One-sided time constraints routing problem in supply chain management- An Ant colony optimization based heuristic

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ABSTRACT
Transportation costs constitute a significant fraction of total logistics cost in Supply Chain Management (SCM). To reduce transportation costs, improve customer service and to achieve maximum customer satisfaction, the optimal selection of the vehicle route is a frequent decision problem and this is commonly known as vehicle routing problem. Vehicle routing problem with one-sided time constraint, where the delivery of products from depots to distribution centers has to take place within the maximum permissible time. In this paper, an ant colony based heuristic is developed on shortest path approach to solve the routing problem with time constraint.

1. INTRODUCTION
Supply chain (SC) systems are nowadays entering the age of adaptive and intelligent supply chains, a new generation of networks that features collaboration and visibility features across the different partners to deal with the system dynamics, such as supplier failures or demand uncertainty (G.P. Cachon, S. Netessine, H. Stadler, 2005). At the operational level, supply chain management (SCM) is now seeking to determine the stock levels at the logistic centers depending on the demand, or the size and frequency of batches produced at the suppliers to feed the producers in time, or even the delivery planning that minimizes the transportation costs and environmental impacts (J.M. Cruz, 2008). Cost with goods transportation have been calling a special attention in the last decades, since logistic expenses minimization is a big concern for many companies. Finding efficient vehicle routes is an important logistics problem which has been studied for several decades. When a firm is able to reduce the length of its delivery routes or is able to decrease its number of vehicles, it is able to provide better service to its customers, operate in a more efficient manner and possibly increase its market share. This problem is of economic importance to businesses because of the time and costs associated with providing a fleet of delivery vehicles to transport products to a set of geographically dispersed customers. The problem typically involves finding the minimum cost of the combined routes for a number of vehicles in order to facilitate delivery from a supply location to a number of customer locations. Since cost is closely associated with distance, a company might attempt to find the minimum distance travelled by a number of vehicles in order to satisfy its customer demand. In doing so, the firm attempts to minimize costs while increasing or at least maintaining an expected level of customer service. The research in this field has tackled mainly the interaction between the agents and the optimization issues are usually solved through some simple dispatching rules. However, these methods are usually not sufficient to deal with the complexity of the real world problems and the agents need to use more powerful optimization technique. This paper introduces a multi-agent supply chain management methodology based on the description of the supply chain as a set of different distributed optimization problems and using the ant colony optimization (ACO).

The paper proceeds as follows: Section 2 describes the VRP that is used in this paper. Section 3 presents a short literature survey on supply chain management and models the management problem as a distributed optimization problem. Section 4 describes about Ant Colony Optimization techniques in VRP with time Constraints. Section 5 shows how the ant colony optimization can be used to solve this problem as a multi-agent system. The simulation results are presented in Sections 6 and Section 7 says Conclusion and future work.

The vehicle routing problem has been an important problem in the field of distribution and logistics since at least the early 1960s (Clark G, Wright JW, 1964). It is described as finding the minimum distance or cost of the combined
routes of a number of vehicles \( m \) that must service a number of customers \( n \). Mathematically, this system is described as a weighted graph \( G = (V, A, d) \) where the vertices are represented by \( V = \{v_0, v_1, \ldots, v_n\} \), and the arcs are represented by \( A = \{(v_i, v_j) : i \neq j\} \). A central depot where each vehicle starts its route is located at \( v_0 \) and each of the other vertices represents the \( n \) customers. The distances associated with each arc are represented by the variable \( d_{ij} \) which is measured using Euclidean computations. Each customer is assigned a non-negative demand \( q_i \), and each vehicle is given a capacity constraint, \( Q \). The problem is solved under the following constraint.

\[ \text{Each customer is visited only once by a single vehicle.} \]

\[ \text{Each vehicle must start and end its route at the depot, } v_0. \]

\[ \text{Total demand serviced by each vehicle cannot exceed } Q. \]

Additionally, the problem may be distance constrained by defining a maximum route length, \( L_m \), which each vehicle may not exceed. This maximum route length includes a service distance \( d \) (translated from service time) for each customer on the route. An example of a single solution consisting of a set of routes constructed for a typical vehicle routing problem is presented in Fig. 1, where \( m=3, n=10 \). The VRP studied here is symmetrical where \( d_{ij}=d_{ji} \) for all \( i \) and \( j \).

![Diagram of VRP](image)

A vast amount of research has been accomplished on the vehicle routing problem (Christofides N, Eilon S., 1969, Christofides N, Mingozzi A, Toth P., 1979) including advanced metaheuristic approaches such as Tabu search (Gendreau M, Hertz A, Laporte G., 1994, Kelly J.P., Xu J., 1999) and Simulated Annealing (Osman L.H., 1993). A limited amount of research addressing the vehicle routing problem has used ACO with candidate lists and ranking techniques to improve the ability of a single ant colony to solve the VRP (Bullinheimer B, Hartl RF, Strauss C., 1998, Bullinheimer B, Hartl RF, Strauss C., 1999). The research in this paper uses multiple ant colonies and experiments with different candidate list sizes in order to improve the ability of ACO to solve known instances of the VRP in Supply Chain Management by optimizing the distribution facility.

### 3. Supply Chain Model

We consider a generic supply chain model that comprised three systems: a logistic system, its suppliers and the distributors. A previous study considering only the suppliers and the logistic system was presented in (C.A. Silva, J.M.C. Sousa, T. Runkler, J.M.G. Sá da Costa, 2003). The logistics–distribution system proposed in the paper takes full advantage of the distribution optimization by considering all echelons of the supply-chain. The logistic system collects the orders from the customers, purchases the components from external suppliers and schedules the components delivered by the suppliers as orders. This system is also responsible to manage the cooperation between the partners in the network and for the communication between the clients and the supply chain. The supply system is a network of
external suppliers that manufacture the components and deliver them to the logistic system. The distributors are responsible to pick up different items at the warehouses of the logistic system and distribute them to clients. Fig. 2 presents a schematic representation of such multiple echelon system. The modeling approach proposed in this paper consists of describing basically distribution subsystem of the supply chain by a benchmark optimization problem: the logistic system is described by the general assignment optimization problem (C.A. Silva, J.M.C. Sousa, T. Runkler, R. Palm, 2005); the supplying system by the manufacturing scheduling optimization problem (I. M. Pinedo, 2002); and the distribution system by the vehicle routing problem (I. M. Pinedo, 1959).

3.1 LOGISTIC SYSTEM
At each day, the logistic system has an order list O of n order waiting to be delivered. An order oj ∈ O with j = 1, . . . , n is a set of ℓ different types of items, called the components Cj with i = 1, . . . , ℓ, in certain quantities qij.
Therefore, an order can be defined as an ‘ℓ-tuple oj = (q1j, . . . , qij). When a new order oj arrives, it receives two labels: the arrival date or release date rj and the desired delivery date or due date dj, which is the date when the client wishes to receive the order. The order is delivered at the completion date Cj. Assuming that the system does not deliver orders if they are ready before the due date, the difference between the completion date and the due date is called the tardiness Tj = Cj - dj. The objective is to match both dates, i.e. to have for all orders Tj = 0.
However, two disturbances may influence the system: the fact that suppliers service may not be respected and the fact that some clients ask for desired delivery dates not compatible with the supplier services.

Fig-2. Supply Chain System

3.2 SUPPLYING SYSTEM
The supplying sub-system is a network of m different suppliers or manufacturers Mi with i = 1, . . . , m, each one producing its own set of jobs JMi , where each job refers to a type of component ci requested by the logistic sub-system. Each supplier is independent and therefore it optimizes its own problem called the local supplier problem. However, from the point of view of the logistic system, the suppliers can be virtually considered as one single entity, and the optimization problem is called the global supplier problem.

3.3 DISTRIBUTION SYSTEM
When the scheduling method has decided which orders must be delivered, a distribution company will pick-up the assigned components and deliver them to the different clients. There is a direct correspondence between clients and orders, but clients are described in this case by their geographical location. A simple but realistic model of the supply chain distribution problem is the vehicle routing problem (VRP) (I. M. Pinedo, 1959), where each vehicle has a limited load capacity C and each truck as a limited distance autonomy R. This problem considers the set O of n orders to be delivered by vehicles i = 1, . . . , s. The function to minimize
is the sum of the individual travel costs of each vehicle i of the total number of vehicles s required to deliver all the n orders in the set OD of delivered orders

\[ f_r = \sum_{s=0}^{s} \sum_{u=0}^{u} \sum_{v=0}^{v} W_{DUV} Y_{UVi} \] (route cost) (1)

Where \( Y_{UVi} \) is 1 when vehicle i has travelled between clients u and v and 0 otherwise, and \( W_{DUV} \) is the travel cost between client u and client v expressed in Km or monetary units. If a client requests by any chance more than one order, the distribution company considers the existence of more than one client at the same location.

3.4. Performance index for supply chain management

The definition of performance measurements for supply chain has not become yet a mature subject (B.M. Beamon, 1988). There are already different approaches that depend on: the variable that is measured, e.g. cost, time or customer responsiveness; the measurement framework, e.g. aggregation expressions or multi-criteria decision measures. Since it the most widely used performance index (B.M. Beamon, 1988). The general expression of this index is given by

\[ P_{SCM} = \sum_{i=1}^{i} \omega_i X_i \] (2)

where i = 1, . . . , n is the number of partners in the supply chain, \( \omega_i \) is the weight that measures the importance of the partner in the network and \( X_i \) is the contribution of each of the partners to the evaluated cost of the supply chain, e.g. monetary units.

3.5 Distribution optimization in SCM

The supply chain problem can be described as the management problem \( X_{SCM} = \{ X_L; X_M1 : . . . ; X_Mm ; X_D \} \), where \( X_L \) is the logistics scheduling problem, \( X_Mi \ i = 1; . . . ; m \) are the local supplying problems and \( X_D \) is the distribution problem. We consider that the supply chain cost functions

\[ f_{SCM} = f_{L} \cdot f_{M1} \cdot . . f_{Mm} \cdot f_{D} \] (3)

where \( f_{L} \); \( f_{M1} \) and \( f_{D} \) are the expressions for the cost functions of Logistic system, Supplying respectively system and Distribution system respectively.

Note that the supply chain management is done at two distinct moments in time:

First, the suppliers decide about their own scheduling policy, that may be influenced or not by the logistic system before it receives the new components at the cross-docking center. However, the distribution system is not related to this decision process, since there are no items to distribute.

Then, the logistic process has to decide which orders to deliver after it receives the new components, under the influence or not of the distribution system. However, the components are already produced and the supplying system is not related to this decision process.

Thus, the daily supply chain management problem \( \text{min}[f_{SCM}] \) is naturally divided into two sequential cooperation problems at each day, which are the supplying-logistic problem \( \text{min}[f_{SL}] \) and the logistic–distribution problem \( \text{min}[f_{LD}] \).

\[ \text{min} \ [f_{SCM}] = \text{min} \ [f_{SL}] \rightarrow \text{min} \ [f_{LD}] \]

The research in this paper focused on the logistic-distribution problem, as we have to optimize our distribution schedule by minimizing cost and under certain time constraints. The logistic–distribution problem is defined as \( \text{min} \ [f_{LD}] = \text{min} \ [f_{L}] \cdot \text{min} \ [f_{D}] \)

Observe that one advantage of this formulation is that it allows a total separation between the suppliers and the distribution systems. It is possible for the logistic system to use the distribution optimization technique with one of the partners and use a completely different coordination mechanism with the other partner. In this paper we have considered the logistic-distribution problem which can be independently optimized through ACO.

Next section shows how this procedure can be easily implemented using the ant colony optimization algorithm.

4. Ant colony optimization

Ant colony optimization is a part of the larger field of swarm intelligence in which scientists study the behaviour patterns of bees, termites, ants and other social insects in order to simulate processes. The ability of insect swarms to thrive in nature and solve complex survival tasks appeals to scientists developing computer algorithms needed to solve similarly complex problems. An artificial intelligence algorithm such as ant colony optimization is applied to large combinatorial optimization problems and is used to create self-organizing methods for such problems. Ant colony optimization is a meta-heuristic technique that uses artificial ants to find solutions to combinatorial optimization problems. ACO is based on the behaviour of real ants and possesses enhanced abilities such as memory of past actions and knowledge about the distance to
other locations. In nature, an individual ant is unable to communicate or effectively hunt for food, but as a group, ants possess the ability to solve complex problems and successfully find and collect food for their colony. Ants communicate using a chemical substance called pheromone. As an ant travels, it deposits a constant amount of pheromone that other ants can follow. Each ant moves in a somewhat random fashion, but when an ant encounters a pheromone trail, it must decide whether to follow it. If it follows the trail, the ant’s own pheromone reinforces the existing trail, and the increase in pheromone increases the probability of the next ant selecting the path. Therefore, the more ants that travel on a path, the more attractive the path becomes for subsequent ants. Additionally, an ant using a short route to a food source will return to the nest sooner and therefore, mark its path twice, before other ants return. This directly influences the selection probability for the next ant leaving the nest. Over time, as more ants are able to complete the shorter route, pheromone accumulates faster on shorter paths and longer paths are less reinforced. The evaporation of pheromone also makes less desirable routes more difficult to detect and further decreases their use. However, the continued random selection of paths by individual ants helps the colony discover alternate routes and insures successful navigation around obstacles that interrupt a route. Trail selection by ants is a pseudo-random proportional process and is a key element of the simulation algorithm of ant colony optimization (M. Dorigo, T. Stützle, 2004).

4.1. Distribution optimization using ACO

To solve the vehicle routing problem (VRP) that models the distribution process in the logistic supply chain, the artificial ants construct solutions by successively choosing clients to visit until all the clients have been visited, and thus all the orders have been delivered. Whenever the choice of a location leads to infeasible solutions, due to reasons of vehicle capacity or total route length, the depot is chosen as a final location to close the tour and a new tour with a new vehicle is started.

The heuristic information $\eta_{uv}$ used in this case is the weighted saving function, as proposed in (B. Bullinheimer, R.F. Hartl, C. Strauss, 1999): ants choose the different clients to visit based on the general framework of the algorithm of ACO. When the ant $k$ cannot visit any other client, in order to avoid the violation of any of the constraints (maximal tour cost $R$ or maximum load capacity $F$), the ant returns to the depot node 0 and updates the admissible nodes list $N^k$. At the next step, the ants, starting again at

$$S_{uv} = W_{0u} + W_{0v} - w_{uv} + b \left| w_{0u} - c_{0v} \right|$$

Where $w_{uv}$ is the distance cost between clients $u$ and $v$, and $w_{0u}, w_{0v}$ are the distance costs between clients $u$ and $v$ and the docking center 0. In this implementation, we use $a = 2$ and $b = 1$ as indicated in (B. Bullinheimer, R.F. Hartl, C. Strauss, 1999). The heuristic matrix $\eta$ is a normalized version of this heuristic:

$$\eta_{uv} = S_{uv} - \min(S_{uv}) / \max(S_{uv}) - \min(S_{uv})$$

All the ants started at the depot node 0. Then, the node 0, repeat this procedure for the remaining clients until all the clients are visited. At the end, the solution of ant $k$ will be a sequence of the type $(0, u, . . . , 0, v, . . . , 0)$. The number of used trucks will be equal to the number of 0’s minus one.

The ant colony optimization is by definition a multi-agent system: several autonomous agents are solving their own problems, communicating with each other over the pheromone matrix $\tau$ and solving the optimization problem through cooperation. The exchange of information between ants of the same colony can be extended to ants of different colonies. This approach is denominated as parallel implementations of ACO (M. Dorigo, T. Stützle, 2004) and has been applied to problems that require considerable computational effort, such as the VRP.

For distribution optimization, each subsystem of the supply chain can be optimized through a pheromone matrix that indicates the weights on arcs connecting different nodes. The different optimization problems can be described in similar graphs, and therefore, different entities from different problems may be represented by the same nodes and arcs. In this way, it is very easy to exchange the pheromone matrix between different problems. Each colony is solving its problem autonomously taking into consideration relevant information of the colonies that are solving different problems. Consider now the distribution optimization problem described by (3), introduced in Section 3. The symbol $^\circ$ represents the way in which information is exchanged between the different systems that are being optimized.

The literature considers that in ACO parallel implementations it is better to exchange solutions rather than pheromone matrices (M. Dorigo, T. Stützle, 2004). However, in this case, the
problem being solved by each colony is not the same and a solution cannot be directly exchanged from problem to problem. Therefore, the implementation of the distribution optimization is done through the exchange of the pheromone matrix. The pheromone exchange approach has also been followed in (I. Elalibib, P. Calamai, O. Basir, 2007), to solve the VRPWT using multiple ant colonies. The following sections describe the implementation of ACO for logistic-distribution of the supply chain management problem.

5. Optimizing Distribution in Supply Chain Management
Consider the logistic–distribution problem (5):

\[ \min \left[ f_{LD} \right] = \min \left[ f_L \right] \circ \min \left[ f_D \right] \]

After receiving the components from the suppliers at the cross docking center, the logistic system starts the optimization process. The solution search space is defined by the \( n \in \mathbb{N} \) orders waiting in the system to be delivered and the ACO algorithm uses the \( n \times n \) matrix \( f_L \) to search for the optimal solution of \( f_L \). In the distribution sub-system, the solution’s search space is defined by the \( n \cup 0 \) nodes, i.e., it is uses the \((n + 1) \times (n + 1)\) matrix \( f_D \). Note that they both represent a path connecting the clients, although based on different features: the tardiness of the orders and the distance between the clients.

Consider now that after the logistic system has found a scheduling solution, it provides the pheromone matrix \( f_L \) to the distribution system. The distribution system can use this matrix to initialize its own pheromone matrix \( f_D \), such that

\[
f_D = \begin{cases} 0 & (1 \times n) \\ 0(n \times 1) & \tau_L \end{cases}
\]

where \( 0(1 \times n) \) is a row vector of zeros with dimension \( 1 \times n \), and \( 0(n \times 1) \) is a column vector of zeros with dimension \( n \times 1 \). While the distribution problem is optimizing the solution, it sends the pheromone matrix to the logistic system. The logistic system can use the sub-matrix \( f_L \) of the distribution problem matrix \( f_D \) in order to re-optimize the logistic problem using the information provided by the distribution system.

This exchange of information can occur \( Z_{LD} \) times until the logistic partner defines its last scheduling solution. Notice that the solution of the logistic system is dominant and at the end the distribution system optimizes the routing solution provided by the logistic system scheduling.

Fig. 3 shows how the information is exchanged between the different systems. The continuous arrows indicate the information exchanged during the distributed optimization process, while the dotted arrows indicate the exchange of other type of information, such as order lists.

6. Simulation results
This section presents the management results of a multi-echelon supply chain with logistic, supplying and distribution systems, using both decentralized and the distributed optimization approach proposed by this paper. The simulation data emulates supply chain management scenarios of a real-world case of supply chain management at Fujitsu-Siemens Computers (C.A. Silva, J.M.C. Sousa, T. Runkler, R. Palm, 2005). In this case, we do not consider others issues such as pricing or procurement strategy. It is assumed that the orders are placed and agreed on a daily basis with the logistic system and the SC management starts from this point on. No rolling horizon heuristics are used.

All the decisions regarding supplying and distribution are also made with the information available at that day. The supply chain model, the local optimization algorithms and the distribution optimization methodology were implemented in Matlab 2006™.
6.1. Supply chain instances

The instances describe a logistic system already running for 30 days, with orders already waiting to be delivered and some existing stock of components at the cross-docking center and some production orders at the suppliers. Therefore, the data describes a steady-state system. The simulation scenarios start at day D = 31 and concern 30 days of simulation, until D = 60. The three different instances considered in this study, describing different sizes, complexity and disturbance degrees are: instances (5, 5, 3, 10), (10, 10, 2, 30) and (20, 10, 5, 20). The distribution system has an unlimited number of trucks that can be used, but each truck as a maximum quantity of 50 components and a maximum route length of 200. All the clients are considered to be in a 100 x 100 area, where the cross-docking center is located at the geodesic point. While optimizing distribution in supply chain management, the logistic, the supplying and the distribution systems operate independently, while exchanging information in the form of a pheromone matrix during their own optimization processes. All the systems are optimized using the ACO algorithm. The result analysis follows: Table 1 presents the results for the three instances in terms of distribution system, using both approaches: normal optimization and distribution optimization. After solving the logistic-distribution problem, we consider that the initial solution of the logistic system is, in both cases, the solution obtained with the normal optimization method. In this way, it is possible to compare both methods on the logistic-distribution problem case only. As performance index for this problem, we use the partial index \( P_{LD} = f_L + 1/10^4 f_D \) that corresponds to the part of the supply chain management performance index \( P_{SCM} = f_L + f_M1 + f_M2 + 1/10^4 f_D \) covered by the logistic-distribution problem. In this paper one unit of \( f_L \) and \( f_D \) are equivalent to one monetary unit. As it can be seen, the results for the distributed approach are better than the ones following the separate management approach. Again, the logistic system performance is very similar for both approaches, which shows that in general the logistic system only accepts a different scheduling solution when its own performance does not decrease significantly. On the other hand, the distribution system performance increases. In fact, the worst solutions with the distributed optimization (consider the standard deviation) are in general better than the average solutions obtained with the normal approach.

**Table 1**

<table>
<thead>
<tr>
<th>Instances</th>
<th>Methods</th>
<th>( f_L : \mu )</th>
<th>( f_L : \sigma )</th>
<th>( f_D : \mu )</th>
<th>( f_D : \sigma )</th>
<th>( P_{LD} : \mu )</th>
<th>( P_{LD} : \sigma )</th>
</tr>
</thead>
<tbody>
<tr>
<td>(5,5,13,10)</td>
<td>Normal</td>
<td>61.30</td>
<td>15.31</td>
<td>10.04</td>
<td>2.07</td>
<td>62.304</td>
<td>15.517</td>
</tr>
<tr>
<td>Distribution</td>
<td></td>
<td>61.70</td>
<td>16.26</td>
<td>9.57</td>
<td>1.22</td>
<td>62.657</td>
<td>16.382</td>
</tr>
<tr>
<td>(10,10,2,30)</td>
<td>Normal</td>
<td>41.90</td>
<td>0.59</td>
<td>17.41</td>
<td>1.89</td>
<td>43.641</td>
<td>0.779</td>
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<tr>
<td>Distribution</td>
<td></td>
<td>42.05</td>
<td>0.94</td>
<td>16.36</td>
<td>2.39</td>
<td>43.686</td>
<td>1.179</td>
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<tr>
<td>(20,10,5,20)</td>
<td>Normal</td>
<td>58.49</td>
<td>2.15</td>
<td>36.03</td>
<td>4.52</td>
<td>62.093</td>
<td>2.602</td>
</tr>
<tr>
<td>Distribution</td>
<td></td>
<td>58.44</td>
<td>2.51</td>
<td>33.84</td>
<td>2.47</td>
<td>61.824</td>
<td>2.757</td>
</tr>
</tbody>
</table>

Since the supply chain performance index \( P_{LD} \) is a plain sum of the costs of both systems, the logistic-distribution solution definitely improves, due to the improvement of the distribution system. The objective is to emphasize how much the supply chain can improve with the use of the methodology proposed in this paper. The logistic system performance improves significantly when the distributed optimization is used; because it is able to influence the suppliers scheduling in such a way that diminishes the disturbances caused by tight desired delivery dates or delayed stock arrivals at the cross-docking center. On the other hand, these results are slightly worse when the distribution system proposes a different solution. Also here, the logistic decision takes place before the distribution decision. Therefore, the logistic system only accepts a different solution in cases where the logistic performance is not compromised. The distribution system can only influence the decision of the logistic system and it is obvious that the distributed management approach can provide an...
improvement to the distribution system in terms of routing costs.

In conclusion, the distribution optimization approach is able to improve the logistics and distribution systems performance by optimizing the routing schedule and maintain the performance of the local supplying systems, which was the main objective of the management methodology proposed in this paper.

7. Conclusions and future work

This paper proposed a new management technique for operational activities of a generic supply chain, with logistic and distribution partners. The methodology consists of modelling each of the partners as a combinatorial benchmark optimization problem and optimizing each problem using the ant colony optimization algorithm. This algorithm uses a pheromone matrix to keep an information record during the optimization procedure. With this matrix, it is possible to exchange information between the different optimization processes running in parallel and achieve a cooperation mechanism. The exchange of information with a particular partner may bias the solutions of the remaining partners towards a different but still optimal solution, that suits better the solution of the particular partner. The simulation results showed that this strategy was able to improve the supply chain performance. The logistic and the distribution systems improved their performance. Particularly when we optimize the routing with effect to the time constraint, then the distribution systems improves without any changes in logistics systems. As future research work, we intend to evaluate the impact of the proposed methodology under different coordination mechanisms, such as contracts with penalty clauses or when the suppliers do not allow a decrease in their individual goal. We also aim the generalization of this methodology to different types of optimization algorithms, especially to other meta-heuristics.

References

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