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Economical path planning for electric vehicles considering traffic information

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ABSTRACT

Vehicle exhaust pollution and traffic congestion are plaguing the daily life of the citizens. Although electric vehicles represent green travel, the problem of mileage anxiety still troubles electric occupants. Aiming at the existing problems, an electric vehicle energy consumption prediction based on LSTM deep learning technology combined with traffic information is proposed to plan the economical driving path with the best coupling of energy consumption and driving distance. The method has the ability to integrate multi-dimensional data of heterogeneous heads, solves the problem that electric vehicle energy consumption estimation cannot take into account real traffic information. And getting rid of the shortcomings of path planning relying only on driving distance, effectively improving the driving feeling of electric vehicles and bettering travel efficiency to optimize urban traffic conditions.

Keywords: Electric vehicle, Data fusion, Energy consumption forecast, Path planning

NONMENCLATURE

Abbreviations	
APEN	Applied Energy
Symbols	
v_{act}	Actual speed (m/s)
α_i	Integral anti-saturation parameter
K_i	Integral adjustment parameter
Ped	Full scale of the accelerator pedal or brake pedal
P_{acc}	Acceleration depth of the accelerator pedal or brake pedal
K_p	Proportional adjustment parameter
T_{out}	Drive system output torque (Nm)
T_{motor}	Motor output torque (Nm)
P_{motor}	The output power of the motor(kW)
P_{batt}	Power of power battery (kW)
T_t	The maximum torque that an electric car can output (Nm)
η_{tran}	Transmission efficiency
w_{motor}	Motor speed (r/min)
η_{motor}	Motor efficiency
U_L	Load voltage (V)
I_L	Load current (A)
SOC	State of charge
y_{pred}	Predictive value
y_{truth}	Actual value
MAE	Mean Absolute Error
MSE	Mean Square Error
RMSE	Root Mean Square Error
m_{x_1,x_2}	Energy consumption of road x_1 to road x_2
n_{x_1,x_2}	Distance of road x_1 to road x_1

1. INTRODUCTION

Energy storage density of electric vehicle power batteries is low, and the cruising range is not long enough. Considering the real-time energy consumption estimation of traffic information and economic route planning, the problems mentioned above can be improved. A model proposed by Xue Weiqi can be used to support the energy consumption estimation of the electric vehicle ecological path system[1]. The electric vehicle power consumption model including the configuration and status data of the traffic network and vehicle operating condition was created by Arias[2]. It can solve the problem that the traffic data and the electric vehicle data cannot be simultaneously acquired. In my view, the LSTM model of traffic information can solve the problem of real-time prediction of energy consumption based on traffic data, which can alleviate the mileage anxiety of electric vehicles.

In this paper, the traffic network construction and vehicle simulation model are described in the first part. The second part will show the integration of traffic and vehicle data and the prediction of electric vehicle energy consumption. Using the A-Star algorithm to plan the

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economic path will be written in the third part, and the last part describes the experimental results.

2. PAPER STRUCTURE

2.1 Road network construction and vehicle modeling

To establish a joint simulation experiment of the electric vehicle and the traffic road network,we set up a road network. Then collect the electric vehicle working condition data and the traffic road network information data, and use this data as the input of the energy consumption prediction model.

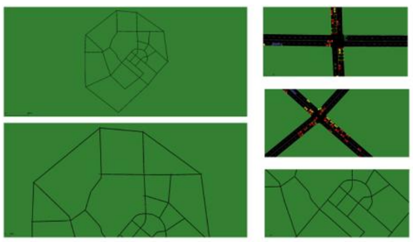

Fig 1. Road network

SUMO (Simulation of Urban Mobility) is used to establish urban traffic road simulation.It mainly includes traffic road network and road network and vehicle parameter design.

Table 1. Vehicle type parameters

Vehicle Type	Quantity
Fuel Vehicle	50%
Electric Vehicle	10%
Bus	10%
Taxi	20%
Truck	5%
Sweeper	5%

Select the traffic entrance and exit, set the road network OD matrix, and put various types of vehicles into the traffic road network.

	Place 1	Place 2	Place 3	…	Place 25	Place 26	Place 27
Place 1		40	220		12	4	21
Place 2	100		350		22	110	30
Place 3	20	80			0	50	80
…	…	…	…		…	…	…
Place28	720	350	90			860	230
Place29	200	220	350		700		150
Place30	190	460	280		180	260	

Fig 2. Road OD matrix

The electric vehicle model was built on a pure electric vehicle modeled after Beiqi EU260. It is discussed from two aspects: vehicle model establishment and model accuracy calibration.

Using PID to establish driver's speed following equation:

$$v_e = v_{pre} - v_{act} \tag{1}$$

$$\alpha_i = \begin{cases} 0 & \left|K_i \int_0^t v_e\, dt\right| > Ped \\ 1 & \left|K_i \int_0^t v_e\, dt\right| \le Ped \end{cases} \tag{2}$$

$$P_{acc} = \frac{1}{Ped}\left(K_p \times v_e + \alpha_i K_i \int_0^t v_e dt\right) \times 100\% \tag{3}$$

v_e is the difference between the desired speed and the actual speed. The PID uses v_e to adjust the accelerator pedal depth to achieve the purpose of vehicle speed following.

Drive system output torque:

$$T_{out} = \mathrm{P}_{\mathrm{acc}} \times T_t \tag{4}$$

Motor output torque is:

$$T_{motor} = \mathrm{T}_{out} \;/\; \eta_{tran} \tag{5}$$

The output power of the motor is:

$$P_{motor} = T_{motor} \times w_{motor} \tag{6}$$

Motor map is used to find the motor efficiency, and the power battery power is calculated by the motor power:

$$P_{batt} = \mathrm{P}_{motor} \;/\; \eta_{motor} \tag{7}$$

The Rint power battery equivalent circuit model is established, and we estimate the power battery SOC by using P_{batt}:

$$\mathrm{SOC} = f(P_{batt}, U_L, I_L) \tag{8}$$

The accuracy of the electric vehicle model was verified by the NEDC based on the actual vehicle bench test and the actual driving conditions of the actual vehicle[4].

Table 2. NEDC comparison

Vehicle Type	Drive Condition	Energy consumption
Real Vehicle	NEDC	20.8%
Model Vehicle	NEDC	21.8%

Table 3. Actual working condition comparison

Vehicle Type	Driven Ddistance	Energy consumption
Real Vehicle	18.01km	6.0%
Model Vehicle	18.01km	6.2%

The model error of both verification methods is less than 1%, so it shows the model vehicle has higher precision.

2.2 Data Fusion and energy consumption prediction

The statistical method is used to initially process the traffic flow, traffic density, average vehicle speed and energy consumption data. The Sequence to Sequence model is then used to fuse the traffic data with the electric vehicle data, and the fused data is used as the input to the LSTM[5].

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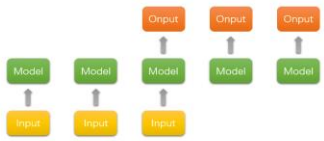

Fig 2. Sequence to Sequence model

The LSTM model accurately predicts data with timing characteristics, and the energy consumption of electric vehicles is data with obvious timing characteristics.Using LSTM technology to form a regression model of the integrated traffic information data with vehicle data and energy consumption.

The formula of lstm is as follows：

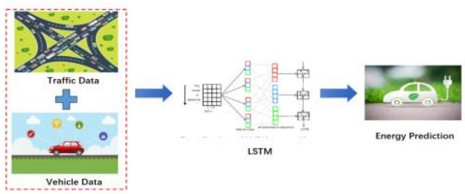

Fig 3. Energy consumption prediction model

$$\sigma(z) = \frac{1}{1+e^{-z}} \tag{9}$$

$$f_t = \sigma(W_t \cdot [h_{t-1}, x_t] + b_f) \tag{10}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{11}$$

$$\tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C) \tag{12}$$

$$C_t = f_t * C_{t-1} + i_t * \widetilde{C}_t \tag{13}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{14}$$

$$h_t = o_t * \tanh(C_t) \tag{15}$$

Where h_t is the output of the LSTM model at time t.Calculate the model error using the following equation to determine the accuracy of the model. Use the Adam function to make the loss function of the model as small as possible.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_{pred} - y_{truth}\right| \tag{16}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_{pred} - y_{truth})^2 \tag{17}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_{pred} - y_{truth})^2} \tag{18}$$

The results are as follows.

Table 4. LSTM model error

Road number	Simulation time	MAE	MSE	RMSE
130	6h	0.1042	0.0177	0.1048

According to the values of MSE, MAE, and RMSE, the energy consumption predicted by the LSTM model is accurate.

2.3 *Economic path planning*

Establish a path resistance function that couples energy and distance:

$$f(x_1, x_2) = am_{x_1,x_2} + bn_{x_1,x_2} \tag{19}$$

Where m_{x_1,x_2} is the energy consumption of road x_1 to road x_2, n_{x_1,x_2} is the distance of road x_1 to road x_1, and a and b are weights.

Based on the A-Star algorithm, the road resistance and the traffic network obtained by the above equation are taken as inputs. Plan the economical driving path with the best coupling of energy consumption and driving distance.

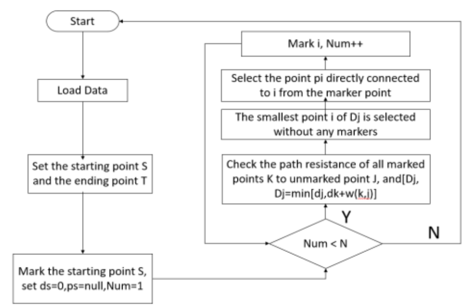

Fig 4. A-Star Algorithm

2.4 *Results*

Set the starting point and the end point, plan the energy consumption of the traffic information to be the same as the economic path with the best distance coupling, and plan the optimal distance path at the same time. Compare the results of the two.

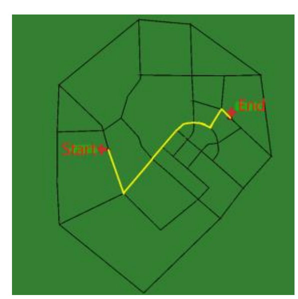

Fig 5. Optimal distance path

Table 5. Optimal distance result

Drive Distance	Energy Consumption	Expected time consuming
3515.3m	0.731kwh	11.7min

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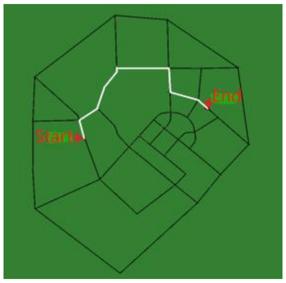

Fig 6. Economic path

Table 6. Economic path result

Drive Distance	Energy Consumption	Expected time consuming
3661.8m	0.486	5.4min

It can be seen from the results that although the economic path travel distance is farther than the optimal distance path, it is obvious that the path with the shortest distance is relatively congested. The economic path is relatively smooth, and the travel time and travel energy consumption are smaller than the shortest path.

2.5 *DISCUSSION*

The work of this paper mainly focuses on the electric energy consumption prediction of electric vehicles that takes into account traffic information and the economical path of optimal coupling of energy consumption and driving distance.

The former makes full use of big data and artificial intelligence technology, combines different dimensional data, and explores the internal relationship between different data. Form a predictive model that can handle multi-dimensional big data, which can accommodate more dimensional inputs than traditional predictive models. The latter combines the energy consumption of electric vehicles with the driving distance and plans an economic path. This not only saves energy consumption of electric vehicles, but also improves travel efficiency.

In the real environment, as long as there is enough traffic data and driving data of electric vehicles, the traffic efficiency can be improved according to the model city of this paper[6].

2.6 *CONCLUSION*

This paper proposes an economical path planning method for electric vehicles that takes into account traffic information. First, establish an electric vehicle and traffic network simulation model to obtain the data set, then use LSTM to fuse the two data and predict the energy consumption of the electric vehicle. Finally, based on the A-Star algorithm, the economic path is planned. Compared with the optimal distance path, the energy consumption of electric vehicles is reduced by 33.5%, and the travel time is reduced by 53.8%.

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