Energy Control of Plug-In Hybrid Electric Vehicles Using Model Predictive Control With Route Preview

Yang Zhao, Yanguang Cai, and Qiwen Song

Abstract—The paper proposes an adoption of slope, elevation, speed and route distance preview to achieve optimal energy management of plug-in hybrid electric vehicles (PHEV). The approach is to identify route features from historical and real-time traffic data, in which information fusion model and traffic prediction model are used to improve the information accuracy. Then, dynamic programming combined with equivalent consumption minimization strategy is used to compute an optimal solution for real-time energy management. The solution is the reference for PHEV energy management control along the route. To improve the system’s ability of handling changing situation, the study further explores predictive control model in the real-time control of the energy. A simulation is performed to model PHEV under above energy control strategy with route preview. The results show that the average fuel consumption of PHEV under above energy control strategy with route preview. Then, dynamic programming combined with equivalent consumption minimization strategy can be reduced compared with optimal strategy and base control strategy.

Index Terms—Energy management, model predictive control (MPC), optimal control, plug-in hybrid electric vehicle (PHEV)

I. INTRODUCTION

The increasing fuel price and pollution problem have aroused the concern for electric vehicle in transportation area. One of the most promising technologies for fuel economy and emission reduction is the plug-in hybrid electric vehicle, in which the vehicle power-train is built with an engine enhanced by a battery and electric machine. The challenge faced by vehicle power-train is the control strategy design of energy management system (EMS), which determines the power split between the engine and battery. In the past decades, there are various studies focusing on the EMS to maximize the energy efficiency for PHEVs. The researches generally believe that a near-optimal fuel economy can be achieved only if the vehicle knows the future traffic condition [1], [2]. A common way to get future information is to adopt a GPS-based navigation system with the driver inputting the destination, which provides speed and topography data to the EMS along the route. However, there are limitations for the method. The predicted traffic condition is not always the actual driving condition. In addition, the existing energy control strategies do not consider the information error, the computational demand should allow for the reasonable limitation, adding constraint on the vehicle model.

However, the recent development trend of automotives is to connect the vehicle with the traffic information center through 3G network. The traffic information center will provide real-time and predicted traffic condition information for the vehicle. Then, it is possible for the vehicle to achieve dynamic energy management. When the user inputs the destination and applies for the dynamic navigation, these data will be transmitted into traffic information center server, which identifies further traffic condition in the route and send back to the vehicle. An optimal strategy will be precomputed based on future information for the vehicle, as showed in Fig. 1.

There are two main constructing blocks of such a system, including route prediction and optimization of the EMS. Several studies have researched different short-term prediction techniques that are used to predict route characteristic from purely historical or real-time traffic data and relate the route to the vehicle operation [4], however this prediction based approach has a shortcoming that it cannot reflect the actual traffic condition accurately in a required prediction horizon. And the information error will affect the performance of energy optimization. A PHEV’s excellent energy economy is not only determined by the absorbed information, but also by the energy control strategy. A number of optimization strategies have been proposed for the EMS combining with traffic condition information [5]. Given the preview of vehicle speed, slope, and drive power demand in a drive cycle, dynamic programming can be used to identify the optimal solution on the powertrain operation globally or in a certain time horizon. The previous study in [6] has showed that knowledge of future trip information can contribute to fuel economy improvement in PHEVs. However, the requirement for future trip information makes it difficult to operate at real time for dynamic control strategy. Existing work lacks integrating route preview information with real-time implementable algorithm [7]. The dynamic programming can calculate the estimated power split based on only the future power demand regardless of past or current state of vehicle. The presumption for dynamic programming computation that may be useful for a route is that the immediate future power demand does not change greatly.
Based on the above survey, this paper makes contributions to the literature in two aspects: 1) it provides a route preview with information fusion of real-time and historic data to improve the accuracy of prediction; 2) proposes a model predictive control model to predict the energy split dynamics with optimal control while retaining the linearity of state evolution equation.

The methodology used in the paper is to identify routes from GPS driving data, using historical and real-time speed data. The data fusion model and short-term prediction model are used for the route speed prediction. As the slope and elevation are static, only speed is necessary to be predicted. After the route character is predicted, the route is identified, which is used to model the driving condition along the route. Then, dynamic programing combining with an equivalent consumption minimization strategy (ECMS) as the real-time control strategy is proposed to compute an optimal solution based on a simplified vehicle model. After the optimal trace is determined, a model predictive control model is introduced to optimize the energy system at real time within a certain prediction horizon while tracing the optimal trajectory. The objective of MPC control is to improve the system’s ability of handling changing situation by measuring and analyzing current state while adhering to constraints of vehicle character and future traffic condition. Recent scholars have put emphasis on the MPC model for the hybrid electric vehicles energy control. The MPC model is used for working with different operating conditions. Through calculating the future control methodology with quadratic programming, the manipulated variable is at real time as well as the changing MPC. The proposed MPC can improve the frequency stabilization of the system [2]. Some scholars also adopt the nonlinear model predictive control for optimizing the energy consumption. The fast and efficient control orientation model integrated with nonlinear MPC model is developed to achieve the global optimum energy control [3]. However, there is a lack of MPC control integrating with the previewed route information, which also affects the energy control for PHEV.

Outline: The paper is organized as follows. Following the introduction, the route identification procedure and the corresponding route parameter prediction are explained. The next section describes the simplified vehicle model used during the precomputations. Then, the section introduces how dynamic programming and ECMS can be used to precompute an optimal control strategy for a route. The detailed MPC model used for real-time energy control is explained in the following section. In the final part of the paper, the simulation study and its results are presented before the paper ends with a discussion and conclusion.

II. ROUTE PREVIEW

In this paper, the concept of a route preview is defined as preview of slope, elevation, vehicle speed and trip distance for the future route. The future power demand is determined by the upcoming road slope and future speed. The road terrain information can be obtained from the onboard 3-D maps and the GPS navigation system [8]. The future speed profile of the route is estimated through using real-time data and historical data.

Trip features: To facilitate the estimation, each trip is associated with a finite number of features, e.g., driving length, starting time, slope, elevation, and GPS coordinates at different positions.

A. Route Prediction

The process of route preview can be viewed as the task of estimates the route features in n links in the specific route. For each link, they have the same feature with the route, and all links get together to make the route [9]. In the study, we adopt the traffic data collected by Guangzhou Transportation Department. The route prediction based on historic and real-time data is achieved with the following procedure.

Speed prediction. The system archives historic and real-time data, the prediction of the speed based on these data is separate. The ground traffic in the same site over several logged data (a week or month) has similar intra-day trend, which has been used as approximate predicted trend. Researchers have proposed several different methods to identify the trend. We adopt a relatively practical method, that is moving average
method to predict the historic speed trend [10]. In the real-time prediction, we emphasize on improving the timeliness of the prediction, a real-time recurrent learning (RTRL) algorithm is proposed to predict future speed in a certain horizon with different steps [11].

Information fusion. In order to take into account the timeliness of the speeds as well the periodic trend, the real-time prediction model is considered to integrate the historic trend. In the study, we relate historic trend with current traffic state through building the information fusion model, and then predicting future steps of the link speed. Mathematically, the information fusion methodology is represented by the following equations:

\[ f(t) = \lambda(t)h(t) + (1 - \lambda(t))r(t) \]  

(1)

Here, \( f(t) \) is fused speed, \( \lambda(t) \) is the weight of history data in the prediction at time \( t \), \( h(t) \) is the historic trend, \( r(t) \) is the predicted speed with RTRL.

Equation (1) is a convex combination which is a standard information fusion technique used for speed estimation.

B. Route modeling

In order to optimize the energy management of PHEV in a specified route, the traffic condition along the route should be modeled in a reasonable way. The route modeling will be processed with following steps:

Step 1. For a defined route, the origin, destination and departure time are determined by the user.

Step 2. Route operation features assignment. It is assumed that there are \( k \) links in the route. All links are assigned with \( q \) features, and a link feature data matrix is formed. The row vector corresponds to the feature vectors of links, including the terrain, speed and length, etc. And the column vectors reflect the observations of the features. As the speed feature varies with time, the speed observation will be a matrix, which represents different speed profiles in \( k \) link at different time.

Step 3. The time consumption for each link at any time point can be obtained based on the speed prediction and link length. Estimate the predicted leaving time \( l_1 \) at first link and the speed of the second link \( s_2 \) with time \( l_1 \), which is used to calculate the travel time in the second link. Repeat the process until arriving the destination and get the time \( l_k \) and the speed \( s_k \) in the final link.

Step 4. Upgrade the feature vectors.

III. VEHICLE MODELING

A post-transmission parallel PHEV is selected for this study. In the vehicle, the electric motor connects with the front axle, the engine is coupled by a clutch and an automatic transmission [12]. In the vehicle model, an inverse method is used to determine the force acting on powertrain, which means that the required wheel torque \( T_r \) follows with the input speed and road slope, it is calculated by the following equation

\[ T_r = r_w \left( \frac{1}{2} \rho C_d A v^2 + m_e a + mg(f_r \cos \theta + \sin \theta) \right) \]  

(2)

where \( v \) is the vehicle speed, \( a \) is the acceleration, \( \theta \) is the road slope, \( \rho \) is the density of air, \( C_d A \) is the air drag resistance, \( f_r \) is the rolling resistance, \( m_e \) is the vehicle mass, and \( m_{ce} \) is the equivalent vehicle mass. The traction torque of the powertrain \( T_p \) is determined by

\[ T_p = \eta_f r_f (T_m + \eta_{gb,i} r_{gb,i} T_e) + T_b \]  

(3)

where \( T_m \) is the motor torque, \( T_e \) is the engine torque, and \( T_b \) is the torque of the friction brakes. \( r_f \) denotes the ratio of the final gear, and the corresponding efficiency \( \eta_f \) depends on the sign of the torque demand at the wheels. The gears, \( i = 1, \ldots, 5 \) are represented by a drive ratio \( r_{gb,i} \) and a mechanical efficiency \( \eta_{gb,i} \). It is assumed that torque responses are instantaneous and that gear shifts and the engine-state transitions are both instantaneous and lossless [8]. The instantaneous fuel mass rate is mapped from the engine torque, and the instantaneous fuel cost \( g \) is thus given by

\[ g = c_f (c_0(\omega_e) T_e + c_1(\omega_e)) e_{on} \]  

(4)

where \( c_f \) denotes the price of fuel, and \( e_{on} \) is the engine state. In addition, the output electrical power of the battery is related with motor torque. The resulting battery power \( P_b \) is given by

\[ P_b = d_0(\omega_m) T_m^2 + d_1(\omega_m) T_m + d_2(\omega_m) + P_a \]  

(5)

where \( P_a \) is the auxiliary electrical load. The coefficients \( c_{0,1} \) and \( d_{0,2} \) are determined by linear least squares from the engine and motor maps. An equivalent circuit is considered to model a Li-ion battery consisting of \( n_e \) battery cells connected in series, the parameters are listed in Table I. The battery with an open-circuit voltage and the series connection with a constant resistance \( R_i \) depends on the battery state of charge (SOC) [13]. The SOC dynamics are described by

\[ \frac{dx}{dt} = f(x, u) = -\frac{v_{oc}(x) - \sqrt{v_{oc}^2(x) - 4P_b R_i}}{2R_i Q} \]  

(6)

where \( Q \) is the battery capacity. As for the control signal \( u \) in the vehicle model, it contains the engine-state decision information, the torques of the engine and the electric motor, i.e.,

\[ u = [e_{on}, T_e, T_m] \in U(\omega_e, \omega_m) \]  

(7)

where \( U \) is the torque constraints of the engine and motor. In addition, the control signal should be selected, for example, \( T_p \) should be equal to \( T_r \). However, the choice of gear is excluded in the control signal, which is determined by a separate gearbox controller.

<table>
<thead>
<tr>
<th>TABLE I ( \text{VEHICLE DATA} )</th>
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<tr>
<td>Vehicle Mass</td>
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<td>Air res.</td>
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<td>Engine Type</td>
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<td>ICE max. power</td>
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<td>Battery Type</td>
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<td>Battery vol./cap.</td>
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<td>Max generator power</td>
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<td>Max motor power</td>
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IV. ENERGY MANAGEMENT STRATEGY

A PHEV can operate in charge-depleting (CD) mode and charge-sustaining (CS) mode. When the battery SOC is nearly depleted, the PHEV will change into CS mode through blending operation of the engine and the electric motor [8]. At the beginning of the trip, the battery SOC is high, the PHEV operates in CD mode: the battery SOC is nearly depleted with either all-electric mode or mode of blending the electric motor and combustion engine. The electric grid energy is generally economical compared with gasoline fuel energy. Thus, it is better to operate the PHEV with all-electric mode in a short trip. For the trips out of the all-electric range, hybrid operation of the electric motor and the combustion engine is presented to achieve fuel saving compared with all-electric mode. With preview of future driving condition, the vehicle can optimize the operation suggestion in all-electric CD mode or blended CD mode.

A. Rule-Based Control Strategy

The energy management control problem is to maximize fuel saving for a PHEV along a route, while adhering to the constraint and dynamics of the vehicle model. The optimal control problem can be formulated as a minimization of the overall expected energy cost:

$$J^*_{x_i}(SOC(t)) = \int_{t}^{t_f} \hat{m}_f(t, u) dt + \phi(SOC(t), SOC_f)$$

where $J^*_{x_i}(SOC(t))$ is the terminal cost at time $t$ from position $x_i$ to the end position at time $t_f$; current SOC is $SOC(t)$; $u$ is the power-split ratio, which is also the control vector. The term $\phi(\cdot)$ represents the recharge cost of the final $SOC_f$ from $SOC(t)$. As the paper focuses on the charge depletion optimization within a charge cycle, $\phi(\cdot)$ is considered to remove in this study. In addition, the solution of the optimization problem should adhere to constraints including powertrain model, physical limitation and SOC operation.

Due to the constraints and nonlinearities, there is no direct analytical solution for the optimization problem. To solve the optimal energy control problem, a two-scale DP solution is provided. In a higher layer, the dynamic programming is used to plan the battery usage with preview traffic information. In the lower layer, an EMCS real-time control strategy tracks the trajectory in the higher layer while subject to the real-time control of energy.

With preview of future velocity and future power demand, the control problem illustrated in equation (8) that subjects to model equations and constraints can be solved according to Bellman’s optimality principle and dynamic programming. In the vehicle model, the power-split controller adopts an ECMS strategy, the optimization problem is transferred to minimize instantaneous equivalent fuel rate $\hat{m}_{f,\text{equ}}$ defined as

$$\hat{m}_{f,\text{equ}}(u) = \hat{m}_f(t, u) + s(t) \frac{P_c(t, u)}{H_f}$$

where $P_c(t, u)$ is the net power charged to the battery; $s(t)$ is the ECMS equivalence factor; and $H_f$ is the fuel lower heating value.

The Hamiltonian for the cost function (8) is as follows

$$H(SOC(t), u, t) = \hat{m}_f(t, u) + \lambda(t)S\dot{O}C(t)$$

where $\lambda(t)$ is the co-state, from which the optimal value is determined by future power demands. Applying Pontryagin’s minimum principle, the co-state $\lambda(t)$ has dynamics:

$$\dot{\lambda} = -\frac{\partial H(SOC(t), u, t)}{\partial SOC(t)} = -\lambda(t) \frac{\partial S\dot{O}C(t)}{\partial SOC(t)}.$$  

As the optimal co-state depends on the future power demands, it is obtained based on future route conditions and current battery’s SOC. However, the future power demand can be obtained because of the uncertainness. We provide an estimation of optimal co-state $\hat{\lambda}(t)$ through using preview information.

From the Hamilton-Jacobi-Bellman equation, the optimal co-state $\lambda^*(t)$ can be written as

$$\lambda^*(SOC(t), x_t) = \frac{\partial J^*_{x_t}(SOC(t))}{\partial SOC(t)}$$

where $\lambda^*(SOC(t), x_t)$ is the optimal co-state determined by $SOC(t)$ and position $x_t$, and $J^*_{x_t}(SOC(t))$ is the optimized cost-to-go in (8).

Through estimating the upcoming power demand based on the traffic preview, a dynamic programming can be used to obtain the estimation of the optimal cost-to-go $\hat{J}^*_{x_t}(SOC(t))$. Then, the estimation of optimal co-state is written as

$$\hat{\lambda}^*(SOC(t), x_t) = \frac{\partial \hat{J}^*_{x_t}(SOC(t))}{\partial SOC(t)}.$$  

V. MODEL PREDICTIVE CONTROL FOR ENERGY CONTROL

A. Model Predictive Control

Model predictive control (MPC) is a methodology to repeatedly determine optimal values online in a rolling horizon for control measures, which uses optimization and prediction model for the optimization problem control [14]. The MPC can handle different constraints on system input and state. MPC also builds a feedback mechanism as it adopts a receding horizon approach.

![Fig. 2. Representation of MPC.](image-url)
The work mechanism of MPC is as follows: (see Fig. 2): the control time interval $T_{ctrl}$ is the time interval, defined as $t = kT_{ctrl}$. At each control step $k$, the current state $x(k)$ of the system is measured and the predictive state over $k$ step horizon is determined. Next, an optimization model combining with system model is used to derive the control inputs $u(k), \ldots, u(k+N_p-1)$ that optimize a given performance criterion over a given horizon $[kT_{ctrl},(k+N_p)T_{ctrl}]$ subject to constraints, where $N_p$ is the prediction horizon. To improve the computation speed, we introduce the control horizon $N_c(<N_p)$, and there is a form of $u(k+j) = u(k+j-1)$ for $j = N_c, \ldots, N_p-1$ [14].

The optimal control values are inputted in the system with a moving horizon concept: at each control time step, only the first control vector $u^*(k)$ of the optimal control sequence $u^*(k), \ldots, u^*(k+N_c-1)$ is applied to the system. Then, the prediction horizon shifts one step forward. In the next state, the optimal control problem is solved again based on the new state and the new optimal control inputs. The process is repeated until the final prediction horizon is got. As the moving horizon concept includes a feedback mechanism, it allows the system to reduce the effect of disturbances and improve the accuracy.

B. MPC Strategy for the Route

MPC can repeatedly solve optimization problems online in a rolling horizon to derive a sequence of control decisions [15]. We focus on how MPC minimizes the cost and improves vehicle energy control.

The process of MPC, seen in Figure 3, can be described in the following steps:

**Step 1:** Prediction model. The prediction model of energy demand can be generally described for

$$SOC(k+1) = f(SOC(k), u(k))$$

where $SOC(k+1)$ is the predicted state, $SOC(k)$ is current state, $u(k)$ is the control input, $f$ is the shifted function.

**Step 2:** Control Inputs. At each control step, the MPC controller obtains or predicts the current state of the vehicle energy state. Since the future slope, speed and elevation are the basic components affecting the energy consumption, control signal $u$ for the MPC problem of control step $k$ includes slope, speed and elevation in the route over the control horizon. To take the future demand of energy into account in the optimization process, we can use autonomous control for vehicle energy control between $t = (k+N_c)T_{ctrl}$ and $t = (k+N_p)T_{ctrl}$. With MPC energy control, the vehicle would be assigned with the energy model of its immediate predecessor energy splitting [14].

**Step 3:** Optimization problem. Assuming that the control interval $T$ has $N$ steps, the optimization problem of MPC can be given as

$$\min_{g(k_{ctrl})} J_{perf} = \sum_{k=k_{ctrl}+1}^{k=k_{ctrl}+N_p} m_f(k, u)$$

where $g(k_{ctrl})$ is the future control input vector for control steps. The performance criteria $J_{perf}(k)$ for MPC is the total fuel consumption in the route, which is evaluated during $[kT_{ctrl},(k+N_p)T_{ctrl}]$. Moreover, to prevent great shifting from the DP based optimal value, the performance criteria adds a penalty on variations between MPC prediction value and DP based optimal value, which results in the total performance function

$$J_{tot}(k) = J_{perf}(k) + \alpha \sum_{j=0}^{N_c-1} \| f(k+j) - f_{optimal}(k+j) \|^2$$

where $f_{optimal}(k+j)$ is the look-up value at time $k+j$ for optimal control strategy.

**Step 4:** Rolling horizon. After the control input is obtained from the optimization, the first optimal vector is transferred to the process and implemented. When the prediction model comes to the next control step, it is updated with real-time traffic data, vehicle state, and the prediction horizon is shifted one step forward, the optimization process begins again. The rolling horizon process makes the control loop close, and enables the control system obtain feedback from
the real driving system. Thus, the MPC controller is robust to disturbances [15].

C. Optimization Methods

One of the challenges in MPC approach is the extensive demand on computation. The prediction model is nonlinear, and the optimization of MPC is a nonconvex optimization problem solved online. Thus, it is essential to select a suitable optimization technology for deriving feasible optimal control vectors. In the study, global or multistart local optimization methods are necessary, including multistart sequential quadratic programming [16], multistart pattern search [17], genetic algorithms [18], or simulated annealing.

D. Performance Measures

Prediction error indices such as mean absolute relative error MARE and root relative square error RRSE are computed with Eqs. respectively.

$$MARE = \frac{1}{K} \sum_{t} \frac{|x(t) - \hat{x}(t)|}{x(t)}$$

$$RRSE = \sqrt{\frac{1}{\sum_{t} x(t)} \sum_{t} \left[ \frac{|x(t) - \hat{x}(t)|}{x(t)} \right]^2 x(t)}$$

To compare and analyze the prediction error indices in different time intervals, the real velocity and the predicted velocity will be analyzed with the prediction error analysis, which indicate the performance of MPC strategy.

VI. SIMULATION AND VEHICLE TEST

To test the proposed MPC strategy in more realistic driving scenarios, a simulation study is implemented using real-world driving condition provided by Guangzhou Traffic Analysis System, whose database contains Geographic Information System (GIS) data and the floating car data from about 16,000 taxis, gathered since 2013 in Guangzhou area. The study simulates a specified route in the system.

The data for driving condition are classified into the training period and the validation period. The training period is four weeks while the validation duration is 1 week. In the training period, the route data is used to represent the route feature as described in Section II. In the route modeling, the trip is assigned with link length, speed profile, terrain, slope, i.e., the validation period is reserved for simulation.

Only knowledge on trip distance is assumed and the simulation results provide key insights to the FE improvement potentials of MPC toward real-world applications. The traffic condition information is described in Fig. 4.

The simulation is studied with federal test cycle and real-world traffic profile. A default rule-based strategy without incorporating route information is used for comparison purpose. The default strategy applies a fixed $\lambda$ calibration that results a 35-mile PER in HWYFET drive cycle at a maximal rate of charge depletion. In the MPC control, the prediction horizon is defined as 120 second. About 2% – 7% FE improvement has been observed in the simulations for MPC strategy. For example, the simulation result from a simulation case with a 120 km trip distance and 75% initial battery SOC is plotted in Fig. 5. By incorporating the trip information, the fuel consumption for MPC is 5.4704 kg while fuel economy for basic control strategy is 5.931 kg. An 8.65% FE improvement is achieved in comparison with the basic control process.

Fig. 4. Speed, elevation and grade in the route.

Fig. 5. Battery SOC and control setpoint for MPC and basic control strategy.

The future study will explore the improvement of MPC strategies compared with optimal control strategy. In Fig. 6, the optimal battery SOC EMCS process is plotted together with that from the MPC control process for comparison. The MPC
controlled $\lambda$ setpoint converges to $\lambda^*$ adaptively. Given the knowledge of driving conditions in a trip, simulation validation is carried out using the optimized SOC profile as reference and the recommended $\lambda^*$ as feed forward $\lambda$ setpoint. The fuel economy for optimal strategy is 5.731 kg. Fig. 6 shows that the fuel consumption for MPC is 5.4704 kg, there is a 5.35% FE improvement achieved for MPC strategy comparing with optimal strategy.

Fig. 6. Battery SOC and control setpoint for MPC and optimal control strategy.

One of the advantages of MPC is its robustness to the uncertainties. To test the robustness of the operation strategy in terms of inaccuracy of the estimated velocity profile, the value of the traffic limitation as well as the configuration parameters of the driver model were disturbed with variables subject to a normal distribution and a standard deviation of 20% of the original value. Then, simulations over the same driving trip are repeatedly performed with these uncertainties and the results are statistically analyzed. The deviations between predicted and actual drive trip result in a far more frequent re-calculation of the variable. However, the fuel consumptions of the disturbed system deviate slightly from the consumptions of the undisturbed system. Fig. 7 shows an example of the simulation. The fuel consumption in disturbed system is 5.5801 kg, which is 1.9% larger than the normal system and 2.7% less than the optimal control system. The performance of the disturbed system (20% variance) with MPC strategy is worse than the normal system with MPC strategy while it is still better than the optimal control system. The result shows that the MPC control system has a good robustness in the disturbed environment. In addition, the result indicates that MPC control system has a good robustness in the energy consumption control.

With the increasing prediction horizon of the route, the vehicle can obtain more future operation state information, the fuel saving effect will be better. However, when the forecast horizon increases to a certain distance, predictive control computation efficiency is very low. Therefore, it is necessary to select a proper horizon, making the computed horizon forecast with a better fuel economy.

Fig. 7. Battery SOC for MPC, optimal control and MPC (20% variance) strategy.

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<thead>
<tr>
<th>Prediction horizon (s)</th>
<th>Fuel economy (kg)</th>
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<tbody>
<tr>
<td>20</td>
<td>5.582</td>
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<tr>
<td>40</td>
<td>5.557</td>
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<td>60</td>
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<td>160</td>
<td>5.371</td>
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<td>180</td>
<td>5.387</td>
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We can see from Table II, with the increase of the prediction horizon, the equivalent fuel consumption is reduced gradually. With prediction horizon increasing, the vehicle can obtain more future traffic information, and modify to special work conditions of the engine earlier. When the forecast horizon is more than 160 second, equivalent fuel consumption slightly increased, this is led by the accumulation calculation error of MPC. Considering a reasonable fuel economy, we select a length of 140 seconds as the forecast horizon. Comparing with the previous control strategies, it is obvious that the fuel economy is better no matter how long the prediction horizon is. Thus, in the actual energy control, it is necessary to combine the MPC model and the route preview information, thus optimizing the system and obtaining the maximum operation effectiveness.

VII. CONCLUSIONS

This paper presents real-time control strategies for PHEV energy management that takes advantage of traffic information preview. The proposed strategies aim at fuel minimization for PHEV. Initially, the route features are identified with information fusion model and prediction model for historical and real-time traffic data. The objective of fuel saving is achieved at three levels: 1) the route preview information is used for global optimization estimation of fuel-electricity usage solution; 2) the ECMS is applied to achieve real-time optimal energy control with information of instantaneous power demand, current value of batter’s SOC and the global optimization parameters; 3) the MPC is designed to control the electricity
consumption ratio along the route based on future power demand, historical and current value of battery’s SOC and instantaneous optimization parameters. The simulation study shows that there is fuel saving by applying the energy control strategies with route preview. MPC control indicates 8.65% improvement compared with base control strategy and 5.35% improvement compared with optimal control combined with ECMS. Another simulation indicates that the MPC strategy has a good robustness. In addition, the prediction horizon of MPC affects the energy control effect, a 140 second prediction horizon leads to a better control result.

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