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TS and ACO in Hybrid Approach for Product Distribution Problem

Khadidja Yachba, LIO Laboratory, University of Relizane, Algeria*
https://orcid.org/0000-0002-7754-2823

Belayachi Naima, LIO laboratory, Normal Hight School of Oran, Algeria

Karim Bouamrane, University Oran 1, Algeria
https://orcid.org/0000-0002-6953-0339

ABSTRACT

In order to solve the transport problem, a set of bio-inspired meta heuristics are proposed. They are based on the natural behavior of swarms, bees, birds, and ants that emerged as an alternative to overcome the difficulties presented by conventional methods in the field of optimization. In this work, the authors use a hybrid of two optimization methods in order to solve the problem of product distribution from a central warehouse to the different warehouses distributed in different cities. The optimization of the distribution process is done by identifying through the proposed contribution the optimal path that combines between a minimum distance with a good condition of the path taken. In order to situate the approach proposed in this article, the authors compare the results obtained with the result obtained using ACO without hybridization. The results obtained by hybridizing the two methods, ant colony optimization (ACO) and tabu search (TS), are better.

KEYWORDS

Ant Colony Optimization, Distribution, Hybridization, Logistic, Optimization Methods, Supply Chain, Taboo Research, Transport

INTRODUCTION

Today's companies are facing fundamental challenges, namely technological change and increased competition as well as the demands of the market. Customer requirements have become more and more unpredictable. Additionally, the challenge of competitiveness has been becoming greater and greater for companies: In this case, companies seek to stabilize and increase their market shares and make acceptable profits in a demanding environment. To do this, companies must be able to thrive in this environment and meet demand to satisfy their customers, given that the objective of all companies is to deliver products to their customers with the requested quality. Consequently, logistics have increasingly become an essential function for companies. Indeed, it is the knowledge and mastery of logistics that will determine companies' performance.

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*Corresponding Author

Logistics are not limited to the organization of transport, raw materials, and goods. They are actually a management control technique, the flow of raw materials and product from their sources of supply to their consumption point. Moreover, several actors have said that the logistic chain appeared by following an evolution that includes industrial logistics: the purchase of raw materials, transport, etc., storage logistics: the transport of finished products and their warehousing, and distribution logistics: the transport of orders to the distribution point, storage, and inventory management in the retail store. The proposed approach in this article is to optimize logistic distribution (the product transport component).

Through this evolution of logistics, we have seen that physical distribution represents the most important part of logistic expenses. In fact, distribution logistics can be defined as a structure formed by the partners involved in the competitive exchange process to make goods and services available to consumers, users, intermediaries, or buyers.

One of the most obvious manifestations of logistic activity is the growth of freight transportation due to the expansion of world trade. The globalization of the industry, including planning, sourcing, manufacturing, and marketing, has resulted in increased trade complexity and the development of transportation networks.

Successful businesses are also those with efficient logistics. Transportation can represent a significant percentage of logistics. Companies always seek to minimize the cost of getting goods from origins to destination while respecting all the constraints, where each researcher offers a solution to this problem. As a result, optimizing transport costs has become a key factor in the success of any business.

The problems of localization, planning, scheduling, and transport are generally NP-hard (non-deterministic polynomial-time hard) problems; their algorithmic complexity is an important problem for a very large number of researchers. However, in an increasingly competitive industrial context, companies are asking for decision support tools capable of integrating a global vision of their organization.

Hybrid techniques based on meta-heuristics are particularly suited to the characteristics of logistics systems.

In this contribution, the authors are interested in the problem linked to the optimization of transport within a company transport network and in proposing a hybrid approach (TS, ACO) to ensure that the production transport to the destinations is well received in order to satisfy customer requests.

The main objective of this study is to provide companies with efficient use of transport to increase their returns. As a result, several questions are required:

- How can the best path to take be properly determined?
- How can the distances travelled be minimized?
- How should we proceed to reduce transport costs?
- How can the productivity of companies be increased by optimizing the product distribution process (transport component)?

This article is organized as follows: the first section presents an introduction to the concept of this study, and the second section reviews some related work, followed by the positioning of the proposed approach. The third section provides the details of the hybridization proposed in this article. The fourth section presents the obtained results, which are followed by a comparative study. The last section presents a conclusion and some perspectives.

RELATED WORK

Transportation in logistics (product distribution) is a problem of finding a Hamiltonian path at minimum cost, for example, finding an optimized scan chain route in integrated chip testing. An effective solution to these problems will ensure that tasks are performed efficiently and thereby increase productivity. Due to its importance in many industries, this problem is still being investigated by researchers from a variety of disciplines (Loubiére, 2016). Certain animals' behaviour can be adapted to solve the problem of transportation in logistics.

The distribution problem in transport has been shown to be an NP-hard problem. Therefore, it is difficult to solve. Consequently, the time taken by an exact method to find an optimal solution is exponential and sometimes inapplicable. For this reason, this challenge can be reduced to an optimization problem to be solved with approximate methods – generally, meta-heuristics, which are designed to find appropriate solutions to NP-hard problems in a reasonable time.

Several searches have been done in this area; in this section, the authors present the most recent searches in chronological order.

Pirkula and Jayaraman (1998) proposed a mixed-integer programming model, PLANWAR, which provided an efficient heuristic solution procedure to the supply chain management problem based on Lagrangian relaxation.

Tuzun and Burke (1999) presented a two-phase tabu search architecture for the solution of the Location Routing Problem (LRP). The two-phase approach offered a computationally efficient strategy that integrates facility location and routing decisions.

In the work of Alptekinoğlu and Tang (2005), the authors developed a model of a general multichannel distribution system subject to stochastic demand through a decomposition scheme that enables users to develop a near-optimal distribution policy with a minimum total expected distribution cost.

In the work of Zhang et al. (2007), the authors proposed a direct solution approach to the reacting transport problem through the inexpensive acquisition of sensitive information. Besides, the approach presented in computational fluid mechanics and biotransport used mathematical programming techniques for the inversion of distributed systems.

Kefi et al. (2015) proposed ant monitored by particle swarm optimization to determine the short path between numbers of customers.

Osaba et al. (2016) used the meta-heuristics bat approach and intelligent bat algorithm. In this work, the authors focused on finding a route, which started and ended at the same node. The cost of the trip between two nodes was identical.

Hertono et al. (2018) proposed a hybrid method; this method used optimization by ant colony, optimization by particle swarm, and the 3-Opt algorithm to solve a problem in order to determine the route of the seller visiting some places (customers) that start and end with a certain customer. The authors presented an improvement of the hybridization of these three algorithms while focusing on three modifications made to the algorithm 3-Opt.

In the work of Bersani et al. (2019), a cooperative distributed model for the control of product flow in a network of cooperative inventory systems was proposed. The proposed solution was based on the dual decomposition of the problem, which allowed for the reaching of the optimal control.

Dahan et al. (2019) used dynamic optimization by ant colony steering wheel (DFACO). An improvement of the approach colony of flying ants optimization was proposed. In addition, the modifications were intended to help the DFACO algorithm find better solutions in less processing time and to avoid getting stuck in local minima.

Gulcu (2019) proposed a two-hybrid approach with 2-opt algorithms hybridization. The authors found circuits for *m* sellers, which all started and ended at the depot so that each intermediate node was visited exactly once and the total cost of the visit nodes was minimized.

Liu et al. (2020) presented an improving ant colony optimization algorithm with the Epsilon-Greedy algorithm and Lévy flight.

To resolve this type of problem, the authors of this article used robust meta-heuristics, which allowed us to minimize the cost of distribution. Ant colony algorithms are known to be very effective for NP-hard problems, but they are very heavy and too greedy in terms of computing time. Hence, the idea of hybridizing this algorithm by the Taboo Search (TS) optimization algorithm is a highly efficient and easy-to-understand operation.

It is undeniable that meta-heuristics have an important role to play to be able to accommodate all the difficulty of a logistics system, but it is equally undeniable that meta-heuristics alone will not suffice. This is why the authors of this article considered highlighting hybrid techniques based on meta-heuristics and chose the two methods: Ant colony optimization (ACO) and Taboo Search (TS).

Hybridization between these two algorithms was previously used in the work of Ho et al. (2006), Eswaramurthy and Tamilarasi (2009), Hoshikawa and Otani (2010), and Lai and Tong (2012). In the works cited above, the solutions proposed are based on a single constraint, but in the presented case, the authors take into account two constraints, namely the distance (the minimum distance) and the reliability of the path (the state of the path taken: good, medium, weak).

The objective of this work is to address the problem of identifying the best path for the commodity distribution problem using meta-heuristics as a solution approach, in particular the ant colony algorithm coupled with the TS algorithm.

CHOICE AND POSITIONING OF THE PROPOSED APPROACH

This work forms part of the research in the field of decision support systems, transport, maritime transportation (Yachba et al., 2016; Bendaoud and Yachba, 2017), logistics (Yachba et al., 2021), optimization (Belayachi et al., 2017; Amrani et al., 2018l; Yachba et al., 2018), and multicriteria methods (Yachba and Bouamrane, 2015; Yachba et al., 2018), (Tahiri et al., 2020). This article addresses the problem related to product distribution and uses a hybridization method (ACO and TS).

The authors were highly motivated to focus on this article and to choose the use of two techniques, ACO and TS. ACO differs from other close meta-heuristics (such as distribution estimation algorithms or optimization by a particulate swarm) in its constructive aspect. Indeed, in combinatorial problems, the best solution may be found even though no ant has actually experienced it. So, in the example of the travelling salesman problem, it is not necessary for an ant to walk on the shortest route, which can be built from the most strengthened segments of the best solutions.

In addition, combinatorial variants may have an advantage over other meta-heuristics in cases where the studied graph can change dynamically during execution. The ant colony adapts relatively and flexibly to the changes. This is interesting for the case treated in this article.

ACO-TS hybridization offers the advantage of the efficiency of the taboo method due to the advantage of having a simplified parameterization. The parameterization first consists of finding an indicative value of iterations during the prohibited movements.

In the presented study, the company (supplier) has only one warehouse for each customer, where customers make their requests for a quantity of products from the warehouse. In cases where the quantity of ordered products is not available, the order is processed by the supervisor (the main warehouse). The more the number of customers increases, the more the number of orders increases. Consequently, companies must ensure that their products are well transported to their warehouses to satisfy their customers. Furthermore, the particularity of the proposed work is articulated in the use of two optimization methods to better exploit the search space and improve the best solution found. This hybridization allows us to find an optimal and reliable way to transport a product from a warehouse to a customer.

THE ACO AND TS OPTIMIZATION METHOD

In this section, the authors present the proposed contribution, which is based on the hybridization of the two algorithms ACO and TS. Before detailing the contribution, an overview of the behaviour of the two algorithms will be presented.

Hybrid ACO-TS

The ACO is one of the algorithms that was formalized as a new metaheuristic by Dorigo and Di Caro in 1999 (Dorigo and Caro, 1999). It is a stochastic technique which uses artificial ants to find solutions to combinatorial optimization problems (Yun et al., 2013) in an acceptable time. The ACO algorithm is based on imitating the behaviour of the ant colony when collecting food (Dreo, 2004).

Each ant leaves the nest and heads for food until it reaches an intersection, where it must decide which path to select. At first, this choice is random, but after a while, the majority of ants will move along the optimal path.

This happens due to the collective intelligence colony, where each ant moves and deposits a chemical called a pheromone to mark the route taken. The pheromone trail evaporates over time. As a result, a shorter path will have more pheromones as they will have less time to evaporate before settling again. Each ant chooses paths that have more pheromones, so shorter routes will be selected with higher probabilities until almost all ants follow the shortest path. However, this is a dynamic change, with a new obstacle or a new passage, in which the ants will quickly adapt to a new situation (Tuba and Javonovic, 2013). Figure 1 shows how the ants find the shortest branches (Min and Yant, 2005).

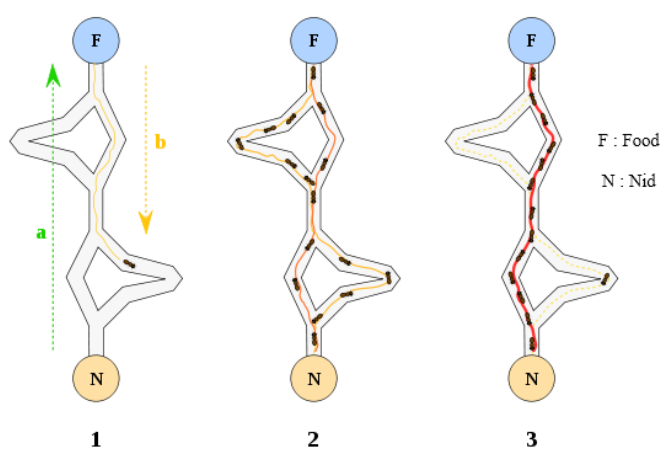
AN ADAPTATION OF ACO IN THE PROBLEM OF IDENTIFYING THE BEST PATH FOR THE DISTRIBUTION OF FINAL PRODUCT

In the ACO algorithm, each ant is initially placed on a randomly chosen customer. Besides, each has a memory that stores the partial solution which was built before. Initially, the memory contains the departure customer. Starting from this customer, an ant iterates from one customer to another. When it is in a customer *i*, an ant *k* chooses to go to a customer not yet visited, *j*, with a probability given by Alaya (2009):

$$p_{ij}^{k}\left(t\right)=\frac{\left[T_{ij}\left(t\right)\right]^{\alpha}*\left[\eta_{ij}\right]^{\beta}}{\sum_{y\in N_i^k}\left(\left[T_{iy}\left(t\right)\right]^{\alpha}*\left[\eta_{ij}\right]^{\beta}\right)}\text{ if j}\in N_i^k\ \text{ 0 else} \tag{1}$$

such that:

Figure 1. Selection of the Shortest Branches by an Ant Colony (Men, 15)



- T_{ij} (t) is the intensity of the pheromone trace in the edge (i, j) at time t; and
- $\eta_{ij} = 1/d_{ij}$ is heuristic information valid a priori, where d_{ij} equals $dist_{ij}$ (the distance between city i and city j [customer i and customer j]) multiplied by $etat_{ij}$ (the path state between them), the idea being to attract ants to the nearest cities with a reliable path.

$$d_{ij} = dist_{ij} * etat_{ij} \tag{2}$$

with $etat_{ij}$ $\{1,2,3\}$:

$$etat_{ij} = \begin{cases} 1: \text{ if the state of the path is Good} \\ 2: \text{ if the state of the path is Medium} \\ 3: \text{ if the state of the path is Low} \end{cases}$$

- α and β are two adjustable positive parameters, which control the relative weight of the pheromone trail and the heuristic information; and
- N_i^k is the feasible neighbourhood of ant k, (all the cities not yet visited by ant k (Alaya, 2009)).

Solution-building ends after each ant has completed a turn. Then, the pheromone traces are updated. First, the traces of pheromones are reduced with a factor (the evaporation of pheromones), where p is a random variable uniformly distributed in [0,1] and is used to avoid the unlimited accumulation of pheromones. Also, it allows the algorithm to forget bad decisions previously made.

The pheromone update formula is as follows (Alaya, 2009):

$$T_{ij}\left(t+1\right) = \left(1-p\right) * \ T_{ij}\left(t\right) + \sum_{k=1}^{nbAnts} \Delta t_{ij}^{k} \tag{3}$$

- $nbAnts$: the number of ants.
- Δt_{ij}^{k} : the quantity of pheromones that ant k deposits on the edge (i, j), defined by:

$$\Delta t_{ij}^{k} = \begin{cases} 1/L^{k(t)} & if\ arc\ (i,j)\ used\ by\ ant\ k \\ 0 & otherwise \end{cases} \tag{4}$$

such that L^k is the length of the generated turn by ant k.

With this formula, the edges of the most reliable lathe will receive the greatest amount of pheromones (Stutzle and Dorigo, 1999). In general, the edges, which are used by several ants and belong to the most reliable towers, will receive more pheromones. Consequently, they will be more favoured in future iterations of the algorithm (Alaya, 2009). The algorithm would not be complete without the pheromone track evaporation process to avoid being trapped in suboptimal solutions. See Figure 2 for our algorithm (Costanzo et al. 2006).

$0 \leq p < 1$
$\alpha \geq 0$
$\beta \geq 0$

Figure 2. ACO Algorithm

For each ant K = 1 ... m **Do**

Choose a customer randomly

For each customer not visited i **Do**

Choose a customer i from the J_i^k list of remaining customers according to formula (1)

end for

Depositing a track $\Delta T^{k}_{i,j}$: on the route $T^{K}(t)$ accordance with formula (4)

end for

Evaporate the tracks according to the formula (3)

THE TS ALGORITHM

TS was formalized by Glover (Glover and Laguana. 1997). Its main particularity lies in the implementation of mechanisms inspired by human memory (Glover et al, 2007).

The Basic Principle of the TS Algorithm

The TS algorithm works with only one configuration at a time (at the beginning, any solution), which is updated during successive iterations. The principle is to choose the most robust solution at each iteration.

The danger, then, is of returning to an already selected configuration. To avoid this phenomenon, a List-tab list is created to store the last visited solutions and prohibit any movement to a solution from this list. This List-tab list is called a taboo list.

The solutions remain only in List-tab for a limited number of iterations. The List-tab list is therefore a short-term memory. If a solution is in List-tab, it is said to be a taboo solution. Likewise, any movement that leads us from the current solution to a List-tab solution is called a taboo movement. The flowchart of this algorithm is represented in Figure 3 (Glover et al, 2007).

HYBRID APPROCH: ACO-TS

The main idea behind the design of algorithm hybridization is simple: For a given optimization problem, we have two algorithms, each one with its strengths and weaknesses. We want to create a powerful algorithm that combines the strengths of both or to improve one algorithm by using the other to optimize the solution found.

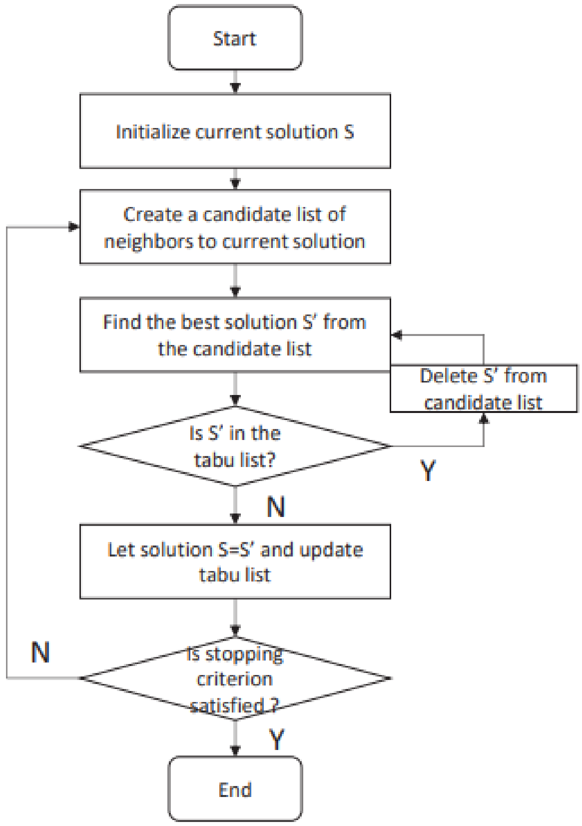
Heuristics are directly related to the physical problem in that they try to solve it, while meta-heuristics adjust the parameters of heuristics.

The hybrid approach between the ACO algorithm and the TS algorithm addresses the distribution problem to find the shortest and most reliable path (the optimal path). The TS algorithm will take last as the initial solution S0 ranked best S * solution for the moment. Taboo chooses a new solution S in the vicinity of the best solution s *. This operation is repeated for each of the 200 iterations (see Figure 4).

EXECUTION SCENARIO

This section is completely dedicated to the implementation of the proposed study relating to the optimization of product distribution. The authors explain the operation of the hybridization (ACO-

Figure 3. Flowchart of TS Algorithm (wang et al, 17)



TS) algorithm, which is the kernel of this study, across the unfolding of a scenario to give an optimal solution for the treated problem.

The following figure illustrates an example of the execution of the algorithms with and without hybridization.

The authors applied the proposal of product distribution, which is shown in Figure 5, where the lines represent the information's relating to the different warehouses (the warehouse identifier, the warehouse name, etc.). The list of warehouses (clients) with their geographical coordinates (pos$x$, pos$y$) is shown in the figure.

In this experiment example, we had 10 cities to visit (10 customers to supply) from a central warehouse. The goal was to find the best way to supply the 10 clients while taking into consideration the state of each path and the minimum distance (see Figure 5). In addition, each client had x and y coordinates to be able to locate them, and the starting data was chosen randomly.

After the location of the different customers, the matrix distance was calculated to calculate the minimum distance (Figure 6), and the path state was recorded (Figure 7).

The calculated distance represents the distance between the central warehouse and the different clients.

Figure 7 displays a sample of path states. For each path, we calculated its state (1 if the state of the path was Good, 2 if the state of the path was Medium, or 3 if the state of the path was Low).

Then, according to the objective function, which includes two constraints – path state and minimum distance – the reliability matrix was calculated (see Figure 8).

Figure 4. The Hybridization Flowchart Between the Two Methods ACO and TS

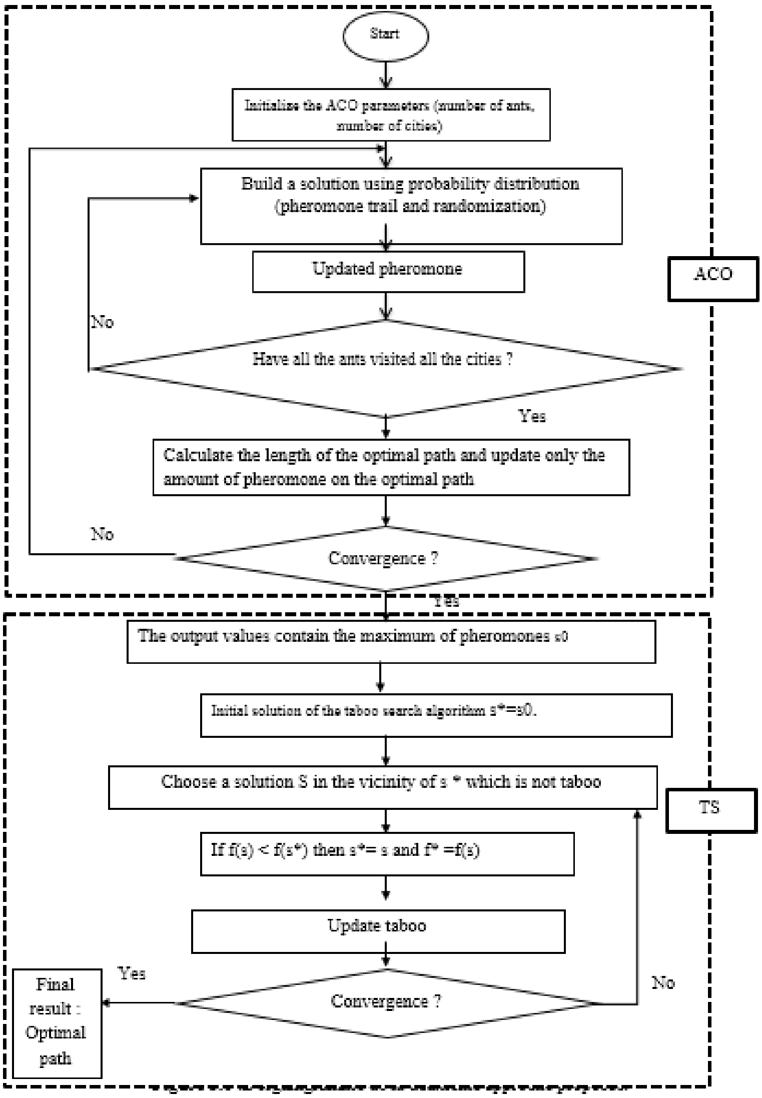


Figure 5. Example of Customers (Clients)

id_entrepot	nom	zone	wilaya	pos_x	pos_y
1	entr01	ouest	oran	35.68	-0.62
2	entr02	ouest	bouira	36.3536	3.8415
3	entr03	ouest	ghardaia	32.49	3.64
4	entr04	ouest	Tiaret	35.1117	1.2873
5	Entr05	ouest	béchar	31.63	-2.21
6	Entr06	est	Bordj Bou Arréridj	36.08	4.78
7	Entr07	est	sétif	36.1696	5.4047
8	Entr08	ouest	El Bayadh	33.6947	1.0257
9	Entr09	ouest	tissemsilt	35.59	1.81

Figure 6. Distances Matrix

Distances Matrix

0.0 1117.98 44.21 1445.78 340.69 3082.52 225.25 421.25 819.99 172.1

1117.98 0.0 1592.81 1664.48 292.17 1327.69 2332.84 2903.82 382.58

44.21 1592.81 0.0 1194.2 536.3 3430.61 70.72 195.51 849.83 333.44 3

1445.78 1664.48 1194.2 0.0 706.0 2738.44 1036.28 1111.44 558.96 81

340.69 292.17 536.3 706.0 0.0 1377.65 978.79 1359.19 160.72 28.51 1

3082.52 1327.69 3430.61 2738.44 1377.65 0.0 4217.64 4922.95 904.35

225.25 2332.84 70.72 1036.28 978.79 4217.64 0.0 31.23 1215.99 705.9

421.25 2903.82 195.51 1111.44 1359.19 4922.95 31.23 0.0 1610.41 10

819.99 382.58 849.83 558.96 160.72 904.35 1215.99 1610.41 0.0 291.5

172.14 472.39 333.44 814.14 28.51 1801.46 705.93 1034.1 291.56 0.0

614.66 3216.12 335.27 564.2 1571.92 5098.71 140.16 139.53 1766.15

Figure 7. Path States Matrix

Path States Matrix

0	2	1	2	2	1	3	3	1	2	3
2	0	3	2	2	2	2	1	1	2	2
1	3	0	2	3	3	1	2	3	2	3
2	2	2	0	3	3	3	1	3	2	1
2	2	3	3	0	1	2	2	2	2	3
1	2	3	3	1	0	2	3	2	1	3
3	2	1	3	2	2	0	3	3	3	2
3	1	2	1	2	3	3	0	3	3	2
1	1	3	3	2	2	3	3	0	2	2
2	2	2	2	2	1	3	3	2	0	1
3	2	3	1	3	3	2	2	2	1	0

Figure 8. Reliability Matrix

Reliability Matrix

0.0 2235.96 44.21 2891.56 681.38 3082.52 675.75 1263.75 819.99 344

2235.96 0.0 4778.43 3328.96 584.34 2655.38 4665.68 2903.82 382.58

44.21 4778.43 0.0 2388.4 1608.9 10291.83 70.72 391.02 2549.49 666.8

2891.56 3328.96 2388.4 0.0 2118.0 8215.32 3108.84 1111.44 1676.88

681.38 584.34 1608.9 2118.0 0.0 1377.65 1957.58 2718.38 321.44 57.0

3082.52 2655.38 10291.83 8215.32 1377.65 0.0 8435.28 14768.85 1808

675.75 4665.68 70.72 3108.84 1957.58 8435.28 0.0 93.69 3647.97 211

1263.75 2903.82 391.02 1111.44 2718.38 14768.85 93.69 0.0 4831.23

819.99 382.58 2549.49 1676.88 321.44 1808.7 3647.97 4831.23 0.0 58

344.28 944.78 666.88 1628.28 57.02 1801.46 2117.79 3102.3 583.12 0

1843.98 6432.24 1005.81 564.2 4715.76 15296.13 280.32 279.06 3532.

To achieve the main goal set in the objective function of this work, the best path had to combine a minimum distance and a good path state, hence the need to calculate the credibility matrix.

As soon as the parameters were saved, we could start the optimization process (the best path identification). To do so, we launched the ACO algorithm with and without hybridization.

The following figure (Figure 9) shows the result of the ACO execution without hybridization. The cost found by this algorithm was 8595,32 with alpha = 1, beta = 5, and a vaporization coefficient of 0.995. The path is displayed in the figure using l (identifying customers 0, 2, 10, etc.).

The authors thought of improving the solution found without hybridization (ACO) by the hybridization of the two algorithms ACO and TS by using sequential hybridization. The result found marks a reduction in cost; it changes to 7 177.71 (see Figure 10).

In Figure 10, the optimal path is displayed (Alger, Bouira, BordjBouariridj,Sétif, Biskra,Ghardaia, Elbayed).

Figure 9. The Results of the ACO Algorithm

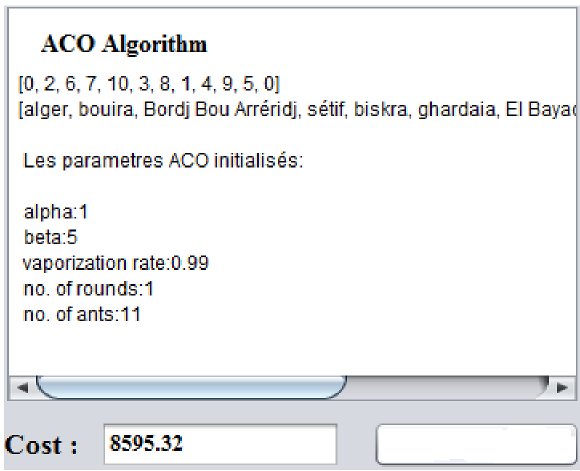
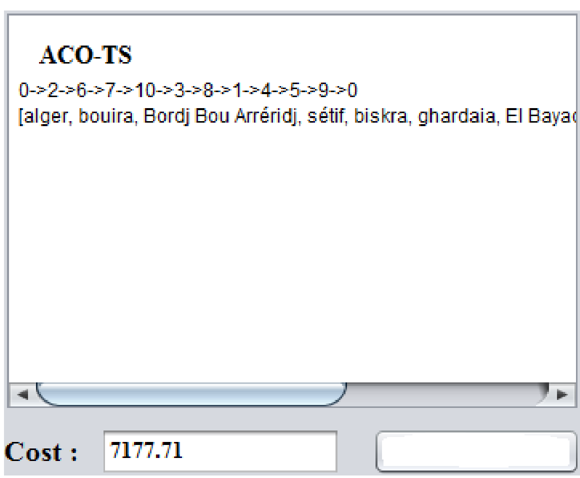


Figure 10. The Optimal Solution (Best Path)



By adding the TS algorithm to the ACO algorithm, the authors of this article aimed to increase the quality of the solution found by ACO. Indeed, the system became responsible for providing the best solutions.

COMPARATIVE STUDY

To position the proposed approach in this article, a comparative study was considered. As a result, the authors implemented ACO without hybridization and ACO hybridized with TS. Additionally, a random solution was implemented, and the results of the three approaches were compared. These approaches were implemented in the same environment (same number of customers and distance between customers), and the costs obtained by the three methods were calculated.

In the experiment, the authors obtained an improvement in the objective function (taking into account the two constraints: state of the path taken and distance between clients) and also a great improvement in cost minimization. Regarding the advantage of hybridization, this is sequential hybridization. However, the authors opted for this type of hybridization because it is efficient. Indeed, the objective was to combine the advantages of the two methods ACO and TS. Besides, the goal of this hybridization was to reduce the cost as well as improve the optimal solution.

Table 1 presents the results (minimum cost) obtained by each of the mentioned methods.

The obtained results on a set of test functions show the effectiveness of the strategies implemented by the various proposed algorithms (random, ACO, and ACO-TS).

Through these performed tests, we found that the hybrid method between ACO and TS seems to behave better than the ACO method without hybridization. We observed that it gives the best results regardless of the size of the problem. Thus, we noticed that the ACO method is less efficient and the random method gives bad results.

Cost is reduced using the proposed approach. This reduction of cost is due to the combination of the two methods: ACO and TS. The hybridization allows the control mechanism to be based on the alternation between the conditions, which are restrictive (taboo restriction). The result was obtained through a diversification strategy using long-term memory, which serves to guide research in new areas.

Experiments have shown that the proposed approach significantly improves the quality of the solution. This approach can identify the optimal path to obtain goods.

DISCUSSION OF RESULTS

The authors introduced the TS at the end of the ant colony algorithm to improve the resulting solutions. The solution found by the ant colony algorithms represents an initial solution of a TS. The two hybrid methods used were chosen for their speed and efficiency of resolution. In this research, the authors

Table 1 Comparative Study

Number of Customers	Costs		
	ACO	ACO-TS	Random Solution
5	6,345.61	3,916.34	7,590.88
11	8,636.68	6,676.65	7,013.45
14	11.988.73	9,018.96	12,276.43
19	9,398.69	6,498.46	9,963.77
20	10,650.55	8,350.66	11,378.23
30	21,500.33	10,900.56	22,485.44

Figure 11. Histograms Obtained by the Implemented Methods

have paired ACO with TS to give a rapid solution, which will subsequently minimize computation time, thus improving the cost function (objective).

Ant colony algorithms have several interesting features, including:

- **Flexibility:** An ant colony can adapt to changes in the environment.
- **Robustness:** A colony can maintain its activity if a few individuals fail.
- **Decentralization:** A colony does not obey a centralized authority.
- **Self-organization:** A colony itself finds a solution, which is not known in advance.

The analysis of results shows that the approach used to solve the problem of distribution of goods is efficient in comparison with existing approaches. The method used derives its efficiency from the hybridization of two meta-heuristics (ACO and the TS algorithm).

CRITICAL LIMITATIONS OF THE PROPOSED APPROACH

Despite the progress made by the proposed approach, limitations of this approach exist:

- The sequential execution of the algorithm influences the quality of classification since the choice of which branch an ant will take depends on the ants already classified. Therefore, the initial sort represents a major factor because of the total lack of parallelism in the movements of the ants.
- Another weak point of ACO is the insignificance of the random movement of ants in the case where the similarity between two ants (fi and f +) is lower than the dissimilarity threshold of fi. Fi's random movement will move it away from its actual search area.

CONCLUSION AND FUTURE RESEARCH DIRECTIONS

Logistics play a major role in daily life. The work presented in this article has been done to provide solutions to transport companies to reduce costs and improve their performance and profitability.

Repository and transportation management has been shown from many quarters to help managers organize and implement the management system in a way that suits the needs of the business.

Today, optimization has become an indispensable area for solving many problems, whether in industry or other sectors (Hachimi, 2013). In fact, in recent years, we have witnessed a very rapid growth in work through using optimization methods. This trend can be observed in all fields of science

In this article, the important approach of this research is the resolution of the problem of distributing product from a central warehouse to different warehouses in different cities.

This problem is of major interest to companies. This highlights the need to develop optimization algorithms capable of dealing with these problems with reasonable response times. The main idea of the study was to combine the strengths of ACO with TS to enhance the optimal solution through sequential hybridization.

The purpose of the research was mainly the proposition of a hybrid solution between two optimization methods: ACO hybridized with the TS for the resolution of the problem of the most reliable path according to the distance criterion and the path state.

To conclude this work, the obtained results can affirm that hybridization used in this approach gives effective results compared to what was given by the random and ACO approaches. In the near future, the authors plan to implement other optimization methods to observe the behaviour of this proposal and enrich the comparative study.

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REFERENCES

Alaya, I. (2009). *Optimisation multi-objectif par colonies de fourmis: cas des problèmes de sac à dos* (Doctoral dissertation). Université Claude Bernard-Lyon I; Université de la Manouba, Tunisie.

Alptekinoğlu, A., & Tang, C. S. (2005). A model for analyzing multi-channel distribution systems. *European Journal of Operational Research*, *163*(3), 802–824. doi:10.1016/j.ejor.2003.11.005

Amrani, F., Yachba, K., Belayachi, N., & Hamdadou, D. (2018). A decision-making system for container storage management in a seaport using the ant-colony optimisation algorithm. *International Journal of Management and Decision Making*, *17*(3), 348–367. doi:10.1504/IJMDM.2018.093501

Belayachi, N., Gelareh, S., Yachba, K., & Bouamrane, K. (2017). The Logistic of Empty Containers¢ Return in the Liner-Shipping Network. *Transport and Telecommunication Journal*, *18*(3), 207–219. doi:10.1515/ttj-2017-0018

Bendaoud, Z., & Yachba, K. (2017). Towards A Decision Support System for Optimization of Container Placement in a Container Terminal. *International Journal of Strategic Information Technology and Applications*, *8*(3), 59–72. doi:10.4018/IJSITA.2017070104

Bersani, C., Dagdougui, H., Roncoli, C., & Sacile, R. (2019). Distributed product flow control in a network of inventories with stochastic production and demand. *IEEE Access: Practical Innovations, Open Solutions*, *7*, 22486–22494. doi:10.1109/ACCESS.2019.2898648

Costanzo, A., Luong, T., & Marill, V. (2006). *Optimisation par colonies de fourmis*. Academic Press.

Dahan, F., El Hindi, K., Mathkour, H., & AlSalman, H. (2019). Dynamic flying ant colony optimization (DFACO) for solving the traveling salesman problem. *Sensors (Basel)*, *19*(8), 1837. doi:10.3390/s19081837 PMID:30999688

Dorigo, M., & Di Caro, G. (1999, July). Ant colony optimization: a new meta-heuristic. In *Proceedings of the 1999 congress on evolutionary computation-CEC99 (Cat. No. 99TH8406)* (Vol. 2, pp. 1470-1477). IEEE. doi:10.1109/CEC.1999.782657

Dréo, J. (2004). *Adaptation de la méthode des colonies de fourmis pour l'optimisation en variables continues. Application en génie biomédical* (Doctoral dissertation). Paris 12.

Eswaramurthy, V. P., & Tamilarasi, A. (2009). Hybridizing tabu search with ant colony optimization for solving job shop scheduling problems. *International Journal of Advanced Manufacturing Technology*, *40*(9-10), 1004–1015. doi:10.1007/s00170-008-1404-x

Glover, F. (1997). Tabu search and adaptive memory programming—advances, applications and challenges. In *Interfaces in computer science and operations research* (pp. 1–75). Springer. doi:10.1007/978-1-4615-4102-8_1

Glover, F., Laguna, M., & Martí, R. (2007). Principles of Tabu Search. In Handbook of approximations Algorithms and meta-heuristics. University of California.

Gulcu, S. D., & Ornek, H. K. (2019). Solution of multiple travelling salesman problem using particle swarm optimization based algorithms. *International Journal of Intelligent Systems and Applications in Engineering*, *7*(2), 72–82. doi:10.18201/ijisae.2019252784

Hachimi, H. (2013). *Hybridations d'algorithmes métaheuristiques en optimisation globale et leurs applications* (Doctoral dissertation). INSA de Rouen.

Hao, P., Wang, Z., Wu, G., Boriboonsomsin, K., & Barth, M. (2017, October). Intra-platoon vehicle sequence optimization for eco-cooperative adaptive cruise control. In *2017 IEEE 20th International Conference on Intelligent Transportation Systems (ITSC)* (pp. 1-6). IEEE. doi:10.1109/ITSC.2017.8317879

Hertono, G. F., & Handari, B. D. (2018, March). The modification of hybrid method of ant colony optimization, particle swarm optimization and 3-OPT algorithm in traveling salesman problem. *Journal of Physics: Conference Series*, *974*(1), 012032. doi:10.1088/1742-6596/974/1/012032

Ho, S. L., Yang, S., Ni, G., & Machado, J. M. (2006). A modified ant colony optimization algorithm modeled on tabu-search methods. *IEEE Transactions on Magnetics*, *42*(4), 1195–1198. doi:10.1109/TMAG.2006.871425

Kefi, S., Rokbani, N., Krömer, P., & Alimi, A. M. (2016, November). A new ant supervised-PSO variant applied to traveling salesman problem. In *International Conference on Hybrid Intelligent Systems* (pp. 87-101). Springer. doi:10.1007/978-3-319-27221-4_8

Lai, M., & Tong, X. (2012). A metaheuristic method for vehicle routing problem based on improved ant colony optimization and Tabu search. *Journal of Industrial and Management Optimization*, *8*(2), 469–484. doi:10.3934/jimo.2012.8.469

Liu, Y., Cao, B., & Li, H. (2020). Improving ant colony optimization algorithm with epsilon greedy and Levy flight. *Complex & Intelligent Systems*, 1-12.

Loubiere, P. (2016). *Amélioration des métaheuristiques d'optimisation à l'aide de l'analyse de sensibilité* (Doctoral dissertation). Paris Est.

Min, L., & Yant, J. (2005). A shortest path routing based on ant algorithm. Journal of Communication and Computer, 2(9).

Oluwagbemiga, B. A., Basri Shuib, S. J. A., Mariam, G., & Thabeb, A. A.(n.d.). *A Hybrid ant Colony Tabu Search Algorithm for Solving Next Release Problems*. Academic Press.

Osaba, E., Yang, X. S., Diaz, F., Lopez-Garcia, P., & Carballedo, R. (2016). An improved discrete bat algorithm for symmetric and asymmetric traveling salesman problems. *Engineering Applications of Artificial Intelligence*, *48*, 59–71. doi:10.1016/j.engappai.2015.10.006

Pirkul, H., & Jayaraman, V. (1998). A multi-commodity, multi-plant, capacitated facility location problem: Formulation and efficient heuristic solution. *Computers & Operations Research*, *25*(10), 869–878. doi:10.1016/S0305-0548(97)00096-8

Stützle, T., & Dorigo, M. (1999). ACO algorithms for the traveling salesman problem. *Evolutionary Algorithms in Engineering and Computer Science, 4*, 163-183.

Tahiri, H., Yachba, K., & Bouamrane, K. (2020, December). A container placement approach in a containership based on the electre 2 method. In *2020 4th International Symposium on Informatics and its Applications (ISIA)* (pp. 1-5). IEEE. doi:10.1109/ISIA51297.2020.9416536

Tuba, M., & Jovanovic, R. (2013). Improved ACO algorithm with pheromone correction strategy for the traveling salesman problem. *International Journal of Computers, Communications & Control*, *8*(3), 477–485. doi:10.15837/ijccc.2013.3.7

Tuzun, D., & Burke, L. I. (1999). A two-phase tabu search approach to the location routing problem. *European Journal of Operational Research*, *116*(1), 87–99. doi:10.1016/S0377-2217(98)00107-6

Yachba, K., Bendaoud, Z., & Bouamrane, K. (2018). A Technique for Resolution of the Assignment Problem Containers in a Container Terminal. In *Handbook of Research on Biomimicry in Information Retrieval and Knowledge Management* (pp. 120–132). IGI Global. doi:10.4018/978-1-5225-3004-6.ch008

Yachba, K., Bendaoud, Z., & Bouamrane, K. (2018). Toward a Decision Support System for Regulation in an Urban Transport Network. *International Journal of Strategic Information Technology and Applications*, *9*(2), 1–17. doi:10.4018/IJSITA.2018040101

Yachba, K., Bouamrane, K., & Gelareh, S. (2015, October). Containers storage optimization in a container terminal using a multimethod multi-level approach. In *The International Conference on Computers & Industrial Engineering (CIE45)* (pp. 28-30). Academic Press.

Yachba, K., Chaabane, A., & Benadda, M. A. (2021). Un système d'aide à la décision pour l'optimisation de processus de distribution des produits finaux. Séminaire international sur les mathématiques et l'informatique, Oran.

Yachba, K., Gelareh, S., & Bouamrane, K. (2016). Storage management of hazardous containers using the genetic algorithm. *Transport and Telecommunication Journal*, *17*(4), 371–383. doi:10.1515/ttj-2016-0033

Yun, H. Y., Jeong, S. J., & Kim, K. S. (2013). Advanced harmony search with ant colony optimization for solving the traveling salesman problem. *Journal of Applied Mathematics*, *2013*, 2013. doi:10.1155/2013/123738

Zhang, L., Kulkarni, K., Somayaji, M. R., Xenos, M., & Linninger, A. A. (2007). Discovery of transport and reaction properties in distributed systems. *AIChE Journal. American Institute of Chemical Engineers*, *53*(2), 381–396. doi:10.1002/aic.11018

Khadidja Yachba (born in Oran, Algeria) is a Teacher (Assistant Professor) in Computer sciences department of University Centre Relizane and a research assistant at LIO Laboratory, Oran, Algeria. She received her Ph.D. in transport maritime and optimization at University of Oran 1, Ahmed Benbella in 2017. Her research interests are in Decision Support Systems (urban, road, maritime transportation, and health), Optimization, Simulation, Cooperative and Distributed System, Knowledge bases and Multi Criteria Decision Making. Khadidja Yachba has published in journals such as transport and telecommunication, International Journal of Decision Sciences, Risk and Management.

Naima Belayachi (born in Oran, Algeria) is a Teacher in the Exact Science department of the Higher Normal School of Oran. University study: Engineer in Computer Science (2009) from the Oran1 university; Master of Diagnosis, Assistance in Making Decisions and Human Interactions Machine (2012). PhD Degree in computer science (2018) from the University of Oran1, Ahmed Benbella, Algeria. She is member of the Computer Science Laboratory (LIO). Fields of research: decision support system (urban, road, maritime transportation), optimization, cooperative and distributed system, Knowledge bases.

Karim Bouamrane received the PhD Degree in computer science from the Oran University in 2006. He is full Professor of computer Science at the same university. He is member of computer science laboratory (LIO). He is the head of the team decision and piloting system. His current research interests deal with decision support system in transportation system, risk management, metaheuristic. He participates in several scientific committees' international/national conferences in Algeria and other countries in the same domain and collaborate in Algerian-French scientific projects. He is co-author of more than 30 scientific publications.