

Article

A Distance-Adaptive Refueling Recommendation Algorithm for Self-Driving Travel

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Abstract: Taking the maximum vehicle driving distance, the distances from gas stations, the route length, and the number of refueling gas stations as the decision conditions, recommendation rules and an early refueling service warning mechanism for gas stations along a self-driving travel route were constructed by using the algorithm presented in this research, based on the spatial clustering characteristics of gas stations and the urgency of refueling. Meanwhile, by combining ArcEngine and Matlab capabilities, a scenario simulation system of refueling for self-driving travel was developed by using c#.net in order to validate and test the accuracy and applicability of the algorithm. A total of nine testing schemes with four simulation scenarios were designed and executed using this algorithm, and all of the simulation results were consistent with expectations. The refueling recommendation algorithm proposed in this study can automatically adapt to changes in the route length of self-driving travel, the maximum driving distance of the vehicle, and the distance from gas stations, which could provide variable refueling recommendation strategies according to differing gas station layouts along the route. Therefore, the results of this study could provide a scientific reference for the reasonable planning and timely supply of vehicle refueling during self-driving travel.

Keywords: intelligent transportation; recommendation algorithm; distance adaptive; spatial cluster; K-Means; refueling; APP

1. Introduction

1.1. Motivation

Self-driving travel is a kind of independent travel that is an organized and planned form of tourism based on the primary transportation means of driving oneself [1]; at present, self-driving travel has become the most popular travel form in the world, as well as a family gathering pattern [2]. This prevalence of self-driving travel has not only brought vitality and prosperity to the global tourism market but has also placed higher demands on the infrastructure and management services that support self-driving travel; in particular, the challenge of refueling a vast number of self-driving vehicles is one of the issues gas station owners and drivers focus on. Stories of vehicles breaking down on the road due to fuel exhaustion have been reported [3]. Some such vehicles have caused traffic accidents [4], and Saarinen's study also revealed an increase in drivers who ran out of fuel on the roadside in Great Britain in 2014 [5]. Although it is feasible to solve the embarrassing situation of fuel exhaustion during travel by road rescue and other means, no self-driving traveler wishes to experience such an accident. This indicates that timely refueling on the road is one of the most fundamental

guarantees for the safety of self-driving travel [2]. Currently, the vehicle refueling strategy is judged and executed mainly by relying on the driver's experiences during self-driving travel [6,7]; although this kind of "experience refueling" method is feasible, it still has the following obvious defects.

First, the "experience refueling" method requires the driver to be familiar with the conditions of the road and the self-driving vehicle, so that the driver can determine where and when to refuel. However, in most cases, the drivers in self-driving travel are not always familiar with the road conditions or even the vehicle condition (for example, when renting a car), which often causes excessive or insufficient refueling [8]. Second, the "experience refueling" method requires the driver to put considerable effort into the calculation and judgment of refueling, which may increase the risk of fatigue driving and is not conducive to driving safety [9]. Finally, self-driving travel has been characterized by freedom, individuality, and mavericks since its appearance. In order to pursue this travel experience, some self-driving tourists tend to avoid the traditional tourist route and visit more obscure tourist destinations, which generally feature fewer tourists, less modern tourism services and infrastructure, fewer gas stations, and inconsistent oil quality; consequently, the timely replenishment of standard fuel can be difficult after entering such scenic areas [10].

In conclusion, "experience refueling" is a common method for self-driving vehicles to refuel on the road, but this method also has some disadvantages: the timing of refueling cannot easily be accurately controlled, tourists' energy is wasted, driving costs are increased, driving safety is adversely affected, and the pleasure of self-driving travel is reduced. Therefore, how to judiciously plan vehicle refueling according to the travel schedule to improve the safety of self-driving travel is an important scientific problem worthy of further study. Being motivated by the refueling problem in self-driving travel, we proposed this study in order to solve that very problem. Considering parameters including the number of refueling gas stations, the maximum driving distance of the vehicle, the distances between gas stations, the route length, and other distance variables, and based on the spatial clustering characteristics of gas stations along the route and the urgency of refueling, the algorithm constructed recommendation rules and a refueling service warning mechanism, which could provide humanized intelligent refueling strategies for the driver so that he would not be distracted by the refueling problem. The results of this study could fundamentally remedy the deficiencies of "experience refueling" and finally achieve the objective of improving the safety and quality of self-driving travel.

1.2. Literature Review

At present, the vehicle refueling problem has led to several research areas, including the following fields: (1) the green vehicle route problem from a low carbon perspective (GVRP), (2) the location problem of gas stations, (3) scheduling of mobile refueling and recharging facilities, and (4) the refueling optimization problem, among others. Field (1) mainly studies the vehicle routing optimization problem as determined according to the minimum driving distance, the shortest driving time, and the fewest dispatched vehicles, and as an extension of traditional VRP research, GVRP focuses on the vehicle routing optimization problem as determined according to the lowest overall oil consumption while driving [11]. The core issue in this field is how to establish the objective function of energy consumption and optimally solve it: for example, Jabbarpour [12] and Kwon [13] studied a multiple-variable GVRP computational model, as well as model solution methods based on the ant colony optimization algorithm and tabu search algorithm. In addition, some researchers took vehicle fuel supply demand as a constraint to solve the vehicle routing problem, forming the Fuel-Constrained Vehicle Routing Problem (FCVRP). For instance, Montoya [14] studied the influence of nonlinear charging time on the route planning of electric vehicles; Sundar [15] studied path planning algorithms for small Unmanned Aerial Vehicles (UAVs) with resource constraints; and Bruglieri [16] examined how to optimally route Electric Vehicles (EVs) to handle a set of customers in a given time considering recharging needs during trips. The research content in reference [17] was similar to that in reference [15], but the objective function and decision variables in reference [17] were more complex, addressing a multiple depot, multiple unmanned vehicle routing problem with fuel constraints. Field (2) mainly studies the

reasonable location problem of gas stations, the core of which is the construction and evaluation of gas station location models, which are typically analyzed and evaluated based on Geography Information System (GIS) spatial analysis and the actual demand for vehicle refueling [18]. For example, based on different route choices and traveling conditions, Hosseini [19] and Miralinaghi [20] studied the construction methods of a gas station location model, as well as its heuristic algorithm, and finally showed that GIS spatial analysis can be used to scientifically optimize the location of gas stations. In Field (3), the major research is concerned with scientific scheduling and routing optimization for mobile refueling facilities, such as airport tankers, space refueling aircraft, etc. For example, Heng [21] and Feng [22] studied a scheduling optimization model and found solutions for an airport tanker based on planning time windows and genetic algorithms.

The vehicle refueling problem we are examining here and the areas of study of the above three fields intersect in part, but there are also some obvious differences in research objective, content, and methods, which are mainly reflected in the following aspects: (1) First, the GVRP or FCVRP problem is aimed at optimizing total oil consumption and does not consider how to refuel along the way; however, refueling en route is the core research content of this study, i.e., where and when the vehicle “can”, “needs to”, and “must” refuel during travel. (2) Second, the location of gas stations is considered when planning gas station construction. In this case, more consideration is given to optimizing the spatial layout of gas stations, and the main object of the research is gas stations themselves rather than vehicles that need refueling. However, the research subjects of the present study are self-driving vehicles and their refueling environment (the driving route, the number of gas stations, and the layout of gas stations along the route), focusing on the scientific planning problem of refueling during travel based on GIS spatial calculations and spatial analysis. (3) Third, the research subjects of the scientific scheduling problem for mobile refueling facilities are mobile; however, the refueling facilities in the present study are gas stations, which are immobile.

Field (4) mainly studies the decision-making model and intelligent management of vehicle refueling, and the correlation between Field (4) and this study may be the closest among the above four fields. Studies have shown that rational planning of the refueling process can help reduce fuel costs; for example, U.S. truckload (TL) carriers developed a software program called “Fuel optimizers” for fuel cost management, which reduces the fuel cost of motor carriers at the “point of purchase” by way of an optimization algorithm [23]. However, Suzuki has argued that these products upset many truck drivers by “confiscating” their freedom to choose truck stops. Then, a decision support system was developed, which reduced the fuel cost of motor carriers at the point of purchase without confiscating the drivers’ freedom to choose truck stops, so that higher driver compliance rates were expected [23–27]. Also, Lin [28] considered the fixed-route vehicle refueling problem, similar to that addressed by commercial fuel optimizers, and developed a linear-time greedy algorithm for finding optimal fueling policies. Nicholas et al. [29] studied whether the refueling of AFVs (Alternative Fuel Vehicles) could be informed by refueling experiences from the traditional petrochemical refueling network. Kuby [30] and Kelly [31] systematically studied the differences in refueling behavior between liquid fossil fuel vehicles and alternative fuel vehicles and proposed a decision model of AFV refueling according to actual refueling data for Alternative Fuel Vehicles in Southern California. As seen from the above references, the existing refueling decision models have mainly studied the problem of how to plan the refueling route to save fuel costs, optimizing the economy of refueling by using mathematical modeling and other methods, which has been very useful for guiding people to save more in fuel costs. However, these decision and optimization models might also deprive drivers of the choice freedom of “where to refuel”: not only are the mathematical formulas used in these models often comparatively complex, but the refueling recommendations are difficult to understand during the actual refueling process, and therefore the models’ decision-making effectiveness is far from satisfactory.

To sum up, the refueling decision-making model for moving vehicles is still a scientific problem worthy of current study in the field of intelligent transportation. Thus, taking vehicle refueling with traditional liquid fossil fuels as an example, a distance-adaptive refueling recommendation algorithm

for self-driving travel was put forward in this study in order to assist in refueling decision-making for moving vehicles. Utilizing the strong geo-computation ability of GIS, this refueling recommendation algorithm calculated various distance variables affecting the refueling behavior of moving vehicles, and an optimized spatial clustering algorithm was used to calculate the refueling priority at gas stations along the route; finally, the refueling recommendation results were visualized based on the rich mapping function of GIS to verify the practicability and effectiveness of the algorithm. Although the work we did may be relatively simple, we propose that our study may be quite helpful for self-driving drivers to make reasonable choices about the timing and location of refueling. The expectation of this study is that our work and results can promote the intersection and integration of intelligent transportation and GIS, as well as other geospatial sciences, and can also provide a theoretical foundation and feasible technical means for rational refueling of and automatic warnings in self-driving vehicles.

2. Materials and Methods

2.1. Algorithm Description

The refueling problem in self-driving travel can be described as follows: how does one determine when and where to refuel according to the travel route and the layout of gas stations along the way? This is actually a refueling strategy optimization problem, which is described in Figure 1 and can be summarized as follows: (1) the closer the vehicle runs to the maximum driving distance, the more it needs to be refueled; (2) the more gas stations along the route from the starting position to the maximum distance, the stronger the refueling ability. Therefore, the number of gas stations, the relative positions of the vehicle and gas stations, and the relative distance variables are the key conditions for solving the refueling problem in this study. In particular, we use three distance variables, two distance differences, and two counters of gas stations along the route [32]. Among them, the three key distance variables are the maximum driving distance of the vehicle ($D_{to_maxdriving}$), the route length (D_{route}), and the distance from the starting point to a given gas station (D_{to_node}); all of the distances used in this study are curve distances obtained by driving from the starting point (P_{start}) along the traveling route. The two distance differences are the difference between the maximum driving distance of the vehicle and the route length ($\Delta D_{maxdriving_route}$) and the difference between the maximum driving distance of the vehicle and the distance from every gas station along the way ($\Delta D_{maxdriving_to_node}^i$, i represents the i th gas station). The two counters of gas stations are the total number of gas stations along the traveling route ($N_{gas_stations}$) and the total number of refueling gas stations within the maximum driving distance of the vehicle ($N_{used_gasstations}$).

According to the diagram illustration of the refueling recommendation problem described above (Figure 1), a distance-adaptive refueling recommendation algorithm for self-driving travel was developed for this study; the algorithm flowchart is shown in Figure 2.

The main steps and explanation of the algorithm are as follows:

Step 1: The three key distance variables and the number of gas stations along the route $N_{gas_stations}$ are calculated.

Step 2: The first distance difference $\Delta D_{maxdriving_route}$ is calculated by using the distance variable.

Step 3: If $\Delta D_{maxdriving_route} > 0$, then Strategy 1 is recommended (see Table 1 for details); otherwise, go to Step 4. In Strategy 1, the remaining fuel is sufficient for the vehicle to complete travel from this point, and no refueling is required along the route.

Step 4: If $N_{gas_stations} = 0$, then Strategy 2 is recommended; otherwise, go to Step 5. In Strategy 2, the remaining fuel is insufficient for the vehicle to reach the nearest gas station, and hence the driver should have filled up the gas tank in advance or carried gas with him.

Step 5: All of the gas stations along the route are traversed, and the second distance difference $\Delta D_{maxdriving_to_node}^i$ is calculated by using the distance variable. The i th gas station is located within the refueling range if $\Delta D_{maxdriving_to_node}^i > 0$, in which case the position and distance difference of the i th

gas station are saved to construct the recommendation rules of Strategy 3 and Strategy 4; meanwhile, the counter of refueling gas stations is increased by 1 ($N_{used_gasstation}++$).

Step 6: If $N_{used_gasstations} \leq 3$, then Strategy 3 is recommended; otherwise, go to Step 7. In strategy 3, moderate fuel remains, but refueling is needed along the route to ensure that the vehicle can reach the destination. Which gas station will be chosen for refueling depends on whether the number of gas stations is 1, 2, or 3.

Step 7: According to the positions of the refueling gas stations and the value of the second distance difference ($\Delta D_{maxdriving_to_node}^i$), clustering analyses of the refueling gas stations are conducted; refueling service levels for each gas station can be marked and evaluated based on the clustering results, consequently providing a calculation basis for the construction of Strategy 4. In Strategy 4, the choice of gas stations for refueling depends on the clustering of available gas stations.

Step 8: The recommended strategy for refueling during self-driving travel obtained by the above calculations is displayed and counted, and the program ends.

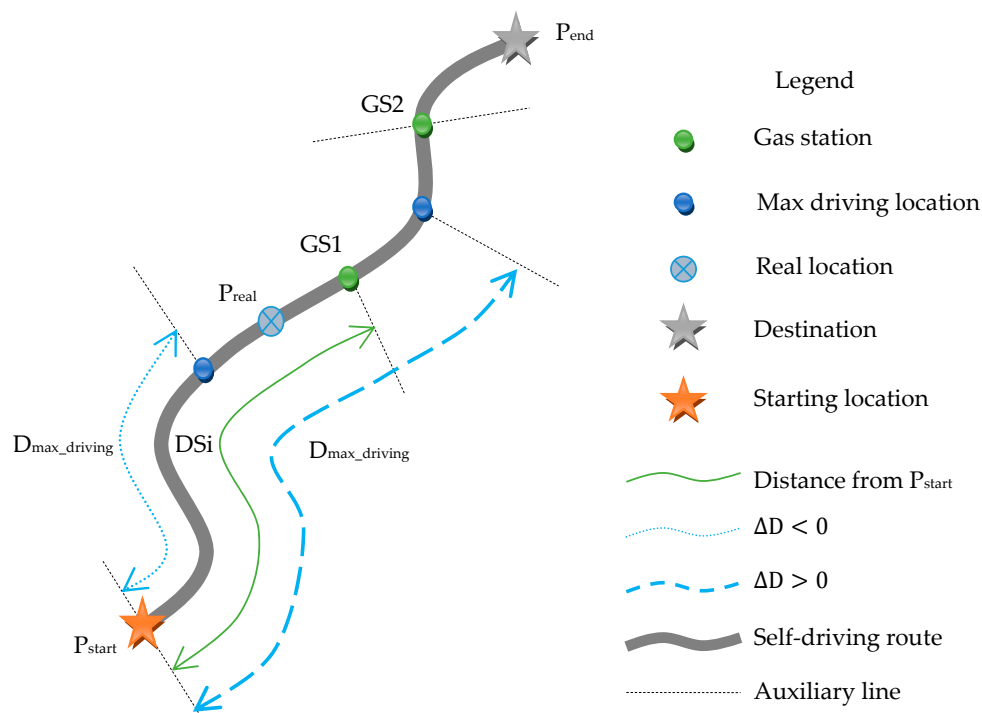


Figure 1. Diagram of the refueling recommendation problem.

Table 1. Recommendation rules and strategies of refueling for self-driving travel.

Determination Condition	Value Range	1	2	3	4	5	6	7
The total number of gas stations	= 0		T					
	= 1				T			
The number of refueling gas stations	= 2					T		
	= 3						T	
	> 3							T
The distance from aggregate mileage	> 0	T		F	F	F	F	F
The distance from gas stations	> 0			F	T	T	T	T
Recommendation strategy		Strategy 1	Strategy 2	Strategy 2	Strategy 3	Strategy 3	Strategy 3	Strategy 4

T indicates that the condition must be satisfied, F indicates that the condition must not be satisfied, and a blank indicates that the condition does not need to be judged.

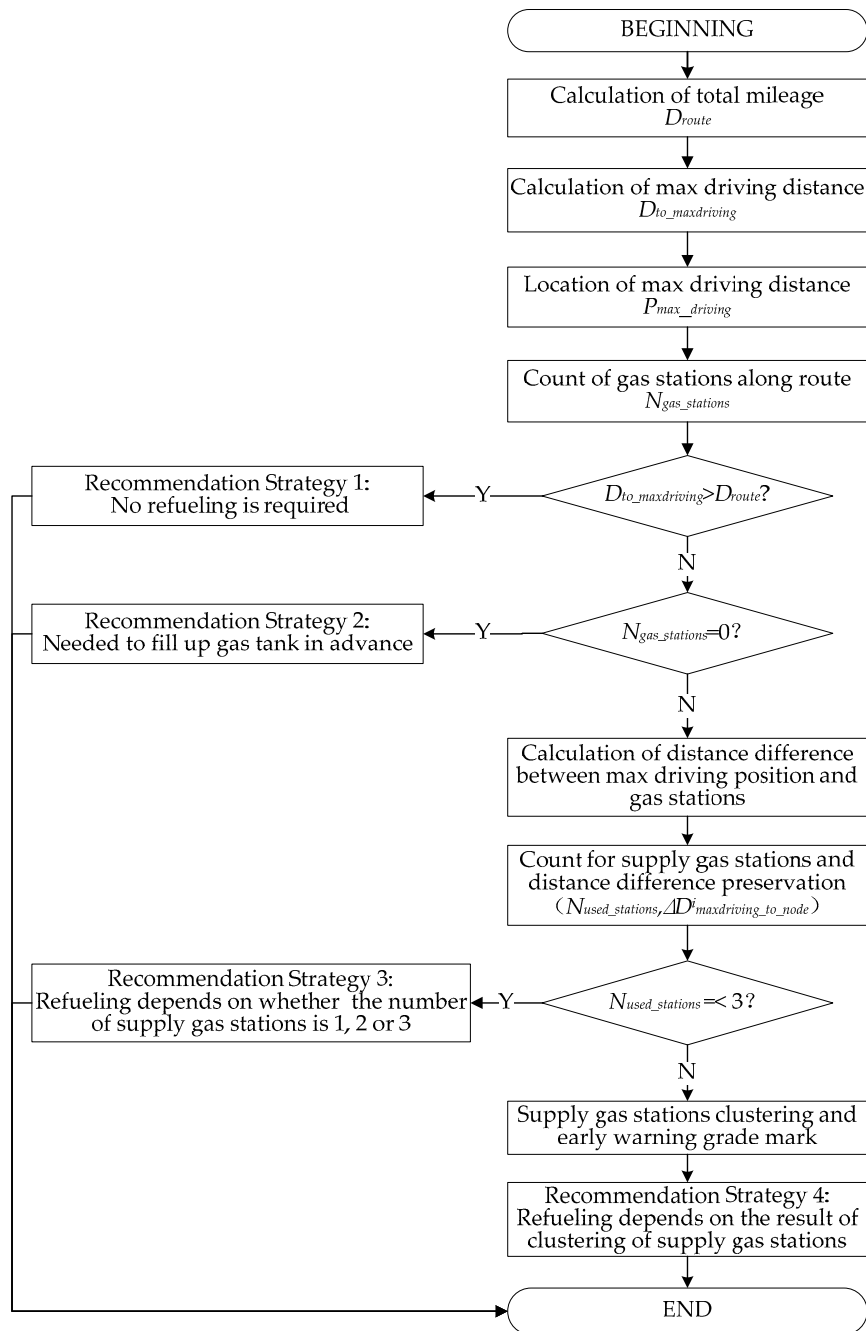


Figure 2. Procedure of the refueling recommendation algorithm.

2.2. Key Decision Variables and Calculation Methods

2.2.1. Calculation of the Three Distance Variables

Two methods were used to calculate the maximum driving distance of the vehicle ($D_{to_maxdriving}$): one was manual entry of the distance; the second was an estimation based on the fuel consumption per hundred kilometers (FC_{100}) and the remaining fuel (G_{left}), which is shown in Formula (1):

$$D_{to_maxdriving} = \frac{G_{left}}{FC_{100}} \quad (1)$$

Mathematically speaking, there is considerable similarity between the calculation method of the route length (D_{route}) and that of the distance from the gas station to the starting point along the route (D_{to_node}), which were both solved by using the arc length calculation method [33]. However, gas stations in real life are usually located on both sides of the road, and their locations do not intersect with the curve formed by the route of self-driving travel, so there are some differences between the calculations of the two distances, and the calculative process of the route distance from the gas station to the starting point is often more complicated. As shown in Figure 3, InPoint represents the actual location of the gas station, NearPoint represents the closest position of the gas station to the road, the blue dotted line represents the nearest distance between InPoint and NearPoint, and the route distance of the self-driving travel between the gas station and the starting point can be approximated as the route length from the closest position (NearPoint) to the starting point. It is not easy to design algorithms separately to calculate these two distances [34]. Fortunately, many GIS software programs now provide calculation methods for these two distances. For example, Environmental Systems Research Institute (ESRI)'s ArcGIS software provides many computing tools and functions for curve distance [35]. Specifically, the PolyCurve component provided by ESRI ArcEngine was used to solve these two kinds of distance calculation problems in this study; the PolyCurve OMD (Object Model Diagram) used is shown in Figure 4. This component uses the ICurve interface, and the calculation methods for the curve length and the route distance are both defined in this interface, according to the following function prototype and calling method:

$$\begin{cases} D_{route} = Geometry_{route}.get_Length(length) \\ D_{to_node} = Geometry_{route}.QueryPointAndDistance \\ \quad (null, InPoint, false, NearPoint, distanceAlongCurve, distanceToCurve, false) \end{cases} \quad (2)$$

where $Geometry_{route}$ represents the geometric object of the vector element of the self-driving route, $length$ is the return value of the route length, $distanceAlongCurve$ represents the distance from the input point InPoint (the actual location of the gas station) to the starting point (of the self-driving travel) along the route, $distanceToCurve$ represents the nearest distance from InPoint to the route (the length of the blue dotted line in Figure 4), and the other parameters are either default or empty.

In addition, InPoint overlaps with NearPoint when InPoint is just on the curve, and the distance function still can work normally and yield the correct result. Therefore, for convenience of calculation, the later test data were designed such that InPoint was on the curve, and this did not affect people's understanding of the fact that gas stations are off the center line in reality.

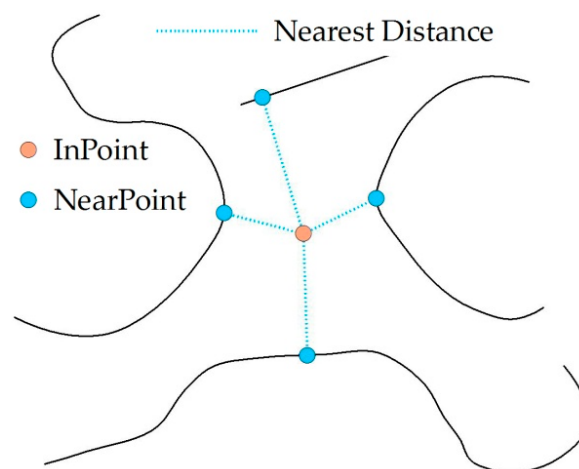


Figure 3. Relationship between InPoint, NearPoint, and Nearest Distance.

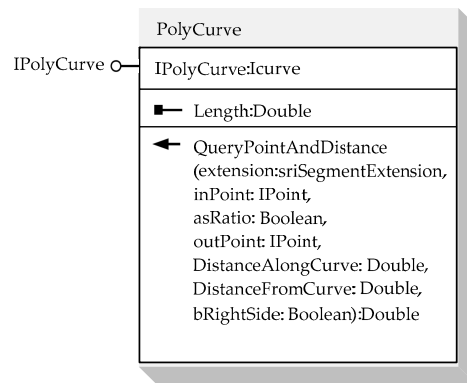


Figure 4. Object Model Diagram (OMD) of PolyCurve component.

2.2.2. Calculation of the Two Distance Differences

In order to preserve the direction of the distance difference calculations, the maximum driving distance of the vehicle ($D_{to_maxdriving}$) was stored as the subtrahend, and the route length (D_{route}) and the distance from the gas station to the starting point (D_{to_node}) were stored as the minuends; the calculation of the two distance differences is shown in Formula (3) (i represents the i th gas station).

$$\begin{cases} \Delta D_{maxdriving_route} = D_{to_maxdriving} - D_{route} \\ \Delta D_{maxdriving_to_node}^i = D_{to_maxdriving} - D_{to_node} \end{cases} \quad (3)$$

2.2.3. Calculation of the Two Counters of Gas Stations

The calculation method and process for the two counters of refueling gas stations along the route can be seen in Step 1 and Step 5 of the algorithm flow above.

2.3. Construction of Recommendation Rules and Design of Warning Mechanism

It was apparent from the problem-solving principle and the overall process of the algorithm that the refueling recommendation strategies were closely related to the two distance differences and the two counters of gas stations along the route, so the construction of recommendation rules needed to comprehensively consider the influences of the above variables on the refueling process. In addition, because the gas stations along the route were located at different points, it was necessary to rationalize the refueling order according to the location difference, and the refueling priority needed to be evaluated and marked as well; consequently, a scientific refueling warning mechanism was formed [8]. The recommendation rules and refueling warning mechanism in this study were designed based on the consideration that the recommendation strategy should reflect the necessity and urgency of refueling caused by changes in distance and fuel consumption during vehicle operation [36] (Table 1).

Three refueling warning levels were set in this study, corresponding to three color symbols (green, orange, and red). The warmer the color, the higher the level of refueling warning, indicating a greater necessity of refueling at that gas station. In order to improve the readability of the recommendation strategy, the words “Can”, “Need”, and “Must” were used to represent the refueling recommendations of the three respective warning levels. Accordingly, four recommendation strategies of refueling were formed as follows:

(1) Strategy 1: The remaining fuel is sufficient for the vehicle to complete travel from the current point, and hence no refueling is required along the route.

(2) Strategy 2: The remaining fuel is insufficient for the vehicle to reach the nearest gas station, and hence the driver should have filled up the fuel tank in advance or carried fuel with him.

(3) Strategy 3: The remaining fuel is moderate at the moment, but refueling is needed along the route to ensure that the vehicle can reach the destination. At this time, there are no more than three

gas stations within the refueling range, and the refueling warning level cannot exceed the default total number of refueling priority levels (three refueling warning levels of green, orange, and red); therefore, it is not necessary to classify the refueling warning level of all gas stations that could provide refueling by using the clustering algorithm. However, when there are fewer than three available gas stations that could provide refueling, the refueling warning level should be increased with decreasing opportunity for refueling, indicating that the necessity for refueling at the corresponding gas stations is also increased. The possible recommendation results are as follows:

- When $N_{used_gasstations} = 1$, there is one and only one refueling gas station along the route, which is marked with a red warning.
- When $N_{used_gasstations} = 2$, beginning from the direction of the starting point, the first gas station is marked with an orange warning and the second gas station is marked with a red warning.
- When $N_{used_gasstations} = 3$, beginning from the direction of the starting point, the first gas station is marked with a green warning, the second gas station is marked with an orange warning, and the third gas station is marked with a red warning.

(4) Strategy 4: $N_{used_gasstations} \geq 4$ at the moment; first, cluster analyses of refueling gas stations are conducted according to the second distance difference $\Delta D_{maxdriving_to_node}^i$, and then the warning levels of resupply urgency at refueling gas stations are marked based on the classification results.

2.4. Layout Optimization of Refueling Service Based on Cluster Analysis

Clustering is the process of grouping spatial data objects into a series of meaningful clusters so that objects within a particular cluster share similarities while being dissimilar to other clusters [37,38]. The most commonly used spatial clustering algorithms are as follows: partitioning methods, such as K-Means [39]; hierarchical methods, such as CURE (Clustering Using Representatives) [40]; and density-based methods, such as DBSCAN (Density-based Spatial Clustering of Applications with Noise) [41]. In fact, no particular clustering method has been shown to be superior to its competitors with regards to all of the necessary aspects [42]. To date, the advantages and disadvantages of various algorithms have been extensively analyzed [43–46]. Clustering attributes are the most important judgment criteria in clustering calculations. For spatial data, clustering attributes generally come from the characteristics of the sample data, which generally include not only some spatial features such as position, shape, and size but also some other nonspatial features such as name, quantity index, evaluation index, etc. [47]. Therefore, the clustering of spatial data tends to be more complex, considering not only the similarity of spatial relations but also the influences of nonspatial features in clustering. The distance difference between gas stations was used as a clustering attribute in this study, which was mainly based on the following ideas: proximal gas stations were similar in their refueling ability, and could be classified as one category; by contrast, the farther apart the gas stations were, the more different the refueling effects were, and the less likely the gas stations fell into one category [46].

Based on the above analyses, considering the diversity and convenience of clustering attributes in distance calculations, a hierarchical clustering algorithm was chosen as the clustering analysis tool in this study. Meanwhile, in the test section of this paper, the clustering effects of the hierarchical clustering algorithm and K-Means clustering algorithm were compared to verify the performance of the selected clustering algorithm. The spatial clustering steps for calculating the gas station layout by using the hierarchical clustering algorithm were as follows:

- (1) Cluster attribute evaluation. Take $\Delta D_{maxdriving_to_node}^i$ as a cluster attribute.
- (2) Calculate the two–two distance matrix. The form of the two–two distance matrix is shown in Table 2, where D_{ij} indicates the relative distance between gas stations. Because the clustering attribute itself is an actual distance value, “absolute distance” was used to calculate the value of D_{ij} ,

the calculation method and properties of which are shown in Formula (4), where n is the number of gas stations that could be used for refueling along the route.

$$\begin{cases} D_{ij} = |D_i - D_j| \\ D_{ij} = D_{ji} \\ D_{ij} = 0 \Leftrightarrow i = j \end{cases} \quad i, j \in n \quad (4)$$

(3) Clustering and warning level assignment. The shortest distance method was used to classify the following: first, the shortest distance $D_{pq} = \min\{D_{ij}\}$ was determined from the nondiagonal elements of the $n \times n$ distance matrix, and the corresponding gas stations D_p and D_q were merged into a new class, D_r ; second, the distance between the remaining classes and the new class was recalculated according to Formula (5), generating a new $(n - 1)$ -order distance matrix; finally, we looked again for the shortest distance and categorized the results based on the new distance matrix, and repeated this until all gas stations were placed into one category [40].

$$D_{rk} = \min\{D_{pk}, D_{qk}\} (k \neq p, q) \quad (5)$$

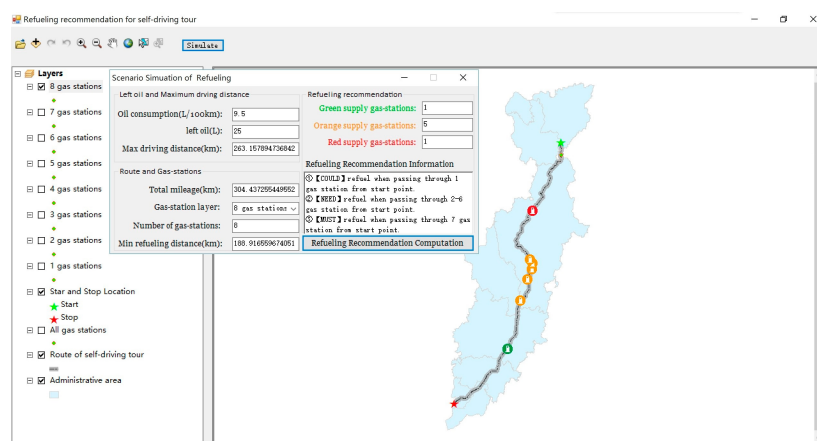
Table 2. Matrix of distance.

D_{ij}	1	2	3	4	n
1	0	D_{21}	D_{31}	D_{41}	D_{n1}
2	D_{12}	0	D_{32}	D_{42}	D_{n2}
3	D_{13}	D_{23}	0	D_{43}	D_{n3}
4	D_{14}	D_{24}	D_{34}	0	D_{n4}
n	D_{1n}	D_{2n}	D_{3n}	$D_{4n} \dots \dots$	0

3. Results and Discussion

3.1. Design and Development of the Scenario Simulation System

The algorithm's scenario simulation system was designed and developed by utilizing ArcEngine and Matlab2012b, and the development environment was VS C#.net 2012. ArcEngine was mainly used to solve routing and gas station problems such as data entry, map display, and computing, and Matlab was mainly used for spatial clustering analysis of gas stations. The simulation system interface based on the above mixed design idea is shown in Figure 5a, and the clustering algorithm and its results (clustering spectral pattern diagram) are shown in Figure 5b.



(a)

Figure 5. Cont.

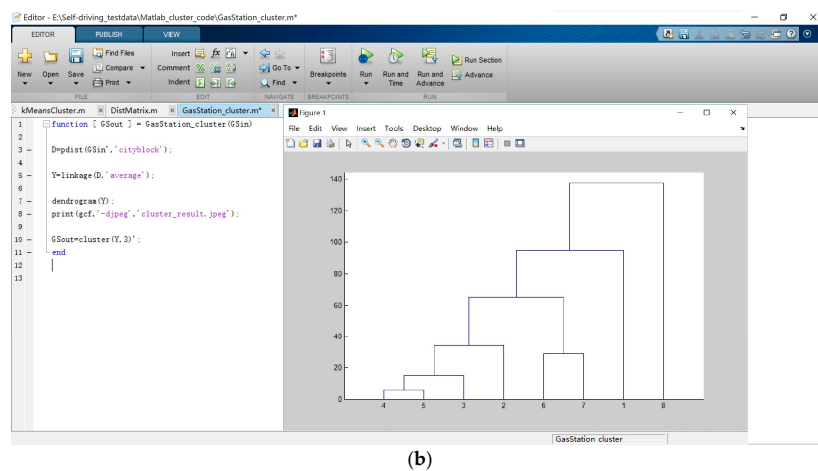


Figure 5. System development of scenario simulation based on ArcEngine and Matlab. (a) Interface of scenario simulation; (b) cluster analysis of gas stations based on Matlab.

3.2. Comparison and Sensitivity Analysis of Clustering Algorithm

In order to determine which clustering algorithm was more suitable for the distribution optimization and refueling ability classification of gas stations, based on the two common clustering algorithms of K-Means and hierarchical clustering, the sensitivity of clustering attributes and the clustering results of the two methods were compared and analyzed to verify the rationality of the selected clustering algorithm. The verification test was divided into two parts:

(1) Sensitivity analysis of clustering attributes. The clustering operation was carried out based on the judgment criteria of the route distance between two gas stations and the locations of the gas stations, and then the influence of clustering attributes on the classification rationality of gas stations in different gas station layouts was analyzed.

(2) Effects comparison of the clustering algorithm. Cluster analysis was conducted for a given gas station layout by using the K-Means and hierarchical analysis clustering algorithms, and the clustering results of the two algorithms were compared and analyzed according to the actual refueling needs for the given gas station layout, so that a more scientific and efficient clustering method could be identified.

3.2.1. Sensitivity Analysis of Clustering Attributes

The S-type route and corresponding gas station layout shown in Figure 1 were designed for this study. This kind of S-type road exists in many places around the world, especially in mountainous areas where the original ecological environment is well maintained, such as the sky mountain road in Zhangjiajie, Hunan Province, China. In addition, another reason for designing this kind of S-type route with twists and turns was that this kind of curve could better reflect the difference between the route distance and the linear distance, which supported testing the sensitivity of clustering attributes. The clustering calculation was conducted by using two clustering attributes (the Euclidean distance between two gas stations and the route distance between two gas stations), and then the clustering results were evaluated. The analysis process and evaluation results of the clustering calculation are shown in Table 3 and Figure 6.

Table 3. Clustering effects comparison of different clustering attributes.

Item Gas Station	Original Data ($\times 10^4$)			Attributes and Results of Clustering		
	X-Coordinate of the Gas Station/m	Y-Coordinate of the Gas Station/m	The Distance between the Gas Station and the Starting Point/km	The Clustering Result under the Constraint of Euclidean Distance and Route Distance	The Clustering Result of Euclidean Distance	The Clustering Result of Distances between the Gas Stations
1	−6.6425	−4.2083	0.0494	c1	c1	c1
2	−3.6308	−4.4530	0.0463	c2	c2	c1
3	−2.0886	−1.8608	0.0355	c2	c2	c2
4	−6.7309	−0.6905	0.0306	c1	c1	c2
5	−2.0426	1.5114	0.0244	c3	c3	c2
6	−3.0601	5.3208	0.0111	c3	c3	c3
7	0.9865	7.2768	0.0001	c3	c3	c3

c1, c2, or c3 indicates that the corresponding gas station is classified into the green, orange, or red warning level, respectively.

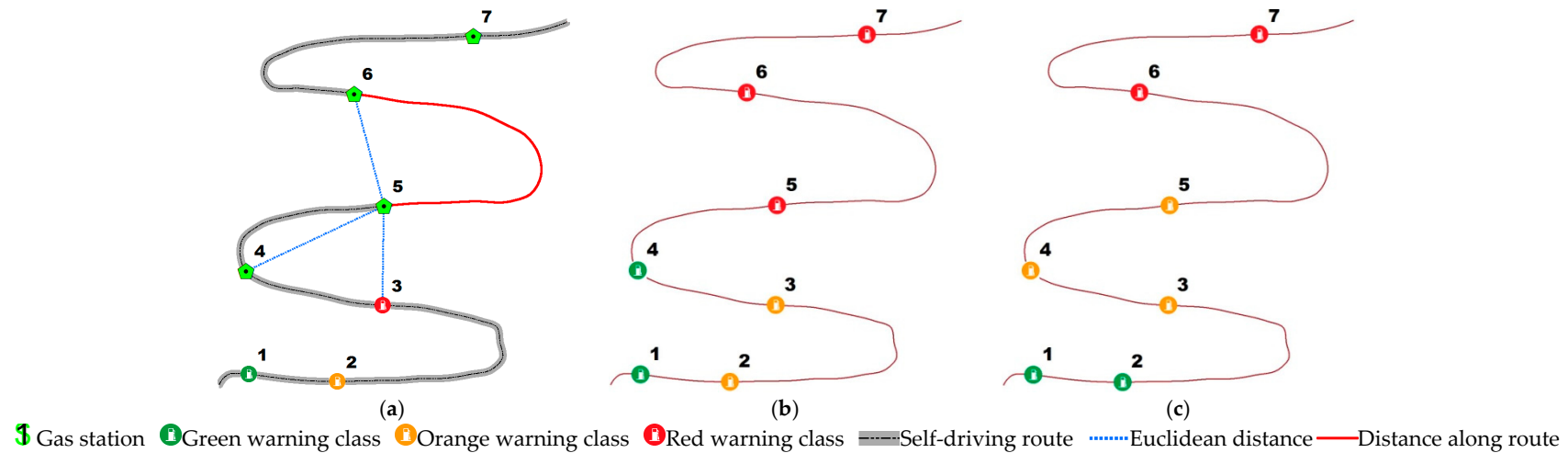


Figure 6. The impact sensitivity analysis of clustering attribute changes on clustering results. (a) Hypothetical gas station layout under complex road conditions; (b) calculation result based on Euclidean-distance and mixed-distance clustering attributes; (c) calculation result based on the distance between the gas station and the starting point as a clustering attribute.

As seen in Table 1 and Figure 2, there was no difference in the clustering effect between Euclidean-distance and mixed-distance clustering attributes, calculated by Euclidean distance and the route distance from a gas station. The clustering results of this approach had the following deviations: (1) the first and the fourth gas station were improperly clustered into one category; (2) the second gas station (closer to the first) and the third gas station (closer to the fourth) were improperly clustered into one category; (3) the fifth gas station, which was clearly more suitable for the c2 class, was classified into the c3 class. The probable reason causing the deviation in clustering from the actual situation is that Euclidean distance is a linear distance between two points, so clustering is free from the restraint of route (the actual driving path) when taking Euclidean distance as the determining criterion for clustering, resulting in a deviation. The above results indicated that this approach was an effective clustering analysis method for gas stations based on the clustering attribute of the distance difference between two gas stations along the route, and the clustering results well reflected the availability and refueling urgency level of the gas stations along the route.

3.2.2. Comparative Analysis of Clustering Algorithms

The classical K-Means algorithm, belonging to the partitioning clustering method, was selected for comparison with the hierarchical clustering method used in this study. Theoretically, the ability of the K-Means algorithm to identify noise and outliers is relatively weak, and the initial center of mass is the key to the calculation; the hierarchical clustering method can identify noise and outliers without needing to specify the initial center of mass, but this convenience also comes with extra computing overhead in time and space [40]. Fortunately, the distribution of gas stations along the route is generally sparse, so this computing overhead is almost negligible when the amount of data is small. The S-type route and the corresponding gas station layout designed above were used again as comparison test data; the Matlab clustering tool developed by Ph.D. Kardi Teknomo was adopted to implement the K-Means algorithm (<http://people.revoledu.com/kardi/copyright.html>), and the hierarchical clustering tool was developed by the authors using Matlab. Finally, a clustering effect comparison is shown in Table 4 and Figure 7; cells in Table 4 with the same color indicate inconsistencies between the calculation results of the two clustering methods when the number of gas stations is the same.

Table 4. The effect comparison of clustering by different clustering algorithms.

$D (\times 10^4)/\text{km}$		Clustering Algorithm and Result Comparison							
		K-Means				Hierarchical Clustering Method			
		4 Gas Stations	5 Gas Stations	6 Gas Stations	7 Gas Stations	4 Gas Stations	5 Gas Stations	6 Gas Stations	7 Gas Stations
1	0.0494	c1	c1	c1	c1	c1	c1	c1	c1
2	0.0463	c2	c2	c2	c1	c1	c1	c1	c1
3	0.0355	c3	c3	c2	c2	c2	c2	c2	c2
4	0.0306	c3	c3	c3	c2	c3	c2	c2	c2
5	0.0244		c3	c3	c3		c3	c2	c2
6	0.0111			c3	c3			c3	c3
7	0.0001				c3				c3

D means the distance between the gas station and the starting point. c1, c2, or c3 indicates that the corresponding gas station is classified into the green, orange, or red warning level, respectively.

It can be seen from the effects of the two clustering algorithms that the K-Means algorithm was greatly affected by the initial center of mass and was prone to producing outliers and excessive merging, and some clustering did not realistically reflect the distance relationship among gas stations. By contrast, the results of the hierarchical clustering algorithm were more stable, largely avoiding the phenomenon of isolating or far-fetched merging of gas stations, and the clustering results of this algorithm basically reflected the distance relationships among gas stations. From the analyses above, we can see that the reasonability of clustering results obtained by the hierarchical clustering algorithm was superior to that of the K-Means algorithm, proving that the hierarchical clustering algorithm is more suitable for clustering analysis of the gas station layout along the route.

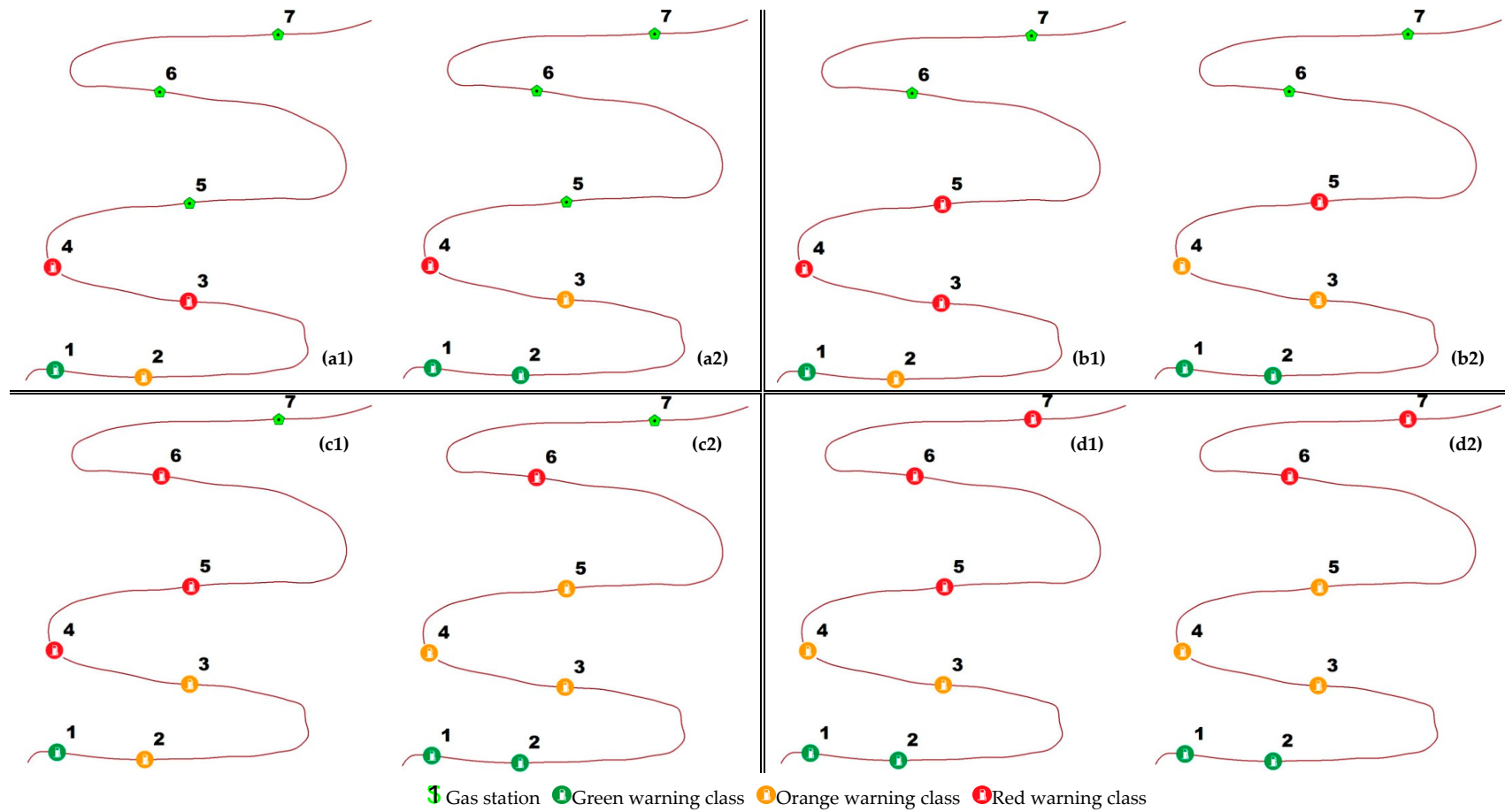


Figure 7. Results comparison between the hierarchical clustering algorithm and the K-Means clustering algorithm. (a1, b1, c1, and d1) show the clustering results of the K-Means algorithm when the number of gas stations is 4, 5, 6, or 7; (a2, b2, c2, and d2) show the clustering results of the hierarchical clustering algorithm when the number of gas stations is 4, 5, 6, or 7.

3.3. Test Data and Scenario Simulation Scheme

In this study, a real geographical environment and simulated positions and distributions of gas stations were used as test data, and the testing procedure of the algorithm was as follows:

- (1) The self-driving route: A real path was used as the self-driving route, the starting point of which was located in Kunming, Yunnan Province, and the terminus of which was located in Zhaotong City, Yunnan Province, represented by red and blue stars, respectively.
- (2) Gas stations along the route: Several point elements representing gas stations were manually created near the route. According to the requirement for the scenario simulation, ten layers of gas stations were set up in this study; the number of gas stations per layer increased from 1 to 10, and these gas stations were located in different positions.

Testing schemes for the scenario simulations designed in this study are shown in Table 5. A total of nine testing schemes of four simulation scenarios were set up to test the accuracy and applicability of the algorithm presented in this research, as described below:

- (1) Scenario 1: There was one testing scheme designed in Scenario 1. In this scenario, the maximum driving distance was greater than the aggregate mileage, and refueling was not required along the route. Scenario 1 was utilized to test the adaptability of recommendation Strategy 1.
- (2) Scenario 2: There were two testing schemes designed in Scenario 2 (Scheme 2-1 and Scheme 2-2). Scheme 2-1 indicated that the current remaining fuel was not enough for the vehicle to reach the nearest gas station along the way; Scheme 2-2 indicated that there was no refueling gas station along the route, recommending that the driver bring gas or fill up the gas tank in advance. The two testing schemes in Scenario 2 were utilized to test the adaptability of recommendation Strategy 2.
- (3) Scenario 3: There were three testing schemes designed in Scenario 3 (Scheme 3-1, Scheme 3-2, and Scheme 3-3). Supposing that the vehicle needed to refuel on the way, the impacts of a change in the number of refueling gas stations along the route on the recommendation strategy were explored in this scenario. The three testing schemes in Scenario 3 were mainly used to test the adaptability of mixed recommendations from Strategy 3 and Strategy 4.
- (4) Scenario 4: There were three testing schemes designed in Scenario 4 (Scheme 4-1, Scheme 4-2, and Scheme 4-3). Supposing that the vehicle needed to refuel and that there were plenty of gas stations along the way, the influence of a change in the maximum driving distance of the vehicle and the number and layout of refueling gas stations on the recommendation strategy were explored in this scenario. The three testing schemes in Scenario 4 were mainly used to test the adaptability of mixed recommendations from Strategy 2 and Strategy 4.

Table 5. Schemes of scenario simulation.

Scenario Type	Testing Scheme	Adaptive Strategy	Aggregate Mileage/km	Maximum Driving Distance/km	Initial Accessible Position	Total Number of Gas stations	Number of Refueling Gas stations	Recommendation Result
1	1-1	1	304.43	315.79	Figure 8(a1)	NULL	NULL	Figure 8(a4)
2	2-1	2	304.43	52.63	Figure 8(a2)	NULL	NULL	Figure 8(a4)
	2-2	2	304.43	NULL	Figure 8(a3)	0	0	Figure 8(a4)
3	3-1	3	304.43	178.95	Figure 8(b1)	2	2	Figure 8(b2)
	3-2	4	304.43	178.95	Figure 8(b1)	5	5	Figure 8(b3)
	3-3	4	304.43	178.95	Figure 8(b1)	8	6	Figure 8(b4)
4	4-1	2	304.43	52.63	Figure 8(a2)	10	0	Figure 8(a4)
	4-2	4	304.43	157.89	Figure 8(c1)	10	4	Figure 8(c2)
	4-3	4	304.43	294.73	Figure 8(c3)	10	10	Figure 8(c4)

NULL indicates that the conditional settings had no effect on the results, so no configuration was required.

3.4. Results and Evaluation of Scenario Simulation

(1) Scenario 1: The maximum driving distance of the vehicle exceeded the aggregate mileage, and the excess was greater than the distance between the destination and the nearest gas station; therefore, there was no need to refuel along the way. The initial position is shown in Figure 8(a1), and the simulated recommendation result is shown in Figure 8(a4).

(2) Scenario 2: There was no gas station that could be used for refueling along the way (Scheme 2-2) or the shortest resupply distance was insufficient (Scheme 2-1), and thus it was recommended that the driver bring gas or fill up the gas tank before starting on the trip. The initial position is shown in Figure 8(a2,a3), and the simulation result was the same as in “Scenario 1”, i.e., no gas station could be recommended.

(3) Scenario 3: Assuming that the maximum driving distance of the vehicle was invariant (see Figure 8(b1)), then the refueling strategy would be affected by a change in the number of gas stations along the route.

- Scheme 3-1: There were no more than three refueling gas stations along the route. Beginning from the direction of the starting point, the gas stations were marked with green, orange, and red warning levels in order from beginning to end; the simulated recommendation result is shown in Figure 8(b2).
- Scheme 3-2: There were more than three refueling gas stations along the route. Gas stations were divided into three categories, and the three categories were marked with green, orange, and red warning levels in order from beginning to end; the simulated recommendation result is shown in Figure 8(b3).
- Scheme 3-3: In this case, gas stations along the route were distributed ahead of and behind the initial accessible position of the vehicle, and “Scheme 3-1” or “Scheme 3-2” could be used to recommend the refueling strategy according to the number of refueling gas stations. The initial position is shown in Figure 8(b3), and the simulated recommendation result is shown in Figure 8(b4).

(4) Scenario 4: Assuming that there were plenty of gas stations along the route and the number thereof was invariant, then the refueling strategy would be affected by a change in the maximum driving distance of the vehicle.

- Scheme 4-1: When the maximum driving distance of the vehicle was not sufficient to reach the nearest gas station along the route, the initial position and the simulated recommendation result were the same as in “Scheme 2-1”.
- Scheme 4-2: When the maximum driving distance of the vehicle was half of the aggregate mileage, Strategy 4 was recommended. The initial position is shown in Figure 8(c1), and the simulated recommendation result is shown in Figure 8(c2).
- Scheme 4-3: When the maximum driving distance of the vehicle was near the end of the route, the recommendation method was the same as in “Scheme 4-2”, while the difference in distance and the number of refueling gas stations within that road section resulted in a different recommendation strategy. The initial position is shown in Figure 8(c3), and the simulated recommendation result is shown in Figure 8(c4).

The schemes and results of the scenario simulations are listed in Table 5, which clearly shows that the refueling recommendation strategy changed with varying distance from the refueling gas stations and with the number of gas stations along the route. The simulation results of various scenarios were all consistent with expectations. Therefore, the refueling recommendation algorithm proposed in this study could automatically adapt to changes in route length during self-driving travel, the maximum driving distance of the vehicle, and the distance from gas stations, and hence could scientifically recommend a refueling strategy according to the layout of gas stations along the route.

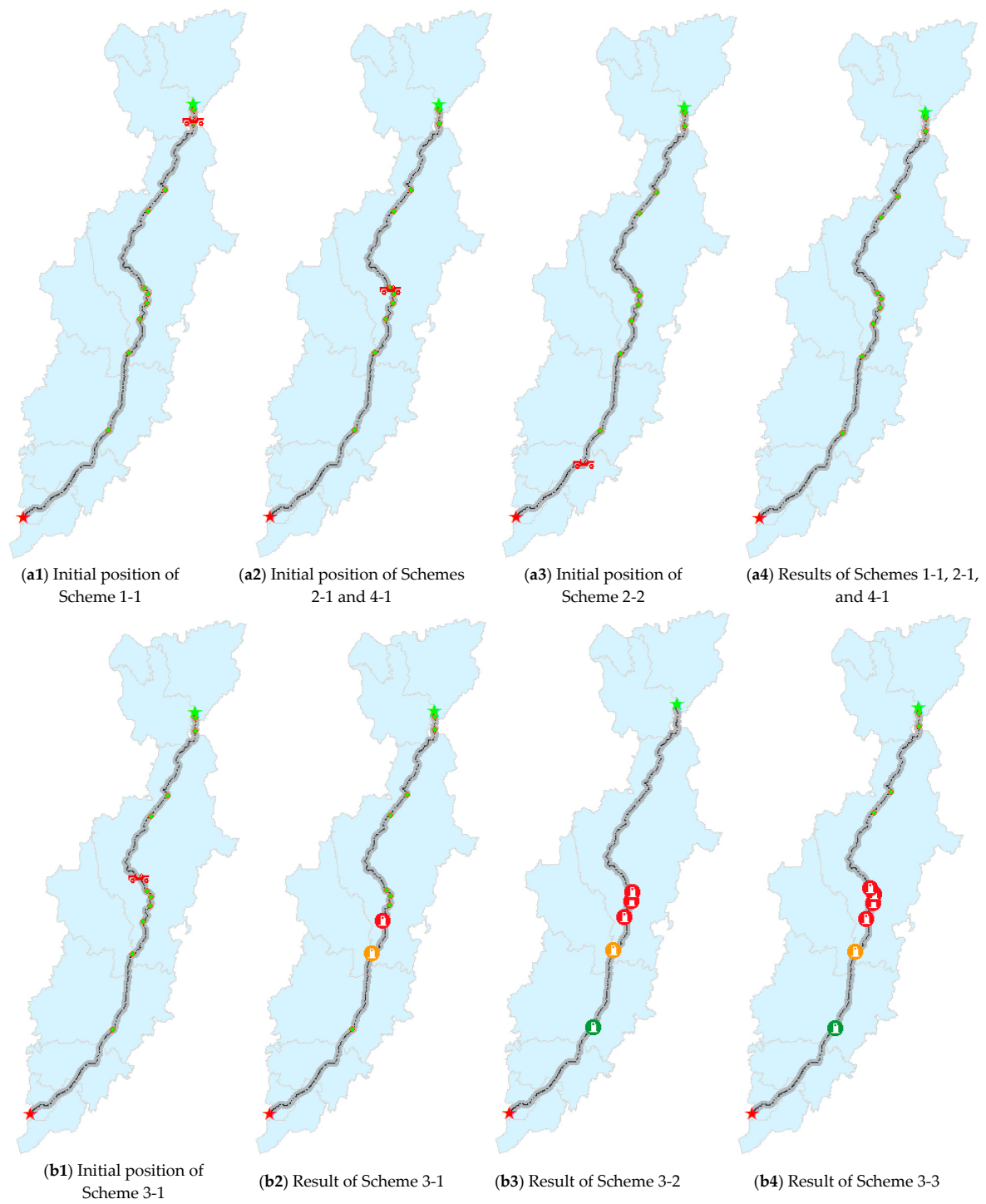


Figure 8. Cont.

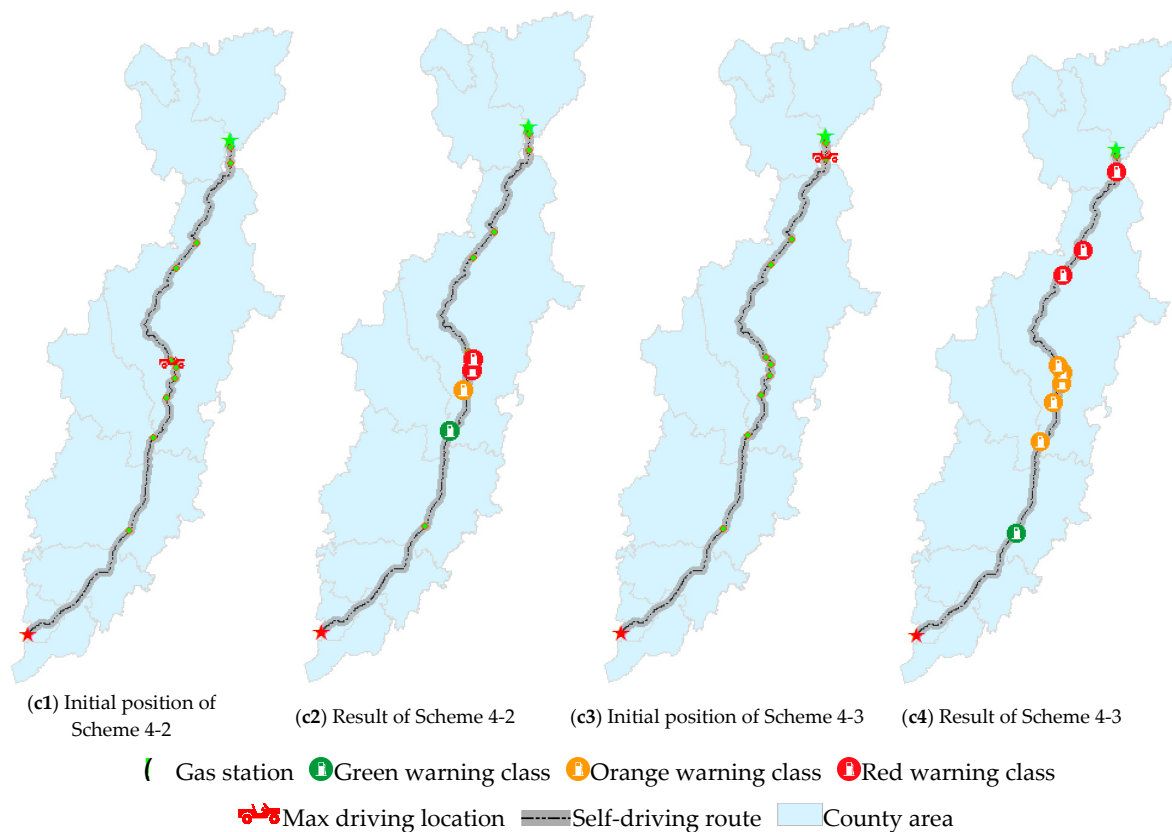


Figure 8. Results and processing of scenario simulations.

3.5. Discussion of Algorithm Applicability

Finally, three issues need to be clarified and discussed here. (1) The route adaptability problem of the algorithm. The vehicle refueling strategies studied in this paper were established based on travel route planning for self-driving travel, and it is not clear whether the algorithm can adapt to refueling processes in other travel paths. This is because there may be different self-driving routes for different travel paths, and the refueling recommendation algorithm designed in this study can only adapt to a single-line path and cannot meet the refueling demands of a complex road network [29,48]. In spite of this, the generality of this algorithm on a single line is very good, and accordingly, we conclude that no matter what travel path is selected, as long as self-driving behaviors exist and the traveling route consists of a series of single lines, the vehicle refueling recommendation strategies based on this algorithm are applicable to this kind of situation. (2) The fuel adaptability problem of the algorithm. The fuels used in this study are liquid fossil fuels, and whether the refueling strategies designed in our work are suitable for current AFVs is a topic worth considering. Some researchers have noted that refueling behavior and station consideration by drivers differs not just between drivers of gasoline or diesel vehicles and drivers of alternative fuel vehicles but also between drivers using different alternative fuels or energy carriers [49,50]. Even so, this paper studied the relationship between vehicle endurance and refueling gas stations in time and space as well as its calculation model, from which recommendation strategies and a visual vehicle refueling warning system were formed, and consequently it was unclear what impact these differences would have on vehicle refueling strategies. Because there are some considerable differences in energy supply time between electric vehicles and traditional vehicles using liquid fossil fuels [14,16], we can infer that the algorithm presented in this study is probably not suitable for charging strategy recommendations for electric vehicles. (3) The applicability of the algorithm to the refueling of autonomous vehicles. Autonomous vehicles can partially replace people to perform driving behaviors, and many well-known

automobile manufacturers now produce cars with autonomous driving functions, such as Tesla, Toyota, Audi, and so on. Although the motivation of this study was derived from the refueling problem during self-driving travel, it is reasonable to believe that the algorithm presented in this paper can also be applied to the refueling process of autonomous vehicles, and the main reasons for this are as follows: (1) The early refueling warning is an important part of autonomous driving technology [15]. The principle of the refueling recommendation algorithm developed in this study is that a computer automatically calculates and carries out the intelligent identification and judgment of refueling timing based on the vehicle fuel conditions and various distance parameters, which is easy to implement by computer and is beneficial to integrated application in autonomous driving control systems. (2) Experiments have shown that the refueling recommendation algorithm proposed in this study has good precision-control characteristics without human involvement or driver intervention, which is in line with the operating requirements and driving features of autonomous vehicles.

4. Conclusions

In order to solve the problem of accurate control of vehicle refueling in self-driving travel, a vehicle refueling recommendation algorithm that was adaptive to changes in the driving distance was presented in this study. With decision conditions including the number of refueling gas stations and multiple distance variables such as the maximum driving distance of the vehicle, the distance from gas stations, and the route length, recommendation rules and an early refueling service warning mechanism for gas stations along the route were constructed based on the spatial clustering characteristics of gas stations and the urgency of refueling, which could provide a humanized intelligent refueling strategy for the driver. A total of nine testing schemes of four simulation scenarios were designed and executed using this algorithm, and the results were in accordance with expectations, which proved that the algorithm presented in this study could well solve the problem of reasonable planning and timely refueling of vehicles in self-driving travel.

The main contributions of this research are threefold: (1) based on the travel mode of self-driving vehicles, a simple but instructive refueling recommendation algorithm that could adapt to changes in the refueling environment was proposed; (2) combining the strong spatial calculation and spatial clustering analysis capabilities of GIS, a priority classification algorithm of the refueling ability of the gas stations along a segmented travel route was proposed, further enhancing the space rationality of the refueling service of the gas stations; and (3) a refueling warning mechanism based on the clustering of gas stations along the route was designed, and the vehicle refueling recommendation strategies were visualized by using the mapping function of GIS, which improved the comprehensibility and practicability of the refueling recommendation algorithm.

Clearly, the results offered by the proposed approach are of great practical use for the refueling of self-driving vehicles. Nevertheless, the approach also demonstrates some notable limitations. First, the refueling recommendation algorithm for self-driving travel studied in this paper used vehicles powered by liquid fossil fuels as the subject of refueling, and further research would be needed to determine whether this algorithm would be suitable for the refueling of alternative fuel vehicles. Second, the current refueling recommendation algorithm could only consider refueling gas stations along the driving path of the vehicle, without including all of the reachable gas stations distributed around the traveling route within the refueling range of the vehicle, which limited the vehicle's refueling possibilities. Accordingly, how to search for refueling gas stations in road networks connected to the self-driving route to expand refueling possibilities is a problem worthy of further study in the future. Third, optimization analysis of the gas station layout along the route was conducted in this study by using the spatial clustering method, which could better identify the priority of each gas station for a single refueling requirement. However, the current study only used the distance parameter as the gas station's spatial clustering attribute and did not consider other factors that might influence the decision-making of refueling by playing a more important role in the driver's choice of stopping for refueling in reality. For instance, the research of Suzuki [23–27] and Wansink and van Ittersum [51] has

shown that road conditions, fuel prices, vehicle weight, and other services provided by gas stations (for example, food, entertainment, showers, etc.) are important factors affecting drivers' parking and refueling. Therefore, in future research, more refueling decision variables will be added to the space clustering algorithm and the weight of these variables will be determined by analysis, so as to obtain gas station supply service priority levels that are closer to reality. Finally, this study mainly focused on the motivation, design principle, implementation method, and test results of the proposed refueling recommendation algorithm, but how to reduce the number of refueling stops to optimize the supply cost and apply the algorithm to actual self-driving travel still requires further study. For example, how to use mobile map services such as Baidu Map and Google Maps to develop an intelligent refueling app based on this algorithm will be the focus of subsequent research work.

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