A Multi-Objective Optimization for Supply Chain Management using Artificial Intelligence (AI)

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Abstract—Supply chain management seeks to solve the complex problems of transporting goods from the suppliers to the end customers. Improving the differentiation between different paths to reduce costs and time may require smart systems. This paper proposes two new algorithms for determining, with Multi-Objective Optimization, the least cost and the most appropriate path between two nodes. First: Ant colony optimization (ACO) algorithm, working alongside with Multi Objective Optimization (MOO), is adopted to determine the shortest path and time between two nodes to reach with the least cost. Multi-Objective intelligent Ant Colony (MOIAC) algorithm improves supply chain management to achieve the optimal and the most appropriate solutions. Second: Particle Swarm Optimization (PSO) algorithm, also working alongside MOO, is adopted to determine the least cost, time, and shortest path. Multi Optimization Intelligent Particle Swarm (MOIPS) algorithm improves supply chain management by determining the shortest path with the least cost. These two proposed algorithms seek the optimal solution by MOO using a JAVA Program. The experimental results show the excellence of the first algorithm in determining the optimal and the most appropriate path while getting throw risks inherent in transporting goods. It also demonstrates excellence in transporting goods in the shortest possible time and with the least cost. The second algorithm also shows excellence in transporting goods with the least possible cost via the shortest path and in the shortest time.

Keywords—Supply chain management; artificial intelligence; particle swarm optimization; ant colony optimization and multi-objective optimization

I. INTRODUCTION

Now-a-days, Supply Chain (SC) networks play a key role among suppliers [1] and end customers. Generally, SC networks involve variant agents such as suppliers, manufacturers, distributors, wholesalers, retailers, and customers [2], beside the interactions between them. SC is more complicated than traditional logistics as it is not limited to the transportation process among variant agents; rather, it has different phases and roles for different agents, such as what is supplied by suppliers [3-5], and what is ordered by customers. SC networks are sophisticated supplier-customer networks encompass agents, information, techniques, activities, [6], and resources. SC networks consist of: suppliers, manufacturing or production factories, stores, distribution centers [7], and customers. This network aims to achieve optimal resource choice to reduce cost and time [8]. SC networks are the main structure of the operations and the interactions among those agents, from the preliminary strategic level [9], to the final operational one. A good practiced SCM is a competitive advantage for organizations working in the field of investment and raising capital. Organizations have variant options in managing such interactions in SC (supplying with goods, assessing products, offering end products to customers) [10-13], according to time, cost, and profit. The problem is that SCM is responsible for a huge number of processes and operations such as production and procurement planning, choosing the optimal product, customer orientation, marketing, distributing products [14], and sales among others. SCM has to balance the SC and each organization's different objectives; some objectives may contradict other objectives in the same organization. So, there must be an appropriate method to coordinate between such objectives taking into consideration that the SC has variant agents in variant phases (i.e. the supplier, the distributor, the seller, and the customer). Suppliers and end customers may have different locations, a thing that may increase the cost of transporting goods in different paths [15-17], and among different nodes to reach the end customer. To achieve this balance among different objectives, companies must consider comparing and differentiating between different timings & time limits and between the added costs for the goods to determine the appropriate path, cost, [18], and timing. Generally, it is clearly noted from previous relevant works and papers that SCM has many dimensions that need to be studied simultaneously to achieve the least cost and [19], the shortest time. In this paper, however, we not only focus on the least cost and the shortest time, but we also try to determine the optimal and the best path alongside with the highest profit while preserving the quality, and improving it if possible. Moreover, this paper focuses on reducing the cost while giving attention to possible risks that may occur in the transportation process. So, we must be precise and careful in improving SCM using the two new algorithms to reach the best possible results, then comparing them to those of other algorithms. Artificial intelligence techniques can help organization improve their objectives) [20]. (the cost - the time limit - the optimal path.In this Work, we use several objectives integrated with AI techniques (i.e. PSO and ACO algorithms)[21-24]. Problem description of SCM covers a wide range of subject. Users, distance, marketing, distribution, least cost path, production and procurement in companies work independently and in parallel in the supply chain. Although each of these companies

has its own objectives and often these objectives are in contradiction with another, so there needs to be a method to achieve these different objectives. We study the problem of the least cost and the shortest time path to improve the transportation process. We propose two algorithms for determining the least cost path: the first algorithm (MOIAC) determines with ZIPF random distributions the shortest and optimal path between nodes to reach to the end customer, while the second algorithm (MOIPS) reduces time and cost in the process of transporting goods from suppliers or producers to end customers. The Main Contribution of the study can be highlighted as follows:

- Solves the problem of determining the optimal path with the least cost to reach the end customer.

- Uses (MOIAC) algorithm to reduce the cost and shrink the distance by choosing the shortest path to the end customer, seeking a balance between the nodes.

- Uses Zipf distributions along with ACO to create random distributions to determine the optimal path to transport goods to the end customer in an appropriate time.

- Uses (MOIPS) algorithm to determine the optimal path to the end customer in the shortest time.

- Apply and test the two proposed algorithms using a JAVA program to verify their superiority over other algorithms.

The rest of this paper is organized as follows. Section I is the introduction. Section II overviews the relevant previous works that addresses the SCs. Section III focuses on the main structure proposed for transporting goods from suppliers to end customers. Section IV focuses on the proposed system; (MOIPS) and (MOIAC) algorithms. Section V introduces the experimental results and compares it with results of other algorithms. Section VI shows the conclusions and recommendations for further research.

II. RELATED WORK

E. Mastrocinque et al. proposes a technique of improving SC using the Bees algorithm with MO to reduce the cost and the time consumed. It also uses the Pareto system to determine the optimal solutions to the problem of cost and time to improve the SC. It proposes new weights in applying the algorithm and compares the proposed system with other algorithms. The results show that the proposed algorithm exceeds other algorithms in reducing the cost and time. This work recommends complicating the problem and improving the Bees algorithm by integrating other objectives in further work [25].

R. Ehtesham et al. improves the SC by integrating other environmental and economic dimensions to the MO. The main goal of this work is to achieve the highest margin of profit by transporting the largest amount of goods, while reducing environmental pollution. This problem has been solved using two algorithms with Multi-Objective Optimization to select the suppliers and to improve the SC. These proposed algorithms have been applied to Mega Motor Company to reduce the cost

and time. The results show that the proposed algorithm exceeds other algorithms in reducing environment pollution. This work recommends improving the algorithm using Meta-heuristic and addressing cost and time simultaneously [26].

H. Banerjee et al. proposes a new technique that is using Pareto Optimization in the cases of the uncertainty of the preliminary assumptions. It uses Pareto Optimization with a Genetic algorithm and Mixed-Integer Linear Programming (MILP). It shows some scenarios of avoiding risks in SC systems that are affected directly by the customer's requirements. The work also improves the process of selecting the nearest suppliers to the customers to reduce the total cost and to avoid risks. This methodology proves that the experimental results are better than those of other algorithms in cases of uncertainty. The work recommends using different algorithms to improve the methodology used in the cases of uncertainty [27].

L. Martínez et al. this work proposes the technique of Meta-heuristic using Water Drop with MO to reduce the cost and the time. It depends on Pareto optimization to determine the number of optimal solutions simultaneously. The results show that the proposed algorithm exceeds other algorithms in reducing the cost and time. This work recommends improving the algorithm using the distances between nodes to determine the optimal and the shortest path [28].

S. Gupta et al. proposes a method of an optimal allocation of suppliers and resources with specific products with the help of decision makers. The work divides the decision makers into two groups: the first group is responsible for the goods transported to distributors, and the second group determines the amounts reasonably. The first group is concerned with transporting goods with least cost, while the second group is concerned with reducing delivery time also with least cost. This paper uses Fuzzy with MO to address Conflicting objectives, reaching a compromise in the process of transportation. The results show that the proposed algorithm exceeds other algorithms in achieving the optimal amounts of products in the process of making a decision. This work recommends using Meta-heuristic with Pareto optimization [29].

R. Sun et al. describes the application of Ant Colony with MO in SCM. It addresses a number of objectives such as cost, time, customer service, and flexibility with the goal of improving the SC. The work also introduces MO system to solve some problem to improve the SC. It recommends improving the algorithm and using other algorithms [30].

P. Phuc et al. focuses on the problem of directing the vehicles for logistic services. While delivering a product to the customer, the vehicle has to pass over all the nodes inherent in the network to reach every customer in their lists. The main objective of this work is to reduce the cost of traveling from one customer to another, considering that not all vehicles are similar. ACO has been used to direct vehicles and detect each vehicle's arrival time. The work recommends analyzing more optimal results by integrating MO and using AI to reach the shortest path, considering time and traffic [31].

Y. Wenfang et al. has designed a new strategy to manage the inventory of the SC, manage the marketing process, and improve companies' response speed. It also improves more than one methodology of ACO algorithm with Fuzzy. This work positively influences the efficiency of the organizations' ability to manage inventory in SC. The work recommends using AI to manage inventory to improve SC [32].

X. Zhang et al. developed ACO algorithm with MO using two different colonies to reduce the cost of the goods in the SC. The work also develops a method to determine priorities and weights, detecting the path of transporting goods and the optimal cost. The results show that the proposed system exceeds other algorithms on a large scale in smart cities. Therefore, this work recommends reducing resource consumption to the minimum, and improving the system with other algorithms that can be applied on a larger scale with addressing objectives such as cost, time, and optimal path to transport goods [33].

A. Discussion and Related Works

It is clearly noted from previous studies and articles that is relevant to this field that SCM has many dimensions that has been largely studied to achieve the least cost and the shortest time. This paper does not only focus on reducing the cost and time, but it also tries to determine the optimal and the best path taking into consideration the highest margin of profit and preserving the quality of the product and improving it without negatively affecting the customer or environment. The paper focuses on reducing the cost while giving attention to possible risks that may occur in the transportation process among nodes as presented in Table I. So, we have to be precise and careful in improving SCM using the two proposed algorithms (PSO & ACO) to reach optimal results.

TABLE I.   RELATED AND THE PROPOSED WORK COMPARISON

Strategy	Year	AI Techniques	Distance	Least Cost Path
Bees Algorithm	2013	√	√	
Intelligent Water Drop(IWD)	2014	√	√	
Ant Colony Algorithm and Fuzzy Model	2019	√	√	
Mixed-Integer Linear Programming (MILP)	2020	√	√	
multi-objective particle swarm optimization (MOPSO)	2020	√	√	
mult iobjective supply chain configuration (MOSCC)	2021	√	√	
My Propsed	2022	√	√	√

III. PROPOSED ARCHITECTURE FOR SUPPLY CHAIN DESIGN CASE STUDY USING THE SWARM INTELLIGENT WITH MULTI-OBJECTIVE

Presented in Fig. 1, this section describes the proposed structure of the smart system of a SC from the supplier to the customer, where agents are referred to by nodes on the network [11]. In our model, we use a Heterogeneous system with AI techniques and MO to determine the optimal path in transporting goods to reach the end customer, considering time and cost problems. The proposed system consists of (i) suppliers (the first node, from which goods are transported via different types of vehicles and different paths to reach the next node), (ii) distributors (the second node, the wholesaler who receives goods from suppliers, classify them, then transport them to the next node), (iii) retailers (the third node, who finally hand the goods over to the next node), and (iv) end customers (the final node). This is clearly shown in the figure.
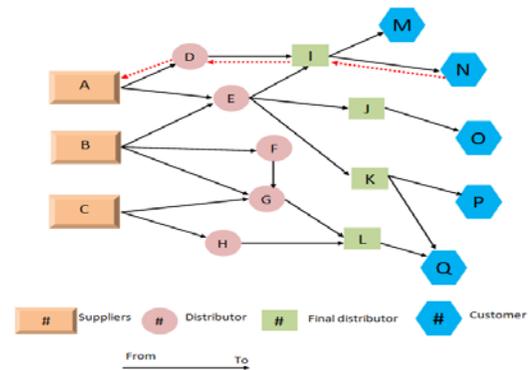

Fig. 1.   Proposed Model Architecture for Supply Chain Management Systems.

Determining the location of the optimal supplier to the customers depends on the latter's needs. Choosing the optimal and the shortest path is accomplished using an AI and a number of mathematical equations concerning time, cost, and distance. When goods are to be transported from suppliers to customers, the proposed algorithm determines the optimal path. The proposed system is divided into four parts: (i) using AI techniques to choose the optimal path, (ii) using an improved ACO algorithm with MO, (iii) using a PSO algorithm with MO to improve the system, and (iv) employing the equations of cost, time, and distance among nodes to reach the destination with the least cost. Finally, the proposed system is applied using a JAVA program.

A. Multi-Objective Optimization in Supply Chain

MOO in the SC is improved using AI techniques to determine the optimal and shortest path among nodes. To accomplish such objectives in the SC, cost and transportation systems have to be improved. That is why we integrate the distance equation among nodes to determine the optimal and shortest paths among suppliers and customers [33].

1) Cost: Costs among different nodes are calculated to reach the optimal cost. Costs of transporting goods from suppliers and customers must be low for the variant means of transportation [34]. We need to consider that the system is a Heterogeneous system.

$$\mathbf{Cost}(c_i) = \sum_{i=1}^{n}\left(cost(c_{ij}) * demand(d_{ij})\right) \quad (1)$$

$c_{ij} \in \{0,1\}, ij = 1, 2, \dots, n \, Node$

2) Distance: The minimum distance among nodes is calculated to determine the optimal and the shortest path among nodes in the system to ensure that goods are handed over to the end customers through the path with the least cost and time.

$$Min \; \sum_{i=1}^{n}\sum_{j=1}^{n} d_{ij}x_{ij} \quad (2)$$

S.T:

$$\sum_{i=1}^{n} n_i x_{i \geq k, x_i \in \{0,1\}} \; (1 \leq i \leq n) \quad (3)$$

3) Time : Time needed to move among different nodes is calculated to reach the optimal time. *LTime_i* is the time among the nodes, while $_i$ is the time of the node. The goal is to shrink the time consumed when transporting goods among nodes.

$$\mathbf{Demand_i} = \sum_{j \in \{downNodei\}} \mathbf{Demand \; j}, i = 1, 2, \dots \dots, \mathbf{nNode} \quad (4)$$

$$\mathbf{LTime_i} = \mathbf{Time_{i,xi}} + \mathbf{MaxUPLT_i}, i = 1, 2, \dots \dots, \mathbf{nNode} \quad (5)$$

$$\mathbf{MaxUPLT_i} = \mathbf{Max_{j \in UpNodei}} \{\mathbf{LTime_j}\}, i = 1, 2, \dots \dots, \mathbf{nNode} \quad (6)$$

Equations (4) and (6) show these functions: the time needed for the SCN to accomplish the work is referred to by T, the total number of the nodes in the network is nNode, the demand quantity of node is Demand$_i$, while the time of the node$_i$ is LTime$_i$. Equation (5) shows the decision vector x with node, where the number of options available for node $_i$ is Option$_i$, and the chosen option of the corresponding node is represented by different values of dimensions. Equation (6) calculates Demand$_i$, where the set of down nodes of node $_i$ is downNode$_i$ and it is previously determined for each customer. Equation (5) calculates LTime$_i$, where the time needed of the node $_i$ to accomplish option $_{xi}$ is Time$_{i, xi}$, the maximum LTime of upNode$_i$, is maxUpLT$_i$ (the set of up nodes calculated as shown in equation (6). The typology of SCN determines the upNode and the downNode.

4) ZIPF Distribution: Zipf distributions create random distributions of goods among nodes. Goods are distributed among nodes according to the different tasks of the suppliers and the end customers [35].

$$p(f_i) = \frac{1}{i^a} \quad (7)$$

Where $i = 1, 2, \dots, n$; and α is a factor of goods distribution, where $0 \leq \alpha < 1$.

IV. PROPOSED PSO AND ACO-BASED ALGORITHM FOR THE SUPPLY CHAIN

A. Multi Objective with Particle Swarm Optimization

The process updates the particle velocity, position and inertia weight is presented in Table II using Eq. (8), Eq. (9) and Eq. (10) as follows [33-36]. We update the velocities for every particle as follows:

$$V^{k+1}_{i,j} = W.V^{k}_{i,j} + C_1 R_1 \left(pbest^{k}_{i,j} - X^{k}_{i,j}\right) + C_2 R_2 \left(gbest^{k}_{i,j} - X^{k}_{i.j}\right) \quad (8)$$

Where

$V^{k+1}_{i,j}$ Refers to the new velocity of a particle

$V^{k}_{i,j}$ Refers to current velocity

C_1, C_2 positive constants acceleration parameters

$pbest^{k}_{i,j}$ personal best position particle

$X^{k}_{i,j}$ position of ith particle in j^{th} swarm

R_1, R_2 two random variables in the range [0,1]

$gbest^{k}_{i,j}$ global best position particle

$$X^{k+1}_{i,j} = X^{k}_{i,j} + V^{k+1}_{i,j} \quad (9)$$

Where

$X^{k+1}_{i,j}$ new position of particle

k iteration population

$i \in 1, 2, 3, \dots, m$ m is the number of members in an iteration

$j \in 1, 2, 3, \dots, d$ d is the size of the swarm

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}} * iter \quad (10)$$

Where

w inertia weight

w_{max} initial value of inertia weight

w_{min} final value of inertia weight

$iter_{max}$ maximum number of iterations

$iter$ current iteration number

Accomplishing the mission of reaching the end nodes, the proposed algorithm is proven to choose the optimal nodes to reach the destination by testing the appropriateness of each node according to the agents in the network. The algorithm uses MOO to determine paths with the shortest distance and the least cost and time. The steps of the MOIPS Algorithm are shown in Fig. 2 and (Algorithm 1):
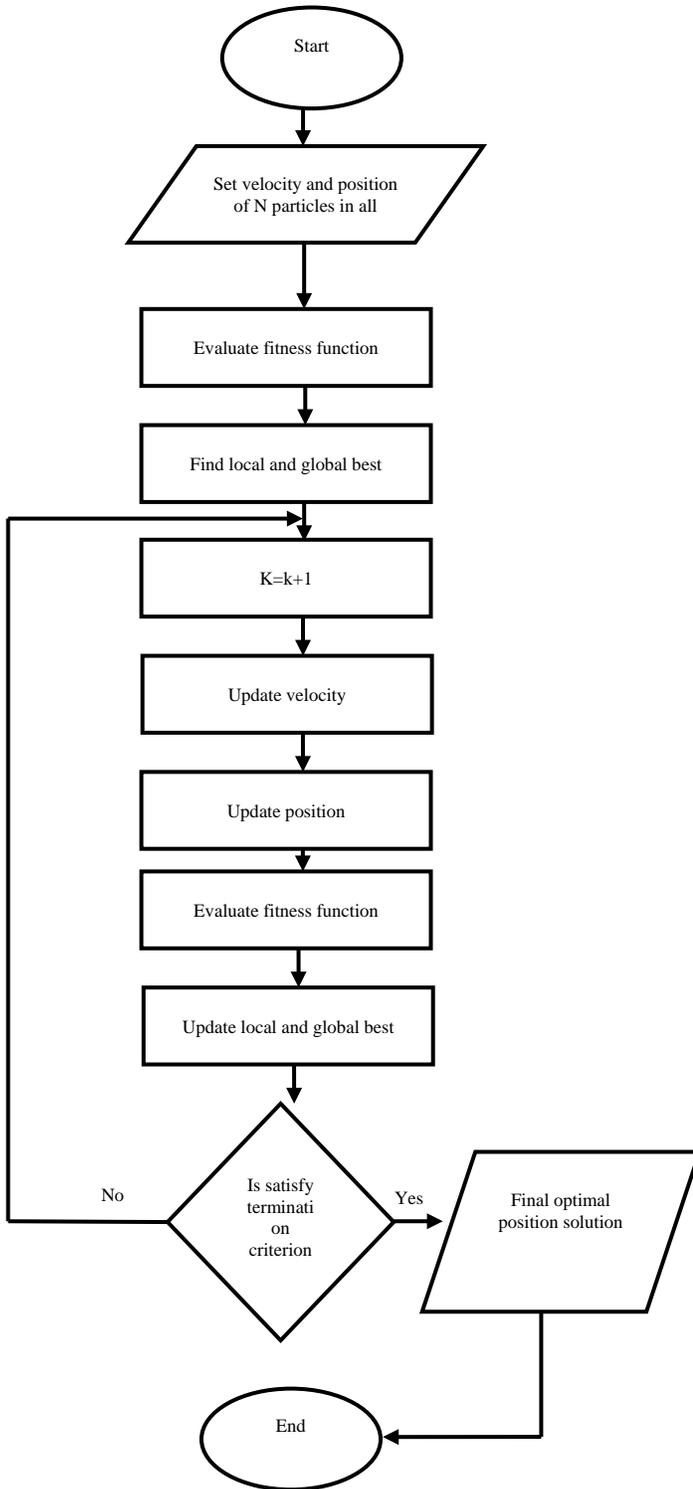

Fig. 2.   Proposed Flowchart MOIPS.

Algorithm 1. The Proposed MOIPS

Input: Size α of Population
    Number of Iterations
    Node
    Cost and Time
    Distance
Output: Selected $P_{position}$ ← (Optimal $_{Best\ node}$, Optimal $_{Total\ Execution\ Time}$ and   Optimal $_{Costs}$)
  Initialization:
    Define Values of parameters, Size of Pop, Num of Iterations and Num of Particles
    Initialize set values of particle swarm (Num of Iteration)
    Initialize availability and unavailability probabilities
    Initialize best node according to costs and time
  Repeat
    Count I = 0
    For j=1 to α do
      For each goods in node do
      Calculate fitness function
      Update velocity
      Update position
      $P_{velocity}$ ←Random velocity()
      $P_{position}$ ←Random position()
      P_{best} ← $P_{position}$
        If $\alpha \leq 0$ then
          Exploitation
        Else
          Exploration
        Select best node
        End if
      Calculate the distance of the node
      Calculate the time of the node
      Calculate the costs of the node
      End for
    End for
  Until maximum number of iterations is reached, or access solution optimal
    Return the optimal best node solution

TABLE II.   PSO PARAMETERS

No.	Parameters	Values
1	*Number of particles*	100
2	*C1*	2
3	*C2*	2
4	*R1*	[0 - 1]
5	*R2*	[0 – 1]
6	w_{max}	0.9
7	w_{min}	0.4
8	*Number of iteration*	1000
9	*W*	1
10	*Population (swarm size k)*	50

B. *Multi-objective with Ant Colony Optimization*

In this section, the MOIAC algorithm is discussed. This algorithm determines the least cost path between nodes depending on time, cost, and optimal distance in order for the supplier to reach the end customer. MOIAC algorithm is applied to choose between one path or another to reach the optimal choice according to the needs of the end customers from the suppliers. MOIAC algorithm is of great benefit in reaching the shortest path with the least cost and time. Both ACO and PSO are types of swarm intelligence. The task of determining the optimal path with the least cost is NP-hard; however, it can be more useful in solving complicated problems than traditional methods as presented in Table IV [9-12]. The positions of the pheromones are calculated on different paths using FF, while moving from one node to another is calculated according to the following:

$$p_{ij} = \begin{cases} \frac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{s \in k}[\tau_{is}]^{\alpha}[\eta_{ij}]^{\beta}} \\ 0 \ otherwise \ if \ j \in k \end{cases} \tag{11}$$

The calculation of the next node that is selected by Eq as follows:

$$i = \begin{cases} arg \ max_{s \in k}\{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}\}, if \ q \le q_0, if \ q > q_0 \\ j \end{cases} \tag{12}$$

The calculation of the detection array of the ant proceeds according Eq. (13):

$$\eta_{ij} = \frac{1}{d_{ij}} \tag{13}$$

The pheromone values on the routes are updated after every repetition. When ants reach the end of their travel path, the pheromone value is a positive constant. The updated local pheromone value can be calculated by Eq. (14) as follows.

$$\tau_{ij} = (1 - p)\tau_{ij} + p_{\tau 0}, \forall(i,j) \in t_k, where \ (0 < p \le 1) \tag{14}$$

After evaporation, every ant adds pheromones to the routes according to the set method, and the updated global pheromone value is calculated by Eq. (15) as follows:

$$\tau_{ij} = (1 - p) + p.\sum_{k=1}^{m}\Delta_{\tau ij} \tag{15}$$

$\Delta_{\tau ij}$: is the amount of pheromone added by ant *k* on their route. It can be represented Eq. (16) as follows:

$$\Delta_{\tau ij} = \begin{cases} \frac{1}{c^k} \ if \ \forall(i,j) \in \ t^k \\ 0 \ otherwise \end{cases} \tag{16}$$

$$p(f_i) = \frac{1}{i^a} \tag{17}$$

Where *i* = 1, 2, …, *n*; and α is a factor determining the data access distribution, where $0 \le \alpha < 1$. As mentioned in Table III, notation of ant colony optimization.

TABLE III.   NOTATION OF ANT COLONY OPTIMIZATION (ACO)

α	Pheromone trial control parameter τ_{ij}
β	Pheromone trial control parameter η_{ij}
S	Probability for slave ant $\forall s \in \{1,2,3, \dots, k\}$
K	Ants
Q	Random variable uniformly distributed in [0,1]
J	Random variable selected to the probability distribution with $(\alpha = 1)$
I	Currently node *i*
J	Choose go to node *j*
P	Evaporation rate
M	Number of ants
τ_{ij}	Pheromone density or node j (amount of pheromone between *i* & *j*)
η_{ij}	Heuristic information (importance between nodes *i* & *j*) $= 1/d_{ij}$
p_{ij}	Probability ant transits. Currently node *i* to node *j*
$p_{\tau 0}$	Initial pheromone
$\Delta_{\tau ij}$	Amount of pheromone that an ant adds to the path it has visited
c^k	The length of tour t^k Which was built by the Ant *k*
t^k	Total lengths of path
t_k	Tour by ant *k* iteration
d_{ij}	Distance between two nodes

TABLE IV.   ACO PARAMETERS

No.	Parameters	Values
1	α	1
2	β	2
3	P	0.3
4	Q	1
5	m	110
6	t_k	800
7	$p_{\tau 0}$	0.8

The algorithm determines the optimal nodes using Zipf and calculating the fitness function for each node,

ZIPF distributions are applied to create distributions to reach the optimal nodes and paths. ZIPF is a random distribution that aims to determine the optimal and shortest paths between the supplier and the customer. The function is as follows: The steps of MOIAC Algorithm that aims at improving its distributions are shown in Fig. 3 and (Algorithm 2):

Algorithm 2. The Proposed MOIAC

Input: Number of Ants
     Number of Iterations
     nodes
     Zipf Distribution
     Min Distance between nodes
Output: Selected Optimally Best distance (Optimal $_{\text{Best node}}$
     Optimal $_{\text{Total Execution Time}}$ and Optimal $_{\text{Costs}}$)
   Initialization:
   Define Values of parameters, Num of Iterations and Num
of Ants
     Initialize distance between nodes
     Initialize costs of nodes
     Initialize time of nodes
  Repeat
    For I=1 to (Num of ants)
       Step = step + 1
       Set all ant distribution in node
     For each node in current system
       Calculate desirability of the movement
       Calculate probability of the movement
      If $q \leq q_0$ then
         Exploitation
       Else
         Exploration
      End if
     End for
     For each dimension do
       Calculate fitness function
       Update local pheromone
       Update global pheromone
       Set local pheromone update
       Set global pheromone update
       Set determine distance in nodes
       Until all nodes are selected
         If the least cost path is long
          Then
           Apply the global update rule
         Else if
          Apply this path
         End if
      End for
    End for
  Until max number of iterations is reached or access solution is
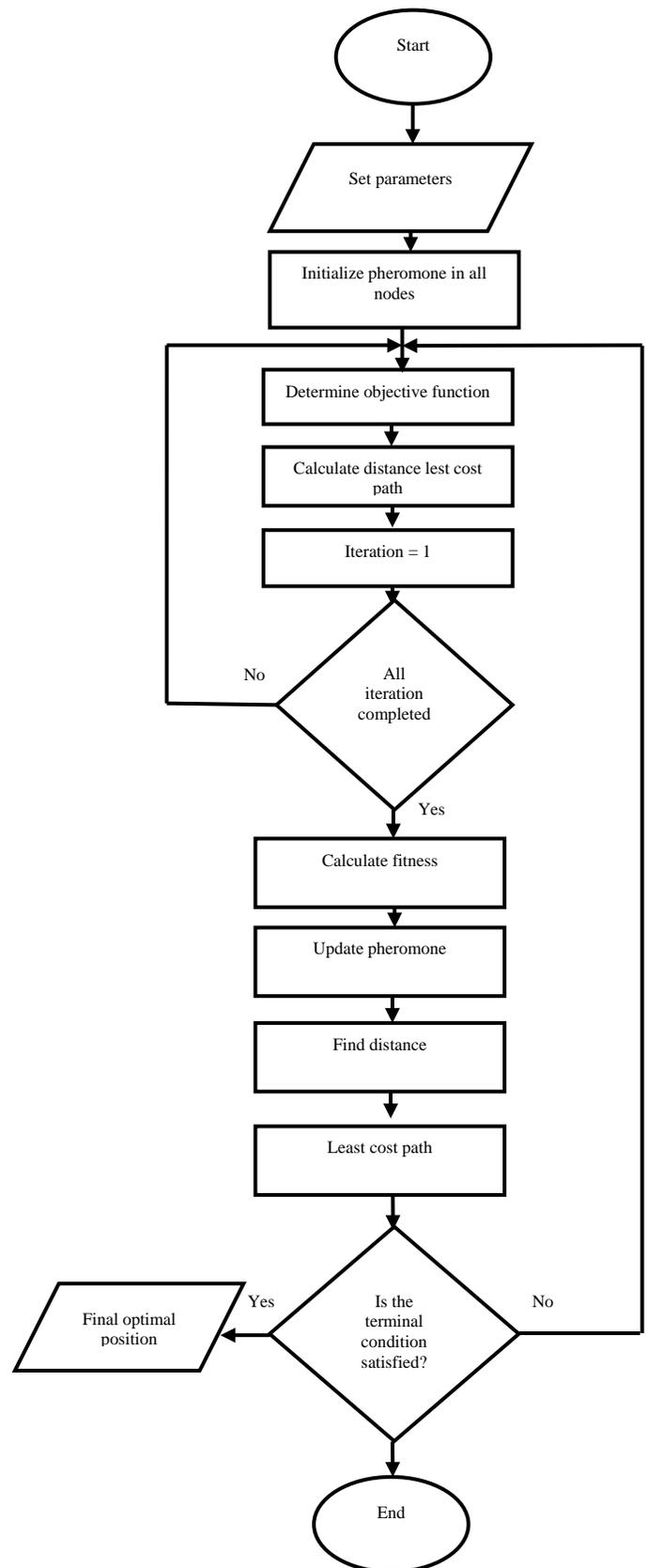found
   Return the optimally best node

Fig. 3. Proposed Flowchart MOIAC.

V. RESULTS AND DISCUSSION

This section discusses the experimental results of the model of determining the least cost path to reach the optimal and the most appropriate path using the proposed algorithms MOIPS and MOIAC in addition to Zipf random distributions. These algorithms are applied on a JAVA program. A comparison between these proposed algorithms and other algorithms has been held on the grounds of the time of their application, the cost, the time consumed, the high availability, determining the optimal and the most appropriate path, and the efficiency of the proposed system. The experiments have been carried out using a JAVA program that provides several classes to simulate and model the proposed system; we improve variant classes for the proposed system.

Fig. 4. Demonstrate the Cost for each Order.

In Fig. 4 compares between three algorithms on the grounds of the transportation rate and cost among suppliers and end customers. The algorithm determines the optimal and the shortest path according to MO with ACO and PSO. The experimental results show that MOIAC algorithm achieves the least cost when compared to MOIPS and MPACA algorithms. It is also the quickest in moving among nodes through the optimal paths. The results also show that the proposed algorithms have proven their excellence over the other algorithms according to the rate of goods transportation to the end customer.
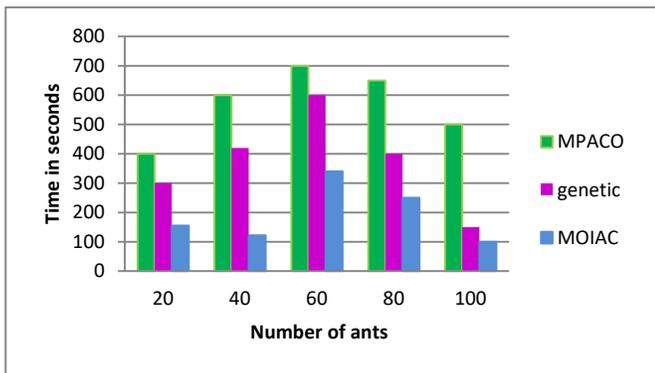

Fig. 5. Task Number of Ants.

Fig 5 shows that the proposed algorithm executes its missions in a lesser time when compared to the other algorithms. It also exceeds the other algorithms' performance when variant numbers of ants and scenarios are addressed. The

results show that the proposed algorithm executes the scenario of 100 ants in a lesser time when compared to MPACS and Genetics algorithms.
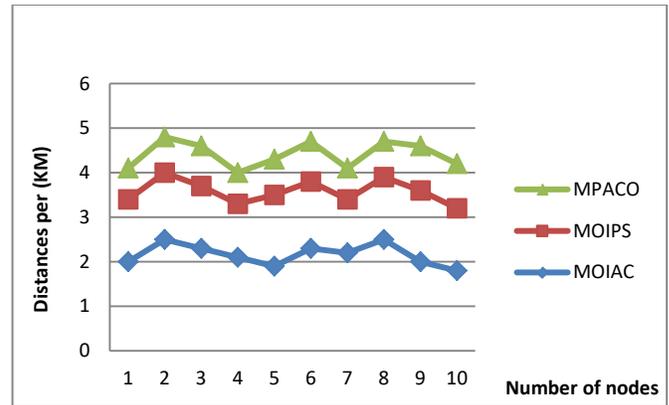

Fig. 6. Distances between the Number of Nodes.

Fig. 6 shows that the relation among the different algorithms reduces the time consumed and the cost of the transportation process done between the suppliers and the end customers using MOPSO and MOACO. The algorithm also considers determining the path with the least cost to reach the end customer. The experimental results show that the proposed algorithm surpasses the other algorithms.
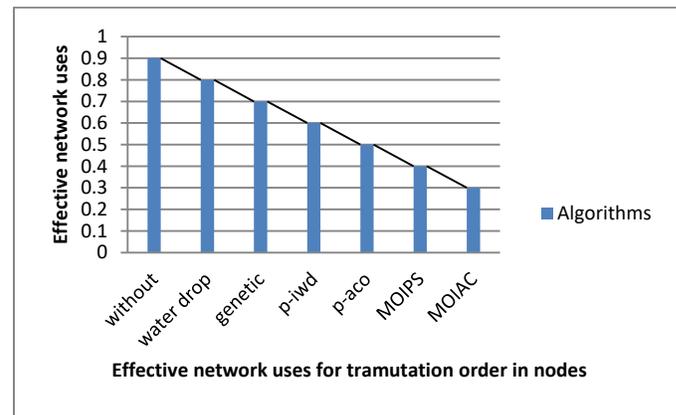

Fig. 7. Effective Network uses for Transmutation Order in Nodes.

Fig. 7 shows an effective version of the network and the percentages of goods crossing the nodes in the range of 0.1 to 1; the system detects the arrival time, the repetition frequency, and the response time among the nodes of the system. The improved bandwidth proves to be more effective with the proposed algorithm; it reaches 0.3 while it reaches 0.9 in the other algorithms. MOIAC algorithm surpasses the other algorithms on the grounds of efficiency, cost, and time.

Fig. 8 shows the determination of the optimal, shortest, and the least cost path among nodes, which positively affects the transportation process among the suppliers and the end consumers. When goods are ordered, the algorithm chooses the optimal, the shortest, and the least cost path among nodes on the proposed system. The proposed algorithm surpasses the other algorithms in the process of determining the optimal, the shortest, and the least-cost path. It is noteworthy that we have

tested the two proposed algorithms MOIAC and MOIPS, and the first surpasses the latter.
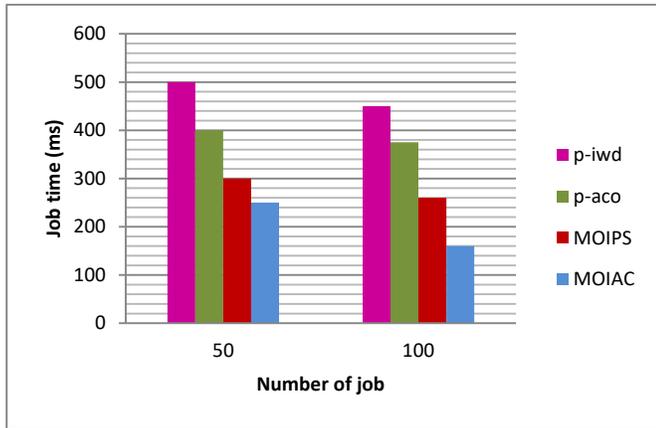

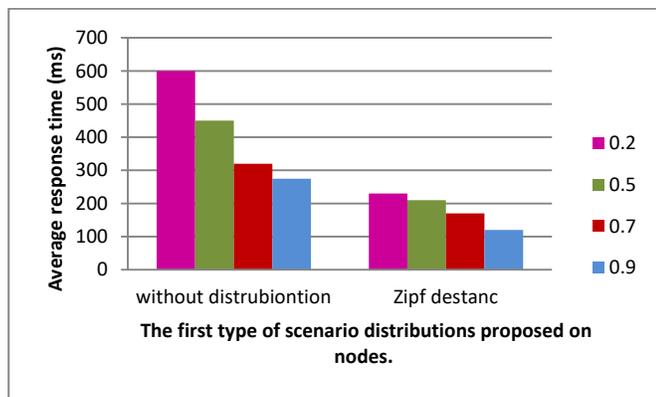Fig. 8.   Distances between the Number of Nodes.

Fig. 9.   Average Response Time of Zipf.

Fig. 9 shows the use of MOIAC algorithm with ZIPF distributions to determine the optimal and the most appropriate path to transport goods from the suppliers to the end customers. In determining the optimal path, variant distribution has ranged from 0.1 to 0.9. The experimental results prove the proposed algorithm's excellence in achieving optimal results in creating variant ZIPF distributions.

VI.   CONCLUSION AND FUTURE WORK

In this paper, we propose two algorithms to solve the problem of determining the optimal path between nodes, improving time-consumption and reducing cost simultaneously. The two proposed algorithms are used with Multi-Objective Optimization to improve the quality of transportation between the supplier and the end customers. MOIAC algorithm is designed to determine the optimal paths (the shortest and the least cost paths) among nodes. ZIPF distributions is integrated to create random distributions to reach the optimal nodes in each process. MOIPS algorithm is also designed to determine the optimal paths while reducing the time consumed in transporting goods from the suppliers to the end customers, and improving the transportation process following the least cost path. The proposed system has been tested on JAVA Program and has been also compared with other algorithms such as Water drop , genetic and bee.

Being integrated with Multi-Objective Optimization in the field of transportation and tested by AI techniques, the simulation results show the efficiency of the proposed algorithms. Many other objectives can be addressed in further works, such as improving means of transportation and reducing resource consumption using the least-cost paths. We also propose addressing other objectives, such as improving the cost, reducing the time consumed between the supplier and the end customer, speeding up the transportation process, and reducing risks. The two proposed algorithms are applicable with other objectives in the field of goods transportation.

REFERENCES

[1]   P. Fiala, "Information sharing in supply chains," Omega, vol. 33, no. 5, pp. 419-423, Oct. 2005. doi:10.1016/j.omega.2004.07.006.

[2]   F. Alawneh and G. Zhang, "Dual-channel warehouse and inventory management with stochastic demand," Transport. Res. E-Log., vol. 112, pp. 81-106, Apri. 2018. doi:10.1016/j.tre.2017.12.012.

[3]   M. Varsei and S. Polyakovskiy, "Sustainable supply chain network design: A case of the wine industry in Australia," Omega, vol. 66, pp. 236-247, Jan. 2017. doi:10.1016/j.omega.2015.11.009.

[4]   M. C. Chen, Y. H. Hsiao, and H. Y. Huang, "Semiconductor supply chain planning with decisions of decoupling point and VMI scenario," IEEE Trans. Syst., Man, Cybern., Syst., vol. 47, no. 5, pp. 856–868, May 2017. doi:10.1109/tsmc.2016.2521740.

[5]   Scheibe, P.Kevin., J. Blackhurst. "Supply chain disruption propagation: a systemic risk and normal accident theory perspective." International Journal of Production Research 56.1-2: 43-59. 2018. doi:10.1080/00207543.2017.1355123.

[6]   K. Govindan, M. Fattahi, and E. Keyvanshokooh, "Supply chain network design under uncertainty: A comprehensive review and future research directions," Eur. J. Oper. Res., vol. 263, no. 1, pp. 108-141, Nov. 2017. doi:10.1016/j.ejor.2017.04.009.

[7]   Z. Hong, W. Dai, H. Luh, and C. Yang, "Optimal configuration of a green product supply chain with guaranteed service time and emission constraints," Eur. J. Oper. Res., vol. 266, no. 2, pp. 663-677, Apr. 2018. doi:10.1016/j.ejor.2017.09.046.

[8]   L. A. Moncayo–Martínez and Gustavo Recio, "Bi-criterion optimisation for configuring an assembly supply chain using Pareto ant colony meta-heuristic," J. Manuf. Syst., vol. 33, no. 1, pp. 188-195, Jan. 2014. doi:10.1016/j.jmsy.2013.12.003.

[9]   X. Zhang, et al., "Cooperative coevolutionary bare-bones particle swarm optimization with function independent decomposition for large-scale supply chain network design with uncertainties," IEEE Trans. Cybern., vol. 50, no. 10, pp. 4454-4468, Oct. 2020. doi:10.1109/tcyb.2019.2937565.

[10] G. Zhang, J. Shi, S. S. Chaudhry, and X. Li, "Multi-period multi-product acquisition planning with uncertain demands and supplier quantity discounts," Transport. Res. E-Log., vol. 132, pp. 117-140, Dec. 2019. doi:10.1016/j.tre.2019.11.005.

[11] Q. Long, X. Tao, Y. Shi and S. Zhang, "Evolutionary game analysis among three green sensitive parties in green supply chains," IEEE Trans. Evol. Comput., vol. 25, no. 3, pp. 508-523, Jun. 2021. doi:10.1109/tevc.2021.3052173.

[12] G. Soni, V. Jain, F. T. Chan, B. Niu, and S. Prakash, "Swarm intelligence approaches in supply chain management: potentials, challenges and future research directions," Int. J. Supply Chain Manage., vol. 24, no. 1, pp. 107-123, Jan. 2019. doi:10.1108/scm-02-2018-0070.

[13] L. A. Moncayo–Martínez and E. Mastrocinque, "A multi-objective intelligent water drop algorithm to minimise cost of goods sold and time to market in logistics networks," Expert Syst. Appl., vol. 64, pp. 455-466, Dec. 2016. doi:10.1016/j.eswa.2016.08.003.

[14] A. Diabat and A. Jebali, "Multi-product and multi-period closed loop supply chain network design under take-back legislation," Int. J. Prod. Econ., vol. 231, 107879, Jan. 2021. doi:10.1016/j.ijpe.2020.107879.

[15] H. Zhao, Z. G. Chen, Z. H. Zhan, S. Kwang, and J. Zhang, "Multiple populations co-evolutionary particle swarm optimization for multi-

objective cardinality constrained portfolio optimization problem," Neurocomputing, vol. 430, pp. 58-70, Mar. 2021. doi:10.1016/j.neucom.2020.12.022.

[16] X. Zhang, Z. H. Zhan, and J. Zhang, "A fast efficient local search-based algorithm for multi-objective supply chain configuration problem," IEEE Access, vol. 8, pp. 62924-62931, Apr. 2020. https://doi.org/10.1109/access.2020.2983473.

[17] X. Liu, et al., "Coevolutionary particle swarm optimization with bottleneck objective learning strategy for many-objective optimization," IEEE Trans. Evol. Comput., vol. 23, no. 4, pp. 587-602, Aug. 2019. doi:10.1109/tevc.2018.2875430.

[18] H. Zhao et al., "Local binary pattern-based adaptive differential evolution for multimodal optimization problems," IEEE Trans. Cybern., vol. 50, no. 7, pp. 3343-3357 Jul. 2020. Doi:10.1109/tcyb.2019.2927780.

[19] Gunjan, S., et al. "Swarm intelligence approaches in supply chain management: potentials, challenges and future research directions. Supply Chain Management" An International Journal, 24(1), 107-123. (2019)./doi/10.1108/SCM-02-2018-0070.

[20] Hajikhani, Alborz, Mohammad Khalilzadeh, and Seyed Jafar Sadjadi. "A fuzzy multi-objective multi-product supplier selection and order allocation problem in supply chain under coverage and price considerations: An urban agricultural case study." Scientia Iranica 25.1: 431-449. 2018. DOI: 10.24200/sci.2017.4409.

[21] Loni, Parvaneh, Alireza Arshadi Khamseh, and Seyyed Hamid Reza Pasandideh. "A new multi-objective/product green supply chain considering quality level reprocessing cost." International Journal of Services and Operations Management 30.1: 1-22. 2018. doi:10.1504/ijsom.2018.091437.

[22] Cao, Cejun, et al. "A novel multi-objective programming model of relief distribution for sustainable disaster supply chain in large-scale natural disasters." Journal of Cleaner Production 174: 1422-1435. 2018. doi:10.1016/j.jclepro.2017.11.037.

[23] Singh, Sujeet Kumar, and Mark Goh. "Multi-objective mixed integer programming and an application in a pharmaceutical supply chain." International Journal of Production Research 57.4: 1214-1237. 2019. doi:10.1080/00207543.2018.1504172.

[24] Hendalianpour, Ayad, et al. "A linguistic multi-objective mixed integer programming model for multi-echelon supply chain network at bio-refinery." EuroMed Journal of Management 2.4: 329-355. 2018. doi:10.1504/emjm.2018.096453.

[25] E. Mastrocinque, B.Yuce , A. Lambiase and M. S. Packianather, "A Multi-Objective Optimization for Supply Chain Network Using the Bees Algorithm" International Journal of Engineering Business Management. Vol. 5, 38:2018. doi:10.5772/56754.

[26] R. E. Rasi, M.Sohanian "A multi-objective optimization model for sustainable supply chain network with using genetic algorithm" Journal of Modelling in Management. 3 August 2020. Doi: 10.30495/JSM.2022.1911221.1468.

[27] H. Banerjeea , Dr. V. Ganapathyb and Dr. V. M. Shenbagaramanc "Uncertainty Modelling in Risk-averse Supply Chain Systems Using Multi-objective Pareto Optimization" eprint arXiv:2004.13836 . April 2020.

[28] L. A Moncayo-Martínez, D. Zhang, "A Multi-objective Optimization for Supply Chain Network using Intelligent Water Drop" Industrial and Systems Engineering Research Conference. May (2014).

[29] S. Gupta1, A. Haq , I. Ali , B. Sarkar "Signifcance of multi objective optimization in logistics problem for multi product supply chain network nder the intuitionistic fuzzy environment" Complex & Intelligent Systems. 6 March 2021. https://doi.org/10.1007/s40747-021-00326-9.

[30] R.Sun, X. Wang, G. Zhao, "An Ant Colony Optimization Approach to Multi-Objective Supply Chain Model" The Second International Conference on Secure System Integration and Reliability Improvement . DOI 10.1109/SSIRI. 2008. doi:10.1109/ssiri.2008.35.

[31] P.Nguyen, K.Phuc, N. Thao "Ant Colony Optimization for Multiple Pickup and Multiple Delivery Vehicle Routing Problem with Time Window and Heterogeneous Fleets" Logistics, 10 May 2021. doi:10.3390/logistics5020028.

[32] Y.Wenfang, H.Guisheng, X. Pengcheng, L.Jingjing "Supply Chain Joint Inventory Management and Cost Optimization Based on Ant Colony Algorithm and Fuzzy Model" Technical Gazette 26, 1729-1737, 6,2019. doi.org/10.17559/TV-20190805123158.

[33] X. Zhang, , Z.Zhan, W. Fang, P. Qian, J. Zhang, "Multi-Population Ant Colony System with Knowledge-based Local Searches for Multiobjective Supply Chain Configuration" IEEE Transactions on Evolutionary Computation, DOI: 10.1109/TEVC.2021.3097339.

[34] A.Awad, R. Salem, H. Abdelkader , M. Abdul Salam" A Novel Intelligent Approach for Dynamic Data Replication in Cloud Environment " IEEE Access, 09 March 2021. doi:10.1109/access.2021.3064917.

[35] R. SALEM , M. Abdul Salam, H. Abdelkader ,A.Awad, " An Artificial Bee Colony Algorithm For Data Replication Optimization In Cloud Environments " Ieee Access, 03 December ,2019. DOI:10.1109/ACCESS.2019.2957436.

[36] A.Awad, R. Salem, H. Abdelkader , M. Abdul Salam" A Swarm Intelligence-based Approach for Dynamic Data Replication in a Cloud Environment " International Journal of Intelligent Engineering and Systems • March 2021.DOI:10.22266/ijies2021.0430.24.