of samples.

4. Ant colony optimization

(ACO) is an example of a population-based metaheuristic that can be applied to the task of locating approximate solutions to challenging optimization issues. Within the framework of ACO, software agents that are referred to as artificial ants conduct a search for feasible solutions to an optimization issue. To use ACO, the optimization problem must first be converted into the problem of locating the optimal path across a graph that contains weights. The artificial ants, which will be referred to as ants from here on out, piece together answers by travelling around the chart. A pheromone model is a set of parameters associated with graph components (either nodes or edges) whose values are updated at runtime by the ants. The solution creation process is stochastic and is biased by the pheromone model.

Following is an explanation of how the roulette wheel approach is used in the conventional ACO to pick the probability of the following node.

$$P_{ij}^{k}(t) = \left\{ \begin{array}{ll} \dfrac{\left(\tau_{ij}(t)\right)^{\alpha} . \left(\eta_{ij}(t)\right)^{\beta}}{\sum_{s \in allow_k} \left(\tau_{is}(t)\right)^{\alpha} . \left(\eta_{is}(t)\right)^{\beta}} & s \in allow_k \\ 0 & s \notin allow_k \end{array} \right\} \quad (4)$$

$$\eta_{ij}(t) = \frac{1}{d_{ij}} \quad (5)$$

$$d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2} \quad (6)$$

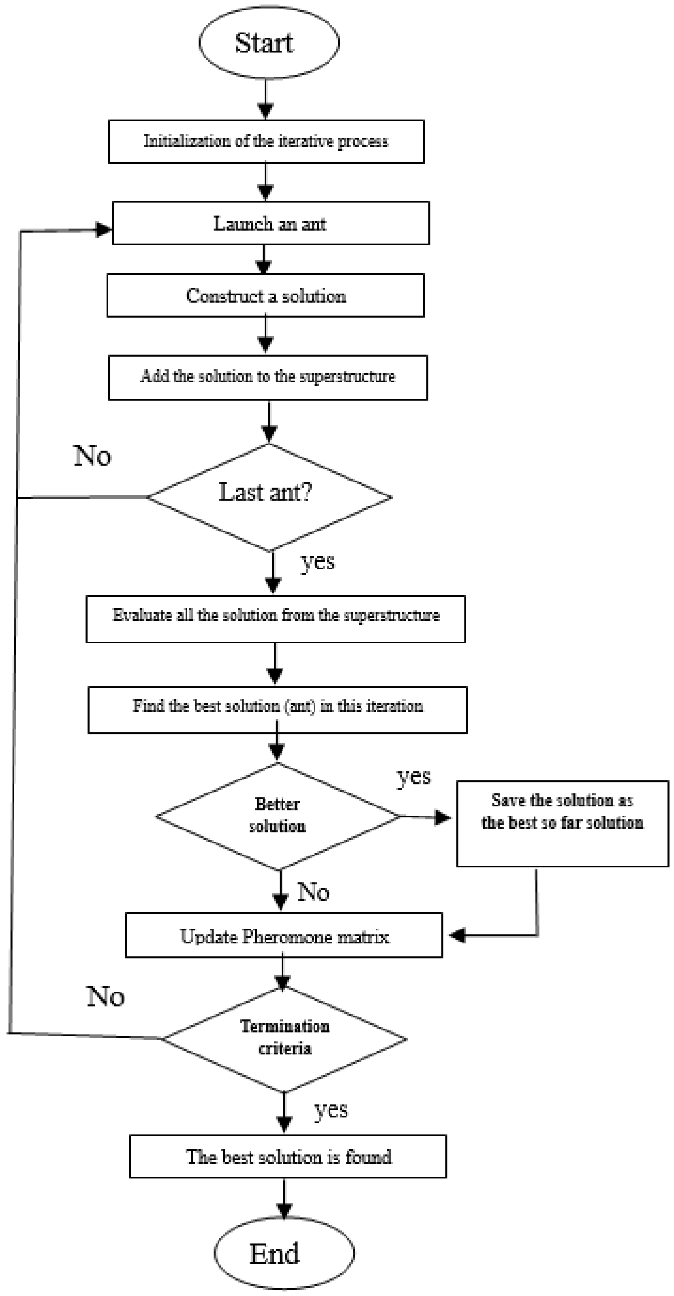

Figure 3. ACO algorithm flowchart

Where $\tau_{ij}(t)$is the pheromone trail from grid i to grid j and $\eta_{ij}(t)$is the grid number. Is the information about how to get from grid i to grid j. α is the factor that makes the quantity of pheromones rise, which determines how powerful the pheromone trail β is Visibility is the driving factor that determines how important heuristic knowledge is. d_{ij} Is the distance between node i and node j. (x_i, y_i) and (x_j, y_j) are the grid i and grid j positions, respectively. Figure 3 shows the main steps of the ACO algorithm.

According to the traditional ACO, the roulette wheel method decides the next node and is repeated and over again till the desired point is reached. Following the completion of each iteration, pheromone trails are modified so that they are in accordance with the length of the path being planned. All defective pheromones are eliminated at the end of each trial that takes place during the pheromone update. Only the best pheromones are added to the history of the trials, which enables the ants to ignore all the poor pheromone trails and improve the effectiveness of their coverage in order to locate a shorter route. At the conclusion of each cycle, the formula is applied in order to bring the quantity of pheromones on each vertex up to date:

$$\begin{cases} \tau_{ij} = (1-\rho)\tau_{ij} + \triangle\,\tau_{ij} \\ \triangle\,\tau_{ij} = \sum_{k=1}^{m} \triangle\,\tau_{ij}^{k} \end{cases} , \quad 0 < \rho < 1 \qquad (7)$$

Where m refers to the total amount of ants. ρ the pheromone evaporation rate is denoted by the symbol. $\triangle\,\tau_{ij}^{k}(k)$ is a number that represents the amount of pheromone that the ant k deposits along the path from grid i to grid j. In this paper, the ant-cycle-system model is utilized, and the definition of $\triangle\,\tau_{ij}^{k}(k)$is as follows:

Where Q_1 is a constant, the length of the path that the ant k is searching for is denoted by the variable $L_k(t)$.

$$\triangle\,\tau_{ij}^{k}(k) = \begin{cases} \dfrac{Q_1}{L_k(t)} if\ arc(i,j) is\ used\ by\ k\ in\ iteration\ t \\ 0 \qquad otherwise \end{cases} \qquad (8)$$

5. Results and discussion

Three scenarios were applied on a network model consisting of 16 nodes, as shown in Fig 1hasbeen used ACO algorithm in three scenarios. The first scenario includes the application of the ACO algorithm, taking into account the cost of connections between nodes only statically and without adding the probability. The following subsection show the results of each approach. In contrast, the second scenario includes Adding the likelihood of failure of each link and this approach is called Robust approaches. The third scenario included adding dynamic data in online time by modelling it as a probabilistic function that follows the Gaussian probability distribution. Table 1 shows the values of the parameters used in the simulation.

Table 1. Simulation parameters

Parameter	Value
$\boldsymbol{\lambda}$	0.7
$\boldsymbol{\gamma}$	0.3
$\boldsymbol{\sigma}$	0.4
$\boldsymbol{\mu}$	0.5
$\boldsymbol{\alpha}$	1
$\boldsymbol{\beta}$	1
$\boldsymbol{Q}$	1
$\boldsymbol{\rho}$	0.05
No of Iterations	40

5.1. Naive scenario

The ACO algorithm was applied to the network in this scenario to choose the optimal routing path. Only the static network condition was considered, i.e., the cost of moving from one node to another within the network without adding the possibility of link failure or the dynamic data of the link state, which is considered the simplest scenario, Figure 4 displays the best course of action following execution of the ACO algorithm. As the ideal path was obtained after (5) rounds of the ACO algorithm, figure 5 illustrates the best cost as a function of the number of iterations in the algorithm. The results of the Naive scenario are presented in Table 2. This table displays the cost of the overall routing path as well as the number of iterations that were required to find the optimal routing path.

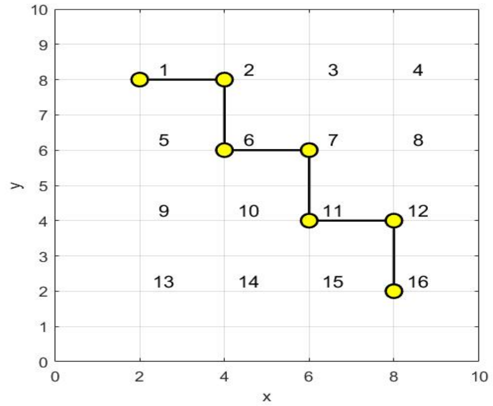

Figure 4. Optimal path in naïve scenario

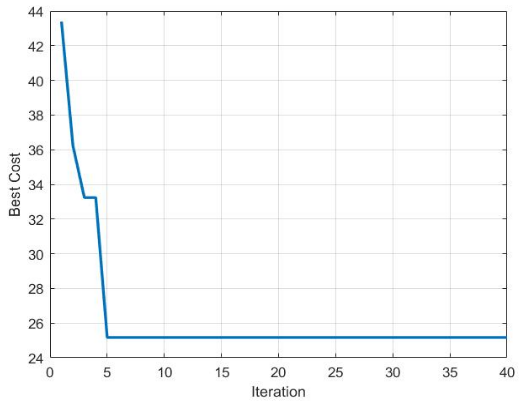

Figure 5. No. of cost vs iterations in naïve scenario

Table 2. Naïve scenario results

Best Cost	25.17
No of Iterations	5
No Middle Nodes	5

5.2. Robust scenario

In this scenario, the probability of a link failure was added to the static data of the network status, as the link wouldn't be selected in this scenario unless its likelihood of failure is zero, the probability of failure was added to some links as shown in Figure 1 in red lines, and Figure 6 shows the optimal path reached after applying the ACO algorithm.

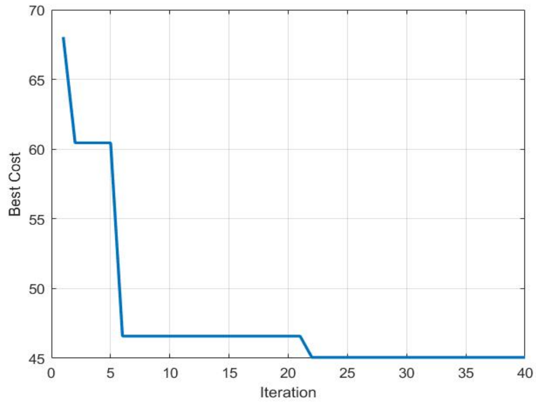

Figure 7. No. of cost vs iterations in robust scenario

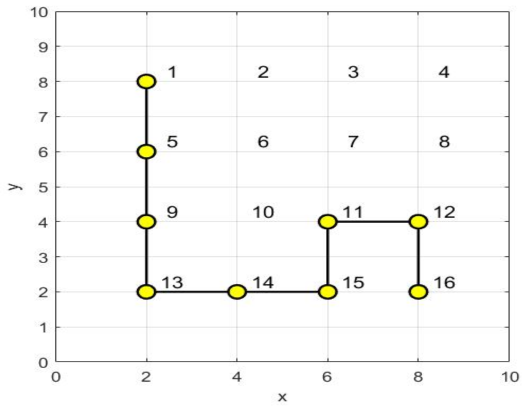

Figure 6. Optimal path in robust scenario

Table 3. Robust scenario results

Best Cost	45
No of Iterations	22
No Middle Nodes	7

As the ideal path was obtained after twenty-two rounds of the ACO algorithm, Fig. 7 depicts the best cost as a function of the number of iterations. The findings of the Robust scenario are displayed in Table 3 in terms of the cost of the overall routing path and the number of iterations required to find the optimal routing path. Because the algorithm in this situation will overlook all links that have a non-zero downtime probability, which constitutes an additional load, we observe a considerable rise in both the cost and the number of intermediate nodes. This is because the burden is caused by the method. This scenario is only utilized in circumstances in which the demand reaches the target node within a predetermined amount of time and with certain constraints. Under no circumstances to be late.

5.3. Online scenario

The active status of the network was reflected in this scenario in a manner that was true to time. For the sake of modelling this situation, an additional cost was assigned to each link in accordance with the typical or Gaussian probability distribution. The best cost is displayed in Figure 9 as a function of the number of iterations in the ACO algorithm. The optimal path was found after twenty-four iterations.

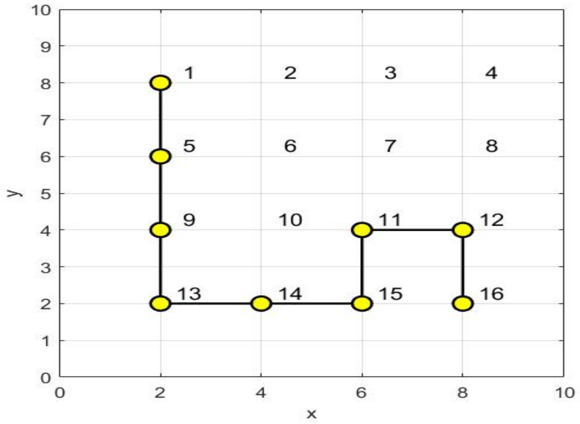

Figure 8. Optimal path in online scenario

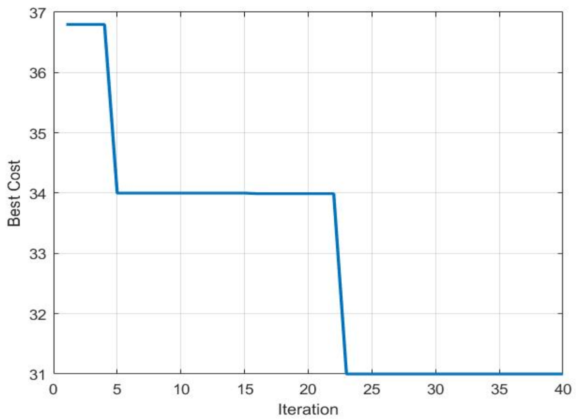

Figure 9. No. of cost vs iterations in online scenario

Table 4 displays the results of the online scenario with reference to the cost of the overall routing path as well as the number of iterations required to arrive at the best routing path.

Table 4. Robust scenario results

Best Cost	31
No of Iterations	24
No Middle Nodes	7

We note a decrease in the cost compared to the robust scenario due to the probability of choosing the link even if it has a non-zero failure probability. Still, we notice an increase in the number of required iterations. This is due to the addition of dynamic data in this scenario, which increases the complexity of calculating the optimal path. Figure 10, Figure 11 shows the comparison between the three scenarios, Naive, Robust and Online in terms of cost and number of iterations, respectively.

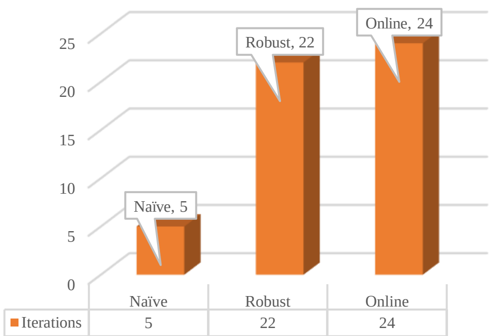

Figure 11. No of iterations

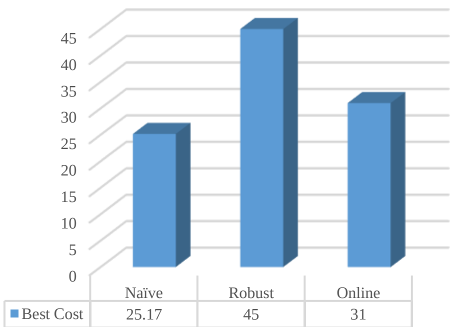

Figure 10. Best cost

6. Conclusions

In this research, it was reached to present a comprehensive and systematic analytical study of the mechanism of choosing the optimal routing path in stochastic networks based on several scenarios that included working according to static and dynamic network data with the addition of the probability of failure of each link, if any, where the ACO algorithm was used in order to discover the optimal routing path between the source node and the target node, and the results showed the effectiveness of this algorithm in discovering the optimal routing path with a simple computational cost and a few iterations, which gives the proposed method the possibility of applying it in real time and making the appropriate decision in the process of determining the optimal routing path based on the data Static and dynamic that describes the status of the network, the results showed that there is an increase in the cost of reaching the optimal routing path was observed in the Robust scenario compared to other methods because it excludes the selection of any link that has a non-zero probability of failure, and for the use of dynamic data in the routing process, there is a slight increase was observed in the number of iterations compared with a significant reduction in cost. Optimization increases logistical effectiveness, which helps contribute to environmental sustainability by minimizing fuel consumption, reducing emissions, and conserving resources.

7. Future work

After reviewing the results obtained in this research, the research recommends applying these scenarios in our applications. In addition, the dynamic data in real time can also be modelled using other probability distributions.

Declaration of competing interest

The authors declare that they have no known financial or non-financial competing interests in any material discussed in this paper.

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