Game-theoretic Energy Management with Velocity Prediction in Hybrid Electric Vehicle

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***Abstract*—This paper studies a game-theoretic energy management for hybrid electric vehicle (HEV), combining of engine-generator, battery and ultracapacitor (UC). Each energy source has different utility function with different preference. Here, we use game-theoretic strategy to dispatch power because it can represent different preferences for different components. In addition, a game-theoretic strategy with velocity prediction (VP) is proposed to improve the basic game-theoretic strategy, ie., game-theoretic management without velocity prediction. Here, a recurrent neural network long short term memory (RNN-LSTM) structure is implemented to predict future velocities. Since the dataset of driving cycles has only one feature, velocity, two different feature engineering methods are proposed to improve the accuracy of VP. Next, Nash equilibrium of game-theoretic management has been realized through the best response functions and the performance of game-theoretic management has been carried out. Finally, four criteria are used to quantify the performance of the proposed energy management and that of the game-theoretic management without VP. A comparative analysis in simulation results validates that the proposed method gives a better performance with less battery power variation, more battery usage power, less engine-generator energy and more UC average energy difference.**

***Index Terms*—Velocity prediction, recurrent neural network long short term memory , hybrid electric vehicle, game-theoretic energy management.**

I. Introduction

Due to energy crisis and global warming, pure electric vehicles have been considered as a promising solution to release the environmental issue [1]. Because of the limited power density of battery, battery-ultracapacitor (UC) hybrid energy system was proposed to protect battery [2], where UC with high-power density works as an energy buffer. Besides, because of the limited energy capacity of battery, the battery-UC hybrid energy system can't serve for a long-distance trip and will cause driving range anxiety [3]. Thus, hybrid electric vehicle (HEV), combining of engine-generator, battery and UC, has been studied in recent years [4]–[6]. However, due to the existence of three energy sources with different charachteristics and demand fluctuation for driving dynamics, it is necessary to design an energy management approach to dispatch power.

Energy management strategies for multiple energy sources have been proposed in HEV [7]–[10]. In a battery/UC hybrid energy system, a fuzzy logic-based energy management strategy had been designed for controlling the state of charge (SOC) of UC while smoothing the battery power profile [8]. Taking advantage of the characteristics of each device in hybrid energy system, a game theory-based control strategy was proposed in [9]. The energy management problem was formulated as a Non-cooperative game and the existence of Nash equilibrium was proved. Besides, a weight coefficients tuning process was proposed to further improve the adaptiveness of the real-time energy management [10]. Although these algorithms presented good performaces, they didn't consider the future information or velocity prediction (VP).

In terms of velocity prediction, many efforts have been made. The future velocity profile of a vehicle is not only determined by the present state of velocity, but also by the traffic conditions, weather, and driving behaviors, etc. Combining historical velocity, traffic conditions, road information and weather, big data based deep learning approach was a proper solution to predict future velocity profile [11]. Based on big data and neural network, a two-level data driven model was proposed to accurately predict future velocity [12]. However, it is difficult to get a large amount of data from various databases [11], [12] and analyze them in real-time running of HEV. Some authors treated the velocity prediction as a time series problem and solved it through neural network [13]. Based on historical velocities, the context-aware nonlinear autoregressive model with exogenous inputs was used to predict velocity [13].

To the best knowledge of the authors, game theory and velocity prediction have not been introduced in the literature of HEV. Game theory has further applications to develop optimal strategies with considering future information. Considering velocity prediction in the preferences of three energy sources (engine-generator, battery, and UC) in HEV will give a better performance. To this aim, a game-theoretic energy management with velocity prediction in hybrid electric vehicle is proposed in this paper. In this way, we can utilize the decentralized control with the prediction benefits. Below are the contribution points of this paper,

1) Comparing with basic game-theoretic management, a game-theoretic management with velocity prediction is proposed in hybrid electric vehicle.
2) Based on limited dataset, two feature engineering methods were proposed to improve the accuracy of velocity prediction.

This paper is organised as follows. Section II describes the system configuration, devices modeling. Velocity prediction using recurrent neural network long short term memory (RNN-LSTM) is implemented in section III. Construction of normal form game of the HEV energy sources with their utility functions are presented in section IV. A comparison analysis of the game-theoretic energy management with/without velocity prediction in simulation is presented in section V. Finally, the conclusion is given in section VI.

II. System Configuration and Modelling

A. System Configuration

As shown in Fig. 1, the system configuration consists of velocity prediction and power distribution parts. In prediction part, we used neural network to predict future velocities. Current and future load demands can be attained through longitudinal vehicle dynamics model. In power distribution, the hybrid eletric vehicle system consists of engine-generator, battery pack, UC pack and load. The engine-generator consists of an engine, a three-phase AC generator, a rectifier for AC-DC conversion and a DC-DC converter [9]. The battery and UC are connected into system through their dc-dc converters. The structure is a parallel-active topology, which can provide more reliability and flexibility than other topologies [14]. The battery and UC Powers can be controlled through tuning the duty cycles of their DC-DC converters.

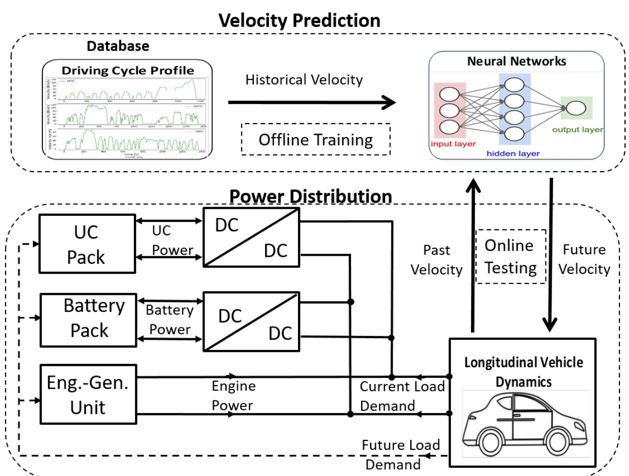

Fig. 1. System configuration.

B. Devices Modeling

As shown in Fig. 1, there are four devices in the system including three energy sources (i.e., engine-generator, UC and Battery) and longitudinal vehicle dynamics.

The engine-generator is modeled based on the engine torque-speed map and generator efficiency map [9]. While, battery and UC pack are modeled through their equivalent circuits, as shown in Fig. 2. The equivalent circuit model of battery consists of open circuit voltage (U_{oc})), internal resistance (r_b) and two resistance networks ($R_{t,s}, C_{t,s}$ and $R_{t,m}, C_{t,m}$), as shown in Fig. 2(a). The equivalent circuit model of UC pack consists of capacitance (C), internal resistance ($R_{c,s}$) and leakage current modelling ($R_{c,p}$), as shown in Fig. 2(b).

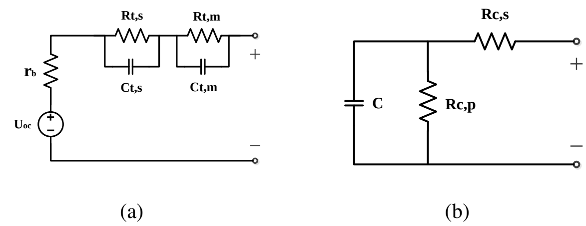

Fig. 2. The equivalent circuit models of (a) Battery pack. (b) UC pack.

Through the longitudinal vehicle dynamics model, we can calculate the power consumption (Load demand) of vehicle. To calculate the power consumption under certain velocity, acceleration and road condition, we consider a widely-used model to represent the power demand for propelling the vehicle. The longitudinal vehicle dynamics model is based on the free body of the vehicle shown in Fig. 3, where aerodynamic force (F_{aero}), friction force (F_{Tire}), gravity force ($F_{grav} = mg\sin(\theta)$) and acceleration force ($F_{Traction}$) are the applied forces of the vehicle.

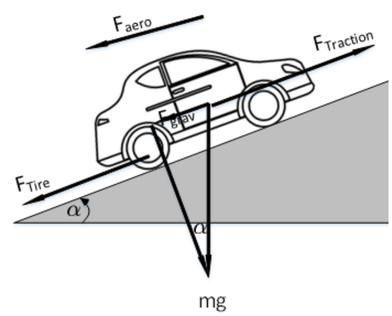

Fig. 3. Longitudinal vehicle dynamics model.

III. Velocity Prediction

Velocity prediction is a nonlinear problem with highly dynamics so that we can't type down an equation for it. Here, we use neural network (NN) to predict the velocity since it can be trained to learn a highly nonlinear input/output relationship [15]. Since it is hard to get enough historical driving data, weather information, traffic condition, road information, etc, we decide to use typical driving cycles as dataset and treat it as a time series [15]. A RNN-LSTM structure is well-suited to predict time series because it can capture the long-term dependency in time series [16]. Therefore, we use RNN-LSTM structure to predict future velocity.

We first collect 18 typical driving cycles and build the database, and then use neural network to predict future velocity. The time step for driving cycles is one second.The RNN-LSTM has three layers: input, output and one hidden layer in between. The hidden layer has 30 neural cells while the number of neural cells in input and output layer are decided by the dimension of the input sequence h_i and prediction horizon h_o, respectively. Here, we define $h_i = 5h_o$. The input of RNN-LSTM is historical sequence and the output is the future velocity sequence. Each input-output pattern is composed of a moving window of fixed length, which can be expressed as:

$$[v^{k+1}, \ldots, v^{k+h_o}] = f_{NN}(\Gamma^{k-h_i+1}, \ldots, \Gamma^k), \tag{1}$$

where $\Gamma^k = v^k$ means the velocity at time k, and f_{NN} represents the nonlinear map function of the RNN-LSTM.

Here, there is only one feature, velocity, in the input sequence , which limits the prediction potential of RNN-LSTM. Thus, we pay more attention to feature engineering to improve the prediction accuracy.

A. Feature Engineering

Many features can be derived from historical velocity sequence and used to characterize the operating dynamic state of the vehicle, such as acceleration, average speed and average acceleration. Two feature engineering methods are introduced to improve prediction accuracy.

1) First Method: We treat the prediction problem as a time-series problem. Based on historical velocities, we can get accelerations and the input $\Gamma^k = [v^k, a^k]$ becomes a vector of velocity and acceleration (a^k) at time k respectively. Each input-output pattern as shown in Fig. 4(a). Since the hidden layer has 30 neural cells and each input will go through LSTM structure, then the h_i inputs in this method have go through $30h_i$ cells.

2) Second Method: In the second method, we treat the prediction problem as a multi-series problem. Inputs are classified into h_o groups. Each group of inputs is corresponding to one instant output, as shown in Fig. 4(b). Each group has $\frac{h_i}{h_o}$ instants input and go through $30 * \frac{h_i}{h_o}$ cells. Here, $\frac{h_i}{h_o} = 5$ and it should be a positive integer.

$$Inputs = \begin{cases} [\Gamma^{k-h_i+1}, \ldots, \Gamma^{k-h_i+(N-1)h_o+1}], \\ [\Gamma^{k-h_i+2}, \ldots, \Gamma^{k-h_i+(N-1)h_o+2}], \\ \quad \ldots \\ [\Gamma^{k-h_i+h_o}, \ldots, \Gamma^k]. \end{cases} \tag{2}$$

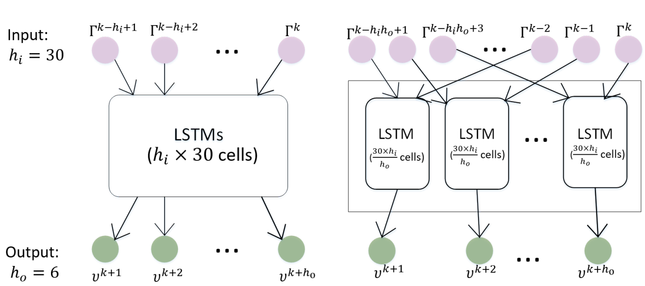

Fig. 4. Feature engineering of (a) First method. (b) Second method.

B. Performance of Velocity Prediction

Here, we compare the performance of the two feature engineering methods which are described in previous section. We choose NEDC and UDDS cycles as two testing sets, and use three evaluation criteria to evaluate the performance.

1) Mean Absolute Error (MAE):

$$MAE = \frac{1}{T}\sum_{t=1}^{T} |y_t - y_t^*|\,. \tag{3}$$

2) Mean Absolute Percentage Error (MAPE):

$$MAPE = \sum_{t=1}^{T} \frac{|y_t - y_t^*|}{y_t} \times 100\%. \tag{4}$$

3) Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{1}{T}\sum_{t=1}^{T} (y_t - y_t^*)^2}. \tag{5}$$

where y_t is the actual velocity at time instant t, and y_t^* is the predicted velocity.

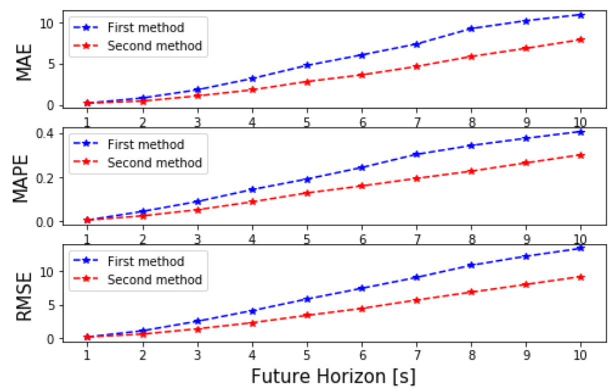

Fig. 5. Performance comparison in velocities prediction.

The performance comparison of two feature engineering methods is shown in Fig. 5, where X axis is prediction horizon. We observe that the accuracy of second method is better than that of first method. Thus, we choose the second method for feature engineering in velocity prediction. The velocity prediction for NEDC and UDDS driving cycles are shown in Fig. 6, where the prediction horizon is 6.

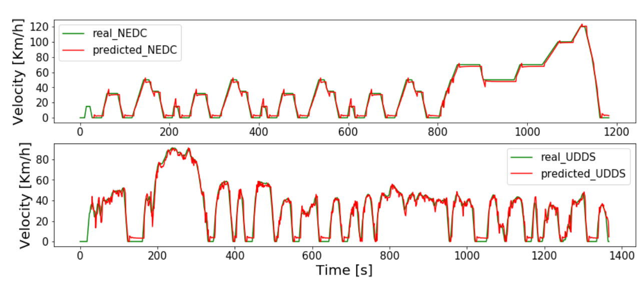

Fig. 6. Driving cycles.

IV. Game-Theoretic Energy Management

In this section, we introduce game theory as a mathematical tool to solve the energy management in the HEV. Game-theoretic energy management with/without velocity prediction is proposed and can be solved using a normal form game $G = [3, (P_g, P_b, P_c), (U_g, U_b, U_c)]$. The engine-generator, battery and UC pack are treated as selfish players and form an Non-cooperative game. At each time instant, each player needs to determine its strategy, i.e., the value of the corresponding power (P_g, P_b, P_c). Appropriate utility functions for three energy sources (U_g, U_b, U_c) have been defined, which can quantify the degrees of preference across alternatives. Nash equilibrium in game-theoretic energy management has been solved through the best response functions.

A. Utility Functions

1) Engine-generator: wants to maximize its fuel economy. Here, we define the utility function of engine-generator to provide power as close as possible to the optimal power for maximizing fuel economy. The utility function of engine-generator is defined as follows.

$$U_g = 1 - n_g(P_g - P_g^*)^2, \tag{6}$$

where P_g is the power of engine-generator and P_g^* is the optimal power that maximizes fuel economy [10]. The n_g is a normalization factor [0,1] which can be defined as follows,

$$n_p = \frac{1}{(P_g^*)^2}. \tag{7}$$

Because the optimal power for maximizing fuel economy is decided by the characteristics of engine-generator [17], the utility function with velocity prediction is the same as that without velocity prediction.

2) Battery Pack: wants to extend its cycle life, which can be achieved by minimizing the amplitude and the variation of battery power [18]. The two-objective function of battery pack is defined as

$$U_b = w_{b1}U_{b1} + w_{b2}U_{b2}, \tag{8}$$

where w_{b1} and w_{b2} are weight coefficients, U_{b1} and U_{b2} are the sub-utility functions for minimizing the amplitude and the variation of battery power respectively.

First, to minimize the amplitude, the sub-utility function U_{b1} is defined as,

$$U_{b1} = 1 - n_{b1}(P_b - P_{bave})^2, \tag{9}$$

where P_b is the battery power, P_{bave} is the mean value of P_b over a period of time and n_{b1} is a normalization factor [0,1] which can be defined as follows,

$$n_{b1} = min\left\{\frac{1}{(P_{bmax} - P_{bave})^2}, \frac{1}{(P_{bmin} - P_{bave})^2}\right\}, \tag{10}$$

where P_{bmax} and P_{bmin} are the maximum and minimum values of P_b.

Without VP, the P_{bave} is the mean value of P_b from beginning to current control instant. If considering VP, the battery pack will minimize the amplitude with considering future battery power. Thus, the P_{bave} is shown in Eq. (11-13).

$$P_{bave} = \begin{cases} \frac{1}{T}\sum_{i=1}^{T} P_b(i), & without\ VP, \\ \frac{\sum_{i=1}^{T} P_b(i) + h_o P_{bpre}}{T + h_o}, & with\ VP, \end{cases}, \tag{11}$$

$$P_{bpre} = \lambda \frac{\sum_{i=t+1}^{t+h_o} P_{lpre}(i)}{h_o}, \tag{12}$$

$$\lambda = \frac{1}{h_o}\sum_{i=t-h_o}^{t} \frac{P_b(i)}{P_l(i)}, \tag{13}$$

where t is the current control instant and T is the period time from beginning to time t. h_o is the prediction horizon of VP. P_{bpre} is the mean value of future battery power over horizon h_o, determined by future load power P_{lpre}. λ is the ratio of battery power to load power P_l, which is calculated by historical battery power and load power.

Second, to minimize the variation, the sub-utility function U_{b2} is defined as,

$$U_{b2} = 1 - n_{b2}(P_b - P_{blast})^2, \tag{14}$$

where P_{blast} is the battery power in the last control instant and n_{b2} is a normalization factor [0,1] which can be defined as,

$$n_{b2} = min\left\{\frac{1}{(P_{bmax} - P_{blast})^2}, \frac{1}{(P_{bmin} - P_{blast})^2}\right\}. \tag{15}$$

3) Ultracapacitor Pack: works as an energy buffer and aims to maintain energy capability. Thus, we define the stored energy be as close as possible to its initial state by assuming the desired initial voltage as,

$$V_{cini} = \sqrt{\frac{V_{cmax}^2 + V_{cmin}^2}{2}}. \tag{16}$$

The desired power can be formulated as,

$$P_c^* = 2P_{cmax} \cdot \left(\frac{v_c^2 - V_{cini}^2}{V_{cmax}^2 - V_{cini}^2}\right) - P_{cmax}, \tag{17}$$

where V_{cmax} and V_{cmin} are the upper and lower bounds of the UC pack voltage, P_{cmax} is the maximum power of the UC packand v_c is the UC voltage.

The utility function of the UC pack is defined as,

$$U_c = 1 - n_c(P_c - P_c^*)^2, \tag{18}$$

where n_c is the corresponding normalization factor.

Without VP, the v_c in Eq.(17) is the UC voltage at current control instant t, $v_{c,t}$. If considering VP, it will be represented as $v_{c,pre}$, i.e.,

$$v_c = \begin{cases} v_{c,t}, & without\ VP, \\ v_{c,pre}, & with\ VP, \end{cases} \tag{19}$$

4) Three Utility Functions: P_g, P_b, P_c must satisfy the energy conservation law which is formulated as follows.

$$P_c = P_l - P_g - P_b. \tag{20}$$

To combine this equality constraint with the utility functions, we change three-players game into two-players game $G = [2, (P_gc, P_bc), (U_{gc}, U_{bc})]$. The utility function of UC pack is added to the other two functions because the UC pack is working as an assistive device in this system. The utility functions of engine-generator U_{gc} and battery pack U_{bc} are modified by adding several weights as follows,

$$U_{gc} = w_g U_g + w_{cg} U_c, \tag{21}$$
$$U_{bc} = w_{b1} U_{b1} + w_{b2} U_{b2} + w_{cb} U_c. \tag{22}$$

where these weights can been determined similar to [9].

B. Nash Equilibrium

As all of them want to maximize their own profits, the Nash Equilibrium in game-theoretic energy management can be obtained through the best response functions. The best response functions are to choose the strategy to maximize their own utilities given the strategies of the others are fixed, which are obtained by taking the partial derivatives of utility functions as follows,

$$\frac{\partial U_{gc}}{\partial P_g} = 0, \frac{\partial U_{bc}}{\partial P_b} = 0. \tag{23}$$

Solving the functions, we can get the power dispatch.This also proves the existence and uniqueness of the pure strategy Nash equilibrium of normal form game.

$$P_g = \frac{2n_g w_g P_g^* + 2n_c w_{cg}(P_l - P_b - P_c^*)}{2n_g w_g + 2n_c w_{cg}}, \tag{24}$$
$$P_b = \frac{2n_{b1} w_{b1} P_{bave} + 2n_{b2} w_{b2} P_{blast} + 2n_c w_{cb}(P_l - P_g - P_c^*)}{2n_{b1} w_{b1} + 2n_{b2} w_{b2} + 2n_c w_{cb}}. \tag{25}$$

V. Simulation Results and Analysis

The simulation is implemented under Python environment. The time step is one second. Here, we first evaluate the performance of velocity prediction, and then the performance of the GTEM with/without VP.

A. Determination of Prediction Horizon

In this section, we define the best horizon for the velocity prediction based on the overall performance of the proposed game theoretic energy management with velocity prediction. The overall criterion constructed from four criteria which represent the performance of each player, as shown in Eq.(26).

$$P = \sqrt{\mu_{Eg}^2 + (1 - \mu_{pb})^2 + (\sigma_{pb}^2)^2 + (1 - \mu_{Ec})^2}. \tag{26}$$

where μ_{pg} is the average engine power, μ_{pb} is the average battery power, σ_{pb}^2 is the variance of battery power and μ_{Ec} is the average energy difference between the energy stored in the UC pack and the desired initial energy with the following formulas.

$$\mu_{Eg} = \frac{1}{T}\sum_{i=1}^{T} P_g(i), \tag{27}$$
$$\mu_{pb} = \frac{1}{T}\sum_{i=1}^{T} P_b(i), \tag{28}$$
$$\sigma_{pb}^2 = \frac{1}{T}\sum_{i=1}^{T} (P_b(i) - \mu_{pb})^2, \tag{29}$$
$$\mu_{Ec} = \frac{1}{T}\sum_{i=1}^{T} \left| \frac{1}{2} C v_c^2(i) - \frac{1}{2} C V_{cini}^2 \right|. \tag{30}$$

An offline simulation is carried out to decide the prediction horizon h_o. Here, we use historical driving profile to do offline simulation, and then get their criteria for 10 prediction horizons. We normalize each criterion, that is the range set for each criterion is $[0, 1]$. Finally, use Eq.(26) to calculate the overall performance for each prediction horizon. Since the less engine power μ_{Eg}, more average battery power μ_{pb}, less variance of battery power σ_{pb}^2 and more UC average energy difference μ_{Ec} are preferred, the lower P value means better the performance. From Fig. 7, we can see that P value of energy management with prediction horizon 6 is lowest. Therefore, prediction horizon $h_o = 6$.

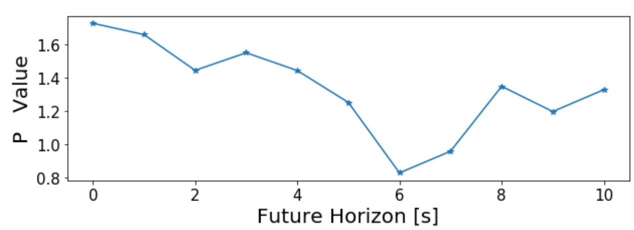

Fig. 7. Overall-performance comparison for different horizons.

B. Performance Comparison

We will compare the results represented by the four mentioned criteria for the two types of game, the GTEM without VP (GT-NVP) and the proposed GTEM with VP (GT-VP). Here, two driving cycles NEDC and UDDS are used for testing.

The simulation results for NEDC driving cycle are shown in Fig. 8. In the three sub-figures, green curves are the simulation results for GT-NVP while the red curves for GT-VP. From the second sub-figure, we can see that the battery power of GT-VP is more smooth and steady that of GT-NVP, while the comparison of other two sub-figures aren't clearly. Thus, we quantify the comparison of GT-NVP and GT-VP by four preformance criteria, as summarized in Table. I. The variation of battery power σ_{pb} of GT-VP is smaller than that of GT-NVP and it has decreased 6.84%, i.e., more smooth and steady. The average battery power μ_{pb} of GT-VP is larger than that of GT-NVP, almost increase 8.21%, which means more battery power was used in GT-VP. Besides, less engine-generator energy and more average energy difference for UC pack are preferred. The simulation results for UDDS driving cycle are also quantified by four preformance criteria, as shown in Table. I. In sum, four criteria of GT-VP are better that of GT-NVP in two testing driving cycles. By that, our proposed game-theoretic energy management with velocity prediction is better than game-theoretic energy management without velocity prediction.

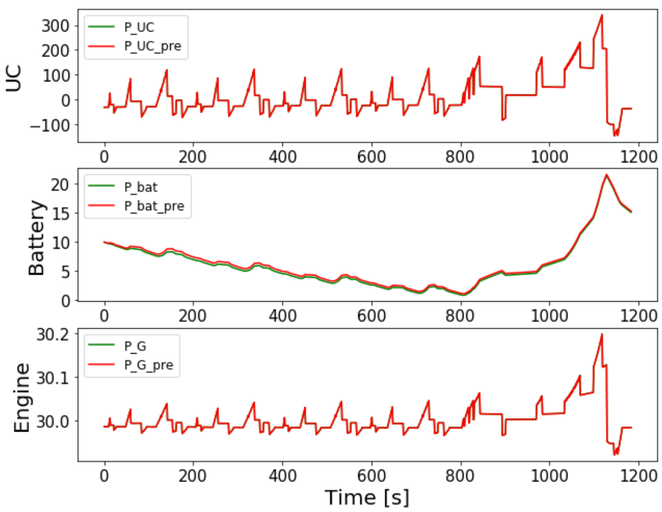

Fig. 8. Simulation results.

TABLE I
EVALUATION CRITERIA COMPARISON

Cycles	Approach	μ_{pg} (w)	μ_{pb} (w)	σ_{pb} (w^2)	μ_{Ec} (J)
NEDC	GT-NVP	35552	12.194	59.231	29409
	GT-VP	35551	12.215	55.178	29451
	Comparison	$-0.03‰$	8.21%	-6.84%	0.143%
UDDS	GT-NVP	40731	12.570	55.496	30065
	GT-VP	40731	12.619	54.659	30079
	Comparison	$=$	$3.90‰$	-1.51%	$0.465‰$

VI. CONCLUSION

In this paper, a game-theoretic energy management with velocity prediction for hybrid electric vehicle is proposed to dispatch power among three energy sources, ie., engine-generator, battery and ultracapacitor. Here, based on 18 typical driving cycles, we train a recurrent neural network long short term memory structure to predict future velocity. Due to the limited feature of the dataset, two different feature engineering methods are used to improve the accuracy of velocity prediction. Besides, three evaluation criteria are used to evaluate the performance of velocity prediction. Moreover, the game-theoretic energy management problem has been solved through the best response functions and the existence of Nash equilibrium has been proved. Finally, two testing driving cycles, NEDC and UDDS are used to perform the online simulation and the performance of game-theoretic management has been carried out. Four criteria are used to quantify the performance of the proposed energy management and that of the game-theoretic management without velocity prediction. The comparative analysis in simulation results demonstrated that the proposed method gives a better performance with 6.84% decrement of the battery power variation, 8.21% of increment of the battery usage power, less engine-generator energy and more UC average energy difference.

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