Predictive Eco-Driving Application Considering Real-World Traffic Flow

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ABSTRACT Eco-approach and departure (EAD) systems in connected vehicles are capable of providing the speed recommendations to drivers so that vehicles can pass through successive intersections at the appropriate instants to save time and energy. However, most of existing control strategies and global optimization algorithms for EAD systems have extremely high requirements for computational resources, which make EAD systems not easy to popularize and apply to real vehicles. To overcome this problem, this paper designs a traffic flow prediction model based on deep learning regression machine, and establishes a dynamic effective red-light duration model based on traffic flow queuing effect. To facilitate real-time update of the optimal speed, a constrained optimization model is proposed as an approximation approach, which can obtain similar optimal results to that of the pseudo-spectral method while greatly reducing calculating time. The effectiveness of the proposed control algorithm for EAD system on passing intersections and energy saving has been validated on the real vehicle under real-world traffic environment. Compared with the uninformed driver, the proposed EAD system saves 2% time and 4.6% energy on average in case that driver is informed and 8% time and 12.1% energy in case of autonomous driving.

INDEX TERMS Energy consumption, optimization model, speed strategy, traffic prediction.

I. INTRODUCTION

The development of the world economy is facing severe resource constraints, especially strategic resources such as oil. The scarcity of these resources has become a bottleneck for the sustainable economic and social development. According to the surveys of the U.S. Department of Transportation surveys, 28% of total energy is consumed in the field of transportation [1]. Along with the growing energy crisis, many researchers and car manufacturers looked for different solutions to reduce transportation-related fuel consumption and emissions from different perspectives. For example: 1) Building more environmentally friendly vehicles, such as electric-powered vehicles. 2) Using the transportation infrastructure to improve the driving efficiency of vehicles [2]. With the application of vehicle-to-vehicle (V2V) wireless communication such as 5G, the connected eco-driving technology is expected to be a promising candidate in reducing transportation energy consumption and pollutant emissions.

Among all application scenarios, eco-driving at a signalized intersection is particularly promising for energy saving in urban areas. The Eco-Approach and Departure (EAD) application is one primary example in which drivers are guided to travel through signalized intersections in an eco-friendly manner based on signal phase and timing (SPaT) and traffic flow information [3]. Therefore, the traffic jams or unnecessary stop-and-go behavior at signalized intersections in the main road can be avoided.

Over the past several years, the optimal eco-driving problem at intersections has been intensively studied. Reference [4] developed an arterial velocity planning algorithm that provided dynamic speed advice to the driver to maximize the probability of encountering a green light when approaching signalized intersections. Reference [5] proposed that the upcoming traffic signal information in an adaptive cruise control system was used to reduce the idle time at stoplights and thus improving energy efficiency. References [6] and [7]
took advantage of the upcoming traffic signals information to maximize the vehicle’s probability of encountering a green light signal when passing through multiple intersections.

All the above studies were conducted under the assumption of fixed-timing signals, and these methods treated the green light duration as a complete transit time window, which is not the case for the real traffic situation. Due to the vehicle queuing effect at intersections, the actual effective transit time window of the tail vehicle is shorter than the green light duration provided by the SPaT information.

Considering changes in actual driving conditions and the uncertainty of the traffic SPaT, Reference [8] estimated the optimal transit time window for vehicles to reach intersections based on the traffic flow and density. Simulation results showed that when the penetration rate of connected vehicles is 100%, the fuel consumption can be saved by 40%. In [9], the DP algorithm was used to solve the optimal speed estimation under the constraint of uncertain signal lights. The simulation results showed that this method can effectively reduce the fuel consumption of vehicles under the condition that the arrival time remains unchanged. Reference [10] proposed a linear programming model to optimize the speed trajectory that takes into account uncertainties in count-down information, preceding vehicle’s state, and potential driver’s distraction issues. Reference [11] used the neural network to predict the speed of vehicles ahead and estimate the optimal SPaT information system. Reference [12] proposed a near-optimal EAD strategy using the Legendre pseudo-spectral method to quickly determine the behavior of the drive system. Although above-mentioned researches could achieve a desirable energy-saving effect in ecological driving at intersections, the involved mathematical model and solution algorithm are too complicated to be realized in a realistic scenario.

It should also be noted that testing under actual road conditions is important for effective evaluation of an EAD system. In [13], the authors developed an EAD application for actuated signals, which calculated the maximum or minimum time to reach the intersection. Furthermore, the authors of [14] conducted preliminary field operation tests in Riverside, California to evaluate the performance of the EAD system in terms of energy saving. Since the above tests were conducted at a specific test site and there were fewer external interference factors, they are not sufficient enough to reflect the real performance of EAD system in real traffic situations. Considering the dynamic SPaT under real-world traffic, the University of California research team [15] introduced the design scheme of the EAD test scenario in detail and analyzed the impact of EAD on the driver’s behavior through real vehicle tests. Results showed that the EAD system achieved 2% of energy saving for all trips, and 6% energy savings for active EAD stroke segments. Despite its contribution, Reference [15] still has certain limitations because it only took into account the dynamic signal light effects while the queuing effects in the actual traffic environment were not considered.

Most existing EAD applications are developed and tested in a fully connected environment where real traffic flow information is assumed to be available. However, considering the traffic infrastructure at current stage, traffic information is not always available, thus the effective prediction of traffic conditions is the basis of queue estimation. In the case of a low penetration rate of connected vehicles, using a fixed traffic observer to provide necessary traffic information to realize effective queue length estimation at intersections is a relatively feasible solution.

Based on the above problems, a real-time EAD system for energy saving driving at intersection is developed for electric connected vehicle applications. Fig.1 shows the architecture of the proposed EAD system. Firstly, short-term traffic flow prediction will be conducted based on the history traffic information. Secondly, the connected vehicle will calculate the parking queue length it will encounter at the intersection according to the predicted traffic flow, SPaT and its distance to the intersection, and finally derives the effective green-light time window if it wants to pass the intersection without stopping. Thirdly, with the combining constraints of vehicle dynamics and effective green-light time window, optimal control model for EAD system is constructed and its corresponding solution, namely the optimal speed trajectory, is obtained through the approximation solution method. Finally, the optimal speed is used to guide the driver or directly control the automated vehicle.

The main contributions of this paper are as follows:
1) A calculation method for dynamic effective red-light duration (DERD) is proposed to describe the effective transit time affected by the predicted traffic flow at intersections, including base red light time and average queue time
2) An approximation solution method for the optimal speed trajectory is proposed, which can obtain a solution similar to...
the pseudo-spectral method and ensure the real-time performance of the system calculation.

The rest of this paper is organized as follows. Traffic flow prediction is described in Section II. The modeling of DERD is described in Section III. The optimization solution and simulation analyze are presented in Section IV. The design of test vehicle and scenario are described in Section V. and Test results and Conclusions are presented in Section VI and Section VII respectively.

II. PREDICTION OF TRAFFIC FLOW
A. THE METHOD OF TRAFFIC PREDICTION

Due to many influencing factors and strong uncertainty, short-time traffic flow change demonstrates notable nonlinear property, which puts forward higher requirements for the prediction algorithm. The most well-known traffic flow prediction methods are auto-regressive integrated moving average (ARIMA) [16] and its variants [17], which construct traffic flow regression model on time sequences. Furthermore, References [18] and [19] proposed a spatial-temporal weighted k-nearest neighbor based (STW-KNN) model and adaptive multi-kernel support vector machine with spatial-temporal correlation (AMSVM-STC) model respectively to expanded the traffic flow prediction from time domain to spatiotemporal domain. The traditional regression model is relatively simple but their ability to fit traffic flow mutation is insufficient. Recently, the methods based on neural network, such as deep learning (DL) [20], deep belief network (DBN) [21], long-short term memory (LSTM) [22], are more preferred by researchers to predict traffic flow because they have strong fitting capability to capture non-linear change properties involved in traffic flow. However, large number of training samples is needed if desirable prediction performance is wanted. To overcome this problem, hybrid machine learning methods, which combine at least two kinds of data regression or neural network, have been widely used in traffic flow prediction and demonstrate ideal performance.

The traditional traffic flow prediction algorithm based on the neural network has limited processing capabilities in the presence of massive data. However, in deep neural networks (DNN), the model with multi-hidden layers can be developed based on the artificial neural network to model more complex nonlinear relationships with fewer neurons. Restricted Boltzmann machine (RBM) is a randomly generated neural network which can self-learn the probability distribution based on input data. It conducts Markov chain sampling process over states of hidden neural nodes to realize expectation estimation of input data. Considering that most of the collected traffic flow data satisfy the Gaussian distribution, we construct a multi-layer constrained RBM structure to realize the automatic analysis of influencing factors for the input data and achieve the layer-by-layer learning transformation of traffic flow information.

Support vector regression (SVR) is one of the typical methods that is commonly combined with other methods or properly modified to conduct traffic prediction. In [23], SVR and artificial neural network (ANN) were used to predict 235 pieces of traffic accident data. Results proved that the improved SVR algorithm was simple and easy to build, with a stronger comprehensive prediction ability than ANN. Reference [24] improved the prediction accuracy of SVR through data dimensionality reduction processing. Reference [25] used wav25elet analysis to improve the kernel function accuracy of SVR, thus improving the prediction accuracy of traffic flow. However, when the amount of data samples is extremely large, the span will be large or the dimension of kernel function mapping will be high, thus SVR prediction requires higher consistency and accuracy of data, which leads to the increase of model complexity and restricts the application of the algorithm. Combined RBM network can overcome the above disadvantage. References [26] and [27] has successfully combined RBM with SVR to realize distributed probability prediction of shared bicycles and used differential evolution and grey wolf optimizer (DEGWO) algorithms to improve prediction accuracy.

Because DL method has better self-learning ability and prediction performance compared with traditional shallow learning regression algorithm, in this paper, RBM and SVR are combined to construct a deep learning regression machine (DLRM) model to predict short-term traffic flow. The improved algorithm overcomes the dependence on historical training data, enhances the robustness and has desirable prediction performance even when the training data is relatively limited.

B. DESIGN OF PREDICTION MODEL

The transformed information by multi-layer RBM is fed into the radial basis SVR model to construct the DLRM prediction model. As shown in Fig. 2, the visible layer node RBM is used as the input layer (including the Gaussian distribution function conversion node), while several intermediate layers of RBM have a hidden layer respectively, and the radial basis SVR is used as the output layer.

The joint distribution of input data is calculated by:

$$p(v, h | \varphi) = \frac{\exp[-E(v, h; \varphi)]}{Z(\varphi)}$$  \hspace{1cm} (1)
where the \( Z(\varphi) \) is the normalized factor 
\[
Z(\varphi) = \sum_{v,h} \exp[-E(v, h; \varphi)];
\]
where \( v \) refers to the visible layer, the input information that has been captured; \( h \) refers to the hidden layer, the characteristic information to be detected; \( \varphi \) is the fine-tuning parameter for RBM, \( \varphi=(\omega, \beta, \alpha) \), \( \omega \) is the node connection weight, \( \beta \) is the node offset of the visible layer, \( \alpha \) is the node offset of the hidden layer; \( E(v, h; \varphi) \) is the energy function, which is used to realize the equivalent conversion of RBM information between the visible layer and the hidden layer.

\[
E(v, h; \varphi) = -\sum_{i=1}^{I} \sum_{j=1}^{J} \omega_{ij}v_{i}h_{j} - \sum_{i=1}^{I} \beta_{i}v_{i} - \sum_{j=1}^{J} \alpha_{j}h_{j} \tag{2}
\]

where \( I \) and \( J \) represent the number of nodes of the visible layer structure and the hidden layer structure respectively. \( \beta_{i} \) and \( \alpha_{j} \) are the offsets of visible node \( i \) (\( i = 1, 2, \ldots, I \)) and hidden node \( j \) (\( j = 1, 2, \ldots, J \)), respectively. \( \omega_{ij} \) represents the weight of the association between the information \( (v_{i}) \) of node \( i \) and the characteristics \( (h_{j}) \) of node \( j \).

The marginal distribution of \( v \) and \( h \) corresponding to \( p(v, h | \varphi) \) are
\[
p(v | \varphi) = \sum_{h} \exp[-E(v, h; \varphi)] / Z(\varphi) \tag{3}
\]
\[
p(h | \varphi) = \sum_{v} \exp[-E(v, h; \varphi)] / Z(\varphi) \tag{4}
\]

For a given training data set, the goal of deep learning is to maximize the log-likelihood probability \( \log p(v | \varphi) \) and \( \log p(h | \varphi) \). The activation condition probability of RBM visible layer and hidden layer node corresponding to \( p(v, h | \varphi) \) is,
\[
p(h_{j} = 1 | v, \varphi) = 1 / (1 + \exp(\sum_{i=1}^{I} \omega_{ij}v_{i} + \alpha_{j})) \tag{5}
\]
\[
p(v_{i} = 1 | h, \varphi) = 1 / (1 + \exp(\sum_{j=1}^{J} \omega_{ij}h_{i} + \beta_{i})) \tag{6}
\]

The RBM correlation weight can be defined by Contrastive Divergence to update the variation,
\[
\Delta \omega_{ij} = E_{data}(v|h_{j}) - E_{model}(v|h_{j}) \tag{7}
\]
where \( \Delta \omega_{ij} \) is the change of weight update; \( E_{data}(v|h_{j}) \) is the expectations for training data sets; \( E_{model}(v|h_{j}) \) is the expected value defined by the Contrastive Divergence method.

The output of the last layer RBM is the input \( x \) of the radial basis SVR regression machine layer, so the radial basis SVR regression prediction model is,
\[
f(x) = \sum_{n=1}^{N} (a_{n} - a^{*}_{n})K(x_{n}, \bar{x}) + b \tag{8}
\]
where \( x_{n} \) is the \( n \)th \( (n = 1, 2, \ldots) \) input information of SVR; \( a_{n}, a^{*}_{n} \) is the Lagrangian multiplier; \( b \) is the offset; \( K(x_{n}, \bar{x}) \) is the kernel function of radial basis support vector regression (Gaussian),
\[
K(x_{n}, \bar{x}) = \exp(-\|x_{n} - \bar{x}\|^{2}/2\delta^{2}) \tag{9}
\]
where \( \bar{x} \) is the center for kernel function; \( \delta \) is the width parameter of the function, which is used to control the radial range of the function.

### C. MODEL TRAINING AND PREDICTION

The field test was conducted in Beijing, China in November 2019. A traffic observer is arranged 400 meters upstream of the intersection, and the traffic flow \( q \) and the average traffic speed \( v_{q} \) at the observation site are recorded. Fig. 3 shows the traffic flow information under different time scales. It can be seen that a larger time scale will lead to smoother statistical results, but detailed information on the dynamic changes of real-time traffic in a short time will be lost. When the time scale is small, the curve exhibits periodic fluctuations, which is close to the real dynamic trend of vehicle flow changes.

The data collected on consecutive mornings was divided into 500 training samples and 100 test samples. The prediction model is generated by off-line training of the sample set. The mean absolute percentage error (MAPE) and root mean square error (RMSE) are selected as evaluation indexes. After repeated experiments, the layer number of DL is set as 4, the input node number range is 30~65. The penalty factor \( C \) of radial basis support vector regression is 0.012. In order to test the prediction performance of the model, the data of a continuous 1 h on a certain day was randomly selected as the input of the prediction model to predict the traffic volume in the next 6 minutes. To assess the prediction performance of the proposed algorithm, a comparison of prediction accuracy among different algorithms including traditional SVR, improved stacked RBM based on DEGWO [27] algorithm and DLRM is conducted. In comparison, the same training data, test data, and the same parameter settings of RBM were used. In the traditional SVR model, all the optimization parameters were set to the default value of 1.
TABLE 1. Comparison of average precision and real-time from the predicted results.

| Model  | Evaluation indexes MAPE/% | Evaluation indexes RMSE | Computing time(s) |
|--------|---------------------------|--------------------------|------------------|
| SVR    | 9.232                     | 12.591                   | 10               |
| DLRM   | 6.248                     | 9.376                    | 11               |
| DEGWO  | 5.851                     | 8.712                    | 23               |

The predicted results are shown in Fig. 4, and the results of average precision and real-time performance are shown in Table 1. Fig. 4(a) and Fig. 4(b) respectively show the comparison among predicted results and real value during a nonpeak flows and a peak flows. Results show that DLRM and DEGWO have better prediction performance for nonpeak traffic flow than peak traffic flow. As the performance indexes show, DLRM has close prediction performance to DEGWO, but with less calculation time. Because we update the prediction result every 30 seconds, the DLRM based model can meet real-time requirement considering system absolute stability and redundancy.

**III. MODELING OF EFFECTIVE RED-LIGHT DURATION**

The signal intersection is regarded as a single point on the road, with the position of the host vehicle is taken as the coordinate zero points, and $D_i$ represents the position of the $i$th traffic signal. Each traffic signal is modeled by an independent signal cycling clock, and calculated from the current time. The constant periodic cycle time of the $i$th traffic signal is defined as $c_{i,r}^j$. The meanings of all parameters can be seen in Fig 5(a). It should be noted that the yellow light duration is considered impassable and counted into the red light time. Different from the method used in [11], which estimated the queue length using a classic traffic flow model [28], the intersection queue length can be approximately calculated based only on the predicted flow and average speed in this paper. Fig. 5(b) shows the traffic dynamics of vehicles at intersections. According to the average traffic speed $v_q$ and the distance to the intersection, the cycle period of the traffic light encountered by the host vehicle when it arrives at the intersection can be calculated by the following formula:

$$T = (D_i/v_q - c_0^i)/c_i$$

$$j = \begin{cases} \text{INT}(T) \cdot \text{MOD}(T) < 0.5 \\ \text{INT}(T) + 1, \text{MOD}(T) \geq 0.5 \end{cases}$$

where INT represents the integer part of the result, and MOD stands for the fractional part of the calculation result.

Furthermore, according to the predicted traffic flow $q$ and the number of lanes $L$ (assuming that the traffic flow is evenly distributed in each lane and each vehicle occupies a space of 5 m in longitudinal direction), the dynamic effective red-light duration (DERD) is calculated as follows.

Step 1: The position of the head vehicle in the same batch of stopped vehicles, $d^* = D_i - v_q[c_i^0 + (j-1)c_i^1 + (c_i^j - c_i^{j+1})]$
Then, in the space gap between the host vehicle and the head vehicle, the number of vehicles $n$ can be estimated as

$$n = \frac{qd^s}{Lv_q}$$  \tag{12}$$
and the parking queue length $d_p = 5n$.

Step2: The acceleration rarefaction wave $w$ when starting at the intersection is assumed as same as the deceleration shock waves [35] when the traffic is stopped.

$$w = d_0/(D_i - d_0/v_q) - (c_i^0 + (j - 1)c_i^1 + (c_i^j - c_i^{j-1}))$$  \tag{13}$$

Step3: For the host vehicle, the impassable time $\Delta t_c$ during green light due to the queuing effect of traffic can be calculated as,

$$\Delta t_c = d_0/w + d_0/v_q$$  \tag{14}$$

So, The total impassable time $T_{\text{DERD}}$, named DERD, changes from $c_i^j, t$ to $c_i^j, t + \Delta t_c, j = 0, 1, \ldots$. At last, the traffic light model for $s_i(t)$ is

$$s_i(t) = \begin{cases} 0, & c_i^0 + j\dot{c}_i^j - c_i^{j-1} < t < c_i^0 + j\dot{c}_i^j + \Delta t_c \\ 1, & \text{other} \end{cases}$$  \tag{15}$$

where $s_i(t)$ is the status of the $i$th traffic light (1—green, 0—red).

IV. OPTIMIZATION AND APPROXIMATION MODEL FOR EAD SYSTEM

A. OPTIMAL PROBLEM CONSTRUCTION

The nonlinear longitudinal motion of a vehicle at time $t$ can generally be governed by the state update equation:

$$\dot{x}(t) = f(x(t), u(t))$$ \tag{16}$$

where $x(t) = [d(t), v_q(t), e(t)]^T$ denotes the state vector of traveled distance, speed, and energy consumption, and $u(t)$ is the control input. The vehicle energy consumption on a particular segment of the road can be estimated from forces applied to the vehicle.

A one-dimensional vehicle motion equation based on Newton’s second law is shown in Eq. (17), where the tire slip is disregarded and the vehicle is considered as a mass point. The vehicle acceleration is proportional to the difference between the traction force $F_{\text{trac}}$ and the driving resistance forces.

$$v'_x = \frac{F_{\text{trac}} - (Mg_f \cos \theta + \frac{1}{2} \rho A_f C_d v_x^2 + Mg \sin \theta)}{M}$$ \tag{17}$$

where $v_x$ is the real-time speed of the vehicle. $M$ is the equivalent mass of the vehicle, $f_r$ denotes the rolling resistance coefficient, and $\rho$ is the air density. $A_f$ is the frontal area, $C_d$ is the aerodynamic drag coefficient, and $\theta$ is the slope angle of the road.

The speed and traction force have a significant influence on the vehicle’s energy consumption, and various approaches have been proposed in modeling the energy consumption of EVs [29, 30]. The traction force depends on the equivalent mass and control input as $F_{\text{trac}} = Mu(t)$. The energy consumption is equivalent to the resistive powers during cruising at constant [31]. It can be approximated through the curve-fit process with measurement data as $P_{\text{cruise}} = b_3 v^3 + b_2 v^2 + b_1 v + b_0$. The acceleration and deceleration, if only the regenerative energy zone in the hybrid brake system is considered, can be approximated by a similar curve-fitting process with measurement data using a polynomial of the control input as $F_d = a_2 u^2 + a_1 u + a_0$. Therefore, electrical energy consumption can be expressed:

$$\dot{e} = p(v, u) = F_d(p_{\text{trac}}/M) + P_{\text{cruise}}$$

$$= (a_2 u^2 + a_1 u + a_0)(uv) + (b_3 v^3 + b_2 v^2 + b_1 v + b_0)$$  \tag{18}$$

where $P_{\text{trac}}$ is the tractive power, $a_i$ and $b_i$ are the weight coefficients. This model is capable of representing the regenerative braking effect when $u(t) < 0$. In addition, we adopt the first-order internal resistance battery model for study.

Let $t_f$ denotes the endpoint of the DERD, which also means the beginning of the time when the vehicle can pass. With time passing by, the estimation of $t_f$ is periodically updated to account for the newly predicted traffic and signal information. Combined with Eq. (16) to Eq. (18), an optimal control model for minimizing energy consumption is formulated as follows:

$$\min_{u(t)} J = \int_{t_0}^{t_f} F(v_x(t), v'_x(t))dt$$  \tag{19}$$

s.t.

$$\dot{x}(t) = f(x(t), u(t)),$$

$$t_0 \leq t \leq t_f,$$

$$d(t_f) = D,$$  \tag{20}$$

and the lower and upper bounds for state and control variables:

$$v_{\text{low}} \leq v(t) \leq v_{\text{limit}},$$

$$a_{\text{min}} \leq a(t) \leq a_{\text{max}}, \quad \forall t_0 \leq t \leq t_f$$  \tag{21}$$

where $a_{\text{min}}$ represents the maximum deceleration and $a_{\text{max}}$ represents maximum deceleration. In addition to the road speed limit $v_{\text{limit}}$, the minimum speed limit $v_{\text{low}}$ needs to be defined, because driving too slowly might lead to traffic jam. At the same time, constraints like the motor’s maximum speed, maximum torque and speed-torque property are also considered when designing the EAD control strategy.

B. PSEUDO-SPECTRAL SOLVING METHOD AND APPROXIMATION MODEL

The proposed optimal control problem Eq.(16) - Eq.(21) can be solved numerically by the gradient-based method offered by Pseudo-spectral Optimal Control Software (POPS). As a typical direct method for solving nonlinear programming (NLP) problem, the pseudo-spectral method (PM) has been fully verified in terms of its optimality and applicability, and is widely used to solve optimal control problems for various dynamic systems [12, 32, 33]. The PM uses the
orthogonal matching point to discretize the continuous optimal control problem, and approximates the state and control variables through the global interpolation polynomial, thus transforming the problem into an NLP problem. The PM is more attractive due to the merits of high accuracy, lower sensitivity to the initial value and faster convergence [34]. In our previous research [33], the calculation process of the PM algorithm was introduced in detail and successfully applied to the energy management of hybrid electric vehicles. Results showed that the PM algorithm could obtain the same global optimal solution as DP with less time. For simplicity, this paper does not repeat the calculation process of the PM algorithm.

Next, we use a small example to prove the effectiveness of the PM algorithm in solving the scenario studied in this paper. Test 1: simulation environment of a road with one intersection located 900m from the starting point of the vehicle was established. The upper and lower limits of road speed were 90 km/h and 20 km/h respectively. The durations of green and red (include yellow signal time) signal lights are both set to 40 s. And the green signal time has passed 12 s at the beginning (t0 = 12 s). Moreover, the short-time traffic information on the current road segment is assumed as q = 12 veh/0.5min. For intuitive analysis, the simulation uses an intelligent driver model (IDM) as the benchmark for comparison with the optimal eco-driving mode. The IDM is originally developed by Treiber [35] to realize stable car-following between the host vehicle and the target vehicle.

The remaining constraints are the same as Eq. (19). Compared with IDM, the eco-driving vehicle (under PM) adopts lower speed to approach the intersection and avoids stopping at the intersection. At the same time, it shares similar speed with the IDM when crossing the intersection.

The comparison results of energy consumption are shown in Table 2. The driving energy consumption for IDM is 0.1195 kWh while the consumption using PM algorithm is 0.1023 kWh, which means that the PM algorithm achieves 14.4% energy saving. In addition, PM takes 205 s to complete the calculation.

When the optimal speed trajectory that needs to be planned is extremely long or the state variables have relatively wide ranges, it will take a long time for PM to find the optimal solution. If the planned speed trajectory is over a road of 900 m, however, the boundary conditions or constrained parameters are adjusted, the calculation time for PM will take more than 100 s. Therefore, when the optimization problem is large, the PM algorithm cannot meet the real-time application.

When the traffic condition is known in advance, the target of the control algorithm is to find a stable and efficient working state for the vehicle, which is consistent with the result shown in Fig. 6(b), where the vehicle’s speed is relatively stable in most of the time. Based on this kind of optimal speed property, an approximation model is adopted in this paper to simplify the complex problems and reduce the computation time, to realize the real-time online application of the algorithm. The idea of the approximation model is to make the vehicle cruise at the fixed optimal speed v* as far as possible after appropriate adjustment process. The simplified formula is as follows:

$$\min_{a_1, v(t), t} J = \int_{t_0}^{t_f} F(v(a_1, t), a_1)dt + \int_{t_1}^{t_f} F(v^*, 0)dt \quad (22)$$

s.t.

$$v_0 + a_1(t_1 - t_0) = v^*$$
$$v_0(t_1 - t_0) + 0.5a_1(t_1 - t_0)^2 + v^*(t_f - t_1) = D$$
$$v_{low} \leq v^* \leq v_{limit}$$
$$a_{min} \leq a(t) \leq a_{max}$$

The following between the host vehicle and the target vehicle.

**TABLE 2. Comparison of different method under test 1.**

| Model   | Energy consumption | Computation duration |
|---------|--------------------|----------------------|
| IDM     | 0.1195             | ----                 |
| PM      | 0.1023             | 205 s                |
| Approximation mode | 0.1082 | < 0.8 s |

**FIGURE 6. Vehicle response under different driving modes.**

Fig. 6 compares the distance and speed trajectories in the two driving modes under the single intersection simulation. As indicated by the black line in the figure, the IDM follows the traffic flow to the intersection and stops until the queue moves again. The green dotted line in Fig. 6(a) represents the impassable time caused by the queue effect, which causes the DERD to become longer. The traffic in the queue passes the intersection at 90 s. As can be seen from Figure, the PM algorithm ensures that the vehicle is able to cruise to the intersection and catch the tail of the queue just when it is released. Fig. 6(b) shows the actual speed of the vehicle. Compared with IDM, the eco-driving vehicle (under PM) adopts lower speed to approach the intersection and avoids stopping at the intersection. At the same time, it shares similar speed with the IDM when crossing the intersection.
the vehicle from it starts accelerating to it reaches target speed and the moment \( t_1 \) when the vehicle reaches target speed for the first time. From \( t_1 \) to \( t_f \), the vehicle cruises at target speed. After the above approximation changes, the problem-solving process becomes very easy. Under the same simulation conditions, the driving energy consumption obtained by using the approximate model is 0.1082 kWh. Although energy consumption of the approximation model is slightly increased compared with PM algorithm, its calculation time (less than 0.8 s on average) is greatly shorter than PM, which can be used for real-time vehicle control.

In order to verify the effectiveness of the approximation model, we updated the predicted traffic flow information when the vehicle is driving, and then reprogrammed the advisory speed of the remaining distance. The advisory speed curve is shown in Fig. 7, where the blue-green solid line is the optimal speed trajectory solved by PM while the red dashed line is by approximation model. It can be seen that the approximation optimization model can approximate the original objective function well.

![FIGURE 7. Vehicle speed suggested by different models.](image)

V. THE CASE STUDY ON REAL-VEHICLE SETTING

The EAD system used for the real test is developed based on the optimal speed trajectory planning algorithm of the designed approximate model. This system integrates multiple data sources, such as SPaT information, GPS location, vehicle dynamics and information about surrounding vehicles. The vehicle calculates the distance to the intersection based on the current GPS position and the DERD predicted by dynamic traffic flow information.

A. TEST VEHICLE

A modified electric vehicle that supports autonomous driving is used in the test, as shown in Fig. 8. The acceleration command is converted to the voltage signal of the accelerator pedal for the corresponding motor. The brake command is converted into an air brake pressure signal, then sent to the electronic vacuum booster to control the brake cylinder and generate the brake pressure. We have performed an acceleration control analysis of this experimental vehicle in the literature [36]. The communication delay and drive delay are considered in the speed control strategy, and it is proved that the linear controller can accurately realize the preset speed curve.

Besides, the combination of Mobileye camera and Radar is applied in the forward-looking target recognition system to identify the surrounding vehicles and provide information such as the distance, angle, relative speed, and deceleration of the target. The Dedicated Short Range Communication (DSRC) system is a wireless communication module of Cohda MK5, and its maximum barrier-free communication distance reaches 300 m. The vehicle positioning system is the NAV982 GNSS navigator, which can accurately collect real-time geographic location, speed, acceleration, and other information. The AutoBox is used as a vehicle real-time control system that supports automatic code generation and download of models under the Matlab/Simulink compilation environment. The upper software of the computer can realize the display of model data and online parameter adjustment and storage, which facilitates data analysis. Relying on the robot operating system (ROS) of Raspberry Pi, a graphic user interface (GUI) is built for the advisory speed, which is displayed on a 7-inch screen.

The traffic observer includes 4 parts: computer, Raspberry pi, camera, Cohda MK5. The robot operating system (ROS) of Raspberry Pi is used to analyze the video information in the camera and count the traffic flow. The Cohda MK5 is used to send the traffic flow information to the vehicle receiver. According to the traffic flow information, SPaT and current host vehicle status, the appropriate driving speed is planned and displayed on the GUI of the host vehicle for the driver’s reference. The complete hardware wiring diagram is shown in Fig. 9.

The working mechanism of the system is as follows: the SPaT and location information of traffic lights are fed into the traffic observer in advance and will also be broadcast wirelessly in real-time. Traffic observer will count traffic flow through ROS vision system and update traffic flow prediction every 0.5 min based on historical traffic flow. Real-time traffic flow prediction results will then be sent to connected vehicles. When the vehicle receives traffic flow prediction results, it will combine the prediction result with other necessary traffic information to finish green-light passing time.
estimation and eco-speed planning in less than 1 second. To avoid frequent change of optimal speed trajectory, EAD system is allowed to update the results at intervals.

Fig. 10 shows a demonstration of the real-time status display system. In Fig. 10(a), the left side is the scene of the normal driving for the vehicle, and the right side is the screen broadcast by the EAD system. The vehicle in the picture is far from the intersection, and the vehicle gets a recommended speed of 44km/h (green square). In Fig. 10(b), the left side shows the scene when the vehicle stops at the intersection, and the right side shows the broadcast screen of the EAD system at this time. The heavy traffic in the state shown in the figure causes the host vehicle to encounter an unavoidable parking queue. At this time, the EAD system has no advisory speed display. The following information is displayed in an LCD: 1) The current speed (yellow pointer indication); 2) The advisory speed (green square pointer); 3) The SPaT information for the current signal; 4) Signal indicators for DSRC and GPS; 5) The remaining distance to the intersection.

For different distance ranges, we compare the computing time from EAD receives the information sent by traffic observer to the optimal speed trajectory is obtained. The result is shown in Fig.11. It can be seen that when the distance is less than 500m, the approximation model can always obtain the result within 0.8s. Thus, the proposed EAD system can finish the calculation process within 1s even considering the communication delay because communication delay is often less than 0.2s. Therefore, the proposed EAD system can satisfy the real-time application requirement.

B. THE MODE OF EAD SYSTEM

The EAD strategies in the transportation need to be adaptable to the dynamic uncertainty of signals and traffic conditions. When the traffic is smooth, the DRED information is reliable, so that the vehicle only needs to drive at the advisory speed. When the traffic is congested, it is not realistic to design an ideal trajectory if the vehicle is still far from the intersection, because it is difficult to accurately monitor the traffic flow or calculate the remaining time.

At 400m upstream of the intersection, the vehicle plans the optimal consultation speed according to the predicted short-time traffic flow information and allows a traffic flow prediction update at 200m upstream of the intersection. The limited update frequency is for avoiding frequent changes in the recommended speed so the driver’s judgment will not be affected. Since the traffic flow cannot be controlled in reality and it is impossible to reduplicate a same traffic state, the EAD algorithm needs to be extended to any intersection traffic scene for convenience of testing. Thus we drop off the invalid data caused by traffic jams and use big-data analysis method to analyze the advantage of proposed algorithm at relatively smooth traffic scene.

Further, the EAD system should determine the operating mode according to the speed limit and the remaining arrival time as soon as the system is started. The maximum remaining arrival time is \( t_{\text{max}} = \frac{d}{v_{\text{lim}}} \), and the minimum remaining arrival time is \( t_{\text{min}} = \frac{d}{v_g} \). Whether the vehicle will encounter a red light signal (RLS) or the green light signal (GLS) is determined by the following rules, where \( T \) is the signal time of the start point:

1) \( T + t_{\text{min}} \in \text{GLS}, \ T + t_{\text{max}} \in \text{GLS}, \) as shown in Fig. 12(a), the vehicle keeps running at a constant speed.
2) \( T + t_{\text{min}} \in \text{GLS}, \ T + t_{\text{max}} \in \text{RLS}, \) as shown in Fig. 12(b), the vehicle is accelerated to ensure that it can pass the intersection within the green light time.
3) \( T + t_{\text{min}} \in [\text{RLS}], T + t_{\text{max}} \in [\text{RLS}] \), as shown in Fig. 12(c), the vehicle performs optimal deceleration driving to the intersection and stops.

4) \( T + t_{\text{min}} \in [\text{RLS}], T + t_{\text{max}} \in [\text{RLS}] \), as shown in Fig. 12(d), The EAD system provides the vehicle with the optimal recommended speed based on the ERD (or DERD) information and guides the vehicle to drive through the intersection.

VI. EXPERIMENT RESULT ANALYSIS

A. SCENARIO DESIGN

An EAD system driving test was conducted in this paper on the corresponding road in Fig. 3. 400 m upstream of the intersection and 100 m downstream of the intersection was used as our test traffic environment. The traffic observer was set up 200 m and 400 m upstream of the intersection. Secondly, the vehicle speed, EAD status, SPaT, traffic flow, and other information are collected completely.

In order to analyze the impact of the EAD system on driving behavior in detail, and explore the gap between the energy saving performance of human drivers and that of autonomous vehicles when performing the recommended speed, three types of drivers were set up in this paper: uninformed drivers (free driving without knowing the traffic information), informed drivers (The driver drove at the speed recommended by EAD), and autonomous vehicles (EAD control the longitudinal speed). Due to the limited number of equipment and vehicles, two sets of comparative tests were set up under the same scenario. Test 1: Comparison between an uninformed driver and an informed driver. Test 2: Comparison between an uninformed driver and an autonomous vehicle. In each set of tests, the uninformed driver was used as a benchmark for comparison.

In order to make the 2 vehicles in one test comparable, we require them to start at the same time. In addition, the drivers were required to change lanes for a certain distance so that both vehicles can experience all the traffic flow on different lanes, which can minimize the effects of different lanes’ traffic states on test results. The test section was located on a busy main road, and we chose different time periods (crowded and unobstructed) for testing. At least 100 valid data fragments were collected for each set of experiments.

B. RESULTS AND DISCUSSION

Before analyzing the impact of the EAD system on driver behavior, the ability of informed drivers to perform advisory speeds needs to be studied. Fig. 13 shows the driving performance of five informed drivers and autonomous vehicles at the advisory speed. In the legend, an aggressive advisory speed (green dotted line) is introduced for a test. At a distance of 800 m, it includes 4 levels of advisory speed, with a speed span from 25 km/h to 45 km/h. The blue line in the figure is the performance of the autonomous vehicle when performing the advisory speed. Due to the high control accuracy of the system, the autonomous vehicle can drive stably at a small speed fluctuation, and can quickly adjust the speed.

The rest trajectory curves are the performances of informed drivers when driving at the advisory speed. Results show that there is a certain deviation between the actual driving speed of the manual driver and the advisory speed. And a significant speed delay exists in tracking the changed advisory speed. Taking the advisory speed (including the acceleration and deceleration interval) as a comparison benchmark, the mean error of the informed driver during driving is 0.6 km/h, and the mean absolute error is 1.7 km/h. Although the overall performance is not as good as the autonomous vehicle, considering the human operation delay and the error of the EAD system broadcast, the informed driver has a good performance in following the speed advisory.

Further, the recommended speeds were fixed at 30 km/h and 40 km/h, and experiments and error statistics were conducted again. The mean error of the informed driver during driving is 0.6 km/h, and the mean absolute error is 1.7 km/h. Although the overall performance is not as good as the autonomous vehicle, considering the human operation delay and the error of the EAD system broadcast, the informed driver has a good performance in following the speed advisory.

Fig. 14 shows the typical speed behaviors of three driving modes as they pass through an intersection. The blue line indicates the trajectory of the uninformed driver in test 1, and the red line indicates the vehicle speed trajectory of the
informed driver in test 1. Besides, the yellow line indicates the advisory speed for the autonomous vehicle in test 2, and the black dotted line is the driving trajectory. As shown in the figure, the uninformed driver without knowing the traffic information tends to start driving at relatively high speed (about 40 km/h). On the contrary, the informed drivers prefer to approach the intersection at a speed about 30 km/h. The speed of an autonomous vehicle is close to that of an informed driver, and the speed fluctuation is relatively small.

When the uninformed driver arrives at the downstream intersection, the signal is still in the red phase. The driver has to brake hard to decelerate and stop at the intersection. After passing the intersection, it accelerates to relatively high speed again. The informed driver with the EAD system decelerates slightly to 20 km/h near the intersection and recovers to 25 km/h after passing the intersection smoothly. The speed change of the informed driver is due to the consideration of safety when passing through the intersection, so the recommended speed of the EAD system has not been fully implemented. In addition, the autonomous vehicle has a smoother speed trajectory. The speed is always maintained near the advisory speed, and there is no significant speed drop when passing through the intersection.

In summary, the EAD system can effectively influence human driving behavior when providing advice to humans. Although informed drivers do not perform as well as autonomous vehicles, they are much better than uninformed drivers. In addition, crossing the intersection with high speed increases the possibility of collision. From the perspective of safety, the EAD system with people in the loop is helpful to improve the safety of the vehicle.

Furthermore, this paper evaluates how the EAD system affects vehicle dynamics and driving behavior from the overall effect. Fig. 15 shows the speed distribution for all trips based on second-by-second instantaneous speed data at test 1 and test 2. The statistical results show that compared with uninformed human driving, the percentage of low-speed mode (between 0 and 15 km/h) with the assistance of the EAD system drops significantly in informed manual driving and automatic driving. Specifically, the idling or near-idling case (0−15 km/h) for the vehicles with an informed driver is reduced by 28%. Due to the minimum speed limit of autonomous vehicles, the idling or near-idling case is reduced by 63%. These results prove that the proposed EAD system can effectively diminish unnecessary idling or near-idling case under uncertain traffic conditions, thus improving energy efficiency.

On the contrary, the figure also indicates that the EAD system significantly reduces the percentage of relatively high-speed cases (>40 km/h). Compared with uninformed driving, the high-speed ratio of informed driving and autonomous vehicle are reduced by 26% and 53%, respectively. This means that if the SPaT message and advisory speed are provided, an informed driver or autonomous vehicle can better control the high-speed state of the vehicle to avoid unnecessary deceleration behavior at high speeds and reduce the probability of stopping.

In Fig. 16, this paper further shows the distribution of saved trip travel time by the EAD system. The driving time of the uninformed driver is used as the benchmark in both tests. The white bars represent informed drivers, and the red ones represent the informed autonomous vehicles. The negative savings in the figure mean that the driving time is increased compared to the uninformed driving. In test 1, the percentage of the cases where the driving time difference falls within -20 s to 20 s is 87%, while this value is 85% for test 2. This means that most of the vehicles in each group pass through the intersection during the same signal cycle.

In test 1 (white bars), 53% of the informed drivers pass the intersection earlier than the uninformed drivers. In test 2 (red bars), 66% of autonomous vehicles pass the intersection before the uninformed drivers. Specifically, in the two sets of tests, the time interval of most vehicles passing through the intersection has been within 10 s. Ignoring the extreme behaviors with large time gaps, the frequency of the interval between 0 s and 5 s is higher than the frequency of the interval between -5 s and 0 s, which indicates that the EAD system will shorten the travel time slightly.

It is noticeable that there are some cases where the saving time is greater than 45 s. The reason is when the remaining green time is very short, the EAD system can notify the driver to stop.
to accelerate in advance to avoid stopping at intersection while the uninformed driver is often afraid to risk speeding through the intersection. The comprehensive evaluation shows that the average travel time of informed drivers is 2% shorter than the uninformed driver, and the average travel time of the informed autonomous vehicles is 8% shorter than the uninformed driver.

The acceleration/deceleration distribution of the vehicle in the effective EAD segment is shown in table 3. Driver 1 and driver 3 are uninformed; driver 2 is informed; driver 4 is the informed automatic vehicle. The statistics clearly show that in both groups of test, the EAD significantly increases the percentage of cruising state (acceleration between $-0.25$ and $0.25$) compared with the uninformed driver. Specifically, in test 1, the proportion of the informed drivers in the acceleration interval $(0.25, 0.25)$ increases by 62%, and the proportion of the acceleration interval $(-3m/s^2, 1.5)$ and $(1.5, 3)$ decreases by 16%. Since the informed driver obtains the remaining time and recommended speed in advance, unnecessary speed adjustment behavior is reduced.

In test 2, the proportion of the informed autonomous vehicles in the acceleration zone $(-0.25, 0.25)$ increases by 97%, but the proportion of the acceleration zone $(-3, 1.5)$ and $(1.5, 3)$ increases from 13.3% to 21.5%, which is due to the fast response of the autonomous vehicle. When the EAD system provides a new recommended speed, the autonomous vehicle can quickly adjust the vehicle’s state and reach a new speed equilibrium point (this is consistent with the blue line behavior in Fig. 13), which leads to the large acceleration and deceleration. The above analysis shows that the EAD system can significantly reduce the speed adjustment process of the vehicle and ensure that the vehicle runs at a stable speed in most of the time.

This paper further performs a hypothesis test on energy consumption to analyze the energy-saving performance of the EAD system. In the EAD work interval, a hypothesis test is performed to calculate the vehicle’s energy consumption based on the collected vehicle speed, acceleration information, and throttle signal, combined with the motor efficiency map. Other loss factors in actual driving such as slip, slope, transmission efficiency, etc. are ignored in the calculation. In addition, the fuel consumption of the vehicle is also related to the driving route of the vehicle. The different traffic conditions of the two lanes will still cause certain deviations in the statistics, which are inevitable in the statistics.

Fig. 17 shows the energy consumption distribution calculated based on the collected test data. The curve in the figure is a fitted normal distribution curve, and the dashed line is the expected mean value $\mu$. The distribution map shows that in test 1, compared with the uninformed drivers, the informed drivers with the EAD system improve energy efficiency by implementing the recommended speed and reduce the energy consumption by 4.6% on average. In test 2, autonomous vehicles equipped with EAD systems reduce energy consumption by 12.1% on average. Although the proportion of acceleration in autonomous vehicles increases, it still saves more energy than uninformed drivers.

VII. CONCLUSION

The improved Support Vector Regression (SVR) model based on the deep learning algorithm proposed in this paper has better prediction performance than traditional SVR and can effectively improve the prediction accuracy of short-time traffic flow. Based on the estimation of the queue effect of traffic flow, a traffic signal model of dynamic effective red duration was constructed to ensure the smooth passage of electric connected vehicles at the intersection with queue interference. The pseudo-spectral method is used to solve the global optimal energy saving problem, and an EAD system for real vehicle testing is built by using
an approximation model. Simulation results show that the approximation model not only can achieve good energy-saving performance, but also requires only few computational resources.

For the proposed EAD system, a large number of tests in actual traffic scenarios are performed to evaluate the performance of the system, which is also the most valuable and challenging part. It turns out that compared with the uninformed driver, the proposed EAD system can save 2% time and 4.6% energy on average for the informed driver, and save 8% time and 12.1% energy for the autonomous vehicle. Although EAD-guided manual driving cannot achieve the same energy-saving performance as autonomous driving due to the inevitable human operating error, the proposed EAD system can significantly reduce the chances where the vehicle operates at high and low speeds if recommended speed trajectory is informed to the driver.

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**X. Zhang et al.: Predictive Eco-Driving Application Considering Real-World Traffic Flow**

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