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ELECTRIC VEHICLE SHIFT STRATEGY BASED ON MODEL PREDICTIVE CONTROL

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Abstract

In order to satisfy high torque output and high speed driving demand, electric vehicles need a gearbox to adjust the gear ratio. The shift schedule is popular in gear shift research. The most widely used schedule, the two-parameter shift schedule, ignores the influence of dynamic conditions, resulting in that it is hard to suit the road and it causes energy waste. In this paper, a strategy based on model predictive control is proposed. A Recurrent neural network is used to predict velocity sequences in the 5-second horizon. Dynamic programming is adopted to construct a benchmark strategy and also to act as the rolling optimization part of the MPC shift schedule. Simulation results show that this shift strategy can reduce the shift frequency while saving energy consumption.

Keywords: shift schedule, pure electrical vehicle, recurrent neural network, model predict control

NOMENCLATURE

Abbreviations	
RNN	recurrent neural network
DP	dynamic programming
MPC	model predictive control
MAE	mean absolute error
MSE	mean squared error
Symbols	
T_{tq}	required torque
i_g	transmission gear ratio
i_0	final drive ratio
η_t	mechanical efficiency
r	wheel radius

1. Introduction

Electric vehicles have become the mainstream of development due to energy and environmental crisis. To consider the high torque demand during acceleration and climbing, and high-speed demand of the vehicle and to improve the efficiency of the motor, the electric vehicle still needs a Multi-speed gearbox to change the transmission ratio.

Shift schedule [1] is one of the research focuses on the transmission. How to formulate a reasonable shift schedule based on the driver's intention, road environment, and vehicle driving conditions and at the same time effectively solve the problems of frequent shifting and shift failure in special conditions is significant to improve the dynamic and economic performance of the whole vehicle.

The traditional shift schedule is based on rules and is inferred by multiple parameters including vehicle velocity, throttle opening, and acceleration [2]. The rule-based shift schedule can guarantee the optimal dynamic and economic performance in specific driving conditions, but fail to meet the driver’s intention when driving conditions are complicated. Furthermore, the traditional shift schedule only calculates local optimal solutions and ignores the influence of the potential vehicle velocity changes. In this paper, we propose an intelligent shift strategy based on model predictive control (MPC). A Recurrent neural network (RNN) is used to predict velocity and dynamic programming (DP) is used to compute the optimal shift sequence in the predictive time domain. The vehicle model has been established on the Matlab/Simulink platform. The optimal shift strategy has been validated by the Chinese World Transient Vehicle Cycle (C-WTVC).

2. Shift Schedule Based On MPC

2.1 Velocity forecast based on RNN

The Recurrent neural network (RNN) [3] is a network structure to process data with sequence correlation. Compared with the traditional neural network structure, the recurrent neural network increases the connection between the hidden layers, so that the hidden layer features are not only related to the current moment. As a result, it saves the "memory" for the previous input, thus enhancing the process of the timing data. The RNN calculation's process is as shown in Equation 2.1.

$$h_t = softmax(x_t U + h_{t-1} W + b) \qquad (1)$$

In this paper, a recurrent neural network (RNN) is adopted to predict vehicle velocity. We use the vehicle velocity of the past ten seconds to be the input of the RNN, and the output is the velocity of the next five seconds. The training set is composed of multiple working conditions and the testing set is the Chinese World Transient Vehicle Cycle (C-WTVC). The cell size of the RNN is 20 and the activation is sigmoid. In order to contrast the results of the model, a deep neural network (DNN) model is built with five layers and 20 cells per layer.

The result of the RNN and DNN model is shown in TABLE I. The mean absolute error (MAE) and mean squared error (MSE) has been calculated. We also compared the simulation time of calculating the two models.

TABLE Ⅰ VOLOCITY FORECAST RESULT

Network Type	MAE	MSE	times
RNN	2.929219	14.504694	2.989s
DNN	3.168024	19.890326	2. 852s

The MAE of the RNN model has been reduced by 8.54% and the MSE has been reduced by 28.08%. Meanwhile, the time consumption is in the same magnitude. The result indicates that the RNN model forecasts vehicle velocity better.

2.2 Model predictive control

Model predictive control (MPC) is one of the advanced control theories and mainly consists of three steps, including building a prediction model, applying an optimization algorithm and correcting feedbacks. In the current state, rolling optimization can be achieved by three steps, first forecasting related states in a definite time zone, second searching for optimum control sequences, last using only the control variables in the first point then moving to the next point. And repeat these procedures.

When MPC [4] is used to construct the shift strategy， the processes are as follows:

(1) Predict and rationalize velocity sequence in a certain horizon with some prediction methods like RNN;

(2) With the predicted results as inputs, DP (dynamic programming) is adopted in the optimization part to search for optimal control traces;

(3) Implement the first value of every control variable sequence to the transmission;

(4) After the transmission responses, the real or virtual driver changes the velocity requirement in the next moment according to current velocity by manipulating pedals. The current velocity will be delivered to the prediction part to be the start point;

(5) Repeat steps (1) to (4).

2.3 Shift schedule based on MPC

A pure electric truck with 2-gear AMT is used in this paper, and the parameters of the vehicle are listed in Table Ⅱ.

TABLE Ⅱ VEHICLE PARAMETERS

Vehicle parameters	Value
Total weight [kg]	15000
Wheel radius [m]	0.506
Frontal area [m2]	8
Driveline efficiency	0.95
Rolling resistance coefficient	0.008
Air resistance coefficient	0.55
Final drive ratio	9.76
First gear ratio	2.5
Second gear ratio	1

The driving equation of vehicle is:

$$\frac{T_{tq} i_g i_0 \eta_t}{r} = mgf + mgsin\alpha + \frac{C_D A u_a^2}{21.15} + \delta m \frac{du}{dt} \qquad (2)$$

In the DP model [5], the control variables are upshifts and downshifts and the state variables are current gear and SOC. The optimized objective function is:

$$\text{Cost} = \min_{u_k \epsilon U_k} \left(\sum_{k=0}^{n-1} \Delta p\,(x_1, x_2, u_k) + \sum_{k=0}^{n-1} g\,(u_k) \right) \quad (3)$$

In the formula above, $\Delta p(x_1, x_2, u_k)$ is the energy consumption and $g(u_k)$ is the shift penalty.

The required torque and rotating speed of the motor vary according to the transmission ratio.

According to the above formulas, the transmission gear can be selected based on the MPC model which is mentioned in the previous section.

2.4 Simulation results and discussion

In this paper, we use C-WTVC to test the effect of the predictive shift schedule. The length of the unit driving cycle is 1800 seconds and the highest velocity is around 87.8 km/h. The initial SOC is 0.85. In order to compare the simulation results, we also simulated a rule-based (RB) shift schedule. This shift schedule is a kind of two-parameter economic schedule, which is widely used in the vehicles and can achieve good economic performance. DP, MPC and RB shift strategies are simulated with the C-WTVC.

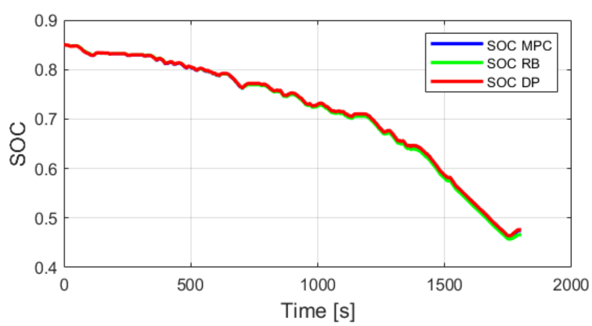

Fig.1 SOC traces of RB, DP, and MPC strategies

Fig.1 shows the SOC traces in the results of RB, DP, and MPC strategies. The SOC declines in the same trend and the final SOC is close. The SOC DP is higher than SOC MPC and the SOC RB is the lowest, which means its energy consumption is the highest.

TABLE Ⅲ RESULT OF SHIFT SCHEDULE

Shift Schedule	SOC	Power Consumption (KWh/100km)	Shift Frequency
MPC	0.4744	76.22	23
RB	0.4660	77.93	32
DP	0.4761	75.88	24

Table Ⅲ shows the detailed data of the simulation results. The power consumption of the MPC, RB and DP shift strategy is 76.22, 77.93 and 75.88 respectively. Shift strategy based on rules consumes around 2.6 percent more than that based on DP. The result indicates that the MPC shift schedule requires 2.2 percent less energy, which is 1.71KWh/100km, than rule-based shift schedule. DP is a global optimum method, so its SOC is the highest. In order to avoid unnecessary and repeated gearshifts, the RB shift schedule includes upshift schedule and downshift schedule. There is a buffer between upshift and downshift, so it doesn't have the best economic performance. The MPC shift strategy doesn't need that buffer, and as a result, it is more efficient than the RB schedule.

At the same time, the MPC shift strategy shifts 23 times during the whole driving cycle while the shift frequency of RB is 32. The traditional shift schedule does not consider the impact of future driving conditions on the current shift decision. When the velocity of the vehicle is near the shift point, the RB schedule may shift frequently for the economic effect of the current moment, thus sacrificing comfort. The MPC shift strategy takes the changing trend of the future velocity into account, so it can effectively prevent frequent shifts and achieve better economic performance.

Fig.2 and Fig.3 are the results of the gear position and vehicle velocity under the C_WTVC of RB and MPC shift strategy, respectively. We can clearly observe that the shift of the RB shift schedule is more frequent than the MPC strategy.

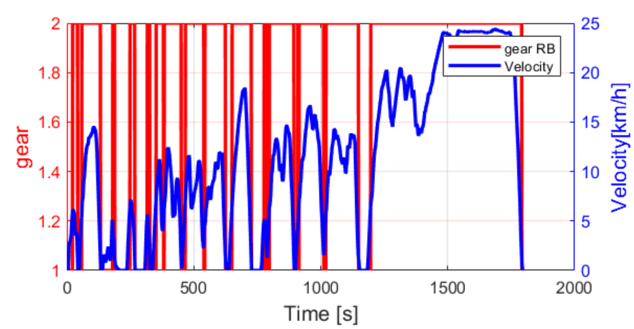

Fig.2 rule-based velocity and shift schedule

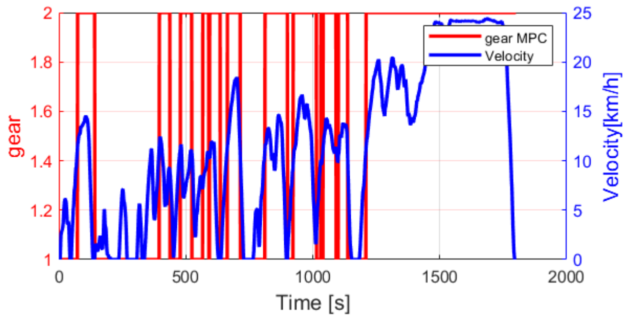

Fig.3 velocity and shift schedule based on MPC

On the one hand, when the vehicle is driving at low speed, according to the predicted results of RNN, if the velocity is only a short amount higher than the shift point, the vehicle is less likely to enter the higher gear. On the other hand, if RNN predicts that the velocity will only be briefly below the shift point and the current gear meets the power demand of the vehicle, the vehicle will not be downshifted. In this way, the MPC shift strategy greatly reduces the frequency of shift under complicated conditions while ensuring economic performance. As a result, this strategy improves ride comfort and reduces the abrasion of the shifting mechanism and saves energy consumption of the shifting process.

2.5 Conclusions

In this paper, we have established an RNN for vehicle velocity forecasts. The MAE and MSE have been reduced by 8.54% and 28.08% compared with DNN. In the framework of MPC, we use the current velocity and the predicted velocity of the RNN as short-term conditions and use the DP algorithm to optimize the gear position. The energy consumption is reduced by 2.2 percent and the shift frequency declines significantly. The results show that the MPC strategy can choose optimal shift gear for pure electric vehicles, which improves the economic performance and ride comfort evidently.

Acknowledgement

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