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Green Cargo Routing Using Genetic Algorithms

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Abstract — We studied a genetic algorithm-based approach for a multi-objective cargo routing application. Apart from the traditional goal of cost minimization with a time constraint, we also explored the problem of green logistics, where carbon dioxide emission levels are to be treated as both an additional constraint as well as a secondary objective of the problem. We also implemented an adapted Martins' algorithm that is able to produce Pareto optimal solutions, despite its longer running time compared to the GA-based approach, and compared the results with our approach. The results of the simulation suggested that our algorithm was able to achieve Pareto optimality in over 90% of the problem instances, with good system running time compared with Martins' algorithm.

***Index Terms* — Green logistics, genetic algorithm, multi-objective optimization, intermodal cargo routing**

I. Introduction

The concept of green logistics [1] has been gaining attention in the past few years. In addition to focusing on the single goal of cost minimization, green logistics also takes into account the environmental impact of the logistics process, typically in terms of carbon dioxide emission levels. Indeed, according to a study conducted in 2009, road transportation accounted for 11% of the increase in global temperatures in the year 2000, and a further 4% was contributed by air transportation [2].

In this paper, we study the problem from the perspective of the freight forwarding industry. Freight forwarders are third-party logistics companies that provide end-to-end cargo transportation arrangement services typically to overseas destinations. In freight forwarding, planning cargo routes is a time-consuming task based on manual planning using ad-hoc rules. This is particularity true for problems involving multiple modes of transportation (e.g., by air, sea, or train). Typically, cargo routing is an optimization task with multiple constraints. For instance, time constraints specify that an item of cargo must arrive at the destination before a certain target delivery date. Capacity constraints require that the weight and dimensions of the item of cargo not exceed the capacity of the cargo container at each leg of the journey. Because of the complexity of the problem, it is often difficult for a planner to verify whether any better solution exists.

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While many studies have already been conducted on topics relating to route optimization, the problem of green logistics is relatively new and it is unique in a few areas. First, green logistics is a multi-objective problem. Traditional logistics problems are modeled typically as a single objective optimization problem, with the goal of minimizing the cost of carrying some cargo items to a destination, while satisfying certain constraints. Green logistics differs in that it adds further constraints and objectives to the problem. In our formulation of the problem, the CO_2 emissions level constitutes both an additional objective, which we want to minimize, as well as an additional constraint, where it cannot exceed a certain user-defined threshold limit.

Second, cargo routing in freight forwarding is an *intermodal* route optimization problem [3][4]. Many existing studies focus on the routing or scheduling of a single form of transportation (e.g., the vehicle routing problem, the optimization of public transit routes [5][6]). The planning of routing in freight forwarding, on the other hand, typically involves multiple modes of transport (vehicles, trains, air and sea transport), each with its own set of schedules and constraints.

In this paper, we propose a genetic algorithm-based approach to tackle this problem. For comparison, we also adapted and implemented Martins' label-setting algorithm [8], which is a well-known graph-searching algorithm for listing all *Pareto optimal* solutions in multiple objective problems [9]. We show by experiments that the GA-based approach outperforms Martins' algorithm in term of computational time, while being comparable in terms of the optimality of the solutions.

The rest of this paper is organized as follows. Section II discusses some related works. Section III provides a formal definition of the problem. Section IV presents our GA-based algorithm. Section V provides an overview of the adapted Martins' algorithm. Section VI describes the results of the experiment. Section VII discusses the issue of the tradeoff in optimality and running efficiency from a freight forwarder's perspective. Section VIII gives the conclusion.

II. Related Works

Although there have been relatively few studies on the multi-objective and multi-mode green cargo route optimization problem, there are a large number of works on the more general problem of multi-objective path optimization [7]. Examples include dynamic programming approaches [10][11], genetic algorithm-based approaches (e.g., for vehicle routing [12] and transportation planning [13]), and an ant colony algorithm-

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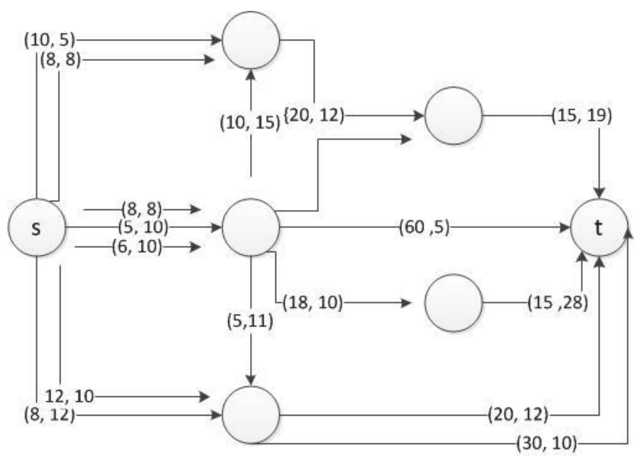

Fig. 1. A simple transportation network between a source node *s* and a destination node *t*. The values marked on each link represent its transportation cost and its CO_2 emissions level, respectively. Note that there can be more than one link between a pair of nodes.

based approach [14]. These approaches target specific single transportation mode applications, and cannot be directly applied to our problem.

There are also works on intermodal international cargo routing optimizations. For instance, a dynamic programming approach is proposed in [15], a Lagrangian relaxation-based method is discussed in [16], and the problem is studied using linear programming relaxation in [17]. These works are similar to ours in that multi-transportation mode routing problems are considered. However, our current work extends the problem further by including the reduction of carbon emission levels as an additional objective and constraint.

In this study, we also implemented Martins' label-setting algorithm [7] as a benchmark for our algorithm. Martins' algorithm is a generalization of the well-known Dijkstra's algorithm to multi-objective problems. Like Dijkstra's algorithm, Martins' algorithm can be used to list all Pareto optimal solutions. Our adaptation of Martins' algorithm to address the multi-mode green logistics cargo routing problem is described in Section 5.

III. Problem Definition

The multi-mode green logistics cargo routing (MGCR) problem is defined as follows. Let t_{start} and t_{end} denote the starting and ending time of the problem being studied (i.e., a cargo shipment's earliest departure time and the target delivery deadline). Let $G = (V, E)$ be a directed graph of the cargo transportation network, where V represents a set of transportation nodes and E represents the set of scheduled transportation links between the nodes (e.g., scheduled flights and train services). A cargo shipment of weight w is to be sent from a source node $s \in V$ to a destination node $t \in V$. For each transportation link $e \in E$, we define *start*(e) and *end*(e) as the starting node and ending node of the respective link, *dep_t*(e) and *arr_t*(e) as its estimated time of departure and arrival, and *carbon*(e) as its estimated level of additional CO_2 emissions per kilogram of cargo payload. Each link also has a remaining weight capacity of *cap(e)* and a per kilogram transportation fee of *cost*(e). The number of nodes is denoted by N.

For each problem, we need to compute one or more transportation paths from the origin to the destination, where each path $p = (e_1, \cdots, e_k \mid e_i \in E)$ is an ordered set of transportation links satisfying the following constraints:

$$start(e_1) = s \text{ and } end(e_n) = t \tag{1}$$

$$\forall (e_i, e_{i+1}) \in p \mid i \neq length(p),\ end(e_i) = start(e_{i+1}) \tag{2}$$

$$\forall e \in E,\ t_{start} < dep\_t(e) < arr\_t(e) < t_{end} \tag{3}$$

$$\forall (e_i, e_{i+1}) \in p,\ i \neq length(p),\ arr\_t(e_i) < dep\_t(e_{i+1}) \tag{4}$$

$$\forall e \in p,\ cap(e) \geq w \tag{5}$$

$$w \times \sum_{e \in p} carbon(e) \leq MAX\_CARBON \tag{6}$$

Constraints (1) and (2) are self-explanatory. Constraints (3) and (4) deal with the time constraint for the problem and for each transportation link, respectively. Constraint (5) is the remaining weight capacity constraint. In freight forwarding, a forwarder needs to reserve cargo spaces from airlines, shipping companies, or freight transportation companies. The weight capacity is the amount of the remaining unused cargo weight (measured in kg) pre-reserved by the forwarder in each link. Constraint (6) is the permitted total CO_2 emissions limit specified by a forwarder for the cargo item. A *valid solution* is a transportation path that satisfies all of the above constraints.

Regarding the objective of the problem, there are two conflicting objectives for this problem. The primary objective requires the route planner to find the lowest-cost valid solution for a given shipment:

Definition 1 (Primary Objective of the MGCR Problem) Given an MGCR problem, the primary objective is to compute a valid solution $p^* = (e_1, \cdots, e_n \mid e_i \in E)$ such that the total cost $cost(p^*) = w \times \sum_{e \in p^*} cost(e)$ is minimized. ■

Apart from cost minimization, the second objective of MGCR is to minimize the total amount of carbon dioxide emissions:

Definition 2 (Secondary Objective of the MGCR Problem) Given an MGCR problem, the secondary objective is to compute a valid solution $p^* = (e_1, \cdots, e_n \mid e_i \in E)$ such that the total level of carbon dioxide emissions $carbon(p^*) = w \times \sum_{e \in p^*} carbon(e)$ is minimized. ■

Note that the carbon emissions level serves as both an additional constraint and a secondary objective in an MGCR problem.

Thus, MGCR is a multi-objective problem by nature. In order to compare two or more solutions in multi-objective problems, many researchers employ the concept of *Pareto optimality* [9]. Briefly, given a number of solution criteria, we say a solution X is *Paretoly dominated* by another solution Y if Y is better than X in at least one criterion, while being not worse in all other criteria. And we say that a solution is *Pareto optimal* if it is not Paretoly dominated.

Definition 3 (Pareto Optimality in the MGCR Problem): Given two valid solutions $p = (e_1, \cdots, e_k)$ and $p' = (e'_1, \cdots, e'_k)$ of an MGCR problem, we say that p is *Paretoly dominated* by p' if $(carbon(p') < carbon(p) \wedge cost(p') \le cost(p))$ or $(cost(p') < cost(p) \wedge carbon(p') \le carbon(p))$. Furthermore, we say that a valid solution p^* is *Pareto optimal* if it is not Paretoly dominated. ■

These criteria will be used in evaluating the GA-based and the adapted Martins' algorithm, which are presented in the next two sections.

IV. A GA-Based Algorithm for the MGCR Problem

A. *Representation*

We have implemented a GA-based solution for the MGCR problem, described as follows. In our system, an $N \times N$ array based data structure is used for storing all transportation links available within the problem time frame between each pair of nodes $(n_1 \in V, n_2 \in V)$. Each element of this two-dimensional array contains an *arraylist* of all scheduled links e between that pair of nodes so that $start(e) = n_1$ and $end(e) = n_2$. In our GA-based solution, each chromosome contains an order set of transportation links $c = (e_1, \cdots, e_n \mid e_i \in E)$ from the origin to the destination, where each set represents a temporary solution with each gene in a chromosome representing a transportation link. Note that during the solution-searching phase, each chromosome may or may not represent a valid solution. In particular, constraints (2), (4), and (6) do not need to be satisfied, although these invalid solutions will have very low fitness scores.

B. *The Genetic Algorithm*

As in other GA-based approaches, our implementation contains procedures for *chromosome initiation*, *cross-over*, and *mutation*. The *cross-over* method we used is a special one-point cross-over. Three types of mutations are defined, namely chromosome shrinking, chromosome extension, and gene transformation. These methods are described as follows.

C. *Chromosome initiation*

The initial set of chromosomes is randomly populated with a valid transportation path using a multi-round bi-directional generation algorithm, to be described as follows. In each round two temporary node lists, L_1 and L_2, are generated, initially containing the origin node and the destination node, respectively. In each step, both lists are expanded by appending a randomly selected transportation link e originating from the last node on the list. A round ends when the new link that is to be added on either list already exists on the other list. In this case, a path is generated accordingly (via the common link) and a new chromosome is initialized according to the path. A round can also end after a pre-defined number of steps is reached. The process is repeated until the required number of chromosomes is generated.

D. *Chromosome selection and cross-over*

The chromosomes are sorted in descending fitness values, so that the ones with higher fitness have a higher probability of being selected for a cross-over. The fitness of a chromosome $c = (e_1, \cdots, e_n)$ is given by:

$$f(c) = \left(\frac{w_{cost}}{cost(c)} + w_{carbon}\frac{MAX\_CARBON}{carbon(c)} + w_{time}\frac{t-s}{arr\_t(e_n)-s} + w_{length}\frac{MAX\_LENGTH}{length(c)}\right) \times Validity(c)$$

where *Validity*() is a function that returns 1 if c represents a valid solution, and returns 0 otherwise. w_{cost}, w_{carbon}, w_{time}, and w_{length} are the fitness weights for shipment cost, carbon emissions level, transportation time, and path length, respectively. *MAX_CARBON* and *MAX_LENGTH* are the user-defined upper thresholds for the amount of carbon emissions allowed and the number of nodes in the path.

The cross-over method that we use is a specially designed one-point cross-over, described as follows. Given two parent chromosomes $c^1 = (e^1_1, \cdots, e^1_m)$ and $c^2 = (e^2_1, \cdots, e^2_n)$ selected for a cross-over, if there exist any genes $e^1_i \in c^1$ and $e^2_j \in c^2$, $i, j \ne 1$, $i \ne m$ and $j \ne n$, such that $end(e^1_i) = end(e^2_j)$, then two new chromosomes are formed:

1) $c^{12} = (e^1_1, \cdots, e^1_i, e^2_{j+1}, \cdots, e^2_n)$
2) $c^{21} = (e^2_1, \cdots, e^2_j, e^1_{i+1}, \cdots, e^1_i)$

Ties are broken randomly if there are more than one pair of links with a common destination. A random node on each list is chosen if no common destination exists.

For each new generation, K_{new} new chromosomes will be generated, and they will be inserted into the next generation together with the $(K - K_{new})$ fittest old chromosomes, where K is the total number of chromosomes.

E. *Mutation*

After a cross-over, all chromosomes will be subjected to a process of mutation, with a mutation probability μ. One of the following three types of mutation operations will be executed with equal probability:

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1. *Chromosome extension*: This operation randomly replaces a gene with two other genes in a chromosome.
2. *Chromosome shrinking* This operation involves the replacement of two randomly selected consecutive genes with one in a chromosome.
3. *Gene transformation* This operation randomly replaces a selected gene with another gene in a chromosome.

Our algorithm terminates after a preset number of generations or when no new chromosomes can be generated.

F. System parameters and flexible population size strategy

The values of the various parameters of our system are determined experimentally and are given in Table 1. These values are chosen for a good balance between system running time and optimality in produced solutions. Note that the *MAX_CARBON* and *MAX_LENGTH* are problem-specific variables based on user inputs, not system parameters.

In order to cater to problems of different sizes, we also employ a flexible population size strategy for determining the number of chromosomes in each instance. The details of this strategy are also listed in Table 1 (where |E| denotes the number of transportation links in the problem instance).

V. ADAPTED MARTINS' ALGORITHM

Apart from the GA-based approach, we also adapted Martins' label-setting algorithm [7] for the MGCR problem. Martins' algorithm is a generalization of the well-known Dijkstra's shortest path algorithm for multi-objective problems (i.e., with multiple decision criteria). Martins', as in Dijkstra's, maintains lists of two types of labels, namely permanent labels and temporary labels. Each label is associated with a list of aggregated costs, one for each criterion. Initially, the only permanent labels are at the node of origin with the costs set to zero for all criteria, while all other nodes are temporary with all costs set to infinity. In each iteration, the temporary labels that are neighbors of the last permanent nodes are updated with the new costs via the respective link, and the label with the lowest overall costs (in the lexicographic order of all criteria) is selected and made permanent. Once selected, the temporary label is converted to a permanent label and the process is repeated. Our adapted version of the algorithm differs from the original version in that in each iteration there is additional checking for i) departure and arrival time, and ii) the accumulated CO_2 emissions level, so that any paths that violate constraints (3) and (5) are pruned away during the search.

Table 1. Parameters used by the GA-based algorithm

Number of chromosomes (*K*)	80 if $\lvert E \rvert < 140$ 100 if $140 \le \lvert E \rvert < 180$ 250 if $180 \le \lvert E \rvert$
Mutation rate (μ)	0.05
Number of generations	50
Weight of cost in fitness (W_{cost})	1
Weight of carbon emissions in fitness (W_{carbon})	0.00001
Weight of time in fitness (W_{time})	0.0000005
Weight of path length in fitness (W_{length})	0.0000025

VI. SIMULATION RESULTS

We conducted a series of simulation experiments to study the performance of our GA-based algorithm with the adapted Martins' algorithm as the benchmark. The mechanisms were tested comprehensively in a total of over 2000 scenarios, with the number of nodes ranging from 100 to 200, the number of links per node ranging from 100 to 200, and with different parameters for the carbon emissions threshold limit, cost, and allowed shipment time. For each scenario, 50 problem instances were randomly generated and were processed separately by the two algorithms. Thus, a total of 84000 test cases were tested and, in each case, the costs, Pareto optimality, and system running times were recorded. The experiment was performed using a high-performance computer with 6G of RAM. The parameters used by our GA algorithm are listed in Table 1.

The results are shown in Figs. 2 to 4. As Martins' algorithm is designed to list every Pareto optimal solution, the focus of our comparison is in terms of: i) the number GA solutions that are Pareto optimal (Fig. 2), ii) the average cost of the two algorithms (Fig. 3), and iii) their average running times (Fig. 4).

From the results, we see that the quality of the solutions produced by the GA-based algorithm is close to that of the adapted Martins' algorithm. In terms of Pareto optimality, the GA-based approach was able to produce Pareto optimal results in over 90% of the 84000 test cases (Fig. 2). And, as expected, the results were particularly good for larger problem sizes with 200 or more nodes, where 98% of the solutions that were obtained were Pareto optimal.

We also compared the total cost of the solutions produced by the two algorithms. The results are listed in Fig. 3 (presented in terms of the cost of the GA solution divided by the cost of the lowest-cost Martins' solution). From the figures, we see that the average obtained cost of GA only slightly exceeded the best cost obtained by Martins' – by less than 2%. Once again, the relative performance of the GA-based approach improved with the size of the problem. For instance, its average solution cost for 200 node problems exceeded the best cost obtained by Martins' approach by only 1.2%.

Once again, recall that Martins' algorithm is guaranteed to produce the optimal solution by definition, at the expense of system running time, figures for which are presented in Fig. 4. From the figure, we see that the GA-based algorithm clearly outperformed Martins' in all cases in terms of system running time.

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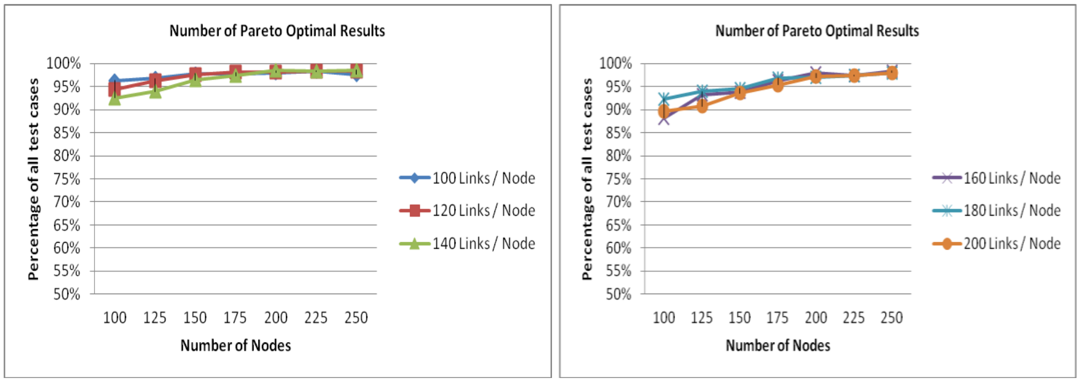

Fig. 2. Comparison of GA and Adapted Martins' algorithm - Pareto optimality

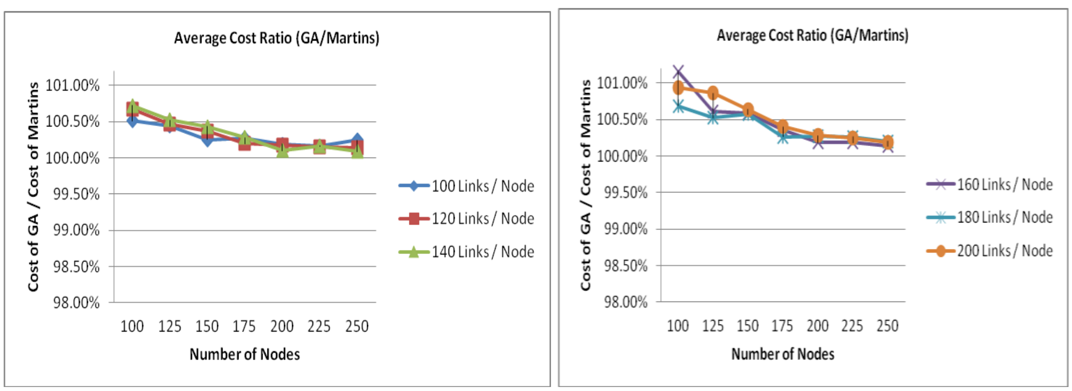

Fig. 3. Comparison of GA and Adapted Martins' algorithm - average solution cost

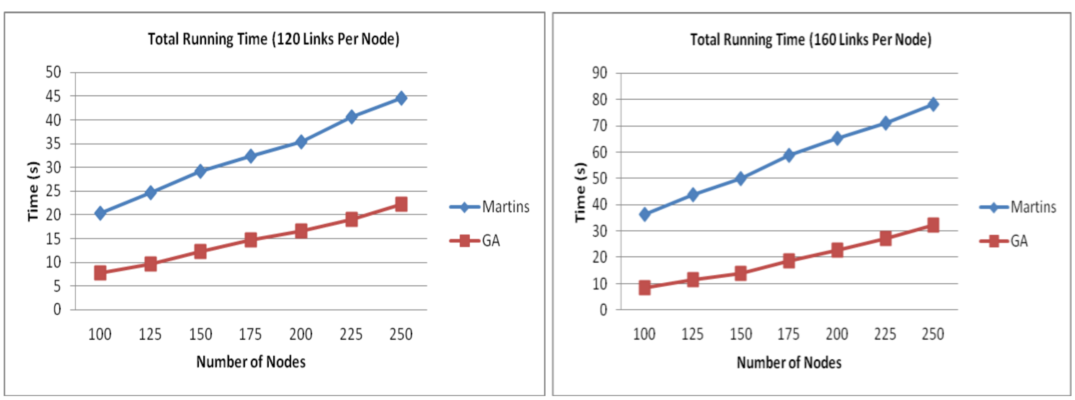

Fig. 4. Comparison of GA and Adapted Martins' algorithm - average running time

VII. Discussion

The above simulation experiment evaluated the GA-based approach quantitatively. As in many cases, we see that there is a small trade-off between solution optimality and system running time, even though the sacrifice in solution optimality is small (less than 2% in terms of solution cost in the simulation).

To understand why such a trade-off can be critical in a decision-support system for cargo routing, it is important to note that freight forwarding is a complex process that can be affected by a number of additional factors. This includes, for example, the reliability of the transportation links and the level of the relationship between the forwarder and the transportation companies. More importantly, some information regarding the availability of cargo spaces and the cost of each transportation link may not be available until the time that the route is being planned, as these may depend on the results of real-time negotiations between the forwarder and the airlines and shipping companies (e.g., for the ad-hoc booking of extra cargo space). As a result of the dynamic nature of the planning process,

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interactive optimization solutions, which allow the user to take part in the decision process, are preferred. In such systems, a short system running time with good solution quality, rather than a longer running time with perfect solutions, is crucial.

VIII. Conclusion

The multi-mode green logistics cargo routing (MGCR) problem is a special multi-objective cargo routing problem. Apart from the traditional objective of cost minimization, MGCR also considers carbon dioxide emission levels as both an additional constraint as well as a secondary objective. In this paper, we explored a genetic algorithm-based approach for MGCR and compared it with an adapted Martins' algorithm that is guaranteed to produce Pareto optimal solutions. The results suggest that the quality of the solutions obtained by the GA-based approach is very close to that obtained by Martins' approach in terms of Pareto optimality and cost, but with a significant reduction in system running time. The results suggest that the genetic algorithm could be a viable method for solving the MGCR problem.

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