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Establishment and Optimization of Green Logistics Fuel Consumption Model Based on Ant Colony Algorithm

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In order to solve the problem of fuel consumption in logistics transportation, a better path planning is designed to reduce the fuel consumption of logistics from the point of vehicle path planning. According to analysis for the shortest path and the most fuel-efficient path, a mathematical model is established, and an improved ant colony algorithm is proposed for the model. After studying China's road standards and construction standards, fuel consumption related technologies for internal combustion engines, a specially designed heuristic factor is introduced to reduce fuel consumption target. The driving distance, the weight of the goods, the type of the road and the road slope are fully considered. The Matlab simulation results show that, under the minimum fuel consumption target, adding a heuristic factor will promote capacitated vehicle routing problem (CVRP) to save about 9% of the fuel oil. The setting of backhaul constraints makes it better for low fuel consumption.
Although the final path length increases by 10%-20% compared with the minimum path target, the final path can save about 30% of the fuel. In conclusion, the fuel saving design based on ant colony algorithm is reasonable and effective, and it is of great significance to the development of green and low-carbon logistics.

1. Introduction

In recent years, the central government gives priority to the adjustment of industrial structure and the improvement of the overall quality of the industry. Green energy, low-carbon, energy-saving and environmental protection are listed as the focus of the work direction, this work should not only be carried out in the construction of urbanization (Das and Wagh, 2015), but also need to be implemented in the upgrading and transformation of traditional manufacturing industry.

In order to achieve green urbanization and green manufacturing, as a solid support for urbanization and manufacturing, the logistics transportation industry is also facing the challenge and pressure to become greener (Akbari et al., 2016). With the increasing competition in the market, more and more enterprises begin to outsource the logistics function module to the specialized logistics service organization (Zuo et al., 2015). Thus, logistics enterprises emerge as the times require. Through the specialized logistics service, the logistics enterprise obtains the profit by reducing the cost of enterprise logistics operation (Jia et al., 2015). However, the average profit margin of China's logistics industry is only about 3%. Logistics cost is mainly composed of transportation cost, storage cost and management cost (Kyriakopoulos et al., 2016). Transportation costs account for the largest proportion. According to statistics, no matter what kind of models, fuel cost accounted for the proportion of total cost of operation is as high as 50%. With the rising oil prices, this proportion continues to increase.

Therefore, the effective management and control of the transportation cost will play an important role in the construction and development of the logistics enterprises' own advantages (Tian et al., 2016). Therefore, based on the environmental protection and national energy security strategy, for enterprise operation, it is of great positive significance to reduce carbon emissions to protect the environment, achieve sustainable economic development and reduce the fuel consumption of vehicles in the logistics and transportation (Tong et al., 2015).

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2. Design and implementation steps of ant colony algorithm

Aiming at the complexity of the energy problem, the heuristic factor of ACS is designed in the algorithm. In the global pheromone updating strategy, the parallel ant colony algorithm is introduced. Combined with ASrank update method and MMAS update strategy, the ant colony behaviour in nature is simulated better (kefayat et al., 2015).

2.1 Construction of heuristic factor

The construction of heuristic factor is very important to the quality of solving, and it is the core component in the construction of ant solving process. If the distance factor is simply considered, it is difficult to adapt to the complexity of freight weight, road type and road slope variation in the CVRP problem. Vehicles tend to produce very large fuel waste because of the choice of shortest path. Therefore, the factors such as customer demand weight, road type and road slope are added into the heuristic factor. Under the goal of minimizing fuel consumption of vehicles, the vehicle routing can be more reasonable, and the fuel utilization rate of the vehicle can be improved (Wang et al., 2016). For the next node selection, it is necessary for the vehicle to take into account the four factors that affect the fuel consumption (Zhang et al., 2016). In order to solve the two different stages of vehicle driving, it is beneficial to solve the ant colony algorithm by designing appropriate transformation mode (Parker and Tyedmers, 2015). Thus, the construction for heuristic factor is shown in formula (1):

$$\eta(\mathrm{i}, j) = \frac{1}{((\sin\theta_{ij} + \cos\theta_{ij}\mu_{\mathrm{ij}})\ \mathrm{d}_{ij})} \tag{1}$$

In the formula, η(i,j) is the heuristic factor between the customer *i* and the customer *j*. μ_{ij} represents the friction coefficient between the road surface and the vehicle tire. θ_{ij} represents the angle between the road surface and the horizontal surface. d_{ij} is the distance between the customer *i* and the customer *j*.

2.2 Implementation steps of the algorithm

According to the basic steps of the general ant algorithm, the detailed implementation steps of the improved ant colony system (ACS) for solving the minimum fuel consumption target CVRP are listed here (Senzig et al., 2015):
(1) Parameter initialization: cycle times record is set to Nc=0, and the maximum cycle index is set to N_{max} (Described in the program as iter_max);
(2) Update of taboo table: such as the setting of pheromone distribution, the finding route of ants to start;
(3) Dispatch ants to start route search: In the choice of the next node, unlike the general ant algorithm, it is not only determined by the state transition probability, but also depends on the random number r_0;
(4) When the ant is traversed, the initial most possible path s is obtained and used as the initial solution of the local domain search;
(5) Construct i_max group neighbourhood and generate random scheme s': The local search methods adopted in this paper are three kinds of elements, such as element exchange within the line, element exchange between lines, and element transfer between lines;
(6) After the local search is completed, if we can get a more optimal path solution, then go back to the previous step (Tang et al., 2015). If it can't be optimized, then finish the local search process;
(7) The circle algorithm continues, and if there is a better solution, it is updated, otherwise, until the circle condition is over;
(8) When all ants have completed the path search, the global update is not immediately started. After the n-th ants complete the path search, pheromone on the path is updated and the optimal solution so far is recorded. After all the loops are finished, the output is finally carried out.

3. Experimental results and analysis

In order to verify the effectiveness of the proposed algorithm under different scales, two sets of data were designed, namely 30 customers and 60 customers. The average weight of the goods is 11, and the variance is 40. The road parameters and other settings are the same as the 30 points, all of these analysis data are compared (Zhao et al., 2016). Relative to the traditional CVRP problem without considering the weight of the goods, we believe that the CVRP with fuel minimization can be equivalent to the CVRP problem with work minimization (Guo et al., 2015). First, the three factors are disassembled separately, and the results are checked individually, which is easier to discover the performance improvements brought about by various improvements (i.e., the decrease of fuel consumption).

3.1 Effect of weight of goods on results

According to the average value of the five simulations of Matlab, the ant colony algorithm with the weight factor of goods has a significant improvement of 9.88%. It is important to note that the group we chosen is a weight group with variance 40. It can be predicted that if the variance is increased, the effect will be further improved. Because the ant colony algorithm with weight factor superimposed on the cargo will have better adaptability to solve this kind of problem. At the same time, it can be observed that the results obtained by adding weight factor to the average travel distance become longer. This actually confirms our logic that the shortest path algorithm is not the least fuel consumption.

Table 1: Fuel consumption after adding weight factor of goods

Customer	Average fuel consumption	Minimum fuel consumption	Average travel distance	Minimum travel distance
Minimum path target	3389.05	3206.53	89.20	88.11
The minimum fuel consumption target superimposed on cargo weight factors	3084.25	3049.41	90.53	90.19
Promotion ratio of the new algorithm	9.88%	5.15%	-1.46%	-2.30%

3.2 Effect of maximum vehicle load on the results

In order to verify the data of vehicle weight in table 1, it is concluded that the optimization space of the path planning will be increased when the maximum load weight is limited, and the optimization comparison of the algorithm should be continued. In a data group, the customer is set to 30, goods weight variance is 40, and the average weight is 11. After changing the maximum load of the vehicle, the horizontal axis is the maximum load, while the vertical axis represents the total fuel consumption and the total driving distance. We do further algorithm simulation, and the simulation results are shown in Figure 1 and Figure 2.
When the maximum load of the vehicle increases continuously, the overall fuel consumption has a process of decreasing first and then rising. This proves our hypothesis that increasing the maximum load of vehicles in a certain range will improve the performance of the algorithm. Because of this, we can leave the algorithm to adjust the weight of different goods in order to save fuel. This also explains the data we set above, that is, the maximum load of vehicles is 50, the variance between the data is 40, and the average value is 11. As shown in the figure, the maximum load is between 50-60, and the overall fuel consumption will be the lowest.
In order to further verify the rationality of the data on larger scale data, the simulation of the 60 customers data set is also performed. The simulation data are shown in Figure 3 and Figure 4

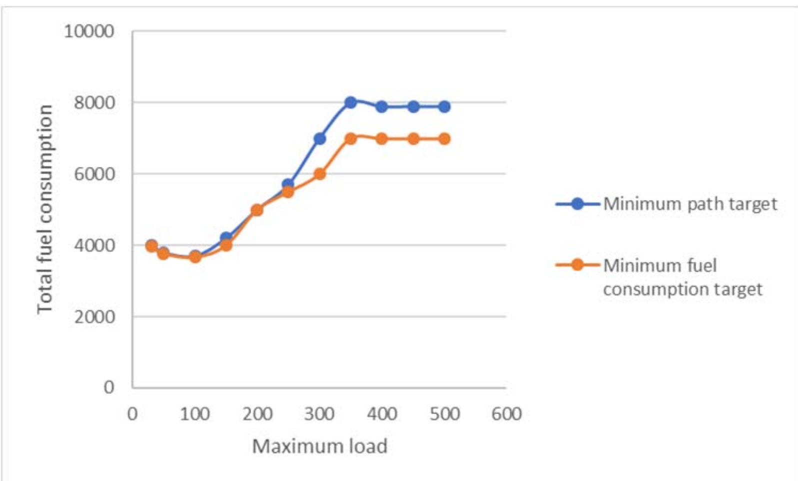

Figure 1: Fuel consumption is changing according to Maximum load's setting

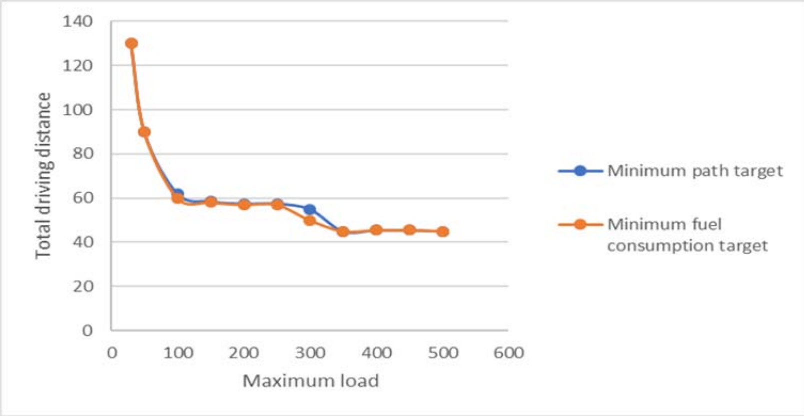

Figure 2: Driving distance is changing according to Maximum load's setting

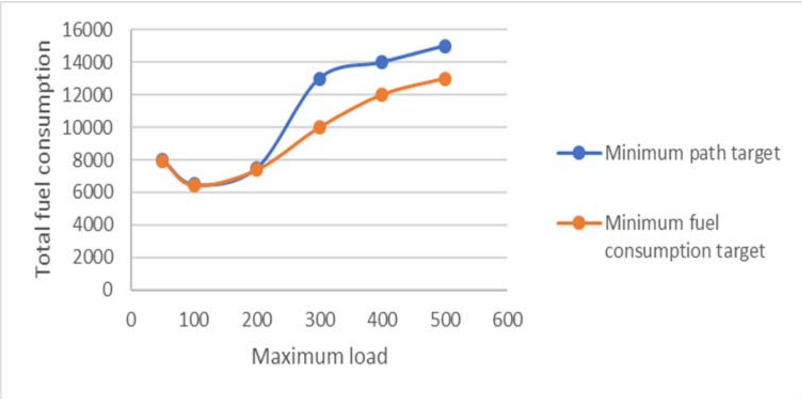

Figure 3: Fuel consumption is changing according to Maximum load's setting

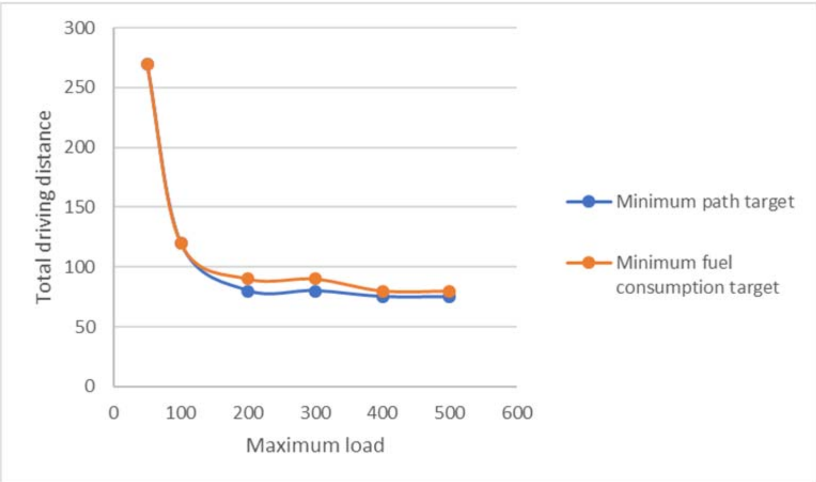

Figure 4: Driving distance is changing according to Maximum load's setting

The simulation results show that when the vehicle load is small, the minimum fuel consumption target has almost no optimization function relative to the minimum path target. Because the maximum load of the vehicle obviously has the maximum limit. Therefore, when the maximum vehicle load is increased, the optimization effect is obvious. In fact, in figure 3, when the maximum vehicle load is 30, 50 and 70, respectively, the data promotion ratio is 2.27%, 3.61% and 6.66%, which shows that it has a good ascension effect.

3.3 Effect of road slope on the result

Slope plays a very important role in fuel consumption. The slope (less than 5%) will double the fuel consumption. Similarly, which is obtained by the mean value according to the five simulations of Matlab. The simulation shows that fuel utilization rate is increased by 8.84%. In this paper, the 30% road has a slope, and the proportion is relatively small, while the slope is divided into uphill and downhill. If the vehicle is on the downgrade, the fuel consumption is only half.

It can be observed that the results obtained by adding the pavement type factor and the road slope factor are longer on the average travel distance. This confirms our logic that the minimum fuel consumption path is not the shortest path for most of the time.

In this chapter, the problem of minimum fuel target in CVRP is described and modeled, while the improved ACS and parameter are proposed. The simulation has achieved excellent results, and has obtained many conclusions which are not consistent with our common sense. This effectively proves that the CVRP with the minimum fuel consumption target is actually significantly different from the CVRP with traditional minimum path target. Simulation analysis shows that the shortest path of CVRP is not the most fuel saving mode, nor the most energy-efficient and greenest distribution mode.

Table 2: Fuel consumption after adding road slope factor

Customer	Average fuel consumption	Minimum fuel consumption	Average travel distance	Minimum travel distance
The minimum fuel consumption target superimposed on cargo weight factors	3084.25	3049.41	90.53	90.19
The minimum fuel consumption target superimposed on cargo road slope factors	2833.71	2800.41	99.41	98.75
Promotion ratio of the new algorithm	8.84%	8.89%	-8.93%	-8.67%

4. Conclusion

Based on vehicle routing planning, a better path planning is designed to reduce the energy consumption in the process of logistics distribution. After determining the goal of energy saving and emission reduction, several factors affecting the fuel consumption of internal combustion engine are decomposed. Through the decomposition of forces, these factors are unified into a vehicle routing optimization model, so that the fuel consumption becomes measurable and computable. Finally, the improved ant colony algorithm (improved by modern heuristic algorithm) is used to solve the problem. In the ant colony algorithm, both the heuristic factor and the pheromone updating strategy are improved, and the ideal results are obtained in order to better conform to the model and imitate the biological parallelism of ants. After that, the reverse logistics condition with simultaneous pickup and delivery is introduced, which makes the complexity and difficulty of the problem further improved, and the improvement of model and algorithm is discussed with the experimental results. Currently, the climate problem is becoming increasingly serious, and the importance of energy issues has significantly improved. China's vehicle ownership and transportation are also rising. The state is working hard to call for energy-saving society and green economic construction. The strategy of energy saving and emission reduction for logistics transportation in this paper is of great significance to the green development of the logistics industry.

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