Planning vehicle routes to optimize fuel consumption

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Abstract:

Introduction/purpose: Models developed for routing transport vehicles with an environmental focus are predominantly dedicated to reverse logistics or transporting environmentally hazardous cargo. Few models in the relevant literature consider the ecological factors for routing vehicles involved in the distribution of consumer goods.

Methods: This paper presents a model for planning vehicle routes to optimize fuel consumption, considering the time windows required for service and payload capacity of vehicles. A heuristic algorithm was developed to minimize fuel consumption. A Simulated Annealing metaheuristic was applied to enhance the solutions obtained by the proposed heuristic.

Results: The results from the heuristic algorithm for fuel consumption minimization and the improved results using the Simulated Annealing metaheuristic are presented. All tests were conducted on Solomon's instances.

Conclusion: The developed approach to vehicle routing ensures a compromise between transport companies and ecology. The results show that applying this approach can simultaneously minimize the costs of the transport company and CO_2 emissions.

Key words: vehicle routing, fuel consumption, simulated annealing, heuristic algorithm.

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Introduction

Environmental protection has become one of the most important factors in carrying out any activity. Road transport vehicles significantly impact the environment negatively, as they use fossil fuels, the combustion of which releases harmful gases that contribute to the greenhouse effect. However, road-transport vehicles remain irreplaceable for cargo distribution. It is crucial to recognize that one of the main contributors to the greenhouse effect is carbon dioxide (CO_2) emitted from fossil fuels by vehicles with internal combustion engines. Moreover, the amount of CO_2 released into the atmosphere is directly related to the fuel consumption of the vehicle; thus, reducing fuel consumption also reduces CO_2 emissions. Globally, there is a trend toward transitioning from fossil-fuel-powered transport to alternative fuels that pollute the atmosphere less.

If transitioning from one type of vehicle to another is not feasible, efforts should be focused on minimizing the harmful impacts of standard road transport vehicles that use fossil fuels. One effective approach is to apply vehicle routing models that also consider environmental factors (Asghari & Mirzapour Al-E-Hashem, 2021). Implementing these models to minimize fuel consumption is highly attractive to transport companies, as it reduces transportation costs while promoting environmentally responsible behavior.

Fuel consumption of a transport vehicle depends on numerous factors. These factors can be divided into those that can be optimized and included in the mathematical model and those that cannot be directly influenced by the optimization model, but can still be managed through appropriate measures.

Factors that cannot be optimized through a mathematical model include driver habits, vehicle age, and vehicle condition. Driver habits can significantly impact fuel consumption. Practical experience indicates that efficient driving can reduce fuel consumption by 1 to 2 liters per 100 km, resulting in substantial monthly fuel savings. To influence the habits of professional drivers, companies can organize training sessions on efficient driving and implement monitoring systems.

Vehicle age can also significantly affect fuel consumption. Truck manufacturers aim to reduce fuel consumption with each new series of trucks, so newer vehicles generally consume less fuel than older ones. Additionally, vehicle condition greatly influences fuel consumption. A well-maintained vehicle in good condition certainly consumes less fuel than a poorly maintained one. Therefore, older vehicles that are properly maintained can sometimes consume less fuel than newer vehicles that are not well-maintained. Consequently, it is not always accurate to assume that newer vehicles have lower fuel consumption than older vehicles.

Factors influencing the minimization of fuel consumption, and amenable to optimization models, encompass cargo volume, distance traveled, journey duration, and vehicle utilization. Notably, fuel consumption varies significantly between an empty vehicle and one at maximum capacity, with differences of up to 10 liters per 100 km (Ćirković, 2018). Conversely, reducing time and distance typically aids in lowering fuel usage. However, many overlooked the importance of time, neglecting that a vehicle covering 100 km in 2 h consumes differently from one doing so in 3 h. Thus, minimizing either factor does not necessarily equate to a fuel reduction. Hence, developing an optimization model that considers distance, time, and cargo volume is imperative for fuel conservation. This study tackled this multifaceted problem, integrating these three factors.

The principal benefit of the mathematical model, which focuses on vehicle routing to reduce fuel consumption, lies in aligning the cost-saving objectives of transport companies with broader societal aims. While companies aim for cost reduction, societies, in general, aspire to curtail environmental pollution, attainable through meticulous route planning.

In this paper, the mathematical formulation of the Vehicle Routing Problem with Time Window (VRPTW) is modified in terms of the objective function. The objective function is an equation that determines the fuel consumption on the route depending on the amount of cargo in the vehicle and the distance traveled. In the paper, heuristic and metaheuristic algorithms designed to minimize fuel consumption are developed and used to solve the mentioned VRPTW problem. To improve the solution generated by the new heuristic algorithm, a Simulated Annealing metaheuristic is adapted and applied to the mentioned problem. Testing the developed heuristic and metaheuristic approaches was performed on Solomon instances, to validate the mentioned approaches. The main contribution of this paper is the application of heuristic and metaheuristic approaches adapted to solve the VRPTW problem, with the goal to minimize fuel consumption, and thus CO_2 emissions. Also, the test results show the possibility of direct practical application of the developed approaches.

The structure of the paper unfolds as follows. After introductory discussions, an extensive literature review is presented in the second section. The third section elaborates on the mathematical model addressing the vehicle routing problem, which incorporates both time windows required for delivery and vehicle capacity as significant factors contributing to increased fuel consumption. Section four delves into the developed heuristic algorithm for fuel consumption minimization, while section five introduces the Simulated Annealing metaheuristic. The sixth section unveils the results of the testing, with the final, seventh section concluding with remarks and outlining ideas for future research.The introduction is an introductory part of the article.

Literature review

Vehicle routing problems that consider ecological factors, including carbon dioxide emissions, fuel consumption, and noise levels, aiming to minimize them through improved planning, fall within green logistic areas (Asghari & Mirzapour Al-E-Hashem, 2021). Considering that oil-fueled vehicles, known for their substantial environmental impact, are predominantly employed in road transport, it becomes imperative to prioritize ecological considerations in vehicle routing to ensure the sustainability of this sector in the future.

Routing is a routine task in the distribution and transportation sectors. Various software applications are used daily to define vehicle routes, aiming to boost company profits or cut costs. However, practical implementation of software that considers both economic factors and environmental protection is rare, largely owing to the recent development of optimization models with this objective. Additionally, environmental constraints further complicate the problem, hindering model formation and resolution.

Some authors have approached the routing problem from the perspective of "green" routing and schedules. Additionally, models related to sustainable logistics have been created (Asghari & Mirzapour Al-E-Hashem, 2021), such as:

– Waste collection problems;
– Transportation of hazardous materials;
– Time-dependent routing problems - indirectly influencing harmful gas emissions by aiming to reduce travel time by avoiding congested routes;
– enhancing the system in question, etc.

Models developed for routing transport vehicles with environmental considerations are mostly dedicated to reverse logistics or transportation of environmentally hazardous cargo. Few models have focused on the environmental concerns used for routing vehicles involved in the distribution of consumer goods. By developing such models, which strike a balance between societal aspects and the goals of transportation companies, a real impact on the environment can be achieved. Another reason to pay attention to these models is that the number of vehicles involved in daily distribution far exceeds the number of vehicles used for cargo collection. By reducing the environmental impact of vehicles during both distribution and collection, significant environmental benefits can be achieved compared with considering environmental factors only in either distribution or collection. Therefore, models addressing environmental concerns and routing vehicles for both distribution and collection should be concurrently developed to achieve the best outcome.

Since the introduction of the first Vehicle Routing Problem (VRP) in 1959 (Dantzig & Ramser, 1959), numerous modifications and extensions to this problem have emerged. Various models have been developed for determining routes during goods distribution, aiming to minimize costs (Herdianti et al, 2021), time (Chen et al, 2021), and distance (Pan et al, 2021), while fewer models consider environmental criteria (CO_2 emissions, fuel consumption, etc.) (Tiwari & Chang, 2015). A detailed overview of VRP problems, solution methods, and objectives can be found in the review articles by Marinakis & Migdalas (2007), Braekers et al. (2016), and Konstantakopoulos et al. (2022).

Reducing fuel consumption and CO_2 emissions during goods distribution can be achieved by defining a set of routes to minimize fuel consumption in the case of internal combustion engine vehicles (Liu et al, 2020; Ramadhani & Garside, 2021; Song et al, 2020), introducing electric vehicles (Napoli et al, 2021), and combining drone and internal combustion engine vehicle operations (Huang et al, 2022). In the study by Liao et al. (2019), a detailed comparison of the advantages and disadvantages of internal combustion engine vehicles and electric vehicles can be found. Due to the insufficiently developed infrastructure for electric vehicle usage (locations of fast chargers) and the high costs of replacing internal combustion engine fleets with electric ones, exclusive use of electric vehicles for goods distribution remains unfeasible for many companies. Therefore, reducing CO_2 emissions is most easily achieved by reducing fuel consumption during goods distribution, which can be accomplished by developing new and improved algorithms. Ramadhani & Garside (2021) addressed the VRP problem using the Particle Swarm Optimization (PSO) metaheuristic to minimize fuel consumption, primarily to reduce costs for distribution companies due to frequent fuel price increases. Liu et al. (2020) solved the Time-Dependent Vehicle Routing Problem with Time Windows (TDVRPTW) problem by considering vehicle speed, travel time, waiting time, service time, time windows, and the influence of driving modes and speeds on CO_2 emissions. Liu et al. (2020) attempted to strike a balance between company and societal goals by solving the stated problem by combining economic (vehicle fixed and driver costs) and environmental (fuel consumption, CO_2 emissions, noise level, etc.) criteria in the objective function. Opportunities to reduce fuel consumption during goods distribution are even more pronounced in cold chains. Song et al. (2020) solved the Vehicle Routing Problem with Time Windows (VRPTW) problem in the cold chain to reduce fuel consumption. In addition to the distance traveled and route completion time, the fuel consumption in the cold chain can be reduced by optimizing temperature maintenance device operations. The latest literature review on "green" VRP problems aimed at reducing fuel consumption, CO_2 emissions, noise levels, etc., was given by Asghari & Mirzapour Al-E-Hashem (2021).

Solving VRP problems to minimize only one environmental criterion is rare. Hence, the motivation for developing algorithms in this paper is to enable the determination of routes for wide-scale goods distribution, respecting time windows and vehicle capacity, to minimize only fuel consumption. Fuel consumption minimization falls under the category of economic criteria from the perspective of the distributing company, while from a societal perspective, minimizing fuel consumption affects CO_2 emissions, making it an environmental criterion. Unlike papers in the literature that exclusively combine economic or environmental criteria in the objective function, this paper focuses solely on minimizing fuel consumption, which simultaneously falls under both economic and environmental criteria, thus achieving the best compromise between the company's interests and those of the community.

Problem description and mathematical formulation

To present the mathematical formulation of the problem, it is necessary to first introduce certain notations. Let G (V, A) denote an oriented transport network, where V is the set of all nodes in the network V (0, 1, 2, 3, ..., n+1), and A is the set of edges (i, j). The nodes 0 and n+1 denote the depot, that is, the places where vehicles start and end their routes, respectively. Let N denote the set of nodes that must be serviced N (1, 2, 3, …, n), that is, the set of clients. The notation q_i represents the quantity of cargo demanded by the client i, and the notation [a_i, b_i] indicates the time window within which the required amount of cargo must be delivered to the client i.

Daily problems related to cargo distribution to facilities can be treated as vehicle routing problems with time windows - VRPTW (Desrochers et al, 1988).

The parameters:

t_{ij} – travel time from the node *i* to the node *j*;

M – a sufficiently large positive number;

w_i^k– variable indicating the start of service at the node *i* with the vehicle *k*;

Q – vehicle capacity;

c_{ij} – transportation cost from the node *i* to the node *j*

a_i – the earliest time when service can start at the node *i*

b_i – the latest time when service can start at the node *i*

S_i – service duration at the node *i*

q_i – demand at the node *i*

k – vehicle

The variable:

$$x_{ij}^k = \begin{cases} 1, \text{if the vehicle } k \text{ after visiting the node } i \text{ visits the node } j \\ 0, \quad otherwise \end{cases}$$

The mathematical formulation of the proposed problem (Desrochers et al, 1988):

Minimize

$$\sum_{k \in \mathrm{K}} \sum_{(i,j) \in \mathrm{A}} c_{ij} \cdot x_{ij}^k \tag{1}$$

with constraints:

$$\sum_{k \in \mathrm{K}} \sum_{j \in \delta^+(i)} x_{ij}^k = 1 \quad \forall i \in \mathrm{N} \tag{2}$$

$$\sum_{j \in \delta^+(0)} x_{0j}^k = 1 \quad \forall k \in \mathrm{K} \tag{3}$$

$$\sum_{i \in \delta^-(i)} x_{ij}^k - \sum_{i \in \delta^+(i)} x_{ij}^k = 0 \qquad \forall k \in \mathrm{K}, j \in \mathrm{N} \tag{4}$$

$$\sum_{i \in \delta^-(n+1)} x_{i,n+1}^k = 1 \qquad \forall k \in \mathrm{K} \tag{5}$$

$$w_j^k \geq w_i^k + S_i + t_{ij} - M\left(1 - x_{ij}^k\right) \qquad \forall k \in \mathrm{K}, (i,j) \in \mathrm{A} \tag{6}$$

$$a_i \leq w_i^k \leq b_i \qquad \forall k \in \mathrm{K}, i \in \mathrm{V} \tag{7}$$

$$\sum_{i \in \mathrm{N}} q_i \sum_{j \in \delta^+(i)} x_{ij}^k \le Q \qquad \forall k \in \mathrm{K} \tag{8}$$

$$x_{ij}^k \in \{0,1\} \qquad \forall k \in \mathrm{K}, (i,j) \in \mathrm{A} \tag{9}$$

The objective function (1) is of a minimization type, representing either total costs or total distance traveled. Alternatively, it can minimize the total time required for the defined routes. Constraint (2) ensures that all clients are serviced, while constraints (3) and (5) guarantee that every vehicle departing from the depot also returns to it. Constraint (4) ensures that every vehicle arriving at a node to provide service also departs from that node. Constraints (6) and (7) pertain to time intervals, and constraint (8) ensures vehicle capacity. Constraint (9) indicates that x_{ij}^k is a binary variable.

As previously mentioned, decreasing fuel consumption not only mitigates emissions of harmful gases but also plays a pivotal role in reducing overall transportation costs. By decreasing fuel usage, we not only cut down on expenses but also contribute to the preservation of finite natural resources (Ćirković, 2018). Statistics indicate that fuel costs represent approximately 60% of total transportation expenses. (Xiao et al, 2012).

Xiao et al. (2012) introduced a modified model for the vehicle routing problem with capacity constraints, aiming to minimize the fuel costs required to visit all nodes within a network. Their model considers fuel consumption as dependent on both the cargo weight in the vehicle and the distances covered with this cargo weight. While accounting for various factors influencing fuel usage, such as driver habits and vehicle age, these are treated as constants within the model.

If Q_0 denotes the weight of the vehicle and Q_1 denotes the weight of the cargo in the vehicle, then the fuel consumption rate per unit length is ρ (Xiao et al, 2012):

$$\rho(Q_1) = \alpha(Q_0 + Q_1) + b \tag{10}$$

During vehicle routing, two extreme situations can arise. The first extreme situation occurs when the vehicle is empty, and the second when the vehicle is fully loaded. When the vehicle is empty, the fuel consumption rate is calculated as follows (Xiao et al, 2012):

$$\rho_0 = \alpha Q_0 + b \tag{11}$$

If Q denotes the maximum cargo capacity that can be loaded onto the vehicle, then the fuel consumption rate when the vehicle is fully loaded is calculated as follows (Xiao et al, 2012):

$$\rho^* = \alpha(Q_0 + Q) + b \tag{12}$$

The value of the coefficient α is obtained by dividing the difference in fuel consumption rates between the two extreme situations by the maximum amount of cargo that can be loaded onto the vehicle (Xiao et al, 2012):

$$\alpha = \frac{\rho^* - \rho_0}{Q} \tag{13}$$

When formula (13) is substituted for the coefficient α in equation (10), the fuel consumption rate is calculated as follows (Xiao et al, 2012):

$$\rho(Q_1) = \rho_0 + \frac{\rho^* - \rho_0}{Q} Q_1 \tag{14}$$

If y_{ij} denotes the quantity of cargo transported by the vehicle from the node i tothe node j, formula (14) is modified as follows (Xiao et al, 2012):

$$\rho_{ij} = \rho_0 + \frac{\rho^* - \rho_0}{Q} y_{ij} \tag{15}$$

The fuel consumption for transporting the cargo quantity y_{ij} over the distance d_{ij} is equal to (Xiao et al, 2012):

$$c_{ij}(y_{ij}) = \rho_{ij} \cdot d_{ij} = \left(\rho_0 + \frac{\rho^* - \rho_0}{Q} y_{ij}\right) \cdot d_{ij} \tag{16}$$

First, it is necessary to determine the cost of the fuel consumed along one edge, that is, when traversing the distance from the node i to the node j. The cost of the fuel consumed along the edge (i, j) is obtained using the following formula (Xiao et al, 2012):

$$c_{fuel}^{ij} = c_0 \cdot \rho_{ij} \cdot d_{ij} \tag{17}$$

where:

c_0 – fuel price;

ρ_{ij} – fuel consumption rate from the node i to the node j; and

d_{ij} – edge (i, j) length.

Given the method for calculating the fuel cost along one edge, the total fuel cost during the realization of a defined set of routes can be calculated as the sum of the products of the fuel cost per edge and a variable indicating whether the vehicle has traversed that edge. The formula for computing the fuel cost along the routes is:

$$C_{fuel} = \sum_{k \in \mathrm{K}} \sum_{(i,j) \in \mathrm{A}} c_{fuel}^{ij} \cdot x_{ij}^{k} = \sum_{k \in \mathrm{K}} \sum_{(i,j) \in \mathrm{A}} c_0 \cdot \rho_{ij} \cdot d_{ij} \cdot x_{ij}^{k} \tag{18}$$

Applying formula (18) yields the fuel cost incurred during the service of n clients - nodes. If instead of fuel cost, the quantity of fuel consumed needs to be determined, this can be achieved by setting the unit fuel price to one, c0 =1. Thus, the resulting value of Cfuel represents the total fuel consumption when servicing n clients. Integrating the fuel consumption coefficient into the standard vehicle routing problem creates a new problem that may contribute to reducing fuel consumption compared to the standard problem.

Development of a heuristic algorithm for solving the given problem

A heuristic algorithm for minimizing fuel consumption developed in this paper was created to reduce fuel usage per vehicle route and consequently lower CO_2 emissions. This algorithm leverages the Nearest Neighbor Algorithm, considering time intervals, vehicle load capacity, and fuel consumption. Fuel consumption, calculated using formula (16), serves as the distance measure between nodes. Therefore, the nearest node is the one with the lowest fuel consumption.

The application of the heuristic algorithm for minimizing fuel consumption is outlined in five steps, and the implementation diagram is shown in Figure 1. The steps for the application are as follows:

Step 1: Calculate the fuel consumption for each pair of the nodes *i* and *j* using formula (16)**.**

Step 2: Begin forming a new route from the node representing the base. Set the departure time from the base to zero (D(0) = 0). Identify the nearest unserved node to the base based on fuel consumption. Include this node and add its demand to the partial route's total demand. Mark the added node as the current node and proceed to Step 3.

Step 3: Calculate the time when the vehicle departs from the current node after completing service. This is done by adding the travel time from the previous node to the current node to the departure time from the previous node, and then taking the maximum of this value and the earliest start time of service at the current node. Finally, add the service time at the current node to this value. Proceed to the next step.

Step 4: Find the closest unserviced node concerning fuel consumption from the current node, ensuring that it complies with the vehicle's capacity and service-time constraints. If such a node is found, incorporate it into the partial route, add its demand to the existing partial route's demand, designate it as the current node, and revert to Step 3. Otherwise, conclude the route, return the vehicle to the base, and proceed to Step 5.

Step 5: Check if all nodes have been serviced. If all nodes have been serviced, calculate the total fuel consumption using formula (18), and terminate the algorithm. Otherwise, return to Step 2.

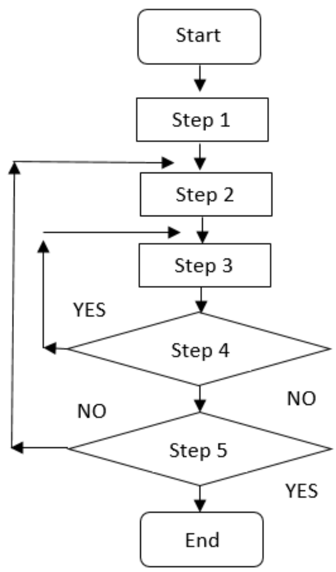

Figure 1 – Diagram illustrating the application steps of the heuristic algorithm for minimizing fuel consumption

Simulated Annealing metaheuristic

For solving combinatorial optimization problems, so-called specialized heuristic algorithms can be used. The heuristic algorithm for minimizing fuel consumption developed in this paper is a typical representative of this group of algorithms. Initially, the heuristic algorithm for minimizing fuel consumption was applied to obtain an initial solution. Subsequently, Simulated Annealing was applied to further improve the solution, that is, further minimize fuel consumption. Simulated Annealing is one of the most commonly used metaheuristics for combinatorial optimization problems. In a large number of papers in the literature, the Simulated Annealing metaheuristic gives excellent results in solving routing problems.

Simulated Annealing, first introduced by Kirkpatrick et al. (1983), is a widely used metaheuristic algorithm for solving intricate combinatorial optimization problems. Its core idea revolves around iteratively applying small, random perturbations, and then assessing the change in the objective function value between iterations. If this change is negative, signifying an improvement, the new feasible solution becomes the initial one for further random perturbations. In cases where the change in the objective function value is positive, indicating that the new solution is worse than the previous one, it should not be discarded immediately. Instead, it undergoes evaluation to determine whether it should be rejected or accepted as a new starting point. This approach prevents getting trapped in local minima from which it is difficult to escape. When evaluating whether a solution should be accepted or not, it is necessary to first calculate the probability that increasing the objective function value by ΔF at a temperature T is acceptable. This probability is calculated as follows (Teodorović, 2007):

$$p = e^{-\frac{\Delta F}{T}} \tag{19}$$

After computing the probability of accepting a new initial solution with $\Delta F \geq 0$, the next step is to generate a random number within the range [0,1]. Comparing this randomly generated number, denoted as r, with the calculated probability (p), a decision is made. If $r < p$, then the new feasible solution is adopted as the new initial solution; otherwise, it is discarded.

If, after numerous iterations, there has been no decrease in the objective function value, thermal equilibrium is reached. Thermal equilibrium is associated with the concept of epochs. An epoch involves defining S feasible solutions, where the parameter S is predefined. The condition for reaching thermal equilibrium is when, after the defined S feasible solutions in one epoch, there is no decrease in the objective function. The number of epochs is denoted as E, with E being predefined. Upon reaching thermal equilibrium, the temperature T is lowered, and then the described process repeats at the new temperature.

In this paper, the Simulated Annealing algorithm has been adapted for solving the standard Vehicle Routing Problem with Time Windows. The developed algorithm is based on the paper of Teodorović & Pavković

(1992). The application of the Simulated Annealing algorithm involves the following steps:

Step 1: Define the initial temperature (*T*), the number of epochs (*E*), the number of solutions to be generated within one epoch (*S)*, and the number of small perturbations during the generation of one solution (*P*).

Step 2: Generate the initial solution using the heuristic algorithm for minimizing fuel consumption.

Step 3: Randomly select two nodes from different routes and swap their positions. When considering the node swaps, ensure adherence to vehicle load constraints and time intervals. Repeat this step as many times as the number of small perturbations defined in step 1.

Step 4: Calculate the objective function value using formula (18). Then, compute the difference ΔF between the value of the new objective function and the value of the old objective function (20), which represents the total fuel consumption during the execution of the defined set of routes.

$$\Delta F = NF - OF \tag{20}$$

where:

NF – total fuel consumption for executing the new set of routes, and

OF – total fuel consumption for executing the old set of routes.

If $\Delta F < 0$, proceed to step 6. Otherwise, proceed to step 5.

Step 5: Using a uniform distribution, generate a random number $r \in [0,1]$. Calculate the probability *p* of increasing the objective function value by ΔF using the formula (19). If $r < p$, proceed to Step 6. If $r \geq p$, retain the old set of routes and proceed to step 7.

Step 6: Save the new set of generated routes and the total fuel consumption required for executing this set of routes. Proceed to step 7.

Step 7: If the number of generated solutions in the current epoch is fewer than *S*, return to Step 3. Otherwise, the epoch is completed. If the number of generated epochs equals *E*, terminate the algorithm; otherwise, if the objective function has not been reduced in the current epoch, decrease the temperature (start a new epoch) and return to Step 3, and if the objective function has been reduced, keep the existing temperature (start a new epoch) and return to step 3.

After generating the predefined number of epochs, the resulting solution represents a set of routes with lower fuel consumption than any other set of routes generated during the Simulated Annealing process. An enhanced application of the Simulated Annealing technique has been developed to improve this solution further.

The key difference between the initial and the enhanced applications of the Simulated Annealing technique lies in the method of generating the route sets. In the initial approach, feasible solutions were generated by randomly selecting and swapping two nodes from different routes, considering the vehicle load capacities and time windows. This meant that the selected nodes always came from different routes. For instance, node 5 might initially belong to route 1, but be reassigned to route 3 after applying the Simulated Annealing technique. By the end of the predefined number of epochs, each node was assigned to a specific route.

In the enhanced application, the nodes' affiliation with specific routes remains unchanged. Instead, only the order of nodes within each route is modified (Teodorović, 2007). This approach involves randomly selecting two nodes within the same route and swapping their positions while considering the time windows. This reordering of nodes is performed a predefined number of times. By altering the order in which the nodes are visited within a route, the goal is to further optimize the initial solution.

The described Simulated Annealing algorithm for improving the initial solution consists of the following steps:

Step 1: The same as in the previous algorithm.

Step 2: Take the best solution found in the previous application of the Simulated Annealing metaheuristic and set it as the initial solution.

Step 3: Select a node randomly. Then, find the route to which that node belongs, and randomly choose another node from that route. Swap the positions of these nodes if possible, taking into account the time intervals. Repeat this step as many times as needed to make small perturbations when defining one feasible solution, as specified in Step 1. Then proceed to Step 4.

Steps 4, 5, 6, and 7: The same as in the previous algorithm.

Results of testing the proposed algorithms

The results of solving the vehicle routing problem with vehicle load constraints and time windows in the context of goods distribution are presented in this section. Two algorithms were used: one for obtaining the initial solution (using a heuristic algorithm) and the other for improving that initial solution (using the Simulated Annealing metaheuristic), both considering fuel consumption. To implement the proposed algorithms, Java programming language was used on a 64-bit ACER computer with an Intel(R) Core(TM) i5 2.50 GHz processor and 8 GB of RAM.

Solomon's instances from rc201 to rc208 were used to test these algorithms (Sintef, 2008). To use any of these Solomon instances, it is necessary to determine the distance between nodes, the travel time between nodes, and the vehicle's load capacity. Regarding vehicle load capacity, the recommended value for these instances is 1000 units. The Euclidean distance is recommended for determining the distance between nodes, and the travel time is considered equal to the spatial distance. That is, traveling one unit of length requires one unit of time (Xiao et al, 2012). When applying these algorithms, the total fuel consumption for the defined set of routes is calculated using formula (18), where the price of fuel is set to one, $c_0 = 1$. To use this formula, it is necessary to predefine the empty vehicle fuel consumption rate, ρ_0, and the full vehicle fuel consumption rate, ρ^*. The empty vehicle consumption rate is set to 2, and the full vehicle consumption rate is set to 3. The fuel consumption of an empty vehicle is one-third lower than that of a full vehicle, hence these predefined values (Xiao et al, 2012). These values for ρ_0 and ρ^* are used to calculate the fuel consumption for the defined routes in both algorithms to enable a comparison of their results.

After determining the distance matrix, travel time, and vehicle load capacity, as described previously, vehicle route formation can begin. It is necessary to find routes that allow visiting all 100 nodes in the network and satisfying each node's demand, i.e., delivering the goods they require. Each route should start and end at node 1, which represents the base. When forming routes, the vehicle load capacity and predefined time intervals must be considered. The total demand on one route must not exceed the vehicle's load capacity of 1000 units. The calculation of the distance matrix and the general characteristics related to the instances (number of nodes, load capacity, relationship between time and spatial distance, full and empty vehicle consumption rates, etc.) are the same when implementing the heuristic algorithm for minimizing fuel consumption and the Simulated Annealing metaheuristic. For the Simulated Annealing algorithm, the number of epochs (E = 15), the number of new solutions generated within an epoch (S = 20), the number of small perturbations (P = 2), and the initial temperature (T = 150) must be defined. Additionally, during thermal equilibrium, the temperature decreases by multiplying the old temperature by 0.9 ($T_{new} = 0.9 \cdot T_{old}$).

The analysis of the test results for the heuristic algorithm and the Simulated Annealing metaheuristic, both aimed at minimizing fuel consumption, is shown in Table 1. The table reveals that both algorithms consistently generated the same number of routes. For each instance, the total distance required to complete the defined set of routes is greater with the heuristic algorithm than with the Simulated Annealing algorithm. Regarding time, for half of the instances, the total time required to complete the defined routes is shorter with the heuristic algorithm, whereas for the other half, it is shorter with the Simulated Annealing algorithm. The most critical criterion is fuel consumption, and in each instance, less fuel is consumed using the Simulated Annealing algorithm. Based on these results, it can be concluded that using the Simulated Annealing metaheuristic to improve the solutions obtained by the heuristic algorithm is fully justified.

Table 1 – Analysis of the results of applying the heuristic algorithm and after their improvement using the Simulated Annealing algorithm

Inst.	Heuristic algorithm				Simulated Annealing			
	Fuel consumption	**Distance**	**Time**	**No. of routes**	**Fuel consumption**	**Distance**	**Time**	**No. of routes**
rc201	425.95	2054.01	6224.19	11	401.45	1930.26	6253.87	11
rc202	434.62	2095.97	6179.30	11	371.42	1782.85	6431.54	11
rc203	417.09	2001.85	5774.57	10	331.34	1569.49	5868.55	10
rc204	284.51	1313.99	4178.67	7	267.20	1218.21	3811.43	7
rc205	435.68	2106.45	6088.63	10	361.82	1732.57	6211.51	10
rc206	352.50	1656.66	3432.71	6	317.07	1474.44	3384.35	6
rc207	333.58	1563.46	3697.37	6	321.22	1506.71	3488.19	6
rc208	281.70	1248.24	2025.92	3	254.11	1116.31	1993.59	3

The developed approaches (Heuristic algorithm and Simulated Annealing) are suitable for solving routing problems of small, medium, and large dimensions. This is shown by testing the approach on Solomon instances. In these instances, the problem of distribution of goods up to 100 objects is considered. For this dimension of the problem, the developed approach reaches a very good solution in a very short CPU time.

Table 2 presents the percentage reduction in fuel consumption, distance traveled, and execution time for the defined set of routes for each instance when the Simulated Annealing algorithm is applied to the heuristic algorithm's solution. Additionally, Figure 2 provides a graphical representation of fuel consumption for each instance, first using the heuristic algorithm to minimize fuel consumption, and then using the Simulated Annealing algorithm. The average percentage reduction in fuel consumption achieved by applying the Simulated Annealing algorithm is

10.93% per instance. The average reduction in the distance traveled is 11.60%, while the average reduction in the total route completion time is 1.16%. These results suggest that using the Simulated Annealing technique in combination with a heuristic algorithm for the initial solution, which considers fuel consumption, can significantly reduce the environmental impact and transportation costs for a company.

Table 2 – Percentage reduction in fuel consumption, distance, and time achieved by the Simulated Annealing metaheuristic compared to the heuristic algorithm

Instance	Simulated Annealing vs heuristic algorithm [%]		
	Fuel consumption	**Distance**	**Time**
rc201	5.75	6.03	-0.48
rc202	14.54	14.94	-4.08
rc203	20.56	21.60	-1.63
rc204	6.08	7.29	8.79
rc205	16.95	17.75	-2.02
rc206	10.05	11.00	1.41
rc207	3.71	3.63	5.66
rc208	9.79	10.57	1.60
Average	**10.93**	**11.60**	**1.16**

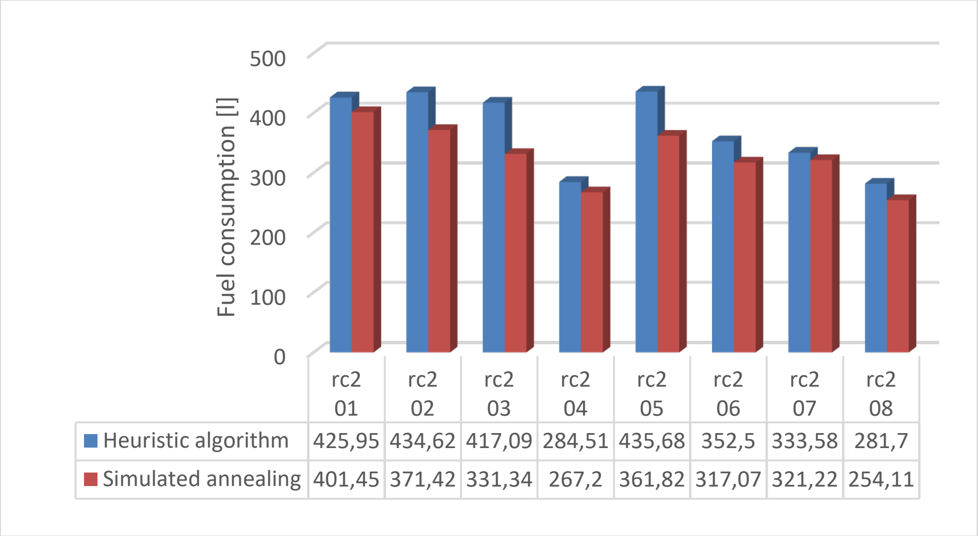

Figure 2 – Graphical representation of fuel consumption for each instance from rc201 to c208 using the heuristic algorithm and the simulated annealing metaheuristic

Conclusions

In-depth research on the standard vehicle routing problem dates back to the second half of the 20th century. At that time, the volume of transportation, and consequently the demand for it, was significantly lower than today. As a result, the harmful effects of vehicle emissions were not at the forefront of concern. However, with the global increase in population and rising living standards, both the need for transportation and customer demands have escalated. Consequently, in recent years, there has been a growing focus on environmental considerations, particularly in minimizing the adverse impacts of vehicle emissions during cargo distribution and collection.

The standard vehicle routing problem, which aims to optimize vehicle routes to reduce environmental impacts, is part of a relatively new research domain that has gained traction over the past decade. This paper demonstrates and substantiates the fact that a vehicle's fuel consumption is directly influenced by the volume of cargo it carries. For instance, when two clients are situated at comparable distances, priority should be given to the client with the larger cargo demand. This strategy ensures that the vehicle traverses the remaining route with a lighter load, consequently lowering fuel consumption, as vehicles with lighter loads consume less fuel.

To tackle this issue, a heuristic algorithm was developed to minimize fuel consumption. This algorithm builds upon the Nearest Neighbor Algorithm, aiming to minimize fuel consumption and, in turn, reduce environmental impact. Furthermore, to enhance the solutions provided by the heuristic, the Simulated Annealing metaheuristic was applied. The goal of Simulated Annealing is to make small changes to the initial solution, further reducing fuel consumption and, consequently, CO_2 emissions.

The analysis of the results after applying these two algorithms showed that using the Simulated Annealing algorithm results in an average fuel consumption reduction of 10.93% compared to using only the heuristic. Another advantage of combining the heuristic and the Simulated Annealing algorithm is the reduction in the total distance traveled and the overall time required for route completion. This approach leads to savings of 11.60% in total distance and 1.16% in total time compared with employing the heuristic alone. Based on these findings, it can be inferred that from both the environmental preservation and transportation company cost perspectives, employing a combination of a heuristic algorithm for fuel consumption minimization and the Simulated Annealing metaheuristic proves highly advantageous. Three directions for future research have been identified. The first relates to testing the developed approach on a real example of a transport company. The second is to extend the model in a way that takes into account other factors that affect fuel consumption, such as: vehicle condition and age, vehicle utilization, etc. The third is to compare the developed approach with other metaheuristics such as Genetic Algorithms, Bee Colony Optimization, etc.

A potential problem when applying the developed approach may be that the fleet size is not considered. Therefore, it may happen that the observed fleet cannot implement all the generated routes. It should also be noted that a homogeneous fleet was observed when developing the approach. The mentioned limitations of the developed approach can be overcome with minor modifications.

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Planificación de rutas de vehículos para optimizar el consumo de combustible

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CAMPO: investigación de operaciones, logística, transporte, tráfico
TIPO DE ARTÍCULO: artículo científico original

Resumen:

Introducción/objetivo: Los modelos desarrollados para rutas de vehículos de transporte con un enfoque ambiental se dedican predominantemente a la logística inversa o al transporte de cargas ambientalmente peligrosas. Pocos modelos en la bibliografía relevante consideran los factores ecológicos para las rutas de vehículos involucrados en la distribución de bienes de consumo.

Métodos: Este artículo presenta un modelo de planificación de rutas vehiculares para optimizar el consumo de combustible, considerando las ventanas de tiempo requeridas para el servicio y la capacidad de carga útil de los vehículos. Se desarrolló un algoritmo heurístico para minimizar el consumo de combustible. Se aplicó una metaheurística de adaptación simulada para mejorar las soluciones obtenidas por la heurística propuesta.

Resultados: Se presentan los resultados del algoritmo heurístico para la reducción del consumo de combustible y los resultados mejorados utilizando la metaheurística de adaptación simulada. Todas las pruebas se realizaron en las instancias de Salomón.

Conclusión: El enfoque desarrollado para las rutas de vehículos garantiza un compromiso entre las empresas de transporte y la ecología. Los resultados muestran que la aplicación de este enfoque puede reducir simultáneamente los costes de la empresa de transporte y las emisiones de CO_2.

Palabras claves: rutas de vehículos, consumo de combustible, adaptación simulada, algoritmo heurístico.

Планирование маршрутизации транспортных средств с целью оптимизации расхода топлива

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РУБРИКА ГРНТИ: 27.47.19 Исследование операций,
73.47.12 Организация управления и автоматизированные системы управления транспортом
81.88.00 Материально-техническое снабжение. Логистика
ВИД СТАТЬИ: оригинальная научная статья

Резюме:

Введение/цель: Модели, разработанные для маршрутизации транспортных средств, ориентированных на охрану окружающей среды, в основном предназначены для обратной логистики или перевозки опасных для окружающей среды грузов. Однако лишь немногие модели в релевантной литературе учитывают экологические факторы для маршрутизации транспортных средств, участвующих в распределении товаров широкого потребления.

Методы: В данной статье представлена модель планирования маршрутизации транспортных средств для оптимизации расхода топлива с учетом временных интервалов, необходимых для обслуживания и грузоподъемности транспортных средств. Для минимизации расхода топлива был разработан эвристический алгоритм. Для улучшения решений, полученных с помощью предложенной эвристики, была применена имитационная метаэвристика отжига.

Результаты: В статье представлены результаты эвристического алгоритма для минимизации расхода топлива и улучшенные результаты с использованием метаэвристики имитационного отжига. Все испытания проводились на «Solomon instances».

Вывод: Разработанный подход к маршрутизации транспортных средств является компромиссным решением для транспортных компаний по отношению к экологии. Результаты показывают, что применение данного подхода позволяет одновременно минимизировать затраты транспортной компании и выбросы CO_2.

Ключевые слова: маршрутизация транспортных средств, расход топлива, имитация отжига, эвристический алгоритм.

Планирање рута возила ради оптимизације потрошње горива

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ОБЛАСТ: операциона истраживања, логистика, транспорт, саобраћај
ВРСТА ЧЛАНКА: оригинални научни рад

Сажетак:

Увод/циљ: Модели развијени за рутирање транспортних возила, са фокусом на животну средину, претежно су посвећени повратној логистици или транспорту терета опасног по животну средину. У релевантној литератури неколико модела разматра еколошке факторе за усмеравање возила укључених у дистрибуцију робе широке потрошње.

Методе: У раду је представљен модел за планирање рута возила ради оптимизације потрошње горива, водећи рачуна о временским оквирима у којима се опслуга може извршити и носивости возила. Развијен је хеуристички алгоритам чији је циљ смањење потрошње горива. Такође, метахеуристика симулирано каљење примењена је да би се побољшала решења добијена предложеном хеуристиком.

Резултати: Приказани су резултати хеуристичког алгоритма за минимизацију потрошње горива и побољшани резултати применом метахеуристике симулирано каљење. Сви тестови су спроведени на Соломоновим инстанцама.

Закључак: Развијени приступ за рутирање возила обезбеђује компромис између транспортних компанија и екологије. Резултати показују да се применом овог приступа могу истовремено минимизирати трошкови транспортне компаније и емисија CO_2.

Кључне речи: рутирање возила, потрошња горива, симулирано каљење, хеуристички алгоритам.

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