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a Stochastic Model Predictive Control Strategy for Extended Range Electric Vehicle

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Abstract

The Energy Management Strategy(EMS) of the Extended-Range Electric Bus (E_REB) plays an important role in the fuel economy and emission performance. This paper presents a Stochastic Model Predictive Control (SMPC) strategy based on Stochastic Dynamic Programming (SDP) and Model Predictive Control (MPC) for E_REB. SMPC applies Markov stochastic prediction model to predict the power demand of driving cycles, converts the SDP algorithm into the local optimization algorithm within the finite horizon, then the global suboptimal strategy can be obtained by solving a finite horizon optimization problem. SMPC can greatly save the online computation and operation time, achieve the goal of real-time online control. Simulation results of E_EVB are presented to demonstrate the effectiveness of the SMPC.

Keywords: Energy Management Strategy(EMS), Extended -Range Electric Bus (E_REB), Stochastic Model Predictive Control (SMPC), Markov stochastic prediction model

1. Introduction

Extended-Range Electric Bus (E_REB) can be regarded as a pure electric bus with an auxiliary power unit, Range Extender (RE), which extends the driving range, but also makes the system control more complicated, so it’s necessary to formulate a reasonable control strategy to achieve the fuel economy and

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emission performance of the vehicle [1]. At present, the research of Energy Management Strategy(EMS) in E_REB more based on that of Hybrid Electric Vehicle(HEV).

Stochastic Dynamic Programming (SDP) is widely used in the HEV, the power demand from the driver is modeled as a random Markov process [2]. SDP needs large amount of calculation and only suitable for offline optimization of the given travel mileage and predict the condition information. Some global optimization solutions such as the whole State of Charge (SOC) trajectory and the equivalent fuel consumption can provide a reference for the local optimization management strategy. Model Predictive Control (MPC) as one of the most advanced control methods, relies on prediction models to obtain a control action by solving an online optimization problem over a finite horizon, which can achieve real-time control [3].

In this paper, we present a SMPC strategy for E_REB, which can greatly save the online computation and operation time, achieve the goal of real-time control.

2. SMPC strategy for E_REB

2.1. Main parameters of E_REB

In this paper, we use a E_REB as a prototype vehicle, the main parameters of the system are shown in Table 1.

Table 1 Main parameters of E_REB

Parameter	Value
Motor rated speed (r/min)	1500
Motor rated power (kW)	132
Generator rated power (kW)	45
Generator Max. current (A)	270
Engine Max. power (kW)	41
Engine Max. torque (N · m)	98
Battery capacity of battery pack (Ah)	355
Battery voltage of battery pack (V)	400

2.2. SMPC predictive control theory

When the E_REB runs under a specified driving cycles, it’s always expected that the battery SOC will be reduced to the threshold at the end of the driving cycles. The SOC operating trajectory of the global optimization can be obtained by the SDP algorithm if the statistical information of the power demand (i.e. Markov model of the travel conditions) are known. In the actual SMPC strategy, the whole range is divided into several segments, within each segment, we use Markov models with the SDP algorithm to form the micro-scale SDP algorithm, which was embedded in the MPC model to get the global suboptimal results through continuous rolling optimization and update the running state over the prediction horizon. The basic principle is shown in figure 1.

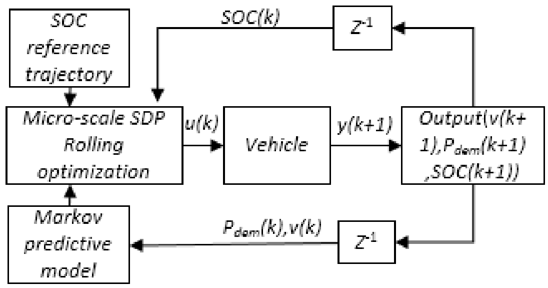

Figure. 1. SMPC principle

Where *SOC* (*k*) is the normalization of battery capacity. The input $u(k)=[Pe(k), Pb(k)]$ are the demand power provided by the RE and the battery pack. *Pdem*(*k*) is the total demand power at the time *k*.

2.3. Markov chain prediction model

Markov chain prediction model refers to a driving power stochastic model within the finite horizon, which was modeled under the current conditions of vehicle speed and power demand. It's the data source of the rolling optimization. The stochastic prediction model is based on the update of system state and Markov chain information, using maximum likelihood estimation approach to build an optimization tree at every time step, as shown in figure 2. From the root node p_0, each node of the tree represents a predicted state. p_0 is defined by the current available measured value *Pdem*(0) and *v*(0), the generation of the next candidate node sequence is obtained by considering all the possible Markov state $Pdem(k+1|k)$ and it's realization probability, then, these nodes are added to the optimization tree with maximum probability. This procedure is repeated until the final time step $k+p$ of prediction area.

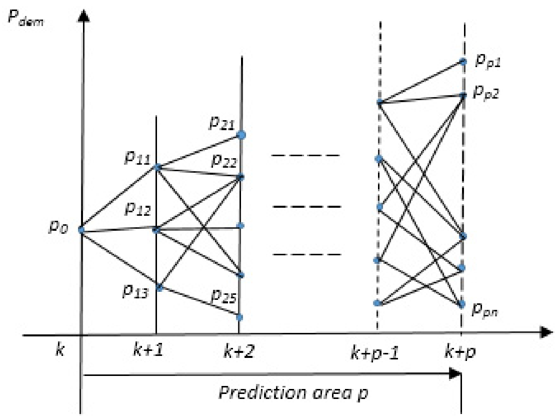

Figure. 2. Markov model optimal tree

2.4. SOC reference trajectory

Under the conditions that the information of the driving condition is insufficient or cannot carry out a large amount of calculation, SOC trajectory follow the law of SOC optimal trajectory: E_REB runs in

Blended Charge Depleting (BCD) mode in the whole range, with the increase of travel mileage the SOC is basically linear attenuation, the SOC is reduced to the threshold at the end of the range. In order to facilitate the predictive control of real-time operation, we define the SOC oblique line shown in figure 3 as the SOC reference trajectory [4].

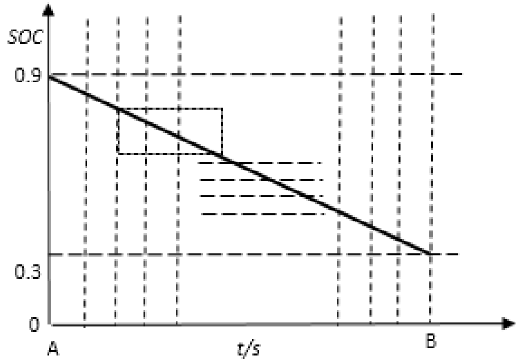

Figure. 3. SOC reference trajectory

In the course of the driving, at time k, the SOC reference value can be calculated by formula 1.

$$SOC_r(k) = \beta\bullet(D_t - t) + SOC_f \quad \beta = (0.9 - 0.3)/D_t \tag{1}$$

Where $SOC_r(k)$ is the *SOC* reference value at the time k, D_t is E_REB total driving time, SOC_f is the *SOC* value at the end of the range.

2.5. Micro-scale SDP rolling optimization

Micro-scale SDP rolling optimization [4] is the most important feature of the SMPC, by which the complex global optimization algorithm is converted to local optimization in finite horizon, and it's working principle is shown in figure 4.

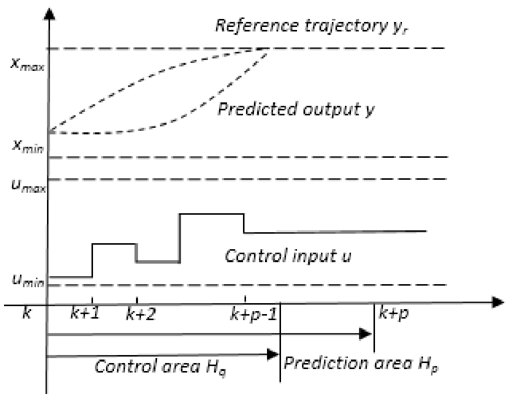

Figure. 4. rolling optimization of predictive control

Where $x(k)$, $u(k)$ are the state variables and control variables of the system, and $w(k)$ is independent random variables. Within the prediction area H_p, E_REB comprehensive fuel consumption objective function is；

$$J_0^{\pi}(x_0) = \min E\left\{\sum_{k=t_k}^{t_{k+p}} g_k(x_k, u_k, v_k)\right\}, k = 0,1.....N-1 \tag{2}$$

Where t_k is the rolling optimization start time, t_{k+p} is the finish time of the prediction horizon. g is the instantaneous cost function:

$$g_k(x_k, u_k, v_k) = \alpha_{fuel} P_{fuel}(k) + \beta * \frac{1}{\eta_{grid}} P_{elec}(k) \tag{3}$$

$$P_{fuel}(k) = \frac{P_e(k) \times dt}{3600}, P_{elec}(k) = \frac{P_b(k) \times dt}{3600}, \alpha_{fuel} = \frac{b}{\rho}, \beta = \frac{0.49}{7.86}$$

η_{grid} refers to the battery charging efficiency

b is the fuel consumption rate, g/kwh, ρ is the diesel oil density 850 g/L.

2.6. SMPC calculation procedure

After determining the SMPC model prediction method and the SOC optimized reference trajectory, the calculation procedures of the optimal control strategy are as follow:

1) At first, determine the output $y(k)$=[$Pdem(k)$, $v(k)$, $SOC(k)$] with the measured value at the current time k, from the time k, set up the Markov model of the driving cycles within a finite predictive horizon interval.

2) Using SDP algorithm to solve the constrained local optimization problem in the H_p interval, and the optimal control strategy is obtained. The optimization objective is to minimum the comprehensive fuel consumption indicator J_k without sacrificing the driving performance of the vehicle. The SOC constraints are points from the $SOC(k)$ to the reference point $SOC_r(k+p)$.

3) Once get control strategy, apply the control variable u(k)=[$Pe(k)$, $Pb(k)$] to the predictive model, then the new measured output values of vehicle system $y(k+1)$=[$Pdem(k+1)$, $v(k+1)$, $SOC(k+1)$] can be obtained.

4) Then take the time k+1 as the new starting point, determine the new finite horizon interval H_p. $SOC(k+1)$ as the starting point, $SOC_r(k+1+p)$ as the end point, [$Pe(k+1)$, $v(k+1)$] as the starting point of driving conditions, then the new Markov model is established.

5) Using the SDP algorithm to solve the optimization problem of the new finite horizon interval H_p, repeat the above procedures to form the rolling optimization. SOC rolling optimization as shown in figure 5.

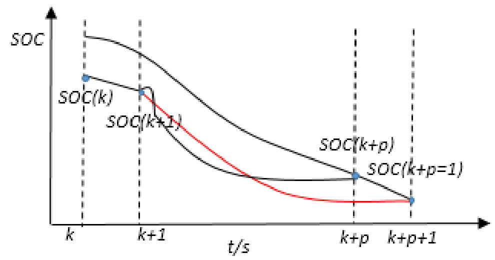

Figure. 5. SOC rolling optimization iterations

The global optimization problem of the entire driving range is converted into the local optimization problem in the finite time interval through SMPC. Because of the short time in the finite predictive horizon interval, so it can reduce the calculation amount and achieve the real-time control for the fuel economy.

2.7. SMPC simulation and results

This paper uses EPA 9× UDDS cycles as the observation sample, set up the SMPC prediction model, then the SMPC algorithm simulated through Simulink. Battery SOC interval is (0.9 0.3), the simulation duration is 12350 seconds, the finite time interval is the range of 60 nodes.

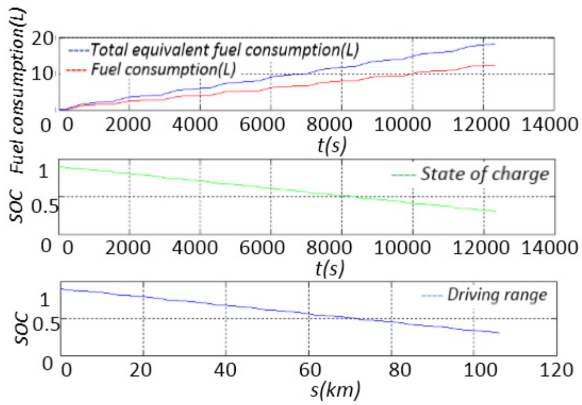

Figure. 6. the simulation results of the SMPC strategy

As seen in figure 6, the target range is 108km, the actual driving range is 106.8km, E_REB runs in (BCD) mode in the whole travel, the SOC end is 0.302, fuel consumption is 12.4L and the total equivalent fuel consumption is 18.25L. SMPC is a local optimization strategy, but it can ensure that the SOC in accordance with the SOC reference trajectory, so that the SOC can reduce to the minimum threshold at the end.

2.8. Conclusions

SMPC is proposed in this paper, the driver's power demand is modeled as a Markov chain which represents the future driver power demand under different driving conditions. With reference to the results of the global optimization, propose the SOC reference trajectory. In the process of SMPC rolling optimization, make the online local optimization results close to the global optimization results by continuous real-time feedback and correction. Compared to the whole travel of the SDP algorithm, the computational speed of the SMPC algorithm is greatly improved, which shows the great potential of the SMPC algorithm in real-time applications.

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