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Modeling and Analysis of Vehicle Energy Consumption at Signalized Intersection Based on Genetic Algorithms

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The unreasonable acceleration and deceleration of vehicles on urban roads at signalized intersections will result in extra fuel consumption. In order to solve this problem, a genetic algorithm is used to analyze vehicle energy consumption at signalized intersections. A vehicle structure model is constructed and dynamic analysis is carried out. A model of a signalized road intersection is established to ensure the validity and coverage of a continuous signalized intersection scenario. In order to reduce the energy consumption, the vehicle operation control mode of the signalized intersection is optimized and combined, in the vehicle energy consumption analysis model based on a genetic algorithm, the corresponding vehicle speed curves under different operation levels or at different signalized intersections are calculated; the population size is 200, the probability of genetic variation is 0.001, and the genetic algebra is 50. The optimal traction energy consumption of vehicles moving along the speed curve is calculated by the optimization method of vehicle energy consumption based on a genetic algorithm. The results show that, compared with the weighted coefficient analysis method, the vehicle running time and total fuel consumption at the signalized intersection optimized by this method are reduced by 5.7% and 20.5% respectively. With this method, the fuel consumption of the optimized vehicle engine is lower than that of the weighted coefficient analysis method by 5.33 g; hence, the analysis of the results of the proposed method shows that its performance is better in terms of its energy consumption optimization.

Keywords: Genetic algorithm; Signal lamp; Intersection; Vehicle operation; Energy consumption; Modeling and analysis

1. INTRODUCTION

With the continuous development of the economy in newly industrialized countries, the demand for vehicles has become more and more intense, which has spurred the automotive industry to achieve amazing development, with the output increasing year by year. At the end of 2015, China, as the world's largest vehicle producer and seller, had manufactured 279 million vehicles, of which 172 million were automobiles. At the same time, the global vehicle ownership reached 1.12 billion vehicles, and is predicted to grow at aa annual rate of 20% (Boubaker et al. 2016, Liao et al. 2018). This continuous increase in vehicle ownership has brought many problems, one of the most significant being the large number of pollutants, such as carbon dioxide (CO_2), carbon monoxide (CO), hydrocarbons (HC), nitrogen oxides (NO_X) and particulate matter (PM) that are emitted by vehicles (Chai et al. 2015). According to the data provided by the U.S. Government's Climate Change Professional Committee, greenhouse gas emissions from the transportation sector accounted for one third of the total emissions in the United

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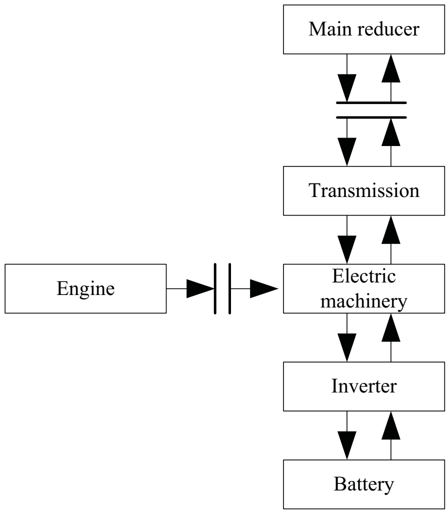


Figure 1 Vehicle powertrain structure.

States in 2004, 80% of which came from passenger cars and trucks in the road traffic system. Moreover, vehicles consume massive amounts of non-renewable fossil fuels More than 50% of China's oil will be used for vehicle operation in the future, and this is expected to greatly increase, thereby exacerbating the global energy crisis. Furthermore, the great number of vehicles on the roads produces traffic congestion and increases the incidence of road accidents causing injuries and fatalities (Gowri & Sivanandan 2015, Lai & Easa 2016). According to a survey by the Texas Institute of Transportation Management, Americans consumed 5.5 billion hours of driving time and 2.9 billion gallons of fuel in 2011 because of traffic congestion.

Given these global problems, the future will see increasingly urgent calls for ways to address vehicle safety, energy saving and environmental protection issues. Nowadays, there are many reasons for the inefficiency of the traffic system and the deterioration of the fuel economy of vehicles. The unreasonable acceleration, deceleration and idling of vehicles at signalized intersections cause congestion and excessive fuel waste (Ren et al. 2016). Therefore, how to encourage and help drivers to drive reasonably and economically is an urgent problem. Scholars in Europe and the United States began to pay attention to this issue in the 1990s, and set up many driver-training programs in the early years to help develop good driving habits. On this basis, further research hopes to improve the fuel economy of vehicles by controlling the workings of the internal combustion engine and the transmission system, and optimizing the vehicle's speed trajectory.

Nowadays, start from the resume and the background of the resume (Wang et al. 2015), the application of information technology is being considered for vehicle control and even the management of the whole traffic field. These studies mainly involve information communication technology and an intelligent control algorithm (Yan et al. 2016). ITS is based on a wide range of traffic information to connect wired and wireless communication technology with traffic systems and vehicles, to ensure the green and safe driving of vehicles while achieving comprehensive and efficient management of the traffic system. In this way, the vehicles traveling on roads with signalized intersections can obtain in advance all the traffic information they need. This is done through the technology of vehicle networking, such as the dynamic timing of signalized lights and the motion information of vehicles around them, which is of great significance for the study of vehicle energy consumption optimization at successive signalized intersections in cities. Therefore, this paper uses a genetic algorithm to analyze a running vehicle's energy consumption at signalized intersections, and uses the vehicle energy consumption analysis model based on a genetic algorithm to calculate the corresponding vehicle running speed curves at different operating levels or at different signalized intersections. Using the optimization method of vehicle energy consumption based on genetic algorithm, the optimal traction fuel consumption of the vehicle running along the speed curve is calculated, which ensures the driving safety and reduces the fuel consumption of the vehicle at the signal intersection.

2. MATERIALS AND METHODS

2.1 Construction of Vehicle Structure Model

In order to establish a general vehicle energy consumption model, the vehicle structure shown in Figure 1 is used as the research object.

Figure 1 depicts a typical parallel hybrid vehicle structure. Its power assembly structure includes: internal combustion engine, single motor, battery, transmission and main reducer (Asaithambi & Anuroop 2016). The single motor can be used as a motor when driving, and can also be used as a generator to charge the battery. Referring to the control strategy adopted in the existing Simulink model of hybrid electric vehicles, the vehicle can be divided into three working states (parking state, driving state and braking state). The specific working mode is shown in Table 1.

The actual working conditions of vehicle energy consumption analysis for HEV at a signalized intersection include pure electric, economical charging, engine working alone, hybrid driving, motor braking and hybrid braking (Moshiri & Montufar 2017, Chai et al. 2015).

Table 1 Hybrid electric vehicle working mode.

Parking condition	Driving state	Braking state
Shutdown	Pure electric	Motor braking
Idling	Economic Charging	Hybrid braking
Idle speed power generation	The engine works alone	-
-	Hybrid drive	-
-	Forced charging	-

The dynamic analysis of the hybrid electric vehicle with this structure (Da et al. 2018) is carried out. The longitudinal kinematics equation of the vehicle is:

$$m_v a = F_t - F_a - F_f - F_s \tag{1}$$

Among them, m_v and a are the mass and acceleration of the vehicle, F_t is the traction of the wheel, F_a is the running air resistance, F_f is the rolling resistance, F_s is the slope resistance. The traction F_t is provided by the power system of the hybrid electric vehicle and reaches the wheels at last. The expressions for calculating other resistance are:

$$F_a = 0.5\rho_a C_d A v^2 \tag{2}$$

$$F_f = mgf_{rcc}\cos\theta \tag{3}$$

$$F_s = mg\sin\theta \tag{4}$$

In the formula, ρ_a, C_d and A are respectively air density, air resistance coefficient and windward area; f_{rcc} is rolling resistance coefficient; θ is current road gradient; v is current longitudinal speed.

On the premise of considering only the primary rolling resistance, taking into account only the longitudinal motion of the vehicle and neglecting the slope factor, it is considered that the vehicle is travelling on a long straight road. Hence according to Bo et al. (2016), the relationship between the powertrain is:

$$T_w = \left(0.5\rho_a C_d A\omega_t^2 R_t^2 + mgf_{rcc} + m_v\dot{\omega}_w R_t\right) R_t \tag{5}$$

$$T_w = \left(T_{\text{mot}} + T_{\text{eng}}\right) f_{\text{drive}}\, f_{\text{gear}}\, \eta_{\text{trans}} \tag{6}$$

$$\omega_{\text{eng}} = \omega_{\text{mot}} = \omega_w f_{\text{drive}}\, f_{\text{gear}} \tag{7}$$

$$rio = T_{\text{eng}} \,/\, \left(T_{\text{eng}} + T_{\text{mot}}\right) \tag{8}$$

In the formula, T_w is the wheel driving torque; ω_{mot} and ω_{eng} are the motor and engine speed; T_{mot} and T_{eng} are the motor and engine output torque; f_{drive}, f_{gear} and η_{trans} are the main reducer, transmission ratio and transmission system mechanical efficiency respectively; rio is the torque distribution coefficient, which represents the proportion of the engine providing torque to the required torque.

2.2 Constructing Scene Model of Signal Intersection

For the vehicle energy consumption analysis model of a HEV signalized intersection, it is necessary to design a feasible road scenario used by the research institute, taking into account the main characteristics of the actual road scene (Hagiwara et al. 2015). The main research objective is to determine the energy consumption of vehicles running longitudinally at signalized intersections. The structure and types of signalized intersections need to be omitted. At the same time, the road and traffic information are known through vehicle network communication. Therefore, the specific simplification and hypothesis of the road scene at signalized intersections are as follows:

(1) The vehicle has been running in a straight line on a lane, without turning or neglecting the effect of turning, and continuously passes all the signal lights that need to be passed.

(2) The phase of the signal lamp considers only the phase of the red lamp and the phase of the green lamp, and the signal lamp changes with time.

(3) The signalized intersection is simplified as a parking line, ignoring the possible internal structure.

(4) It is considered that the intersection can be passed at the moment when the signal is switched, so that each green light phase constitutes a closed set.

(5) In the context of vehicle networking, it is assumed that the timing and phase information of signal lights are known and are non-time-varying.

Specific continuous signal intersection scenarios are shown in Figure 2.

On the other hand, because the variable acceleration model requires optimization in continuous space, it is necessary to discretize first the whole road scene according to a certain step size, and then consider that the vehicle is moving at a uniform speed in each discrete small step, so that the solution and optimization of the vehicle speed curve under the variable acceleration model can be achieved (Boubaker et al. 2016). The whole discrete process diagram is shown in Figure 3.

In Figure 3, v_i is the final velocity of the i segment, so v_0 can be used to represent the initial velocity; a_i and t_i are the acceleration and travel time of the i segment; ds is the discrete step; s_i is the distance from the i signal lamp. Then the kinematic relationship of the vehicle in the discrete step is obtained as:

$$v_i = \sqrt{v_{i-1}^2 + 2a_{i-1} \cdot ds} \tag{9}$$

$$t_i = \frac{2ds}{(v_i + v_{i-1})} \tag{10}$$

Figure 2 Phase map of continuous signal intersection.

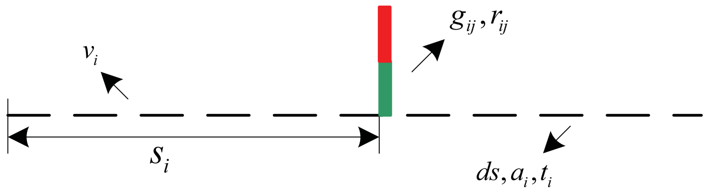


Figure 3 Road scene discretization process graph.

Finally, based on the above discussion, in a reasonable range, we use the random generation method to get the required continuous signal road scene. The specific steps for generating the signal intersection road scene are as follows:

(1) To determine the total length of the road S_{total}, then determine the number of signal intersections to be generated n and randomly determine the length of each signal section L_i to meet $\sum_{i=1}^{n} L_i = S_{\text{total}}$.

(2) For each signal, the values in the green light timing $(\alpha_g,\ \beta_g)$ are randomly selected, and the values in the red light timing $(\alpha,\ \beta)$ are randomly selected (Yi & Bauer 2017).

(3) The phase of the signal lamp at the initial time, without losing its generality (Lee & Choi 2016), can be randomly selected in $(-G_i - R_i, 0]$, $i = 1, 2, \cdots n$, where G_i and R_i are the green light and red light timing length of the i signal lamp.

An example of a 2400 m intersection road scene with six lights is given, as shown in Figure 4.

2.3 Vehicle Energy Consumption Optimization Based on Genetic Algorithms

2.3.1 Vehicle Energy Consumption Analysis Model Based on Genetic Algorithms

In the analysis model of a vehicle's running energy consumption, if the command speed x_i of intersection section in the scene of signalized intersection is expressed by $\{x_{i1}, x_{i2}, \cdots, x_{ik}, \cdots, x_{in}\}$, and the speed of k of speed change point is expressed by x_{ik}, the speed corresponding to P_1. In the algorithm, the value of each speed is in the range of P_1 to P_5, and the resolution of the speed can be set to 1 km h^{-1}. The change point of command speed is to divide the signal intersection into 20–40 equal points according to the distance. The actual ATO speed curve and traction energy consumption along the command speed curve $\{x_{i1}, x_{i2}, \cdots, x_{ik}, \cdots, x_{in}\}$ will be obtained, so the problem can be abstracted as a combinatorial optimization problem of time and energy consumption (Tang et al. 2017):

$$X = \{(x_{11}, x_{12}, \cdots x_{1n}), (x_{21}, x_{22}, \cdots x_{2n}), \cdots, (x_{m1}, \mathrm{x}_{m2}, \cdots, x_{mn})\} \tag{11}$$

$$\text{s.t.} \quad g_1(x_i) \leq J \tag{12}$$

$$g_2(x_i) \leq T \tag{13}$$

Among them: X is a set of vehicle command speed curves; J is the maximum impact rate of vehicles; T is the maximum running time of signalized intersection; $g_i(x_i)$ and $g_2(x_i)$ are the maximum impact rate of vehicles running according to x_i and the running time of signalized intersection (Li et al. 2015).

Constraint Formula (12) indicates that when a vehicle runs in accordance with the command speed curve x_i, the speed change of the vehicle needs to satisfy that the maximum impact rate (the change rate of acceleration) of the vehicle is not greater than the maximum J given by the vehicle. If x_i is expressed as $\{x_{i1}, x_{i2}, \cdots x_{ik}, \cdots, x_{in}\}$ and v_k is set as the speed corresponding to x_{ik} and d_k is the line position corresponding to x_{ik}, then the acceleration a_k and time t_k are:

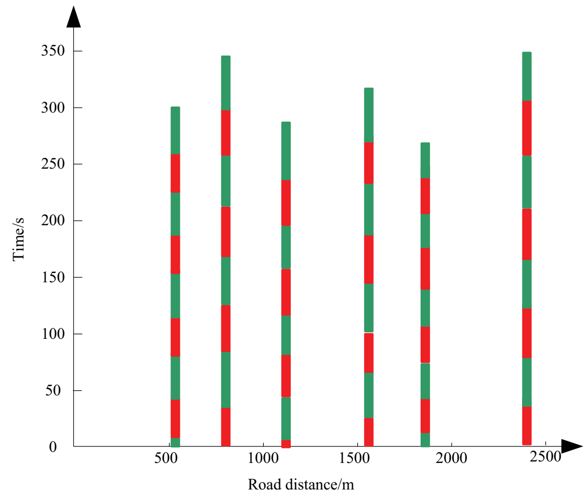


Figure 4 Example of a 2400 m and 6-signal intersection scene.

$$a_k = \frac{v_{k+1}^2 - v_k^2}{2\left(d_{k+1} - d_k\right)} \tag{14}$$

$$t_k = \frac{v_{k+1} - v_k}{a_k} \tag{15}$$

Constraint Formula (12) can be expressed as:

$$J_k = \frac{a_k}{t_k} \leq 1 \quad k \in \{1, 2, \cdots, n-1\} \tag{16}$$

In the Formula: J_k is the impact rate of the vehicle at x_{ik}.

Constraint Formula (13) indicates that when a vehicle runs in accordance with the command speed curve x_i, the running time at the intersection of vehicle signal lights is not more than T. In this algorithm, the constraints are transformed into speed curves corresponding to different running times, and the optimal solutions corresponding to different running times are recorded during the operation, that is, the minimum energy consumption speed curves corresponding to different running times.

2.3.2 Vehicle Energy Consumption Optimization Method Based on Genetic Algorithms

Setting the population size to 200, the vehicle running speed curve consists of the command speed of each line segment of the vehicle at the signalized intersection (Wu & Zhang 2015). The command speed of a line segment is included in each chromosome as a genetic factor. The individual generated by each gene has a certain adaptability to the environment. Through the selection of the fittest, the base with high adaptability is obtained (Cao et al. 2016). The number of genes in Formula (11) is the number of chromosomes. The number of genes depends on the selection of command speed change points in the algorithm; i.e. 20–40 equal points in the algorithm for energy consumption optimization of vehicle speed curve.

The probability of gene mutation is 0.001. In this algorithm, genetic algebra is used as the termination condition. After 50 generations of testing, satisfactory results can be obtained.

The key to study the fitness function of the vehicle speed curve is to calculate the energy consumption of the vehicle running along the curve (Fu et al. 2016). If $f_i(x_i)$ is the traction energy consumption of the vehicle running along the command speed, the fitness function of x_i is:

$$f\left(x_i\right) = \begin{cases} C_{\max} - f_1(x_i) & f_1(x_i) < C_{\max} \\ 0 & \text{else} \end{cases} \tag{17}$$

Among them, $C_{\max}$ is the normal number with a large middle score, which means that if the energy consumption of the vehicle in the test signal intersection is greater than $C_{\max}$, its fitness is 0, and it will definitely be eliminated in the next selection operation. Vehicle traction energy consumption $f_1(x_i)$ is the result of traction force (Yang et al. 2017), which integrates vehicle running resistance and line gradient factors. Vehicles run according to command speed curve set X to get the actual running curve set Y. y_i is the actual running speed curve corresponding to command speed x_i. Vehicle traction energy consumption corresponding to y_i can be obtained by simulation calculation.

Vehicle resistance can be decomposed into basic resistance and additional resistance, namely:

$$F_1(y_{ij}) = F_2(y_{ij}) + F_3(y_{ij}) \tag{18}$$

Among them: $F_1(y_{ij})$, $F_2(y_{ij})$ and $F_3(y_{ij})$ are the total resistance, basic resistance and additional resistance of the vehicle in y_{ij} respectively; y_{ij} is the position j of y_i.

The force exerted on the gradient is obtained by the force of gravity (Ma 2018). If $w(y_{ij})$ is the unit resistance of the gradient on y_{ij}, the total gradient resistance $F_4(y_{ij})$ of the vehicle is as follows:

$$F_4(y_{ij}) = \frac{w(y_{ij})}{1000000} Mg \tag{19}$$

Among them: M is vehicle mass; g is gravity acceleration.

The vehicle's target acceleration is determined by the vehicle controller according to the current state of the vehicle, and the actual force exerted on the vehicle is the way to achieve the target acceleration. The actual force $F_5(y_{ij})$ of the vehicle in y_{ij} is

$$F_5(y_{ij}) = \frac{M(1+\beta)a(y_{ij})}{1000} \tag{20}$$

Table 2 Summary of simulation results of energy consumption optimization by different methods.

Distance and number of lights (m/Number)	Passage coefficient	Dispersion coefficient	Time /s	Overall fuel consumption/g
1800 m/4	0.3911	25.56%	170.41/179.00 (-4.8%)	36.94/42.27 (-12.6%)
2000 m/7	0.2594	13.71%	157.94/149.44 (+5.7%)	40.53/49.68 (-18.4%)
2200 m/6	0.3301	15.91%	214.75/244.00 (-12.0%)	44.66/48.72 (-8.3%)
2300 m/7	0.2846	19.94%	195.70/190.55 (+2.7%)	58.91/73.56 (-19.9%)
2600 m/7	0.3306	18.41%	230.60/221.00 (+4.3%)	64.67/79.37 (-18.5%)
2700 m/7	0.342	13.44%	232.07/291.65 (-20.4%)	59.23/85.40 (-29.0%)
2700 m/8	0.2966	24.44%	253.76/278.00 (-8.7%)	70.24/95.59 (-26.5%)
2800 m/7	0.273	30.00%	281.54/288.00 (-2.2%)	85.73/90.84 (-5.6%)
2800 m/8	0.3297	16.79%	244.43/290.46 (-15.8%)	68.28/91.01 (-25.0%)

Among them: β is the vehicle rotating mass coefficient, the value is related to the number of passengers. In this simulation, the vehicle mass is taken as full-load, the vehicle rotating mass coefficient β is taken as 1.08; $a(y_{ij})$ is the instantaneous acceleration of the vehicle in y_{ij}. When the vehicle is accelerating, $a(y_{ij}) > 0$, when the vehicle is decelerating, $a(y_{ij}) < 0$ (Liu et al. 2017).

Since $F_5(y_{ij})$ is the combined force of traction, braking force, resistance and slope resistance, then:

$$F_5\left(y_{ij}\right)=F_6\left(y_{ij}\right)+F_7\left(y_{ij}\right)+F_1\left(y_{ij}\right)+F_4\left(y_{ij}\right) \quad (21)$$

Among them, $F_6(y_{ij})$ and $F_7(y_{ij})$ are the traction force and braking force of vehicle in position y_{ij} respectively.

If $F_5(y_{ij})+F_1(y_{ij})+F_4(y_{ij})>0$, then the vehicle is in the traction state, the traction force is:

$$F_6\left(y_{ij}\right)=F_5\left(y_{ij}\right)+F_1\left(y_{ij}\right)+F_4\left(y_{ij}\right) \quad (22)$$

If $F_5(y_{ij})+F_1(y_{ij})+F_4(y_{ij})<0$, then the vehicle is in braking state and the traction force is:

$$F_7\left(y_{ij}\right)=-F_5\left(y_{ij}\right)-F_1\left(y_{ij}\right)-F_4\left(y_{ij}\right) \quad (23)$$

If $F_5(y_{ij})+F_1(y_{ij})+F_4(y_{ij})=0$, then the vehicle is parked, traction and braking force are both 0.

The optimal traction energy consumption $f_1(x_i)$ of a vehicle operating at the command speed x_i according to Formula (22) is as follows:

$$f_1\left(x_i\right)=\int F_6\left(y_{ij}\right)dy_{ij}=\int\left[F_5\left(y_{ij}\right)+F_1\left(y_{ij}\right)+F_4\left(y_{ij}\right)\right]dy_{ij} \quad (24)$$

Among them, y_{ij} is between the departure point L_1 and the parking point L_2.

3. RESULTS

In order to verify the performance of this energy consumption analysis method, several scenarios are randomly generated and selected on the simulation platform to analyze the vehicle energy consumption, such as when the engine is idling at the signal intersection. The simulation results of this method and weight coefficient analysis method are compared. The results are shown in Table 2. The left side of time bar and total fuel consumption column is the energy consumption optimization result of this method, and the right side is the result of energy consumption optimization by the weight coefficient analysis method.

In Table 2, vehicle energy consumption is indicated by fuel consumption. It can be seen from the table that in scenarios comprising different distances and number of signal lights, the time and total fuel consumption of vehicles at signalized intersections are reduced by 5.7% and 20.5% respectively when the energy consumption of vehicles at signalized intersections is analyzed and optimized compared with the method of weight coefficient analysis.

Next, the simulation results in Table 2 will be compared and analyzed, using a road scenario where distance is 1800 m, and there are four signalized intersections. Figure 5 is a comparison of displacement of running vehicles optimized by two analytical methods.

From Figure 5, we can see that the method of weight coefficient analysis is used to analyze the energy consumption of vehicles at signalized intersections one by one. In order to minimize the absolute acceleration at each section of the road, the comparison results show a trend of two endpoints passing through the intersection in the traffic time interval. Displacement maps show that in order to pass successfully through the first intersection, the moving vehicles under the two methods have experienced an obvious acceleration section. In the later signal intersection section, the vehicles optimized by this method have accelerated ahead of time because of the characteristics of global optimization, while the vehicles optimized by weight coefficient analysis method have passed through a large increase in the last signal intersection section. Speed ensures passage through the intersection during the green phase of the signal. The following two methods are given to optimize the vehicle motion as shown in Figure 6.

As shown in Figure 6, corresponding to the shift in Figure 5, the optimization result of this method accelerates ahead of time after passing the second signal intersection to ensure the smooth passage of the back signal intersection, while the weight coefficient analysis method considers each intersection

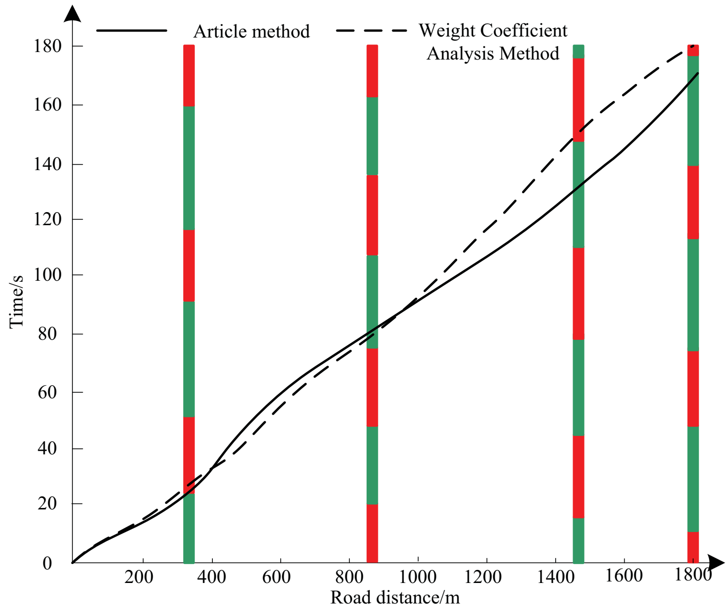
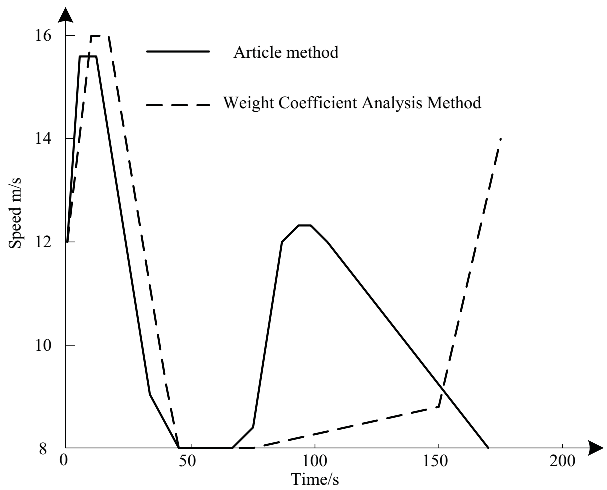
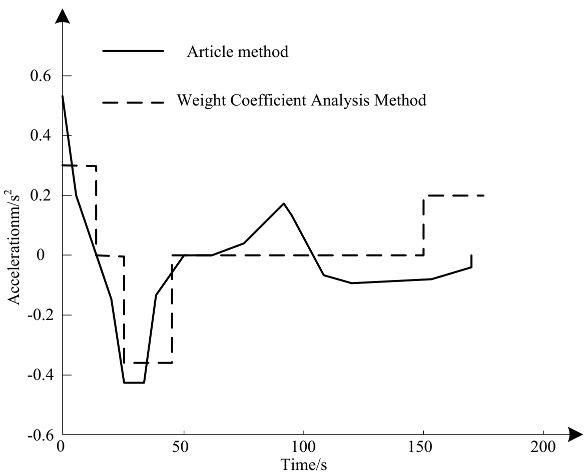


Figure 5 Vehicle displacement contrast map of road scene at 1800 m, four signal intersections.



(a) Speed



(b) Acceleration

Figure 6 Vehicle speed and acceleration map of road scene at 1800 m, four signal intersections.

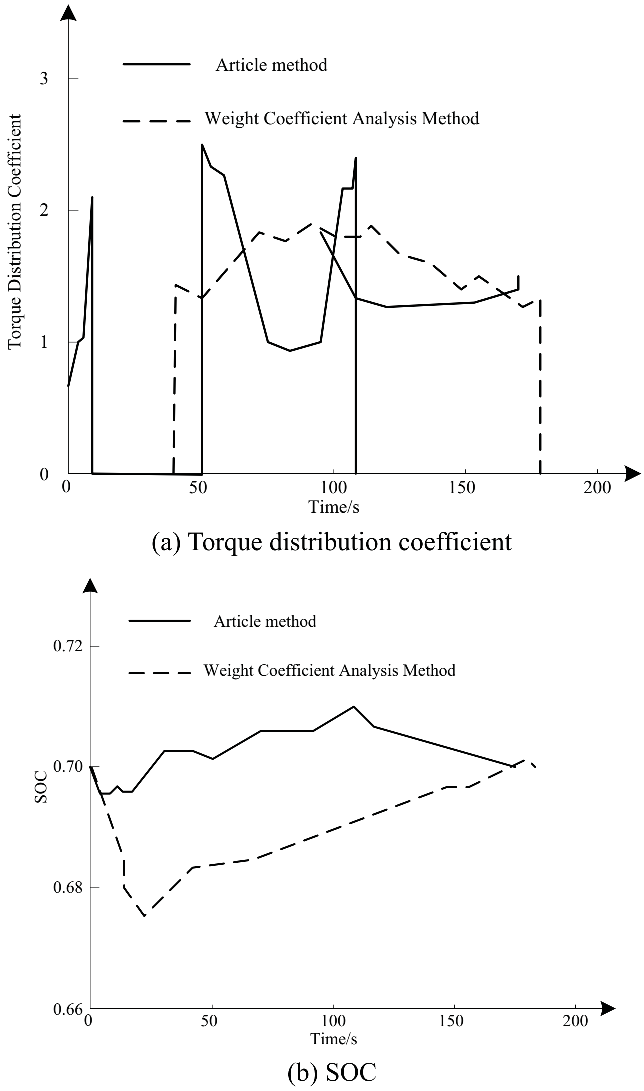


Figure 7 Torque analysis coefficient and SOC chart of road scene at 1800 m, four signal intersections.

one by one, and maintains the low speed at both the second and the third signal intersection, so that it has to be added at the last signal intersection, this also gives the vehicle extra fuel consumption and higher final speed. Figure 7 below shows the results of energy management optimization of the two methods.

From Figure 7, it can be seen that the energy optimization of both methods keeps the initial and final state of the running vehicle SOC (residual electricity) near 70%. Among them, the method proposed in this paper concludes that the vehicle engine participates in the two acceleration stages, in which the initial stage is driven together, while the latter engine charges the battery while the car is travelling, so that the SOC (residual electricity) can be restored. The weight coefficient analysis method is used to analyze SOC consumption in the initial stage. Finally, the SOC rebounds when the engine continues to work under both uniform and accelerated conditions.

Finally, the working conditions of the vehicle engine and the corresponding fuel consumption obtained by different methods are depicted in Figure 8.

Figure 8 shows that the fuel consumption of the two engines increases rapidly after optimization. The greater amount of engine power during the 50–110 s period makes the fuel consumption increases faster than the weighted coefficient analysis method, but the working time is short and concentrated in the high-load area with higher efficiency. The weighted coefficient analysis method makes the engine work in the low-efficiency area for a long time. Hence, the fuel consumption continues to increase, and is obviously accelerated at the beginning of large acceleration in 150 s. Finally, the maximum fuel consumption by the vehicle engine optimized by weight coefficient analysis method is 42.27 g, while the maximum fuel consumption by the vehicle engine optimized by this method is 36.94 g. By comparison, it can be seen that the fuel consumption of engine obtained by this method is lower.

4. DISCUSSIONS

In the third part of the paper, the performance of vehicle energy consumption analysis and optimization at signalized intersections using a genetic algorithm is verified. The results of the two methods are compared in terms of optimization simulation, displacement, speed and acceleration, torque

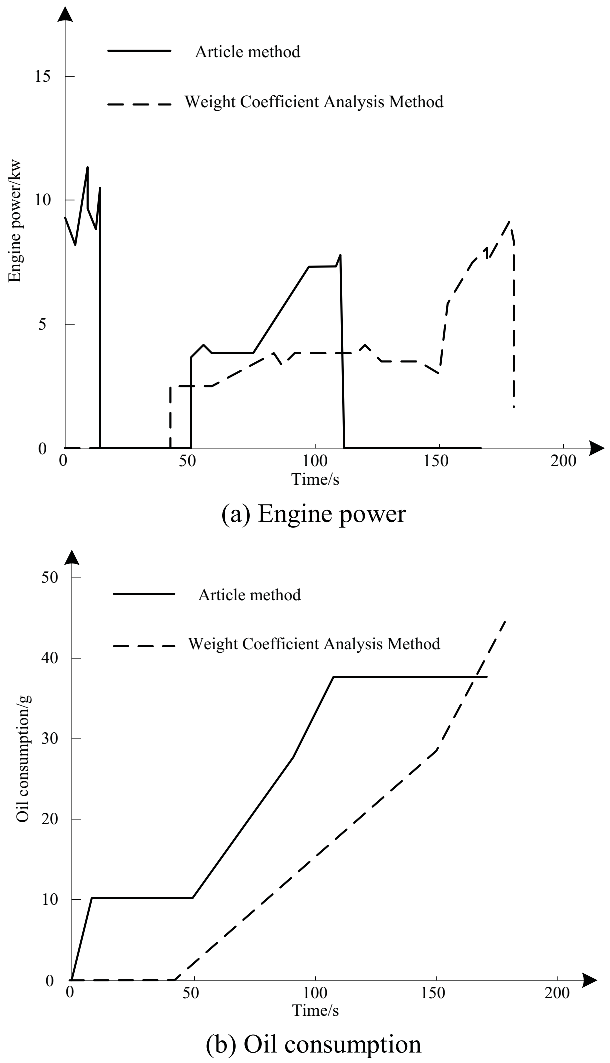


Figure 8 Engine power and fuel consumption charts for road scene at 1800 m, four signal intersections.

distribution coefficient and SOC, engine power and fuel consumption. The results show that, in comparison, the vehicle running time and total fuel consumption at the signalized intersection optimized by this method are reduced by 5.7% and 20.5% respectively. The vehicles optimized by the two methods all experience an obvious acceleration section. The vehicles optimized by this method accelerate ahead of time, while the vehicles optimized by weight coefficient analysis method have a greater acceleration at the last signalized intersection section. The optimized vehicle participates in the work of the engine in two acceleration stages, in which the starting stage is driven jointly, while the latter engine charges the battery while the vehicle is moving, so that the SOC can be restored. The optimized vehicle consumes the SOC in the initial stage by the weight coefficient analysis method, and the SOC recovers when the engine continues to charge under final constant speed and acceleration conditions. The fuel consumption of the optimized vehicle engine by weight coefficient analysis method is 42.27 g, which is higher than that of the optimized vehicle engine by this method (36.94 g). A series of experimental results show that the energy consumption analysis and optimization performance of this method is better. The main reason for this result is that the genetic algorithm is used in the energy consumption analysis of this method. According to the natural evolution rules such as survival of the fittest, the global optimization search calculation and problem solving are carried out in complex space. Without restrictive assumptions, the convergence to a local optimal solution is avoided. By parallel calculation, the calculation speed is increased, and the vehicle running along the speed curve at a signalized intersection is obtained.

5. CONCLUSIONS

This paper uses a genetic algorithm to analyze vehicle running energy consumption at signalized intersections, builds vehicle structure model and scenario model of signalized intersections, uses energy consumption optimization algorithm based on genetic algorithm to calculate vehicle running speed curves at different operating levels or at different signalized intersections, and uses energy consumption optimization method based on genetic algorithm to calculate vehicle running speed. The optimal traction energy consumption of degree curve operation can achieve an accurate analysis and optimization of vehicle operation energy consumption and greatly improve the vehicle's energy saving. The vehicle speed curves generated by this method and the optimal traction energy consumption of the vehicle moving along the speed curve offer valuable practical insights for engineering design.

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