ADVANCES IN TRANSPORTATION STUDIES
An International Journal

Editor in Chief: Alessandro Calvi

Vol. LXIII July 2024

Contents

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Advances in Transportation Studies: an international Journal 63 (2024)

ISBN 979-12-218-1262-6 – ISSN 1824-5463 – DOI 10.53136/97912218126261 – pag. 3-20

Clustering research of vehicle formation shaping based on energy consumption optimization

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subm. 11st September 2023 approv. after rev. 20th December 2023

Abstract

Multi-intelligent vehicles forming and maintaining a specific formation during traveling can save energy consumption and road resources, and improve traffic efficiency and driving safety. Centered around the Cooperative Vehicle Infrastructure(CVI) framework of the Internet of Vehicles(IOV), this paper delves into the control objectives of forming multi-intelligent vehicle formation, explores the theory of formation shaping process, and investigates the optimization of energy consumption in the formation shaping process. First, the clustering design is used to take the kinematic process of vehicles as an optimization process from the bionics, taking the instantaneous consumption indexes as the optimization objectives. Then, optimize the acceleration inputs of the vehicle formation process using the improved Artificial Fish Swarm Algorithm(AFSA), and iterate with the clustering algorithm part, so as to realize the formation shaping process with energy consumption as the optimization objective. Finally, a joint simulation platform built by Simulation of Urban MObility (SUMO) and Python is used for simulation verification, and the results show that the formation shaping process can be realized and achieve the optimal energy consumption under the scenarios proposed in this paper, thus verifying the validity of the clustering model of vehicle formation shaping and the energy consumption optimization algorithm designed in this paper.

Keywords – cooperative vehicle infrastructure, multi-intelligent vehicles, formation shaping, clustering studies, bionics, energy consumption optimization

1. Introduction

The rapid growth in the number of vehicles has brought about a series of traffic congestion, traffic accidents, traffic pollution and other problems, bringing a heavy burden to the existing traffic facilities, the traditional traffic management and vehicle technology is increasingly difficult to cope with these serious challenges [1]. With the rapid development of artificial intelligence and other technologies, CVI came into being, CVI focuses on the use of computer technology, sensor technology, information and communication technology and automatic control technology, etc., through the real-time, bidirectional and efficient communication between the vehicle system and the roadside intelligent system, to achieve the sharing and interaction of information between the vehicle and the vehicle and the vehicle and the road, which can improve the efficiency of the transport system and the safety of the traffic to a large extent [2-3].

As an important part of CVI, IOV is of great significance to the realisation of intelligent transportation [4-5]. Vehicles on the road are no longer independent of each other, and can be interconnected through wireless networks to enhance the vehicle's ability to perceive the outside world. Vehicle formation is one of the important research directions [6]. Vehicle formation is to travel in columns with smaller spacing under the consideration of wind resistance, waiting time and extra expenses, and to achieve the purpose of saving energy by optimising the number of vehicles in formation and the formation shape. The study of vehicle formation includes the processes of formation shaping, formation maintenance, and formation dissolution. Currently, major truck manufacturers have developed vehicle formation technologies and are actively researching them worldwide.

During formation travelling, due to the smaller distance between the vehicles, the air flow between the vehicles is different from that of the vehicles travelling individually, and the vehicles within the formation are subjected to less air resistance [7]. In addition, the following vehicles will have an effect on the head vehicle of the formation, which will result in an increase in the air pressure at the back of the vehicle in the formation, and accordingly a reduction in the difference in pressure between the front and rear of the head vehicle, resulting in a relative reduction in the head vehicle's resistance [8]. Therefore, in comparison with the vehicles travelling alone, energy savings can be realized. to the vehicle travelling alone, the purpose of saving energy consumption can be achieved. At the end of the last century, some scholars proved through wind tunnel tests that the aerodynamic performance of vehicles in formation during the process of lorry formation can improve fuel economy and reduce fuel emissions in the process of formation driving [8]. After that, Liang et al. [9] found that the spontaneous formation of formations was relatively rare and the fuel savings were limited through the analysis of real data, but by making smaller adjustments to the distance between the vehicles, it was found that the fuel savings were limited, but by making smaller adjustments to the distance between the vehicles, it was found that the energy consumption was reduced compared to the vehicles travelling alone. However, by making smaller adjustments to the vehicle collaboration distance, it was found to significantly increase formation efficiency and reduce fuel consumption.

One of the main objectives of formation driving is to save energy consumption, for fuel vehicles, Tan Erlong et al. [10] proposed a dynamic spatio-temporal search strategy to explore the maximum strata length and strata fuel consumption potential, and constructed an integer planning model to solve the problem and get the strata scheme under the maximum fuel saving condition. Di L et al. [11] proposed a commercial vehicle formation strategy based on density clustering, which gives the formation criteria for obtainable fuel consumption gains and defines an equivalent fuel consumption function to determine the final queue form, which achieves clustering of dispersed commercial vehicles and formation of a queue with optimal fuel consumption performance. Zhai X [12] investigated a multi-objective heterogeneous vehicle queue switching control strategy, constructed a fuel consumption table, and transformed the problem into a mixed integer linear problem.

The formation shaping process is the initial task of formation control, which is mainly to make the disordered vehicles in different states form the formation safely and smoothly. In formation shaping control, the motion characteristics of vehicles during the motion of steering can have an important effect on vehicle behavior, which in turn determines the effectiveness of formation shaping to some extent. In the research on formation shaping, I. Navarro et al. [13] addressed the problem of controlling a heterogeneous group of vehicles with the objective of forming a multi-lane convoy using distributed rules implemented in a longitudinal coordinate system parallel to the road, and He J [14] designed a multi-intelligence swarming control algorithm by using an artificial potential field function to solve the positional distance relationship between multi-intelligences and incorporating the principle of consistency; Hossein Chehardoli [15] introduced a new neighbourhood-based adaptive control law to estimate parameter uncertainty in order to study the topology in the following state. Formation shaping is the basis for accomplishing other tasks of subsequent formations, so it is important to study the formation process.

Current research on vehicle formation mainly focuses on maximising the number of vehicles involved in the formation and minimising the vehicle spacing, so as to reduce the energy consumption in the formation driving process. However, the fact that more vehicles are involved in the formation does not necessarily mean that the energy consumption is more economical, and the size of the formation should be flexibly changed according to the road traffic conditions in order to obtain greater benefits. Therefore, in order to further study the formation shaping, this paper, on the basis of previous research, investigates the formation shaping under the vehicle-road coordination environment, takes the lowest energy consumption as the optimisation objective function, and performs two clustering of the vehicles that need to travel in formation, firstly, the individual vehicles are used as the data individuals to achieve the first clustering, then the formation queues are used as the data individuals to achieve the merging between the formations, and by dynamically updating the formation configuration to finally realise that all vehicles form a formation. The kinematic control process of the networked vehicles is considered as an optimisation process, and the instantaneous energy consumption index is considered as the optimisation target, and the acceleration input of the vehicle formation shaping is optimised using the improved AFSA to finally realise the formation shaping with energy consumption as the optimisation target. At the same time, the simulation design of the formation shaping process is carried out under the joint simulation environment of SUMO and Python to verify the effectiveness of the model and optimisation algorithm in this paper.

2. Description of the problem

2.1. Formation scenario description

The formation scenario studied in this paper is a basic section of a highway with dense Road-Side Unit(RSU) [16], which is a unidirectional four-lane roadway with only N multi-intelligent vehicles traveling normally on the roadway. In the formation scenario shown in Figure 1, there are N multi-intelligent vehicles of the same type sending requests to the RSU and MEC at a certain point in time, and when the RSU receives the request, it forwards the Multi-intelligent vehicle's own state information to the MEC, which initially clusters the multi-intelligent vehicles into N clusters based on the vehicle's speed, inter-vehicle spacing, and other elements by using a clustering algorithm. To achieve dynamic clustering, the MEC generates acceleration control information per unit of time through an energy consumption optimization-based algorithm and sends it to the RSU and the multi-intelligent vehicles.

2.2. Platoon vector model

2.2.1. Vehicle kinematic modeling

Based on the assumptions made in this paper, the kinematic model of an individual vehicle in formation p_j can be represented as:

$$\begin{cases} v_{pj}(t) = \dot{x}_{pj}(t) \\ a_{pj}(t) = \dot{v}_{pj}(t) + f(t) \end{cases} \tag{1}$$

where $v_{pj}(t)$ denotes the instantaneous velocity of the vehicles in the formation p_j at the moment t, x_{pj} denotes the coordinates of the vehicle's position at moment t, $a_{pj}(t)$ represents the acceleration of the vehicle at moment t, $f(t)$ denotes the acceleration influence factor.

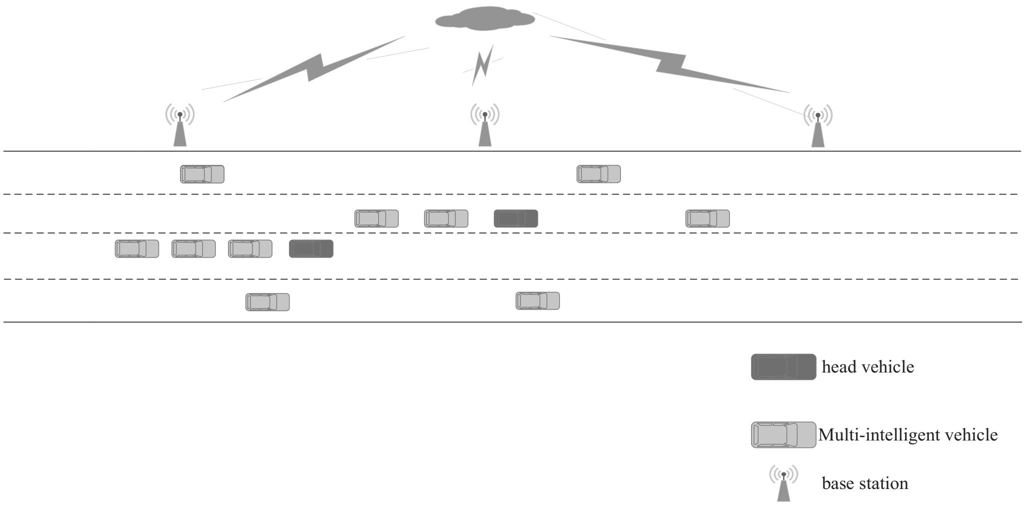


Fig. 1 - Vehicle formation scenario

In this paper, constant time distance is used as the limitation of vehicle spacing within the formation, the relationship between space headway and time headway can be expressed as follows:

$$h_{i,i+1} = \frac{s_{i,i+1}}{v_{pj}(t)} \tag{2}$$

where $s_{i,\ i+1}$ denotes the inter-vehicle distance between the ith vehicle and the i+1th vehicle, $v_{pj}(t)$ denotes the instantaneous speed of the i+1st vehicle at moment t.

That is, the headway between vehicles $h_{i,i+1}$ is the ratio between the inter-vehicle distance between the front and rear vehicles and the instantaneous speed of the latter vehicle. In the cross time distance strategy, the headway time distance $h_{i,i+1}$ is constant and does not change with the workshop distance between the front and rear vehicles as well as the speed of the vehicle. Therefore, when two neighboring vehicles enter into a limited range, the inter-vehicle distance increases when the speed of the front vehicle increases, and in order to maintain the constant time distance, the speed of the rear vehicle also increases; the same is true when the speed decreases. Therefore, in order to maintain a safe distance between vehicles in a formation, the range of speed variation will be reduced.

2.2.2. Formation information matrix

In the scenario assumed in this paper, *N* vehicles upload state information such as *ID* information, instantaneous speed, longitudinal coordinates, and spacing from the vehicle in front. This information is processed by the MEC server and sent to the RSU, which in turn forwards it to the vehicles forming the formation, providing the acceleration information of each vehicle in a unit time interval as a control command. The uploaded information can be represented as:

$$Data = \left\{ \left[ID, v_i, x_i, d_{i,i-1} \right], \middle| \forall i \in N \right\} \tag{3}$$

The uploaded vehicle information is processed into a matrix variable that has a structure of N rows and 4 columns, with each row representing the state information of a vehicle. The first column of the matrix is the *ID* of the vehicle, the second column is the instantaneous speed of the vehicle, the third column is the longitudinal coordinates of the vehicle on the highway, and the fourth column is the distance between the current vehicle and the vehicle in front of it. If the vehicle is the head vehicle of the formation, the fourth column of data is empty.

The MEC computes a matrix of corresponding acceleration control variables based on the uploaded information. Each column of this matrix represents the acceleration control variable of the corresponding vehicle. Each vehicle in the formation updates its own state, including longitudinal coordinates and speed relative to the road, based on the received control variables. If the vehicle does not receive acceleration information, only the longitudinal coordinates are updated. The calculated control information is as follows:

$$Data = \left[a_1, a_2, a_3, a_4, a_5, \ldots, a_n\right] \tag{4}$$

The state information vector of a single vehicle can be expressed as:

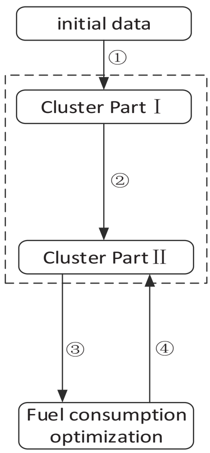
$$\overrightarrow{Car_i} = \left\{x_i, \vec{v_i}\right\} \tag{5}$$

The state information vector of the entire formation queue can be expressed as:

$$\overrightarrow{P_j} = \left\{\overrightarrow{car_1}, \overrightarrow{car_2}, \ldots, \overrightarrow{car_{nj}}\right\}, j = 1,2,\ldots,M \tag{6}$$

where each vector represents the state information of a formation, the j denotes the *ID* of the current formation; n_j denotes the total number of vehicles in the current formation.

After the state update of a single vehicle is realized by controlling the acceleration, the state information of the formation can be operated iteratively until the formation shaping is established by all the vehicles with formation demand. In this way, each vehicle adjusts its state based on the received acceleration control information to form a formation and maintain a safe distance between vehicles. The overall idea of formation shaping is shown in Figure 2.



where, in the left panel:
①Indicates vehicle status information
②Indicates vehicle status information and vehicle formation information
③Indicates vehicle status information and vehicle formation information
④Indicates acceleration control information

Fig. 2 - Formations form an overall idea

3. Clustering design study

The clustering algorithm calculates the differences between all the data and groups similar data into the same clusters as much as possible, while at the same time the differences between the data in different clusters should be as large as possible [17].

The clustering based formation shaping algorithm can define different attributes for the vehicles based on the current state of the vehicle. Vehicles are able to update the next state based on the current state. In this paper, an improved K-mean clustering algorithm is applied to the formation shaping process. The goal of this algorithm is to divide the data points into K-clusters. so that data points within clusters are as close as possible and data points between clusters are as far away as possible. K represents the number of clusters to be categorized eventually and means represents the average of the sample data within the same cluster class.

3.1. Overall process of formation shaping clustering

The traditional K-means algorithm needs to recalculate the clustering center every iteration. It cannot meet the real-time demand and safety requirements of strata. A lot of literature has been proposed to improve the k-mean clustering, Wang Y et al [18] defined a new clustering validity index to sample data for effective effective stratification, quickly determine the clustering range, and obtain the optimal number of clusters based on the evaluation results. Zhu Yibo [19] proposed the principle of weight adjustment for forgetting the second place, applied to the number of categories k and the selection of the initial clustering centre. The improved algorithm in this paper can dynamically adjust the position of the clustering center according to the current state of vehicles. Thus, the formation is shaped more effectively and the safety between vehicles is improved.

In the initial stage of formation shaping, each vehicle is considered as a separate formation. There are a total of N initial cluster classes for formation shaping, and the formation information can be represented by an N × N matrix, where the row index denotes the ID of the head vehicle of the current queue, and the column index denotes the ID of the vehicle that follows under the head vehicle denoted by the current row index. Initially, the values of the elements of the formation information are all zero. The formation information matrix is:

$$P = \begin{pmatrix} 1 & 0 & \cdots & 0 \\ 0 & 2 & \cdots & 0 \\ \cdots & 0 & \ddots & 0 \\ 0 & 0 & 0 & N \end{pmatrix} \tag{7}$$

In addition, the vehicle state information of the formation can be represented by a matrix of N rows and 2 columns. The row index represents the ID of the current vehicle, the first column represents the longitudinal relative coordinates of the current vehicle on the highway, and the second column represents the instantaneous speed of the vehicle at this moment. The current moment can be replaced by the number of iterations. Therefore, the state information matrix of the vehicle can be represented as:

$$V = \begin{pmatrix} x_1 & v_1 \\ x_2 & v_2 \\ \vdots & \vdots \\ x_N & v_N \end{pmatrix} \tag{8}$$

At the initial moment of formation, the formation members are updated through a neighborhood search clustering process and assuming that the formation is a single queue and the formation member update rule is:

Determines the head vehicle of the current formation queue, if the head vehicle of the formation has not already been determined;

If the head vehicle has already been identified, member vehicles in the neighborhood are added sequentially in a backward direction;

Adding members updates the number of formations and the member IDs within each formation queue.

The above update process can help the vehicles gradually gather to form a formation, and the member vehicles in each formation are neighboring and orderly. By gradually updating the formation information and member states, the transition from the initial state of the vehicles to the formation shaping can be realized.

Where the formula for adding member vehicles in a neighborhood is:

$$P = \{ \mathrm{c} \to P | \Delta \mathrm{d} \le \psi \} \tag{9}$$

c denotes the following vehicle after the last vehicle in the current formation p, Δ represents the difference in longitudinal coordinates between the last vehicle in the current formation p and its followers, ψ represents the maximum limited distance that the current formation can add its following vehicles.

The update mechanism of the formation clustering is as follows: the cluster class centers are selected sequentially according to the *ID* order starting from the first vehicle. The first vehicle is selected as the first cluster class center, and after each cluster class center is selected, the adjacency matrix is constructed sequentially backward based on the inter-vehicle distances of the vehicles in the formation, and this mechanism ensures the sequentiality of the cluster class centers in the formation, and takes into account the distances between the vehicles. The selection mechanism of cluster class centers is:

$$C = \{ \mathrm{x} | \mathrm{x} \in \phi \} \tag{10}$$

where x is the first vehicle in the φ formation.

3.2. Form formation first clustering

The first clustering of formation shaping uses as input matrix a vehicle state information matrix containing *N* vehicles, which contains *N* rows and 2 columns representing the longitudinal coordinates and vehicle speed information of each vehicle, respectively. Based on this input data, the initial clustering centers are *N*, indicating that each vehicle is the head vehicle of a formation queue at the initial moment of formation shaping, and the cluster centers can be represented as:

$$C = \{ c_j | c_j = (c_{j1}, c_{j2}), j = 1,2,...,N \} \tag{11}$$

The way to determine whether a vehicle stays in the current stratum or becomes the head vehicle for the next stratum is to calculate the error between the within-cluster class and cluster class center data. First, the number of cluster classes is initially determined based on the relative coordinate information in a first column of the vehicle state information matrix. Then a secondary judgment is performed based on the vehicle speed data in the second column to determine whether the current vehicle stays in the current formation. The intra-class error of the first clustering of vehicle formation shaping can be expressed as follows:

$$SSE\_one = \sum_{xj \in \phi j} dis(x_{j2}, c_{j1}),\ j = 1,2,...,M \tag{12}$$

$$SSE\_two = \sum_{xj \in \phi j} dis(x_{j1}, c_{j2}),\ j = 1,2,...,M \tag{13}$$

SSE_one denotes the sum of squares of intraclass errors for a single cluster class based on the first dimension of data, *SSE_two* denotes the sum of squares of intraclass errors for a single cluster class based on the second dimension of data, x_{j1} denotes the current cluster class Φ_j samples, x_{j2} denotes the second dimension data of the current cluster class, c_{j1} denotes the first dimension of the cluster class center, c_{j2} denotes the second dimension of the cluster class Φ_j.

By the above steps, a number of formation queues can be determined and neighboring vehicles can be added to the same formation. Then, the formation queues are further adjusted according to the threshold condition of average vehicle speed. The multi-intelligent vehicle state information in each formation queue is finally obtained. The formation of the formation queue was initially determined.

3.3. Clustering between formations

Based on the initial formation information matrix, vehicle state information matrix and vehicle acceleration information obtained from the previous clustering, the clustering can be dynamically updated to further improve the formation of the formation queue. Firstly, the average vehicle speed difference between two neighboring formations is defined as the condition to judge whether it can be merged or not, and the average vehicle speed difference is:

$$Rp = \frac{\left|\overline{v_{p_i}} - \overline{v_{p_j}}\right|}{\max\left(\overline{v_{p_i}}, \overline{v_{p_i}}\right)} \tag{14}$$

Each formation queue is then considered as an individual data and these formation queues are selected as the center of the cluster class, which can be represented as some representative vehicle of the formation queue, and the cluster class center can be represented as:

$$c = \{\varphi_j, j = 1,2,...,M\} \tag{15}$$

At this time, the cluster class update mechanism is as follows: the cluster class center is selected sequentially backward from the first formation queue in *ID* order, and the representative vehicle of the first queue becomes the first cluster class center, and for each cluster class center, the next queue is judged whether it is suitable to be added to the current cluster class according to the average vehicle speed difference ratio of different formations. If the average vehicle speed difference ratio between two neighboring formations is less than or equal to a threshold value, the next queue is merged into the current cluster class and the *ID* of the queue is discarded. Repeat the above steps until all the queues are filtered. At this point the inter- and intra-class errors in the inter-formation clustering can be expressed as follows:

$$SSE_{outer} = \sum_{i=1}^{M} \frac{\left|\overline{v_{p1}} - \overline{v_{pj}}\right|}{\max(\overline{v_{p1}}, \overline{v_{pj}})} \tag{16}$$

$$SSE_{\text{inter}} = \sum_{i=1}^{M} \alpha \overline{\Delta d_{pl}} + \beta \overline{v_{pl}}, \alpha > \beta \in (0,1) \tag{17}$$

SSE_{outer} denotes the interclass error, the $\overline{v_{p1}}$ denotes the average speed of all vehicles in formation p_i, and $\overline{v_{pj}}$ denotes the average speed of all vehicles in the neighboring formation p_j of formation p_i, *SSEinter* denotes the intra-class error, and $\overline{\Delta d_{p1}}$ denotes the average workshop distance of formation p_i, and α and β denote the coupling coefficients against the average workshop distance of the formation and the average vehicle speed of the formation, respectively.

Through dynamic updating, it is possible to determine whether or not to merge neighboring formations based on differences in average vehicle speeds. In intergroup clustering, the interclass error indicates the degree of variation in the difference in average vehicle speeds between formations, and the intraclass error indicates the degree of variation in the difference in average vehicle speeds within formations. By comparing the interclass and intraclass errors, the effectiveness of formation shaping can be assessed. If the intraclass error is relatively small and the interclass error is relatively large, the speed difference between strata is large and the clustering algorithm can continue to be optimized.

The inputs to the algorithm include information about the list of vehicles in the header and the acceleration information in each time interval, and the outputs are the number of formations and the vehicles in each formation. The formation queue is continuously adjusted by dynamic clustering, so that the distance between the workshops within the formation gradually decreases and the speed of the vehicles gradually converges.

3.4. Optimization of acceleration

The AFSA computes the optimal or sub-optimal vehicle acceleration control information for the iterative inputs. This acceleration control information will be passed to a dynamically updated clustering algorithm to form a formation queue. The end condition of the clustering algorithm is defined as the case where the formation information matrix ends up presenting only one formation queue. The condition for the end of the intergroup clustering algorithm can be expressed as:

$$P = \begin{pmatrix} 1 & \cdots & N \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{pmatrix} \tag{18}$$

In the formation information matrix, the foremost vehicle is taken as the head vehicle, i.e., ID 1, while vehicles with IDs 2, 3, ..., the vehicles in the order of their own IDs become the following vehicles of the lead vehicle. In the initial state, the relative coordinates of these vehicles are formed in formation in the order of largest to smallest. During the iterative process of the clustering algorithm, according to the dynamically updated rules and acceleration control information, the vehicles continuously adjust their own positions and velocities, and update their formations according to the neighborhood conditions and velocity difference ratios. For the vehicles between two neighboring formations, they are adjusted according to the distance and speed difference between the vehicles, so that the inter-vehicle distance between the vehicles is small and the speed tends to be the same. The clustering algorithm ends when the formation information matrix finally presents a situation where there is only one formation queue. At this time, the speed and longitudinal coordinate information of the formation vehicles at this moment can be output to indicate the formation of the formation queue.

4. Exploration of energy consumption optimization

4.1. Energy consumption function

The purpose of formation driving is to improve transportation efficiency, reduce energy consumption of vehicles and reduce environmental pollution. In this paper, we explore the optimization algorithm of energy consumption in the formation process of vehicle formation under the consideration of kinematics-based vehicle safety, in order to reduce the energy consumption in the formation process while ensuring safety. The vehicle energy consumption function used in this paper is:

$$E_{fuel} = \varsigma \int \Gamma(t) F_{force}(t) v(t) dt \tag{19}$$

where, ς denotes the energy conversion constant for fuel and electric drive consumption efficiency, Γ Represents an indicator function that prevents negative energy from being generated when the vehicle is braked, F_{force} represents vehicle traction.

In this paper, the energy consumption is optimized, and the acceleration per unit time is taken as the optimization index, so the energy consumption function used is in the form of a definite integral over the unit time t. The road slope in the research scenario of this paper is assumed to be 0, and the vehicle's neutral component force in the direction of the road slope is ignored, so the energy consumption function can be simplified as:

$$E_{fuel} = \varsigma \int_0^{tu} \Gamma(m\frac{dv}{dt} + C_R mg + \frac{1}{2}\rho A C_D v^2 f(\Delta d) v dt \tag{20}$$

where tu denotes the unit time length, in order to improve the computational speed of the optimization algorithm and simplify the redundant items in the energy function, the energy function with the speed or acceleration related to the removal of the amount of energy function, the simplified energy function is:

$$E_{fuel} = \int_0^{tu} \Gamma(m\frac{dv}{dt} + \frac{1}{2}\rho A C_D v^2 f(\Delta d) v dt \tag{21}$$

The objective function is related to the derivative of the vehicle speed as well as the square of the vehicle speed and the vehicle correlation coefficients are the same, so the final energy optimization objective function for the same magnitude is:

$$E_{fuel} = \int_0^{tu} v\frac{dv}{dt} + v^3 f(\Delta d) dt \tag{22}$$

4.2. AFSA optimizes energy consumption

In order to find the optimal solution, an improved AFSA is used in this paper. In the improved AFSA [20], each artificial fish represents a feasible solution to the problem to be solved. The input information includes vehicle state information matrix and vehicle information matrix. Among them, AFSA contains two parts: variables and functions. Among the basic steps used by the artificial fish swarm algorithm to solve the vehicle formation problem include:

1) Perform initialisation setup;
2) Calculating the adaptation values of each individual of the initial fish school;
3) Evaluating each individual;

4) Execute the behaviour of the artificial fish;
5) Evaluating all individuals;
6) End or continue the cycle.

The optimization objective of AFSA is to minimize the total energy consumption of N vehicles at the current moment through the acceleration input control variables. Independent variable of the optimization objective function is a 1-row and N-column row vector, which is used to represent the acceleration input control variable of each vehicle per unit of time t. The fish population in the AFSA is represented in vector form as follows:

$$\left[u_1^{p1}\ ,\ \ u_2^{p1}\ ,\ldots,\ \ u_{p_1}^{p1}\ ,\ \ u_1^{p2}\ ,\ldots,\ \ u_1^{pm}\right] \tag{23}$$

where u_1^{p1} denotes the acceleration input control variable for the first vehicle in formation p_1 per unit time t.

The energy consumption function for a single vehicle is:

$$E_{fuel} = \begin{cases} 0,\ \mu \leq 0 \\ \int_0^t (\mu + v^2 b\Delta d)dt,\ \mu > 0 \\ \int_0^t (\mu + v^2 a\Delta d)dt,\ \mu > 0 \end{cases} \tag{24}$$

where μ denotes the current acceleration input control independent variable of the vehicle, *a, b* are positive rational numbers, respectively, denotes the difference between the energy consumption wind resistance when the vehicle is traveling alone and when the vehicle is traveling in formation, so Eqs. 2 and 3 denote the energy consumption generated by the vehicle traveling alone and the vehicle traveling in formation, respectively, but regardless of whether the vehicle is traveling in formation or not, the wind resistance and the spacing of the vehicles are positively correlated, and the energy consumption generated by the vehicle traveling in formation is always smaller than the energy consumption generated by vehicles traveling alone. After the energy consumption function of a single vehicle is determined, the total energy consumption of all vehicles in the formation is:

$$\min\left\{E_{fuel}^{all} = \sum_{i=1}^{N} E_{fuel}^{i}\right\} \tag{25}$$

The acceleration input control information outputted by the AFSA part each time is the instantaneous acceleration variable in unit time t. In this paper, the clustering algorithm is used to update the formation and the optimized acceleration input values are passed into the clustering algorithm module through the AFSA in order to realize the updating of the vehicle position and formation state. Therefore, the parameters of the clustering algorithm and some key parameters of the AFSA will affect the experimental results of formation shaping, and the optimal parameters need to be selected by analyzing the relevant parameters.

In this paper, the vehicle spacing between adjacent vehicles and the average speed difference of formation vehicles are the key to determine whether the vehicles are members of the formation. According to the setting of the simulation experiment, a highway with a length of 6km is used, of which 0-2km is the vehicle loading section of SUMO simulation, the traffic flow is unstable, and the data obtained from this section can not be used for the simulation analysis; the 5-6km section is close to the end of the simulation road, and the default of SUMO simulation environment is that there is no obstruction in front of it, and the vehicle will be traveling at the maximum speed, which does not conform to the actual law, so the data of the road section also cannot be used for data analysis, so the actual data collection section length is 3000m. And the workshop distance threshold is set to 10m, and the speed difference ratio is 0.25. In order to make sure that the formation shaping time is reasonable, this paper sets the time unit of AFSA energy consumption optimization to 1 second. Besides, there are other important parameters in AFSA. Among them, the population size was set to 30, the field of view visual of artificial fish was set to 0.9, the crowding factor δ was set to 0.1, and the number of repetitions trynumber was set to 4.

The initial vehicle information selection also affects the formation shaping time and the number of clustering iterations. Therefore, the initial inter-vehicle distance and vehicle speed settings need to be realistic and ensure the efficiency of the algorithm. In order to reduce the computational volume of the simulation process and consider the speed limit of the highway. In this paper, the initial speed of the formation vehicle is set to 16.7 m/s. The parameter settings in this paper consider the efficiency of formation shaping, the actual situation, and the efficiency of the algorithm, and verify the effectiveness through experimental simulation. The initial state of the vehicle is shown in Table 1:

In addition， vehicles are subject to certain constraints during the formation shaping, taking into account the actual vehicle motion characteristics and safety. The values of these constraints are different for different vehicle technical parameters, road conditions, safety requirements, and specific needs of the formation. In the formation scheme of this paper, the specific limit values as shown in Table 2 are as follows to ensure the safety and efficiency of the formation process：

Tab. 1 - Vehicle initial status information

Vehicle ID information	Vehicle longitudinal coordinates	vehicle speed
1	500m	16.7m/s
2	490m	16.7m/s
3	480m	16.7m/s
4	300m	16.7m/s
5	290m	16.7m/s
6	200m	16.7m/s
7	180m	16.7m/s
8	100m	16.7m/s

Tab. 2 - Specific constraint values

Type of constraint	Constrained parameter values
maximum and minimum speed	16.7m/s, 33.4m/s
maximum and minimum acceleration	$-6m/s^2$, $6m/s^2$
a	0.001
b	0.002
α	0.6
β	0.4

5. Simulation analysis

5.1. Simulation parameter design

In order to verify the reliability of the models and optimisation algorithms developed in this paper, SUMO and Python co-simulation was used for verification.

The general steps of simulation include:

1) Create a road network file in SUMO;

2) Build Traci, the interactive interface between SUMO and Python;

3) Setting relevant parameters for the experiment;

4) Output the simulation results.

The clustering function is defined through python, and the vehicle state information matrix is input into the function to generate the vehicle formation shaping matrix, and the acceleration input information obtained from the AFSA algorithm part is used as input to realize the updating of the vehicle state information in the unit time interval, and the updated information is then passed to the AFSA algorithm to realize the dynamic iteration until all the vehicles are added to the formation.

In addition, this paper rewrites an improved algorithm based on AFSA algorithm, named Platoon_AFSA.py, and the main function afsa_ func (v_info, v_string) defines the parameters including vehicle state information matrix and vehicle formation information matrix. And a parameter transformation is performed with SUMO. In the simulation scenario, only the grid-connected vehicles are considered and all vehicles used for simulation have their respective initial positions and speeds. In the simulation environment, multiple formation queues can exist at the same time, and each vehicle is only based on the neighboring front vehicle, and that vehicle does not consider whether the neighboring rear vehicle has entered the formation queue or not. After modeling the function in Python, the joint simulation is performed with SUMO through Traci interface and the visualization results are obtained in SUMO.

5.2. Analysis of simulation results

5.2.1. Acceleration input analysis

The acceleration input control information row vector is calculated and output by AFSA. In order to improve the simulation efficiency, this paper only takes 8 vehicles as an example to verify the algorithm of this paper, Figure 3 shows the results of the acceleration control information, and from the results, an analysis of the acceleration shows that the vehicle has a large acceleration in the initial phase, which is to reduce the gap between the formations as soon as possible and improve the efficiency of the formation.

5.2.2. Analysis of vehicle clustering results

During simulation, the AFSA is iterated until convergence and the optimal solution of the iterative process is output. At the end of each clustering algorithm, the formation information of the vehicles is recorded, and the vehicle IDs in each formation queue are listed in increasing order from front to back. The termination condition for formation shaping is that all vehicles have formed a formation queue. The vehicle formation information can be processed into the form shown in bar chart, where each bar represents a formation, arranged in increasing order of vehicle IDs, and the value of the bar is the number of vehicles in the current formation. Clustering iteration of the vehicle formation information results as shown in Figure 4.

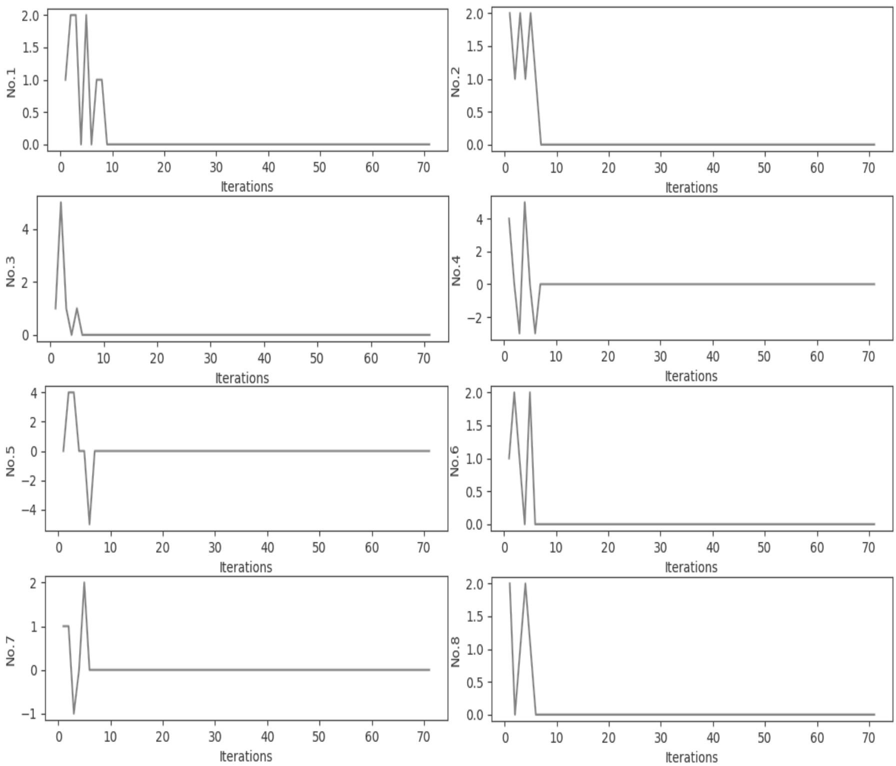


Fig. 3 - Vehicle acceleration control results

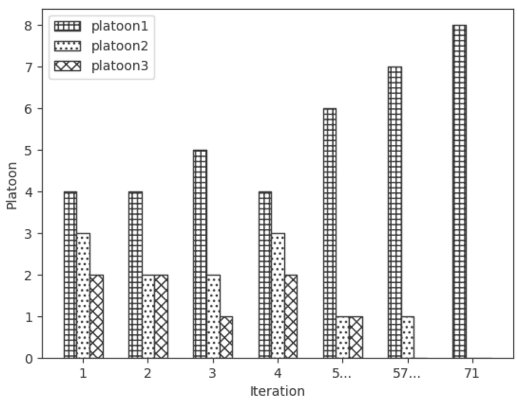


Fig. 4 - Vehicle formation shaping clustering results

From the figure, it can be seen that with the increase in the number of iterations, the number of vehicles in different formations is constantly changing, is due to the control of the acceleration of the input information for the iterative optimization, when the final clustering termination conditions are reached, and ultimately, the eight vehicles in the simulation scenario of this paper form the same formation.

5.2.3. Analysis of vehicle speed results

Based on the input acceleration the velocity values of the vehicles can be obtained, as shown in Figure 5, each vehicle eventually reaches the speed limit condition by accelerating, and when all the vehicles form a formation, the spacing between the vehicles remains unchanged under normal driving.

5.2.4. Analysis of vehicle energy consumption results

The relationship between the analyzed values of energy consumption obtained from the improved AFSA section and the number of iterations is shown in Figure 6 below. In the clustering algorithm based on vehicle formation shaping, there exists the condition of formation queue dissolution, i.e., certain vehicles within the formation are separated from the current formation queue and become vehicles traveling alone. In the vehicle energy consumption objective function, the wind resistance gain coefficient inside the formation queue is smaller than the wind resistance gain coefficient outside the formation queue, so there is a certain degree of increase in the energy consumption analysis value in the first few iterations. However, as the number of iterations increases, the energy consumption results of the vehicles show a decreasing trend, which indicates that the spacing between the vehicles is decreasing and the vehicles gradually form a more compact formation queue. However, during formation shaping without energy optimisation, as vehicles continue to join and the number of vehicles in the formation increases, so does the fuel consumption within the formation.

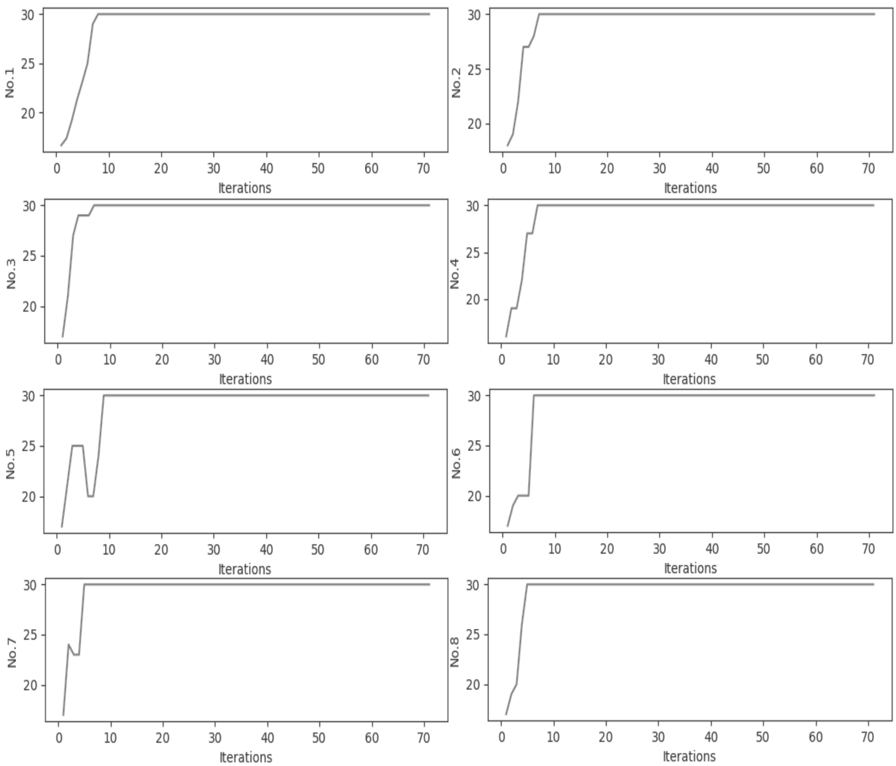


Fig. 5 - Vehicle speed results

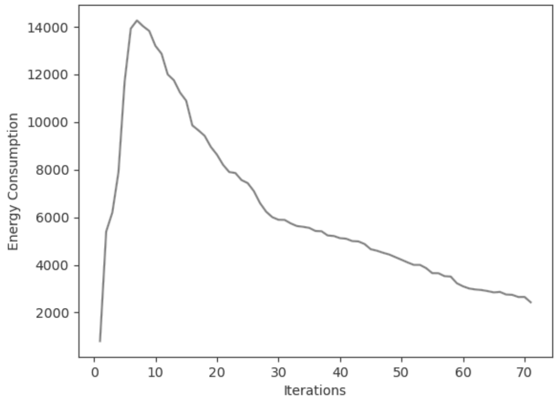


Fig. 6 - Vehicle energy consumption analysis results

6. Conclusion

In this paper, a vehicle formation control algorithm based on energy consumption optimization is proposed, firstly, the clustering design is carried out for vehicles with formation requirements, and the AFSA algorithm is improved to calculate the acceleration used for dynamic iteration, according to the optimization of acceleration so as to achieve the optimal energy consumption in the formation shaping process. The clustering design in this paper consists of two parts, firstly, individual vehicles are clustered, and the clustering class center is selected to form the initial vehicle formation information. Then the initial formation of small formations are merged again, and each group of queues is clustered as a data individual between formations, while the numerically simplified energy consumption function is used as the objective function, and the acceleration obtained from the AFSA calculation is input to achieve the purpose of optimizing energy consumption, dynamically updating the vehicle state information and the vehicle formation information, and ultimately realizing that all the queues are merged into a single queue.

Finally, the simulation results are analyzed to verify the effectiveness of the model established in this paper by building a joint simulation platform of SUMO and Python. The acceleration is larger in the initial stage of formation shaping to satisfy the purpose of reducing the spacing between vehicles as soon as possible. As the number of clustering times increases, the number of vehicles within different formations changes, and when the iteration termination condition is reached, the overall energy consumption of vehicles reaches the optimization, thus proving the effectiveness and feasibility of the algorithm proposed in this paper.

In this paper, we only studied the formation of vehicles to eventually form a single queue, and in the future, we can study the formation of vehicles to form different queues, making it more suitable for a variety of complex traffic conditions. In this paper, a lot of assumptions are made in the simulation process, and the future research increases the influence of communication conditions. And the study of vehicles in the process of driving in formation will also be in and out of the formation of the situation.

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