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Research Article

Ecological and Real-Time Route Selection Method for Multiple Vehicles in Urban Road Network

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Traffic congestion has been a hot topic of research in the field of intelligent transportation, which can be alleviated by efficient route navigation. Most of the existing route planning methods are non-negotiated algorithms, which do not take into account the route conflicts and collaborative relationships between multiple vehicles. Also, most negotiated algorithms have not been comprehensively considered dynamic route collaboration between vehicles, large-scale efficient computation, environmental pollution, etc. Therefore, an ecological multivehicle real-time route selection model (EMR^{2}SM) for urban road networks is firstly proposed in this paper, which combines real-time traffic conditions of the road network with travel time, distance, and exhaust emissions as optimization indicators. In order to solve the large-scale computation problem of traditional negotiated algorithms, an adaptive multiswarm bee colony (AMSBC) algorithm is designed, which efficiently solves the multivehicle dynamic route selection problem. AMSBC searches the optimal route for each vehicle in parallel through multiple population division and self-adaption mechanism, to make multivehicle route selection reach Nash equilibrium. Compared with three non-negotiated optimization algorithms based on swarm technology, EMR^{2}SM is verified by experiments that it improves the efficiency and accuracy of the optimal route selection for multiple vehicles and reduces vehicle emissions, which can effectively reduce traffic congestion and environmental pollution.

1. Introduction

In recent years, with the rapid and continuous growth of the number of vehicles, traffic congestion has become one of the serious problems to be solved in urban sustainable development. First, it seriously leads to air pollution and vehicle noise, affects people's driving comfort and travel efficiency, and aggravates traffic accidents. Second, it also causes vehicles to drive at a low speed, resulting in a great waste of energy and more exhaust emissions and leading to increasingly serious environmental pollution problems [1, 2]. Third, traffic congestion also affects the physical and mental health of traveling individuals, reduces the quality of life and happiness index, and increases life stress and anxiety [3–5]. With the limitation of existing urban space capacity expansion, how to make full use of the existing road traffic resources to ease urban congestion has become a hot issue in the development of modern cities.

Most existing route selection methods are divided into non-negotiated algorithms and negotiated algorithms.

(1) Non-negotiated algorithms mainly include route selection methods based on overall traffic flow and non-negotiated route selection methods based on intervehicle. The former contributes to solving the imbalance of road network resources, and the latter finds the optimal route for vehicles from the perspective of their individual interests. However, the limitation of non-negotiated algorithms are that they do not take into account the conflict and collaboration relationship in the process of intervehicle route selection, which may lead to many vehicles following the same route recommendation, causing congestion on the route and increasing the vehicle travel time in the case of large vehicle scale.
(2) Negotiated algorithms consider vehicle collaboration relationships, mainly including route optimization methods based on master-slave game between overall traffic flow optimization and vehicle individual optimization and route selection methods

based on multivehicle game. The former optimizes and balances the overall traffic flow and individual vehicles from a macroperspective, while the latter avoids congestion caused by the same route of large-scale vehicles. However, the existing negotiated algorithms consider the total cost of the road network or the individual vehicle travel time cost; they consider the single index and do not comprehensively consider the dynamic nature of traffic conditions, efficiency, and accuracy of large-scale calculations.

In order to overcome the problems mentioned above, this paper aimed to supply a negotiated, efficient, and accurate route selection for multiple vehicles in a dynamic road network, to satisfy vehicles demand, balance road network resources, and improve environmental pollution. The main contributions of this paper are summarized as follows:

(1) An ecological multivehicle real-time route selection model (EMR^2SM) is proposed, which effectively avoids the route conflict between vehicles and provides more accurate routes for vehicles on the road network.

(2) A formula is given to calculate the utility of vehicle alternative routes. Considering the optimization of vehicle exhaust pollution, as CO and NOx are the highest components in the exhaust emissions, the utility value index includes the CO and NOx emissions. The purpose of reducing and mitigating pollution is achieved by optimizing it.

(3) Aiming at the large-scale computation and optimization problems faced by traditional game methods, this paper improves the classical artificial bee colony (ABC) algorithm, proposes an adaptive multiswarm bee colony (AMSBC) algorithm, and combines it with game theory to improve the efficiency and accuracy of route optimization through multi-population division and adaptive mechanism, efficiently makes multivehicle route selection to reach Nash equilibrium, and alleviates urban congestion.

The remainder of this paper is organized as follows. Section 2 presents related research work about route selection methods in urban road networks. Section 3 introduces the EMR^2SM model framework in detail including the road network model and noncooperative game model and proposes the calculation method of route utility function. Section 4 introduces the adaptive multiswarm bee colony (AMSBC) algorithm and combines with the noncooperative game model. Section 5 verifies the performance of the EMR^2SM model in urban traffic network scenario. Section 6 summarizes and prospects the future work.

2. Literature Review

In the process of route selection between multiple vehicles, the conflict and cooperation between vehicles plays a very important role in road network resource allocation, road congestion mitigation, and multivehicle demand optimization. Therefore, according to whether to consider the conflict and cooperation relationship in route selection between vehicles, the route selection methods are divided into non-negotiated methods and negotiated methods.

2.1. Non-negotiated Methods. Non-negotiated methods mainly include route selection algorithms from the perspective of macro traffic flow evacuation and microvehicle demand.

In order to effectively guide each vehicle by using real-time traffic information and avoid road congestion, Chen et al. [6] proposed a global algorithm for route guidance strategy for advanced traveler information systems, providing real-time optimal route guidance information for travelers at each intersection, effectively combating the traffic congestion problem. Illhoe and Young [7] developed a dynamic routing algorithm based on reinforcement learning (RL), which utilizes real-time information to effectively guide each vehicle and avoid congestion. Zhao and Zhang [8] established a parallel global route search method to search for multiple relatively static shortest paths, to obtain the global optimal shortest path of the current traffic flow. Charalambos et al. [9] proposed a multiarea network joint route guidance and demand management strategy with macro traffic dynamics, to maximize the travel completion rate of all areas. Mariam et al. [10] proposed a new advanced vehicle guidance system based on hierarchical interval type 2 fuzzy logic model; it is optimized by particle swarm optimization method, which can intelligently, quickly, and dynamically adjust the road traffic network. The above-mentioned methods mainly conducted vehicle route guidance from the perspective of overall traffic flow. It had a significant effect on the overall vehicle distribution and congestion mitigation of the road. However, it ignored the personalized needs of microvehicles, and the route conflict between vehicles was not considered, which was easy to cause a large number of vehicles to rush into the same lane.

In order to maximize the individual values of vehicle routing, Chen et al. [11] proposed a personalized path decision algorithm based on user habits, which makes path decisions from the perspective of user personalization through adaptive ant colony algorithm. Tang et al. [12] used an improved Floyd (pairs shortest routes) algorithm to select the fastest route using travel time values instead of distance values to improve vehicle travel efficiency. Niu et al. [13] proposed a new route coding and decoding method, which can effectively deal with the “path failure” caused by uncertain driver’s personalized needs. Chow et al. [14] proposed an adaptive traffic control algorithm to help the drivers respond to the current traffic state and control settings and find the fastest route to the destination. Lamouik et al. [15] proposed a dynamic route system based on deep convolutional neural networks, which provides fast routes between source and target points, effectively improving vehicle travel efficiency and reducing red light waiting. Chen et al. [16] proposed a daily dynamic learning and adjustment model with bounded rationality, where travelers can dynamically update their departure time and travel route using real-time traffic status information provided by navigation systems and past historical experience. The abovementioned method makes vehicle route selection from the perspective of microscopic multivehicle demand, which meets the demand of individual vehicles. However, it does not consider the overall demand optimization among multivehicles, and the resulting conflict cooperation relationship is not considered.

Non-negotiated methods have made contributions to the evacuation of traffic flow, the allocation of road resources, and the personalized needs of vehicles. But the conflict and cooperation between vehicles is not considered, when the scale of vehicles on the road network continues to grow, many vehicles would flow into the same road section, causing new traffic congestion.

2.2. Negotiated Methods. Negotiated methods mainly include the route selection algorithms from the perspective of macrotraffic flow and vehicle individual equilibrium or micromultivehicle demand equilibrium.

Wie et al. [17] established a dynamic traffic allocation model with scheduling delay under the principles of system optimization and vehicle equilibrium and compared the total travel time and planned delay under different traffic congestion levels. Zhang et al. [18] studied a traffic congestion analysis model based on game theory by using the concepts of user equilibrium with incomplete information (UEII) and system optimization with incomplete information (SOII). Lujak et al. [19] proposed an optimization model to bridge the gap between user-optimal and system-optimal, and a new mathematical planning formulation based on Nash welfare optimization to achieve good averages for all origin-destination (OD) pairs. Yang and Liu [20] studied user-optimal routing and system-optimal routing with the objective of minimizing their individual expected travel cost and system travel time. The abovementioned methods mainly proposed the route selection algorithm from the perspective of macrotraffic flow equilibrium and vehicle individual equilibrium. It played a balanced role in the overall distribution of traffic flow and reduces road congestion. However, it only aimed at the demand optimization under a single vehicle and did not consider the demand balance and optimization between multiple vehicles on the road network.

Bell [21] proposed an evaluation method of road network reliability based on game theory to predict the travel path of users and evaluate the cost. Jiang et al. [22] proposed a route choice analytic method that embeds cumulative prospect theory in evolutionary game theory to analyze how the drivers adjust their route choice behaviors under the influence of the traffic information. Belhaiza [23] proposed a new framework using mixed variable neighborhood tabu search heuristic algorithm, to select Pareto nondominated solutions from the search space of solutions satisfying Nash equilibrium conditions and solve different types of vehicle routing problems. Lu et al. [24] proposed a distributed cooperative routing (DCR) algorithm-based on evolutionary game theory to coordinate vehicles, so as to avoid all vehicles flocking to the same road and causing traffic congestion on that route. Han et al. [25] used the route selection preferences of drivers as route model parameters and established a game-theoretic-based route induction system for deriving game strategies, and the optimal route was determined by the maximum gain of the game in Nash equilibrium. The abovementioned method mainly established the route selection algorithm from the perspective of microscopic multivehicle demand balance, which solved the demand balance and optimization problem among multivehicles. However, the index considered was too single, and the calculation delay of the utility of large-scale vehicles is also faced.

To sum up, the previous route selection methods lack vehicle dynamic negotiation and environmental protection concept and have some problems such as single index and large-scale calculation delay.

3. Proposed EMR^{2}SM Model for Vehicle Route Selection

In this section, the system architecture of the EMR^{2}SM model is described first in Section 3.1, and then noncooperative game model is defined in Section 3.2. Finally, the specific calculation formula of utility function is introduced in Section 3.3.

3.1. System Architecture. In view that the indicators considered were relatively single, mainly including the total cost of road network, travel time and travel distance cost of vehicles, lacking environmental protection concept, and lacking real-time dynamic cooperation and large-scale calculation delay. Therefore, the EMR^{2}SM model is proposed in this paper, and the system architecture of which is shown in Figure 1.

The exhaust emission is regarded as one of the indicators into the optimization goal. By optimizing the vehicle route, the exhaust gas emission during driving can be reduced to achieve the purpose of alleviating environmental pollution. The influence of the change of real-time traffic information on the dynamic route selection of vehicles is considered, and the real-time and dynamic route adjustment of multiple vehicles by combining the game strategy is realized. In addition, in order to improve the efficiency and accuracy of finding the best individual route, an adaptive multiswarm bee colony (AMSBC) algorithm is designed, which is combined with noncooperative game to search the best route in parallel through population division to reach Nash equilibrium. Moreover, each vehicle is equipped with a driver assistance system (DAS) in a road network, and every road network server (RNS) and game router (GR) has its own control areas, which are placed beside the intersection. In their respective control areas, RNS is responsible for collecting dynamic traffic information and publishing the current traffic status to the DAS, GR is responsible for the mutual game between vehicles. Vehicles decide whether to replay the route game when crossing an intersection based on the current traffic status information

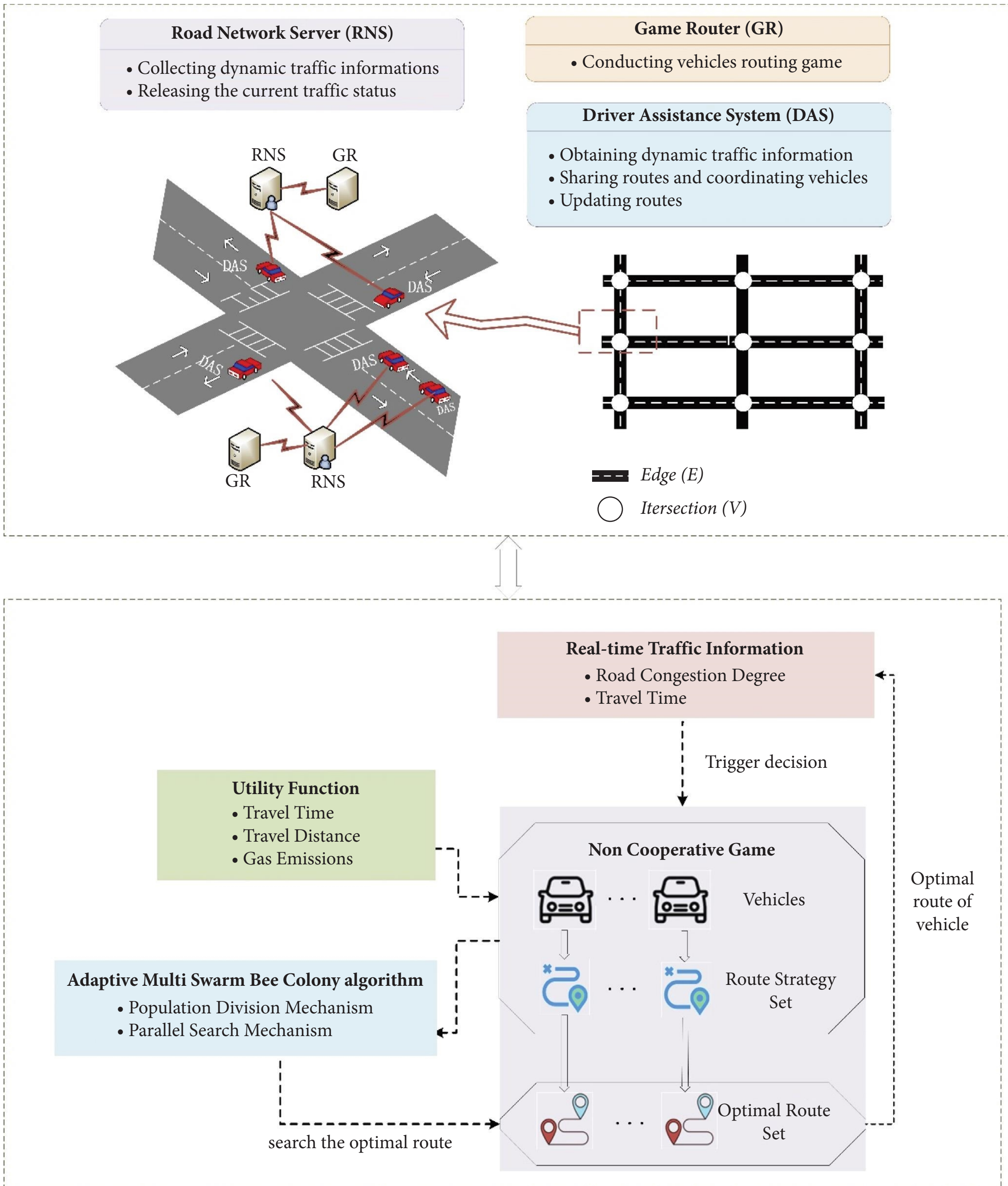


Figure 1: System architecture of EMR^{2}SM model.

collected by the DAS from the RNS. When the critical point for triggering the vehicle to plan a new route is reached, the RNS sends a request to the GR to trigger the vehicle route game.

3.2. Noncooperative Game. During driving, the vehicle DAS system intelligently senses the real-time traffic information and triggers the route selection, optimizes their dynamic route selection strategy through the game mechanism, and improves the speed and accuracy of utility calculation in the game through the AMSBC algorithm, so as to quickly reach the Nash equilibrium and get their optimal route. In order to describe the game model, this paper defines the number of vehicles in the road network as $N = \{1, 2 \cdots n\}$, and $R = \{r_1, r_2, \cdots r_m\}$ describes the number of optional routes, respectively. The directed graph $G = (V, E)$ describes an urban road network consisting of multiple intersections and edges. $V = \{1, 2, \cdots, v-1\}$ denotes the set of intersection nodes, and $E = \{e(\dot{v}, \dot{v}+1) \mid \dot{v} \in V\}$ denotes the set of edges between adjacent nodes. To facilitate this study, the vehicle starting and ending points are also considered as corresponding nodes, where node $\dot{v} = 0$ denotes the vehicle starting point, node $\dot{v} = v$ denotes the vehicle ending point. In the process of playing games, we describe the pure route strategy set for each decision vehicle k by $R^k = \{r_1^k, r_2^k, \cdots, r_m^k\}$, and x^k is the corresponding mixed strategies, which represent the vehicle k chooses a pure strategy $r_i^k (1 \le i \le m, 1 \le k \le n)$ with probability x_i^k. So, the mixed space of the game can be denoted as $x = (x^1, \cdots, x^k, \cdots x^n)$, i.e., the mixed strategy combination formed by vehicles after selecting a mixed strategy. The utility of vehicle k under the hybrid situation x is shown in the following equation:

$$
\begin{aligned}
U^k(x) &= \sum_{i_1=1}^{m}\sum_{i_2=1}^{m}\cdots\sum_{i_n=1}^{m} U^k\left(r_{i_1}^k, r_{i_2}^k, \cdots r_{i_n}^k\right) x_{i_1}^k \cdot x_{i_2}^k \cdots x_{i_n}^k, \\
s.t.\ x^k &= \left\{\left(x_1^k, x_2^k, \cdots, x_m^k \sum_{i=1}^{m} x_i^k = 1, x_i^k \ge 0, 1 \le k \le n\right.\right\},
\end{aligned}
\tag{1}
$$

where $U^k(r_{i_1}^k, r_{i_2}^k, \cdots r_{i_n}^k)$ represents the revenue of vehicle k when vehicle 1 selects pure strategy $r_{i_i}^k$, vehicle 2 selects pure strategy $r_{i_2}^k, \ldots$ and vehicle n selects pure strategy $r_{i_n}^k$. Hybrid Nash equilibrium is achieved when each vehicle is the best route relative to the route selection strategies of the other vehicles, as shown in equation (2). x^* denotes a Nash equilibrium solution of the noncooperative game for vehicles, $U^k(x^* \| x_k)$ denotes the utility of vehicle k when the mixed strategy x^* is replaced by x^k, and the mixed strategies of other vehicles remain unchanged. In particular, x^* satisfies a sufficient and necessary condition for the Nash equilibrium solution as shown in equation (3), that is, for the pure strategy $r_j^k (1 \le j \le m)$ of vehicle k, there is $U^k(x^*) \le U^k(x^* \| r_j^k)$.

$$
\begin{aligned}
U^k(x^*) &= \min_{x_k \in x^k} U^k\left(x^* \middle\| x^k\right), \\
s.t.\ x^* &= (x_1^*, x_2^*, \cdots, x_n^*),
\end{aligned}
\tag{2}
$$

$$
U^k(x^*) \le U^k\left(x^* \middle\| r_j^k\right), 1 \le j \le m, 1 \le k \le n. \tag{3}
$$

In the process of multivehicle driving, the road network environment changes in real time. Therefore, even if the vehicles have selected the route, the congestion degree of roads and travel cost on the route affect the route selection in real time. When DAS recognizes that the travel time of the vehicle's current route and the congestion coefficient of the upcoming roads exceed the vehicle's affordable threshold, GR is triggered to restart the route selection process. Assuming that the vehicle k is going to travel to the intersection node v, the conditions that trigger its reroute selection are shown as follows:

$$
\begin{aligned}
T^{k\_l} &\ge T^{k_{l_{tv}}}, \\
\kappa_{e(v,v+1)}^{l} &\ge \kappa_{e(\dot{v},\dot{v}+1),}^{l\_tv} \\
s.t.\ v &> \dot{v}, v, \dot{v} \in V,
\end{aligned}
\tag{4}
$$

where T^{k_l} represents the travel time and $T^{k\_l\_tv}, \kappa_{e(\dot{v},\dot{v}+1)}^{l\_tv}$ represents the maximum tolerable threshold of travel time and congestion degree of the road section $e(\dot{v}, \dot{v}+1), \dot{v} \in V$, respectively, when the vehicle $k (k \in N)$ selects the route $l (l \in R)$.

3.3. Utility Formulation. For the future route selection standard, the vehicle not only considers the distance and driving time of the route but also considers the impact of exhaust emissions on the environment. Therefore, in order to satisfy the demand of vehicles and environmental optimization, this paper takes travel time, travel distance, and exhaust emission as optimization indicators. Therefore, as shown in equation (5), the effect value U^{k_l} is defined as the comprehensive utility value of vehicle k when it selects route $l (l \in R)$. Thus, the optimization objective of EMR^{2}SM is essentially a multiobjective combinatorial optimization problem, as shown in equation (6).

$$
\begin{aligned}
U^{k\_l} &= \omega_1 T^{k\_l} + \omega_2 D^{k\_l} + \omega_3 \mathrm{GAS}^{k\_l}, \\
s.t.\ \sum_{i=1}^{3} \omega_i &= 1,
\end{aligned}
\tag{5}
$$

$$
\begin{aligned}
U^k(l_k^*, l_{-k}^*) &\le U^k(l_k, l_{-k}^*), l \in R, k \in N, \\
s.t.\ T_{\min}^{k_l} &\le T^{k_l{}^*} \le T_{\max}^{k_l}, \\
D_{\min}^{k\_l} &\le D^{k\_l^*} \le D_{\max}^{k\_l}, \\
GAS_{\min}^{k\_l} &\le GAS^{k\_l^*} \le GAS_{\max}^{k\_l},
\end{aligned}
\tag{6}
$$

where GAS^{k_l} represents the exhaust emission when vehicle k selects route $l (l \in R)$ and $\omega_1, \omega_2, \omega_3$ represent the weight proportion, respectively. In this paper, the travel route of each vehicle contains multiple road sections, and the travel time (TT) is related to the traffic flow of the selected road section. When vehicle k selects route $l (l \in R)$, the travel time can be calculated as shown in the following equation:

$$
T^{k\_l} = \sum_{i=0}^{i=v} T_{e(\dot{v},\dot{v}+1)\_\mathrm{free}}^{k\_l}\left(1 + \alpha\left(\frac{Q_{e(\dot{v},\dot{v}+1)}}{Q_{e(\dot{v},\dot{v}+1)}^{cap}}\right)^{\beta}\right), \tag{7}
$$

where $Q_{e(\dot{v},\dot{v}+1)}, \dot{v} \in V$ represents the actual number of vehicles on road section e, $Q_{e(\dot{v},\dot{v}+1)}^{\mathrm{cap}}$ represents the vehicle threshold of free flow, $T_{e(\dot{v},\dot{v}+1)\_\mathrm{free}}^{k\_l}$ represents the average travel time of vehicles on road section e in free flow, and α, β represent constant coefficients.

Each road section is composed of multiple adjacent nodes. Therefore, if vehicle k selects route $l (l \in R)$, its travel distance (TD) is the sum of the distances between all adjacent nodes on the route, as shown in equation (8), where $D_{e(\dot{v},\dot{v}+1)}^{k\_l} (e(\dot{v}, \dot{v}+1) \in E)$ represents the distance between adjacent nodes on route $l (l \in R)$.

$$
D^{k\_l} = \sum_{i=0}^{i=v} D_{e(\dot{v},\dot{v}+1)}^{k\_l}, i \in V. \tag{8}
$$

In this paper, CO and NO_x emission are used as an optimization index to reduce the environmental pollution caused by vehicles. It is directly determined by the vehicle fuel consumption (FC), CO emission rate (CER), NO_x emission rate (NER), and TD, as shown in equation (9). When the fuel type is known, CER and NER are a fixed value, such as the CER of diesel does not exceed 2.2 g/km, and the NER does not exceed 1.13 g/km. FC is different under different conditions such as constant speed driving, acceleration driving, deceleration driving, and idle parking. In order to simplify the analysis, this paper gives the vehicle with v_a as average speed and travel distance D for the fuel consumption as shown in the following equation:

$$\mathrm{GAS}^{k\text{–}l} = D^{k\text{–}l} \cdot (\mathrm{CER} + \mathrm{NER}) \cdot FC^{k\text{–}l}, \tag{9}$$

$$FC = \frac{P_e \cdot b \cdot D}{1.02 \cdot v_a \cdot \rho \cdot g}, \tag{10}$$

where P_e refers to engine power and the unit is kw, b refers to effective fuel consumption rate, equal to fuel consumption per unit effective work and the unit is $g/kw \cdot h$, ρ refers to fuel density and the unit is g/ml, and g refers to gravity acceleration.

4. AMSBC Algorithm for Multivehicle Route Selection

In this section, the advantage of AMSBC algorithm is described in Section 4.1. Subsequently, the AMSBC subalgorithm description is given in Section 4.2. Finally, AMSBC algorithm in route selection is comprehensively introduced in Section 4.3.

4.1. Advantage of AMSBC Algorithm. The essence of multivehicle dynamic real-time route selection is large-scale dynamic route optimization, which requires real-time, high efficiency, and accuracy of calculation. In order to improve the speed and accuracy of calculating the utility when multivehicles make route decision and solve the calculation problems faced by traditional game methods, an adaptive multiswarm bee colony (AMSBC) algorithm is firstly proposed, which is improved from artificial bee colony (ABC) algorithm and combined with the noncooperative game. AMSBC algorithm regards the vehicle feasible routes as the honey sources. Each feasible route of the vehicle represents a mixed situation in the game. The bees aims to search for the optimal route in the space of mixed strategy combination, and the route representing Nash equilibrium has the optimal fitness value.

ABC algorithm has the characteristics of few parameters, convenient calculation, and easy implementation. However, for large-scale dynamic optimization problems, its optimization speed and accuracy will decrease with the increase of scale, and it is easy to fall into the trap of local extremum. In order to solve the problem of real-time dynamic route selection of large-scale vehicles, the AMSBC algorithm is proposed as shown in Figure 2. Compared with ABC algorithm, AMSBC has made several improvements as follows:

(1) Multiple population division. The feasible routes of each vehicle is considered as a route population, it is divided into multiple subroute populations, which are scattered on different spaces, and it is beneficial to jump out the limitation of local optimal solutions and improve the search process.

(2) Adaptive mechanism. Adaptively updating the number of subroute populations according to the intensity of external environmental changes, it is helpful for bees to search and track the optimal route and improve the search process.

(3) Parallel mechanism. Search the space of subroute populations in different spaces by the parallel way, to increase the search efficiency and improve the search speed.

4.2. Optimal Route Selection in the Subpopulation Based on ABC Algorithm. The optimal route selection in the subpopulation is searched iteratively through the cycle stage of ABC algorithm. We define this process as AMSBC subalgorithm, and the pseudo code is shown in Algorithm 1. It mainly goes through three stages: employed bees, onlooker bees, and scout bees step. The flowchart of AMSBC subalgorithm is described as follows:

Step 1: Employed bees step. Each employed bee is assigned a feasible route and performs a neighborhood search around the current route to find a new route. By modifying the i^{th} solution of the route solutions x, a new neighborhood solution $x'_{i,j}$ is generated. The new route selection process is completed by using the greedy mechanism, if the fitness quality of $x'_{i,j}$ is higher than $x_{i,j}$, $x'_{i,j}$ will replace $x_{i,j}$, otherwise $x_{i,j}$ will be retained, as shown in equation (11), where b is a random route generated by random means, $\phi_{i,j}$ is a random number in the range of [–1, 1].

$$\begin{aligned} &x'_{i,j} = x_{i,j} + \phi_{i,j}\left(x_{i,j} - x_{b,j}\right),\\ &s.t.\ i, b \in \{1, 2, \cdots, SN\},\\ &\quad j \in \{1, 2, \cdots, D\},\\ &\quad \phi_{i,j} \in [-1, 1]. \end{aligned} \tag{11}$$

Step 2: Onlooker bees step. The Onlooker bees first select a route by roulette mechanism, and the formula is given in equation (12). For the selected route, the Onlooker bees perform the employed bees step.

$$p_i = \frac{\mathrm{fit}_i}{\sum_{i=1}^{SN} \mathrm{fit}_i}, \forall i \in \{1, 2, \cdots, SN\}. \tag{12}$$

Step 3: Scout bees step. After a limited number of iterations, the route is discarded when the fitness value is not improved and the employed bees corresponding to the route are transformed into the scout bees, which use equation (13) to generate a new route to replace the discarded route.

$$\begin{aligned} &x_{i,j} = x_{i,j}^{\min} + \dot{\omega}\left(x_{i,j}^{\max} - x_{i,j}^{\min}\right),\\ &s.t.\ \dot{\omega} = \mathrm{Rand}[0, 1],\\ &\quad i \in \{1, 2, \cdots SN\}, j \in \{1, 2, \cdots D\}. \end{aligned} \tag{13}$$

Step 4: Detect termination condition. When the maximum number of search iterations is reached, the search process will be stopped and the best route will be returned; otherwise, the loop will continue to iterate.

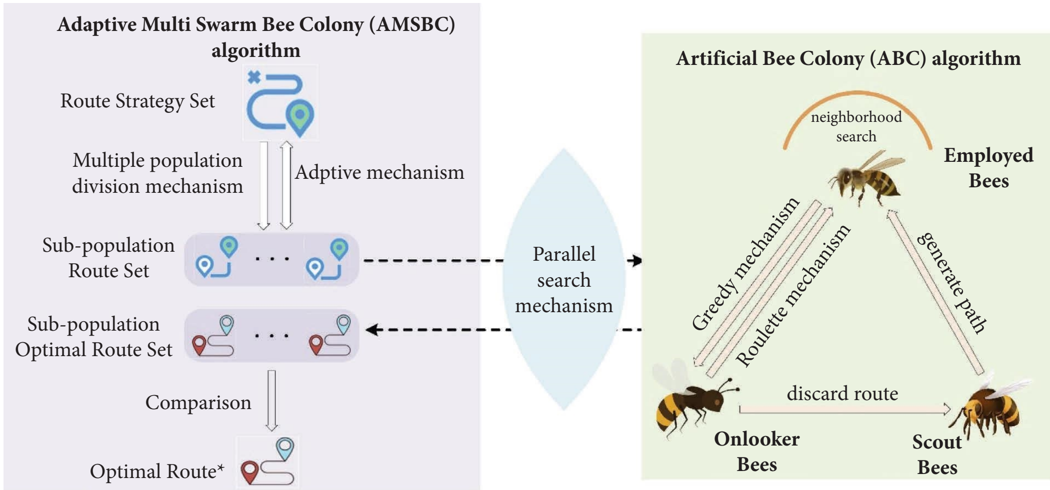


Figure 2: Relationship between AMSBC and ABC algorithm.

Input: Road network $G = (V, E)$, vehicles N, optional routes R, subroute populations;
Output: Vehicle equilibrium routes Line* of subpopulations;
Set Iter = 1;
Repeat
Employed Bees Step
  Distribute a path to each Employed Bee randomly;
  Carry out neighborhood search for x_i', $\forall i \in \{1, 2, \cdots, SN\}$;
  Apply greedy mechanism between x_i' and x_i, $\forall i \in \{1, 2, \cdots, SN\}$;
  if $\mathrm{fit}_{x^i}' > \mathrm{fit}_{x^i}$ **then**
    Execute x_i' replaces x_i;
Onlooker Bees Step
  Apply the roulette mechanism to select the path x_i, which based on the fit value;
  Execute the Employed Bees Step;
Iter = Iter + 1;
if route abandoned **then**
  Execute **Scout Bees Step**
    Turn employed bees into scout bees;
    Generate and mark new paths;
Until Iter = Max It
Return optimal routes of subpopulation

Algorithm 1: AMSBC subalgorithm.

4.3. AMSBC Algorithm Flow. The optimal route of all vehicles is based on the iterative search process of the ABC algorithm. In the iteration of the algorithm, according to the observed game results, the bees will continue to learn, and the vehicle will adjust its own strategy. Therefore, the target route is constantly updated and replaced in the space of the mixed strategy combination of the game and finally tends to the game equilibrium, so as to reduce the driving cost of vehicles and reduce exhaust emissions.

The pseudo code is shown in Algorithm 2. In the initialization stage, set the parameter values, generate the initialization feasible solution, and calculate the fitness of the feasible route based on Nash equilibrium to evaluate the quality of the feasible route. Then, the feasible routes are divided into subroute populations, and the route is iteratively searched and updated in each subroute population, based on ABC algorithm; if it is detected that the fitness value of the subroute population has changed, then calculate and detect the change strength to update the number of subroute populations; if the specified stop condition is reached, the AMSBC algorithm terminates and returns to the optimal route. The AMSBC algorithm flow is as follows:

Step 1: Initialization.

(1) Set parameter values. Initialize the main parameters, including the maximum number of iterations Max It, the population size SN, the parameter dimension of the individual solution D, the number of subroute groups q, the number of colony Bees,

Input: Road network $G = (V, E)$, vehicles N, optional routes set R;
Output: Vehicle equilibrium routes sets Line*;
Initialization:
  Set parameter value Max It, SN, D, Bees, Limit, q;
  Generate the initial route sets $x_i = \{x_{i,1}, x_{i,2}, \cdots x_{i,D}\}$, $i = 1, 2, \cdots SN$ randomly;
  Calculate the fitness of initial routes $\text{fit}_i, \forall i \in \{1, 2, \cdots SN\}$;
SetIteration = 1;
Repeat
  Divide the solutions x_i into q subsolutions;
  For each q
    while *No change in route detected* **do**
      Execute AMSBC subalgorithm;
    end while
  Detecting change strength CS;
  if$CS < CT$ **then**
    $q = q + 1$;
  $q = q - 1$;
  Iteration = Iterantion + 1;
UntilIteration = Max It;
Output optimal route of subroute populations;
Compare the optimal route fit_i of the subroutes;
Output equilibrium routes of vehicles with optimal fit_i;

Algorithm 2: AMSBC algorithm.

and the limit parameter Limit. When the number of iterations reaches the Max It, the algorithm is stopped. Since the optional routes of each vehicle are $R = \{r_1, r_2, \cdots r_m\}$, the scale of routes SN is equal to m, which represents the number of feasible routes of the vehicle. D is the dimension of route solution x_i, which means that x_i is a D-dimensional vector, whose value is the number of vehicles $N = \{1, 2, \cdots n\}$, and D is equal to N. Set the number of subroute populations to q, and the scale of subroute populations to SN/q. Bees is $2q$ times that of SN, the number of bees in each subroute population is twice that of SN, the number of employed and onlooker bees account for half, respectively. In order to diversely search, the Limit parameter limit is set to $SN/q \cdot D$.

(2) Initialize the feasible solutions. Initialize the population routes x randomly, which consists of $SN \times D$ dimensional real-valued parameter vectors, as shown in equation (13) in Section 4.2, and each row vector is considered as a route, and all of them form a candidate solution.

(3) Calculate the route adaptation value and evaluate its quality. The corresponding fitness function converges to zero infinitely when and only when the mixed strategy situation is a Nash equilibrium x^*, as shown in the following equation:

$$\begin{aligned} \text{fit}(x) &= \sum_{k=1}^{n} \max_{1 \le j \le m} \left\{ U^k\left(x \| r_j^k\right) - U^k(x) \right\}, \\ s.t.\ \text{fit}\left(x^*\right) &= 0, \\ \text{fit}(x) &\ge 0. \end{aligned} \tag{14}$$

Step 2: Dividing subpopulations. Each vehicle feasible routes $R = \{r_1, r_2, \cdots r_m\}$ is divided into q subroute populations (size SN/q), and a number of bees with size Bees/q are assigned to explore the search space. Each alternative route solution is randomly assigned to a subpopulation. When it is detected that the fitness value has changed, these subroute populations interact by merging or redividing, and the populations increase or decrease according to the intensity of the change of fitness value.

Step 3: Execute the AMSBC subalgorithm for each subroute population. Find the optimal route in the search space where the subroute population is currently located, until it is detected that the route fitness value changes, then the iteration process stops.

Step 4: Detect change strength (CS). Update the number q of subroute population according to CS, the formula of CS is shown in equation (15). If CS is greater than the threshold value, merge it into other populations and $q = q - 1$; otherwise $q = q + 1$, so as to increase the exploration ability of the search space.

$$\begin{aligned} CS &= \text{fit}_{\text{sub}-y}^{\text{best}}(\text{after}) - \text{fit}_{\text{sub}_y}^{\text{best}}(\text{before}), \\ s.t.\, y &\in \{1, 2, \cdots, q\}, \end{aligned} \tag{15}$$

Step 5: Detect termination condition. If the maximum number of search iterations is reached, the search process will stop and return the best route for each subroute population. Otherwise, all subroute populations are merged to form a single population that is redivided into new subroute populations and the algorithm continues from Step 2 using the new generation process.

Step 6: Compare the subpopulation optimal route fitness values and output the algorithm optimal route. The optimal fitness value $\text{fit}_y^{\text{best}}, y \in \{1, 2, \cdots, q\}$ of the subroute population is the global route optimal.

5. Computational Experiments and Results Analysis

In order to verify the effectiveness of EMR^{2}SM, the SUMO simulation platform is used to simulate the driving process of vehicles. Some scenes of Sioux-Falls-network road network in bstabler data set are imported into SUMO to simulate and track the dynamic driving route of vehicles, and the performance of EMR^{2}SM is analyzed through Python. We compared the performance of EMR^{2}SM with some excellent route selection algorithms, including reverse Stackelberg games (RSGs) [26] algorithm and virus genetic algorithm (VGA) [27], hybrid artificial bee colony (HABC) algorithm [28], and multiobjective particle swarm optimization (MPSO) algorithm [29]. Among them, RSG is a negotiated algorithm, and the remaining three algorithms are non-negotiated algorithm. The latter three algorithms are based on swarm technology, which have in common with EMR^{2}SM.

Section 5.1 sets the random starting point and destination for the Sioux-Falls-network and sets the vehicle inflow speed. Section 5.2 compares the EMR^{2}SM model with a negotiated algorithm and three non-negotiated algorithms to verify its effectiveness.

5.1. Experiment Setup. As shown in Figure 3, some roads of Sioux-Falls-network road network in bstabler dataset are used to track the dynamic decision-making of vehicles, which contain 26 road links and 19 intersections. O_1 to O_{12} and D_1 to D_{12} are randomly used as the starting point and destination of vehicles, respectively. The simulation is used to simulate the vehicles in the road to obtain the real-time speed of vehicles, the traffic flow density, and the length of the road section. In the experiment, in order to represent the traffic situation, it is assumed that the length of each vehicle is 4 meters, the minimum gap between two vehicles is 1 meter, and 50 km/h is the maximum speed. Each vehicle is randomly assigned a starting point and destination, and the inflow speed of vehicles varies from 10 vehs/min to 60 vehs/min, which directly affects the road saturation of the whole road network.

In the experiments, the parameter settings of utility function and AMSBC algorithm in the experiment are shown in Tables 1 and 2, respectively.

5.2. Comparison Experiments. This experiment verifies the effectiveness of EMR^{2}SM from four aspects. In different algorithms, different limit parameters are set to analyze the convergence degree and stability of vehicle route solution in the first part. The second part simulates different traffic flows of the road network by setting different vehicle inflow speeds and analyzes the execution time under different algorithms. In the third part, the effect of different algorithms on the effectiveness of decision utility function is analyzed. The fourth part analyzes the traffic flow distribution of each road section in the simulation time.

(1) In order to verify the quality and stability of the route solutions solved by EMR^{2}SM, a simulation scenario with a road network traffic utilization rate of 0.6 is set to verify the convergence of fit values. Generally, fit is defined in optimization algorithms based on swarm technology. Therefore, EMR^{2}SM is only compared with VGA, HABC, and MPSO algorithms here. As shown in Figure 4, EMR^{2}SM outperforms the other heuristic optimization search algorithms in terms of convergence and solution quality under different iteration values. They are all prone to fall into local optimal solutions, but the AMSBC algorithm helps to jump out of local optimal solutions due to population partitioning and adaptively updating the number of subpopulations according to the intensity of changes.

(2) In order to analyze the execution time, experimental verification was carried out under different traffic flow densities. As shown in Table 3 and Figure 5, the execution time of EMR^{2}SM is better than VGA, HABC, MPSO, and RSG, irrespective of large traffic inflow or small traffic inflow. EMR^{2}SM has ideal computing performance. Especially with the continuous increase of traffic flow, the execution time of RSG has significantly increased, but the growth range of EMR^{2}SM's running speed tends to be stable, and its advantages are more obvious.

(3) In order to evaluate the effect of EMR^{2}SM on reducing the average travel time, average travel distance, and average exhaust emissions of the whole road network, comparison experiments were carried out under different weights. We change the weights of the three types of parameters in the utility formula and conduct different experimental analyses for three cases: case 1, with the average shortest route of vehicle as the goal ($\omega_2 = \omega_3 = 0$); case 2, with the least average travel time as the goal ($\omega_1 = \omega_3 = 0$); case 3, with the least average gas emissions as the goal ($\omega_1 = \omega_2 = 0$). As shown in Figures 6(a)–6(c), EMR^{2}SM satisfies the requirement of minimizing the utility value in different cases, especially with the increase of traffic utilization of road network (ratio of number of vehicles to road capacity), its utility advantage is more obvious, proving that the negotiation and computational parallelism of EMR^{2}SM are more beneficial to the vehicle route finding, effectively reducing the vehicle travel time and distance, exhaust emissions, and satisfying the needs of ecocity development.

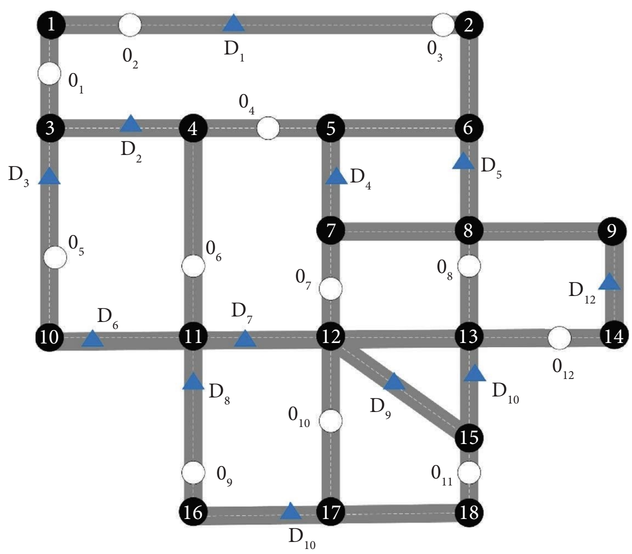


FIGURE 3: Sioux-Falls-network.

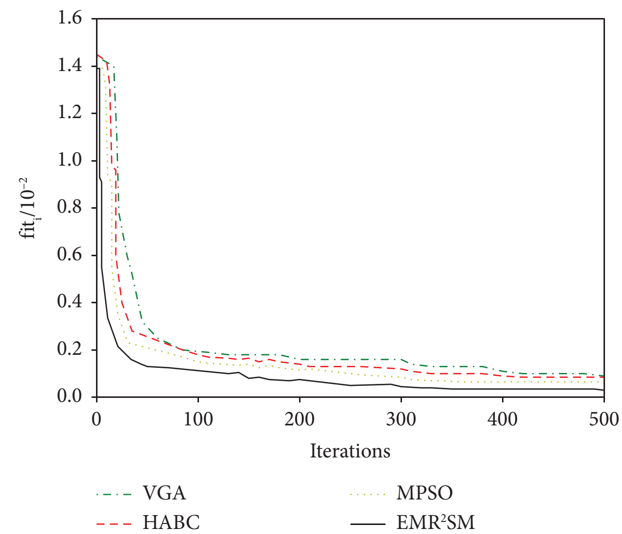


FIGURE 4: Convergence of the fit value.

TABLE 1: Parameter settings of utility function.

Parameters	Settings
α	0.15
β	4
CER	1.85 g/km
NER	1.01 g/km
P_e	[120, 160] kw
b	[170, 220] (g/kw·h)
ρ	[0.83, 0.855] (g/ml)

TABLE 2: Parameter settings of AMSBC algorithm.

Parameters	Settings
Max *It*	200
SN	$SN = m$, equal to the number of feasible routes for vehicles
D	$D = N$, equal to the number of vehicles
q	5
Number of employed bees	$SN \cdot q$
Number of onlooker bees	$SN \cdot q$
Limit	50
TV	0.05

TABLE 3: Execution time of algorithms.

Vehicle inflow (veh/min)	*Execution(s)* VGA	HABC	MPSO	RSG	EMR^{2}SM
50	10.08	10.86	11.15	13.37	6.91
40	5.38	5.20	5.51	6.82	3.63
30	2.56	2.43	2.97	3.34	2.08
20	1.57	1.29	1.41	1.74	1.23

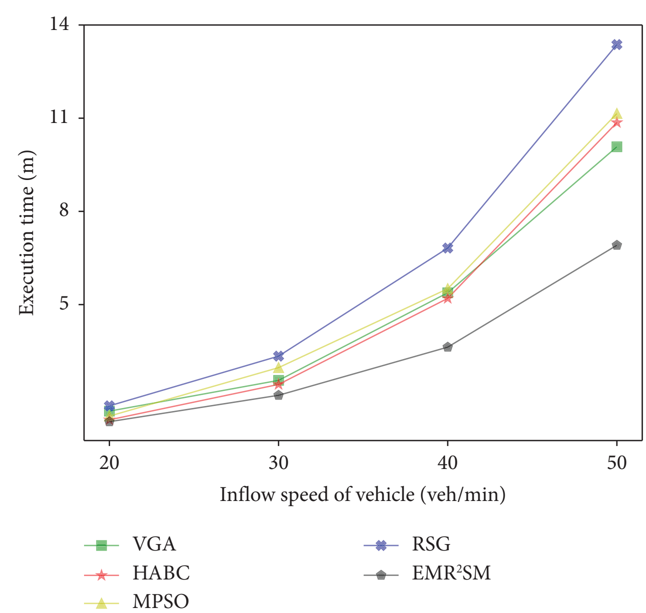
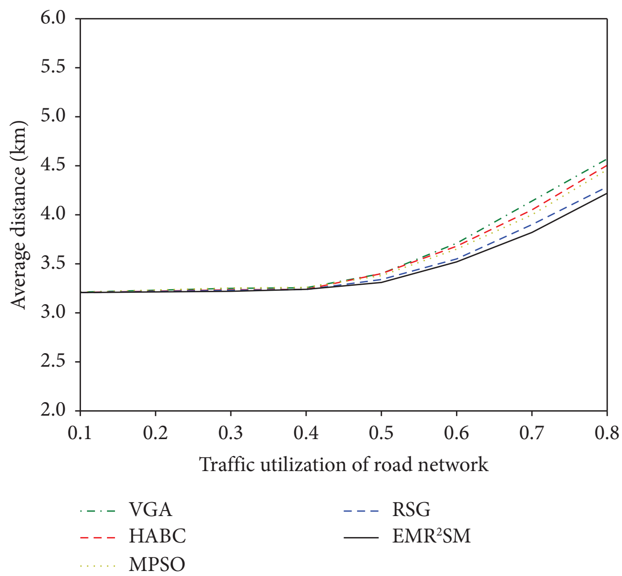
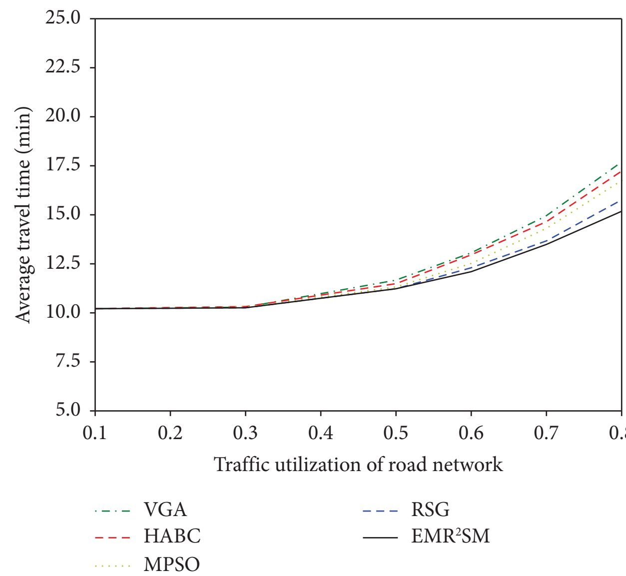


FIGURE 5: Execution time.

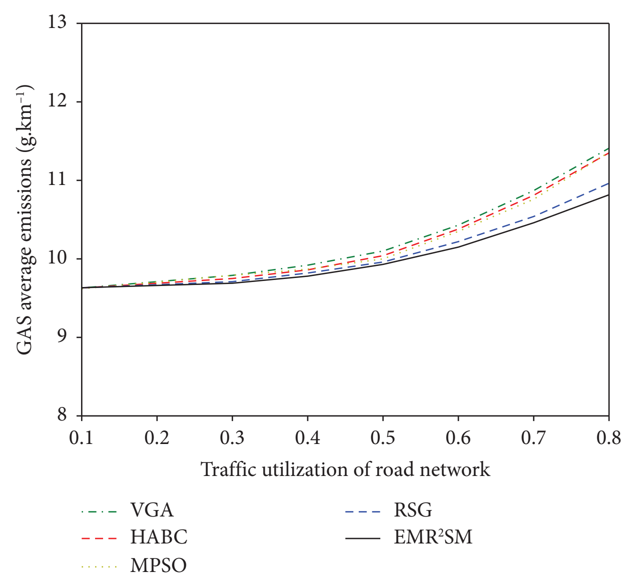
(4) In order to evaluate that EMR^{2}SM can effectively alleviate traffic congestion, this paper simulates the points ($O_1 - O_{12}$) at a constant inflow speed of 40 veh/min. Measure the traffic utilization of each road section during the sampling time period. From Table 4 and Figures 7(a)–7(e), it can be seen that in the whole, the negotiation ability of EMR^{2}SM and RSG can more effectively equalize the road vehicle density, effectively disperses traffic congestion on key sections. Compared to the other methods, the variance value of EMR^{2}SM is effectively reduced, making the distribution of traffic flow on each section more balanced, thus making the city's road resources more fully utilized.



(a)



(b)



(c)

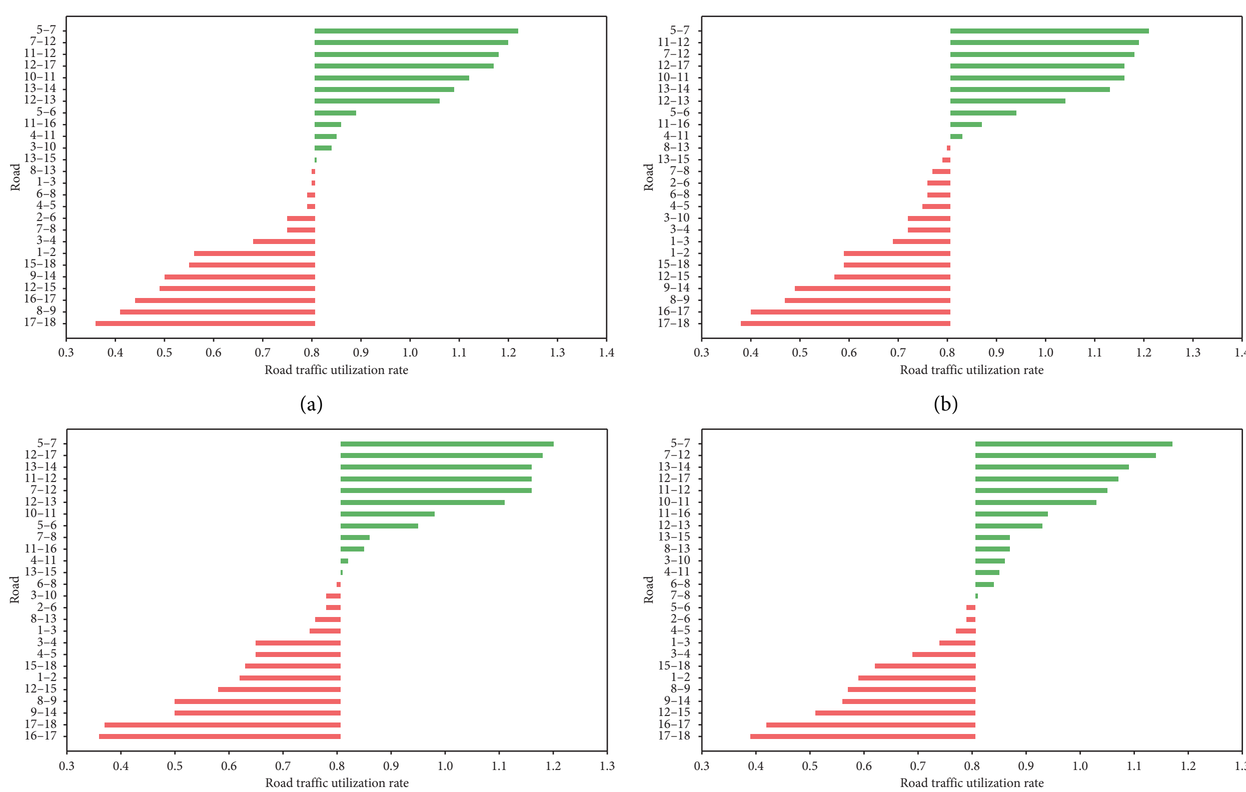
Figure 6: Different traffic utilization of road network. (a) Average distance. (b) Average travel time. (c) Average exhaust emissions.

Table 4: Traffic utilization of road section.

Roads	*Traffic utilization of road section*				
	VGA	HABC	MPSO	RSG	EMR^2SM
1-2	0.56	0.59	0.62	0.59	0.66
1–3	0.8	0.69	0.75	0.74	0.77
2–6	0.75	0.76	0.78	0.79	0.81
3-4	0.68	0.72	0.65	0.69	0.73
3–10	0.84	0.72	0.78	0.86	0.79
4-5	0.79	0.75	0.65	0.77	0.77
4–11	0.85	0.83	0.82	0.85	0.87
5-6	0.89	0.94	0.95	0.79	0.75
5–7	1.22	1.21	1.2	1.17	1.12

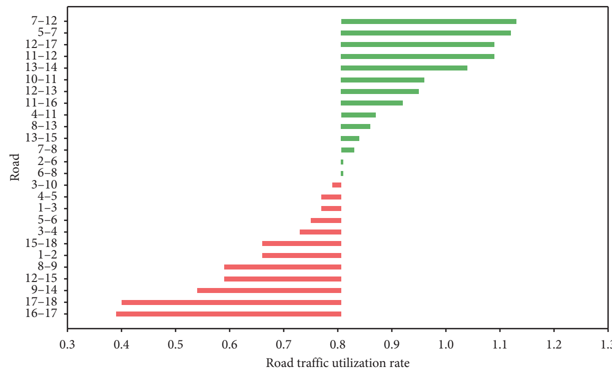
Table 4: Continued.

Roads	*Traffic utilization of road section*				
	VGA	HABC	MPSO	RSG	EMR^{2}SM
6–8	0.79	0.76	0.8	0.84	0.81
7-8	0.75	0.77	0.86	0.81	0.83
7–12	1.2	1.18	1.16	1.14	1.13
8-9	0.41	0.47	0.5	0.57	0.59
8–13	0.8	0.8	0.76	0.87	0.86
9–14	0.5	0.49	0.5	0.56	0.54
10-11	1.12	1.16	0.98	1.03	0.96
11-12	1.18	1.19	1.16	1.05	1.09
11–16	0.86	0.87	0.85	0.94	0.92
12-13	1.06	1.04	1.11	0.93	0.95
12–15	0.49	0.57	0.58	0.51	0.59
12–17	1.17	1.16	1.18	1.07	1.09
13-14	1.09	1.13	1.16	1.09	1.04
13–15	0.81	0.79	0.81	0.87	0.84
15–18	0.55	0.59	0.63	0.62	0.66
16-17	0.44	0.4	0.36	0.42	0.39
17-18	0.36	0.38	0.37	0.39	0.40
Average	0.806	0.806	0.807	0.806	0.806
Variance	0.068	0.065	0.063	0.047	0.042



(a) (b) (c) (d)

Figure 7: Continued.



(e)

Figure 7: Deviation analysis of traffic utilization of road section. (a) VGA. (b) HABC. (c) MPSO. (d) RSG. (e) EMR^{2}SM.

6. Conclusion

In order to improve the urban environment and alleviate urban traffic congestion, this paper proposes an ecological multivehicle real-time route selection model (EMR^{2}SM) for urban road networks, which takes into account the environmental indicators, the route change problem of multiple vehicles under the dynamic change of traffic status, and the conflict and collaboration relationship between vehicles in route selection. Then, an adaptive multiswarm bee colony algorithm (AMSBC) is designed, which is integrated into the game theory. The optimal route of each vehicle is searched in parallel through multiple swarm methods and adaptive mechanisms to reach Nash equilibrium. Through the comparison experiments, the EMR^{2}SM model has been verified to have more advantages in terms of convergence and solution quality than non-negotiated optimization algorithms. With the increase of the number of vehicles, the advantage of is more obvious. Whether the traffic density is large or small, the EMR^{2}SM has more advantages in execution time. It has effectively reduced the average vehicle travel time, average travel distance, and exhaust emissions under different road network saturation scenarios, especially making the reduction more obvious when the utilization of road network is above 0.5. Finally, by analyzing the traffic flow of each road section, the negotiation ability of EMR^{2}SM is more effective in balancing the road vehicle density, effectively dispersing the traffic flow and alleviating the road traffic congestion.

In spite of the progress in this paper, there is still some work required to be further studied. First, considering predicted routes for driving vehicles to plan routes should be helpful. Second, the effect of waiting for traffic signals at intersections on vehicle route selection should also be considered to make the route selection more precise.

Data Availability

The scene of this study comes from Sioux-Falls-network road network in stapler data set, and other data used in this study cannot be made available due to policies.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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