

Article

# Model Predictive Control Based Energy Management Strategy of Series Hybrid Electric Vehicles Considering Driving Pattern Recognition

Jinna Hao <sup>1</sup>, Shumin Ruan <sup>2,\*</sup> and Wei Wang <sup>3</sup>

<sup>1</sup> College of Computer & Information Engineering, Central South University of Forestry and Technology, Changsha 410004, China

<sup>2</sup> School of Mechanical Engineering, Beijing Institute of Technology, Beijing 100081, China

<sup>3</sup> School of Information and Communication Engineering, Dalian University of Technology, Dalian 100081, China

\* Correspondence: hakima@outlook.com

**Abstract:** This paper proposes an energy management strategy for a series hybrid electric vehicle based on driving pattern recognition, driving condition prediction, and model predictive control to improve the fuel consumption while maintain the state of charge of the battery. To further improve the computational efficiency, the discretization and linearization of the model is conducted, and the MPC problem is transferred into a quadratic programming problem, which can be solved by the interior point method effectively. The simulation is carried out by using Matlab/Simulink platform, and the simulation results verify the feasibility of the condition prediction method and the performance of the proposed method. In addition, the predictive control strategy successfully improves the fuel economy of the hybrid vehicle compared with the rule-based method.

**Keywords:** pattern recognition; condition prediction; model predictive control; energy management strategy; hybrid electric vehicles



**Citation:** Hao, J.; Ruan, S.; Wang, W. Model Predictive Control Based Energy Management Strategy of Series Hybrid Electric Vehicles Considering Driving Pattern Recognition. *Electronics* **2023**, *12*, 1418. <https://doi.org/10.3390/electronics12061418>

Academic Editors: Danial Karimi and Amin Hajizadeh

Received: 1 February 2023

Revised: 11 March 2023

Accepted: 15 March 2023

Published: 16 March 2023



**Copyright:** © 2023 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

## 1. Introduction

With the increasing interest and investment in the field of new energy in the world, we have reason to believe that a revolution in vehicle technology is coming. Against this background, many new energy vehicles have mushroomed. At present, the most common and mature plug-in hybrid vehicles in the civil vehicle market are the Toyota Prius and hybrid versions of various models. There are also plug-in pure electric vehicles. Under the policy guidance, the demand for pure electric vehicles is increasing. In addition, fuel cell vehicles can realize the vision of no fossil energy consumption and zero emissions, which is also a hot research field for new energy vehicles. However, the development direction of hybrid electric vehicles is more flexible because of the characteristics of multiple energy sources. In hybrid electric vehicles, according to the layout structure and output energy form of power components, they can be divided into three types: series, parallel, and serial-parallel [1].

### 1.1. Literature Review

For series structure, the engine and generator are combined in series and connected in parallel with the battery. The electric power is transferred to the motor through the bus and then converted into mechanical energy, which is output to the driving wheel. This connection mode has a relatively low occupancy of space, so the degree of freedom of space layout is quite large. In addition, since the type of energy output to the motor is electrical energy, the engine generator set is not mechanically connected with other components, so the fluctuation of vehicle speed is all regulated by the motor, which can realize the

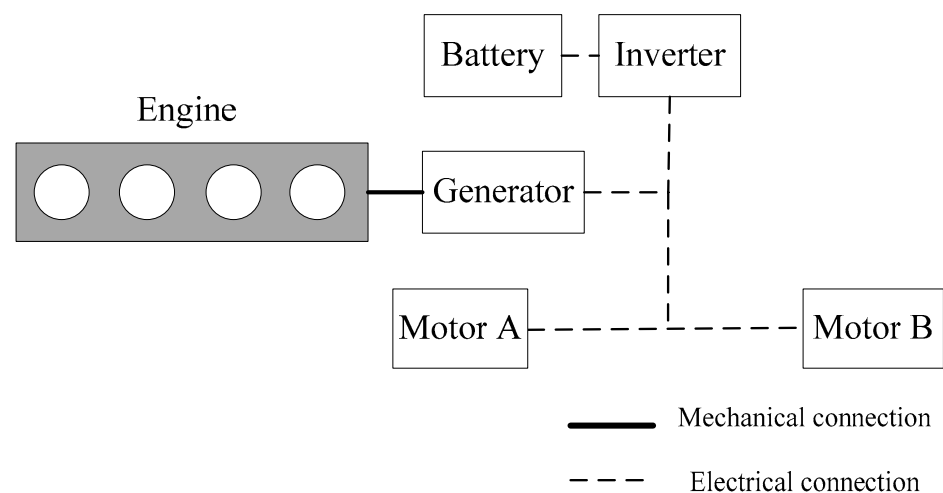
decoupling between the engine and the ground, and is conducive to the efficient work of the engine [2].

For parallel structure, the engine is connected in parallel with the battery and the motor. The mechanical power generated by the former and the power generated by the latter need to be transferred to the coupling mechanism and then distributed to the driving wheel, which leads to the engine not completely decoupled from the ground. When the vehicle is driving in the hybrid mode, its working point is bound to be affected by the speed change, and it cannot always be guaranteed to work in the efficient area. However, this connection mode has a high energy utilization rate, and the power requirement of the engine is not very high. The energy source outputs mechanical power and electrical power.

The feature of serial-parallel structure is that it includes both series and parallel structures, so it also has the characteristics of both structures, which can more flexibly combine the working modes of various energy sources. This structure is adopted by the Toyota Prius.

This study is mainly aimed at series hybrid electric vehicles, as shown in Figure 1. Additionally, the improvement of vehicle performance by good control strategies is mainly reflected in the following aspects:

1. As a complex power component, the performance of the engine in dynamic response is often unsatisfactory. In addition to the characteristics of preheating before stable operation, the battery output can be dominant when the vehicle is started. This is due to the fast response of the battery and the characteristics of the motor-low speed and large torque. Under this condition, the vehicle can start quickly and smoothly, the acceleration performance is significantly improved, the power output is stable, and the emission reduction of the vehicle is also significantly improved [3].
2. The service life of the engine will be correspondingly increased because it can avoid the engine working in the inefficient area.
3. During braking and downhill deceleration, the braking energy can be recovered and stored in the battery.

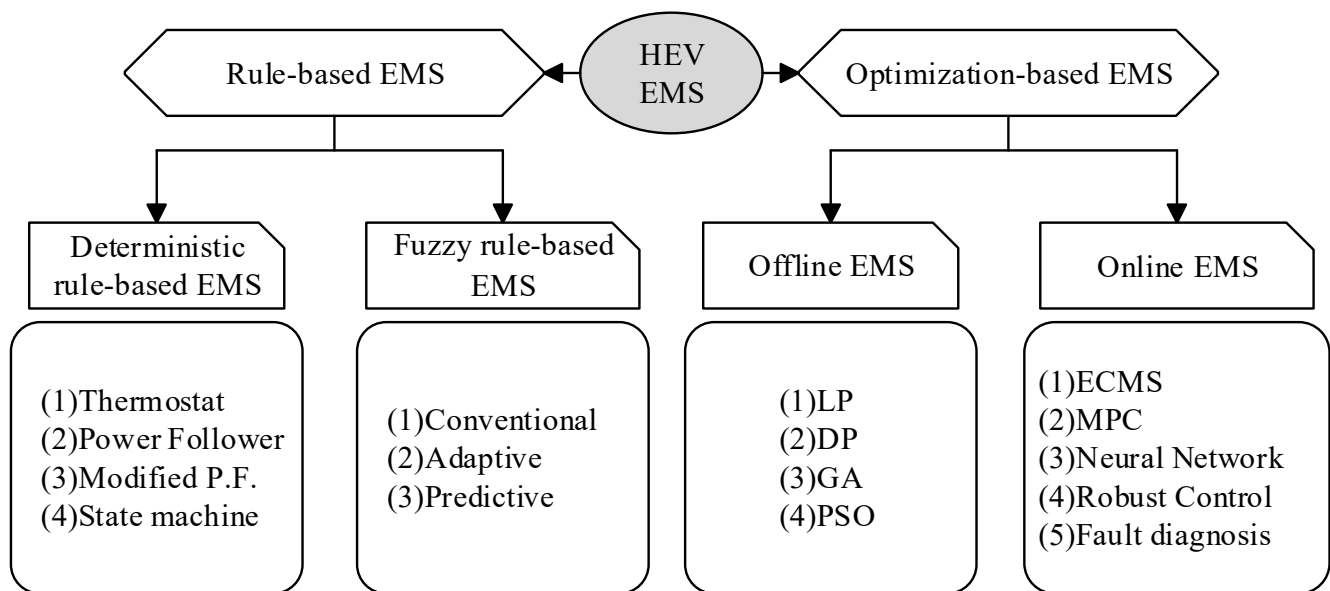


**Figure 1.** Structure of the series hybrid electric vehicle.

For these reasons, for systems with multiple energy sources, the coordination of power distribution among energy sources is crucial to fuel economy, driving performance and emission reduction. Especially for the series non-plug hybrid electric vehicles, the battery capacity is generally small, and the energy is mainly provided by the engine. The battery plays the role of instantaneous supplement of insufficient power. Controlling the charging and discharging of the battery is extremely important to maintain the health of the battery and the energy utilization rate of the whole vehicle. The challenges of the current energy management control strategy lie in the following aspects:

1. The system description of vehicles is often complex and nonlinear, which has caused a huge obstacle to simulation modeling and control strategy design. How to describe the system reasonably, reasonable simplification, and mathematical processing are essential.
2. The conditions encountered by the vehicle during the driving process are changeable and the speed of change is extremely fast, and the basis of energy management decision-making is difficult to accurately determine.
3. The driving styles of drivers are different, and the terrain that vehicles encounter at every moment is also changeable [4,5]. Therefore, in future research, vehicles should be considered as a part of a larger system, and energy management should be allocated in combination with various information.

Energy management strategies can be divided into two categories in terms of control methods: rule-based control strategies and optimization-based control strategies, as shown in Figure 2 [2,6–10].



**Figure 2.** Classification of EMS for HEV.

At present, the most widely used and relatively mature strategy on hybrid electric vehicles is the control strategy based on various rules [1]. Once this kind of control strategy rule is formulated, real-time control can be realized through simple judgment, and the efficiency and stability that can be exerted are very good. For instance, Peng et al. proposed a rule-based energy management strategy for a series-parallel plug-in hybrid electric bus, and a recalibration method is employed to improve the performance of the rule-based method through the results calculated by the dynamic programming (DP) algorithm [1]. However, its formulation requires high experience of designers and requires a lot of experimental support, so the design cycle is very long. In addition, in view of the complexity of vehicle driving conditions, it is difficult to fully cover these conditions by artificially set rules. Therefore, the control effect is not very satisfactory, and there is still much room for optimization of such strategies. Now, the control strategy based on optimization-based methods has been applied more and more, and the optimal solution obtained is very convincing. The optimization methods can be categorized into offline optimization and online optimization. The offline optimization methods, such as DP, can obtain the best solution theoretically [11,12]. However, its disadvantages are also obvious. When solving the problem, it is necessary to know the driving conditions of the whole or a long time in the future, and the calculation is large and time-consuming. Many

people call it the “curse of dimensionality”. Therefore, the DP algorithm is suitable for situations where the running track is known, fixed, and the traffic conditions are not particularly complex, such as suburban buses or commuters [11–13]. In addition, due to its good control effect, it is often used as a comparison to consider the advantages and disadvantages of other control strategies. To realize the real-time optimization while ensuring the computational efficiency, the online optimization based methods, such as equivalent consumption minimization strategy (ECMS) and model predictive control (MPC), are utilized for the energy management of the HEV [14,15].

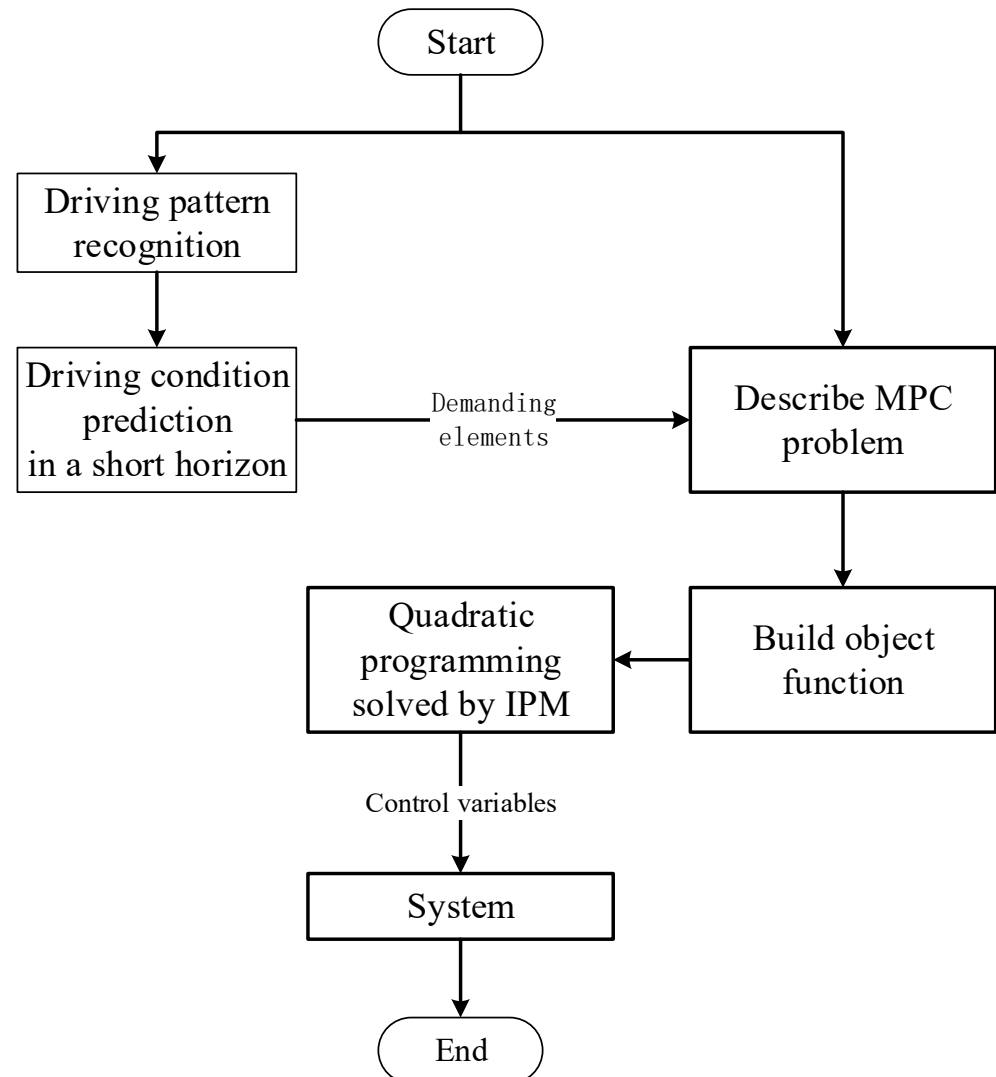
The control method to be studied in this paper is Model Predictive Control (MPC). In the process of energy management, this control not only takes into account the possible operation state of the vehicle system in the future for a period of time, but also does not have too much calculation, so it may be applied more in the field of online optimization. However, in the past decade or so, such methods have only been applied in slow dynamic processes. Recently, much effort has been applied for the application of the model predictive control method in the automotive field [16,17]. For instance, Meng et al. proposed a nonlinear extension of MPC charge control structure for lithium-ion batteries and an extended Kalman filter is adopted for battery state estimation. Numerical validation with real experimental data has shown that the e battery’s electrical constraints are respected well during the whole process [18]. Xiang et al. developed a real time energy management strategy for a hybrid electric vehicle where a speed predictor is developed with a neural network structure [19]. Martin presented a model predictive control algorithm for energy management in aircraft with hybrid electric propulsion system [20]. Moreover, the MPC based methods has been already applied in the area of the energy management strategy for the series hybrid electric vehicles, the architecture of which are the same with that of the vehicle studied in this paper. For instance, Guo et al. proposed a real-time predictive energy management strategy for a plug-in hybrid electric vehicle for the coordination control of fuel economy and battery lifetime [21]. Wang et al. presented a MPC-based strategy for a series hybrid electric tracked bulldozer. The main objective of the MPC algorithm is to achieve optimal fuel economy by tracking the battery reference value [22].

Model predictive control is often applied to constrained optimization problems. Because of its characteristics of rolling optimization, the control actions in the future finite time domain can be optimized at each sampling time, and a good planning can be carried out [23,24]. However, only the first group of optimal solutions will be applied to the system, instead of using all the control variables in the time domain. This is because the driving state of the vehicle at the next sampling time will feed back to the control module, so as to solve the optimal control quantity at the next time. After all, the control quantity in the future time domain solved previously is obtained on the basis of the vehicle state prediction, but there may be a large deviation between the predicted state and the actual state of the vehicle. Such a mechanism reflects the ability of model predictive control feedback correction. This is just suitable for vehicle systems with complex prediction models and inaccurate description, and it can also have a certain degree of resistance to external interference. In addition, mastering the current and future driving status of the vehicle is conducive to improving the predictive control effect of the model. This requires the prediction of the future driving conditions of vehicles. The prediction methods currently used include Markov chain model prediction and neural network prediction [25].

### *1.2. Motivation and Contribution*

The above-mentioned methods have shown excellent performance improvement on the energy management strategy of hybrid electric vehicles. However, for the future speed prediction, they predict the future speed of the vehicle only based on the past and current speed information with the utilization of different methods, such as Markov chain model or neural networks, and the impact of different driving status on vehicle was not considered. The speed varies significantly when the vehicle drives in an urban area, and the speed is almost constant on the highway.

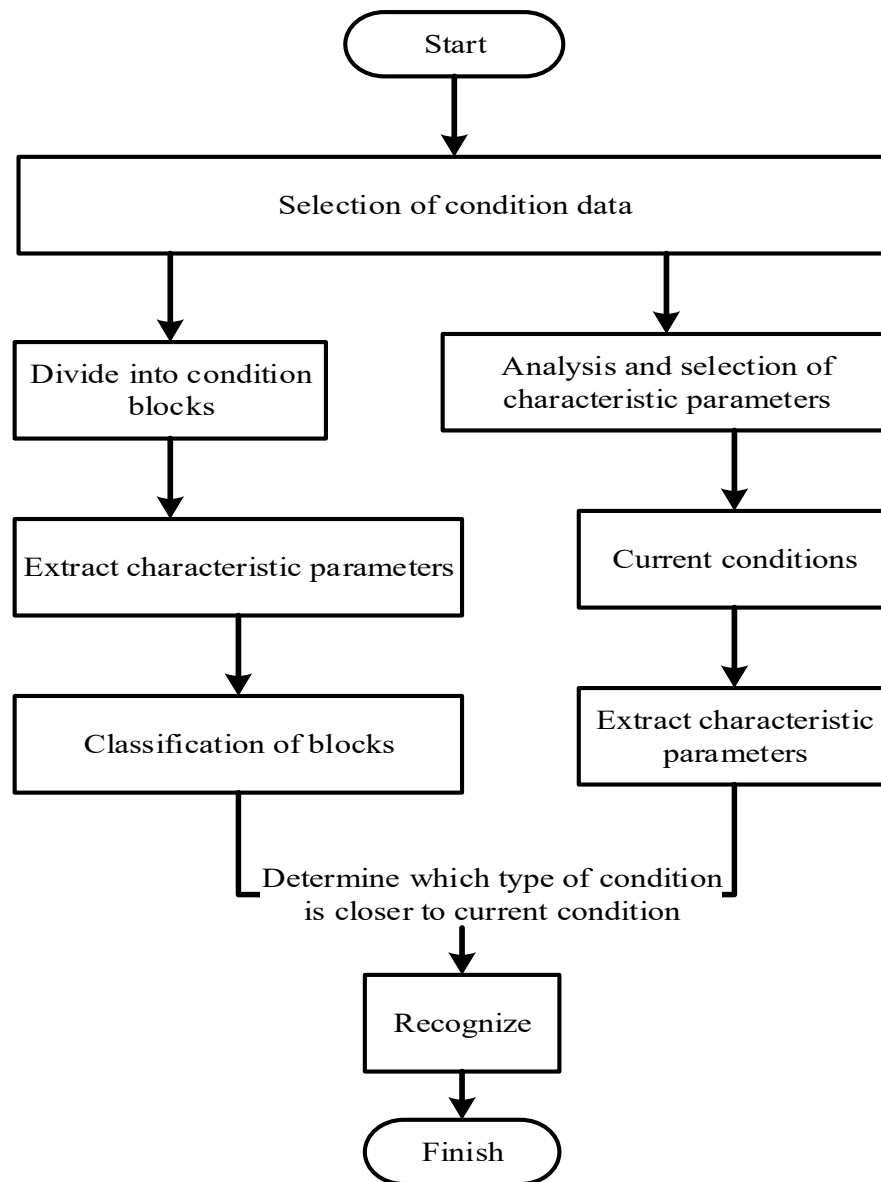
To cover the gap, in this paper, a MPC-based energy management strategy with driving pattern recognition mechanism is proposed. The control process is shown in Figure 3. By select a large number of cycle conditions, the paper extracts different characteristic parameters and recognizes driving pattern by using the clustering method and Euclidian distance to predict the future driving condition based on Markov chain model. By combining MPC with multi-objective optimization function and converting it to quadratic programming, the optimal control variables are solved by the interior point method, so as to realize the control of engine operating points. Finally, the simulation results of control strategy proves the effectiveness of the strategy.



**Figure 3.** Control process of the method.

## 2. Driving Pattern Recognition and Speed Prediction

The condition recognition process is shown in Figure 4. Since the HEV will operate in various scenarios, the sample data used to identify the vehicle conditions must contain as comprehensive driving conditions as possible to ensure that the effectiveness of the identification results is closer to the actual situation. This study selected up to 17 driving cycle conditions, such as FTP, UDDSHDV, and WVUINTER, to cover various working conditions, such as cities, highways, and mountains.



**Figure 4.** Flow chart of condition recognition.

It is crucial to consider if the choice of feature parameters is representative since distinctive parameters of the working circumstances reflect cycling characteristics. The optimal range of numbers for pattern recognition is 3 to 13, with the accuracy increasing first and then decreasing as the number of distinctive factors grows [6].

Due to the possibility of repeated representation of the same feature between feature parameters, after calculating the correlations of parameters of each condition block, three characteristic parameters, average speed, average acceleration, and parking time proportion, are selected, which eventually can fully describe the speed of the vehicle, the smoothness of the working conditions, and the smoothness of the road.

To determine the driving characteristics more clearly, it is necessary to classify condition blocks for patterns.

Based on the maximum likelihood estimation and Jensen inequality, the EM algorithm is divided into two steps: E-step, expectation; M-step, maximum; and E-step and M-step are iterated until the algorithm converges to the local optimal solution.

Here, all blocks are divided into five categories using the EM clustering algorithm. The classification results and five cluster centers are shown in Figure 5

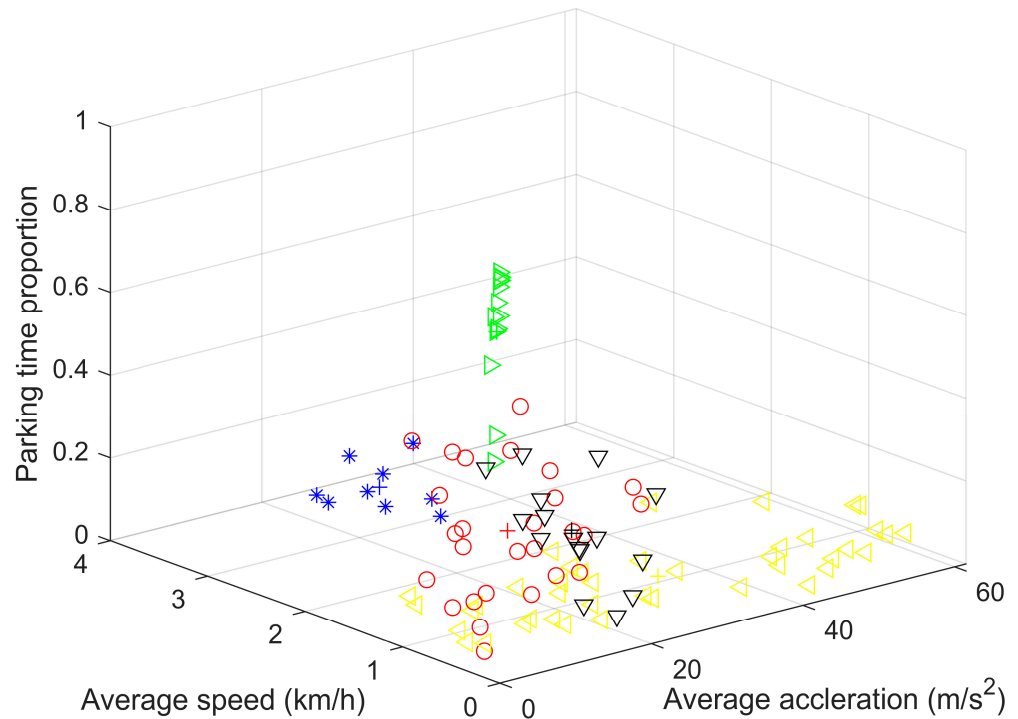


Figure 5. Classification results of the EM algorithm.

In order to select the driving pattern of the vehicle, historical vehicle speeds are recorded for a period of time, its characteristic parameters are calculated, and the Euclidean distance is used to select the clustering center that is closest to the operating conditions. To illustrate the advantage, a K-means algorithm-based pattern recognition method is developed, where the number of type is also selected as 5, as shown in Figure 6. Additionally, the Davies-Bouldin Index (DB) is utilized to evaluate the performance of different methods [26].

$$DB = \frac{1}{k} \sum_{i=1}^k \max_{j \neq i} \left( \frac{\bar{C}_i + \bar{C}_j}{\|w_i - w_j\|_2} \right) \tag{1}$$

$$\bar{C} = \frac{1}{|\Omega|} \sum_{x_n \in \Omega} \|x_n - w\|$$

where  $k = 5$ ,  $\bar{C}$  is the average distance within one type,  $\Omega$  is a collection of all elements of a type,  $x_n$  is the three-dimensional characteristic parameter of this type, and  $w$  is the three-dimensional coordinate of the center of the type. Smaller DB means the smaller the intra-class distance and the larger the inter-class distance, that is, the more obvious the classification feature. Substitute the characteristic parameters of each working condition into the formula, and the DBs of K-means and EM are 0.6228 and 0.3309, respectively.

The DB of EM is smaller, which indicates that the difference between the clusters of this algorithm is greater, and the similarity between the elements within the cluster is greater. It can be concluded that EM algorithm is more suitable for the research object in this paper than the K-means algorithm.

For each classification, the principle of Markov chain model is utilized to predict the future speed of the HEV. To predict the future speed of the vehicle, it is necessary to calculate the transition probability between states, that is, the state transition probability matrix. The specific calculation process is as shown in (2) [27]. Results obtained are shown in Figure 7.

$$T_{ij} = \Pr [N(a_{k+n+1} = a_j) | N(V_k = V_i)] \tag{2}$$

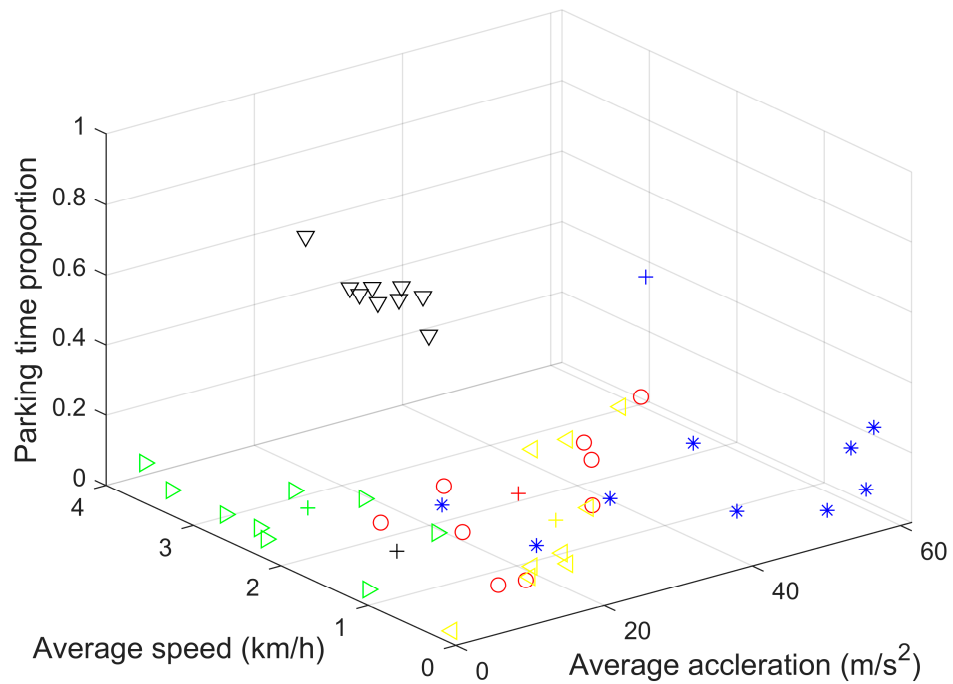


Figure 6. Classification results of the K-means algorithm.

Among them,  $n$  is the future time to be predicted,  $N(V_k = V_i)$  is the number of vehicles whose speed is  $V_i$  at the current moment,  $N(a_{k+n+1} = a_j)$  is the number of acceleration equals to  $a_j$  at the next moment,  $T_{ij}$  is the probability that the future acceleration is  $a_j$ , and the current vehicle speed is  $V_i$ .

According to the Markov chain model above, the next-time acceleration weighted value corresponding to each vehicle speed is calculated, the vehicle acceleration at the next moment can be predicted at the current time, and the next-time vehicle speed is obtained. This method is used for the WLTC driving cycle, and the predicted horizon is set to 5 s. The result is shown in Figure 8.

To further illustrate the superiority of the proposed method, the comparison results about the prediction error and the root-mean-square-error (RMSE) are shown in Tables 1–3.

Table 1. Prediction error with pattern recognition.

Time Error	1st	2nd	3rd	4th	5th
Max error (km/h)	0.3572	0.5236	0.7692	1.0751	1.7846
Ave error (km/h)	0.2918	0.3982	0.6732	0.8736	1.2358

Table 2. Prediction error without pattern recognition.

Time Error	1st	2nd	3rd	4th	5th
Max error (km/h)	0.6723	0.9762	1.3674	2.3268	3.1469
Ave error (km/h)	0.4174	0.7214	0.9826	1.6746	2.3478

root-mean-square-error (RMSE).

Table 3. Values of RMSE.

Condition Predict Method	RMSE
Prediction error with recognition	1.1834
Prediction error without recognition	2.0762



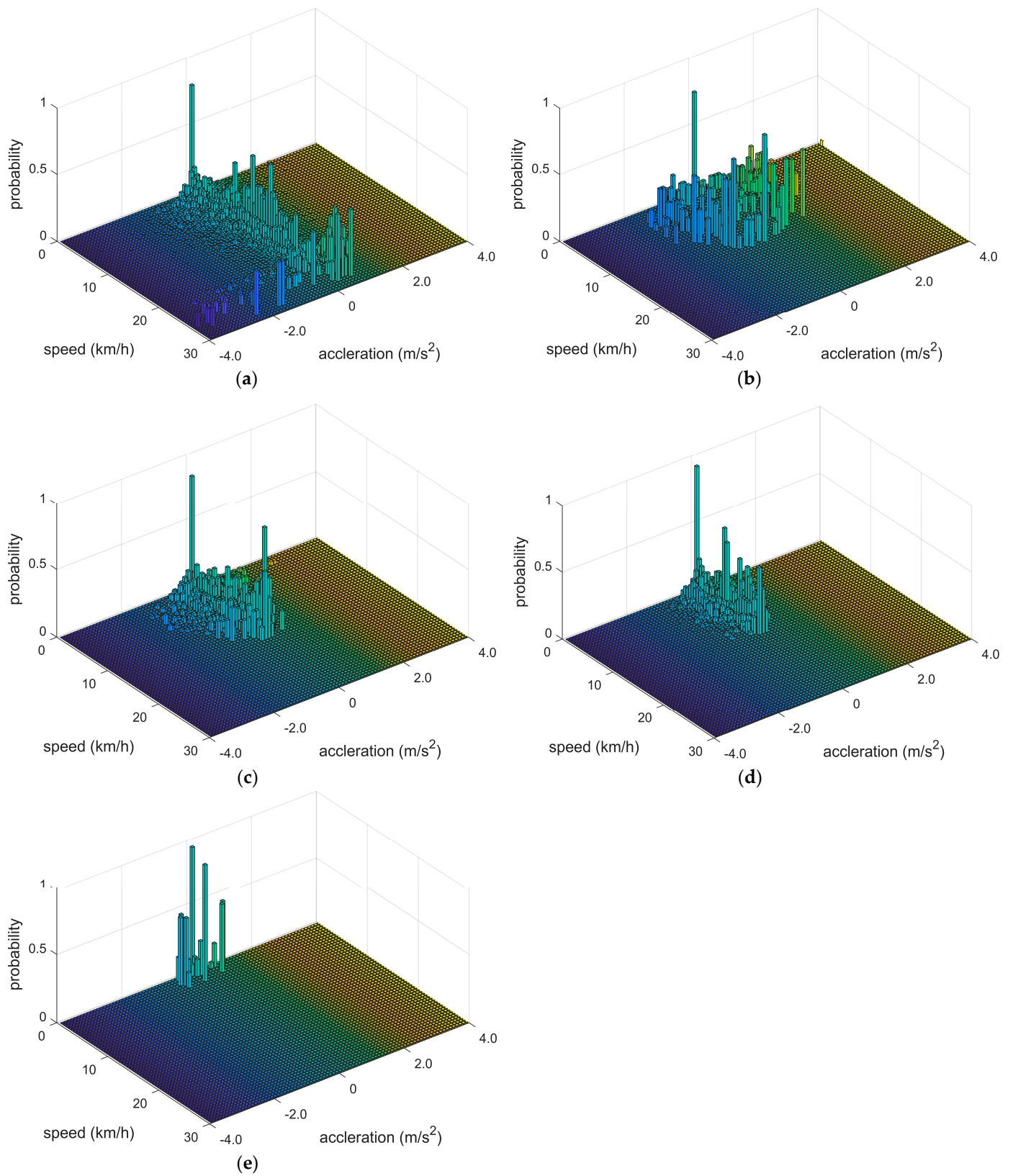


Figure 7. State transition probability of next 5 s (a–e).

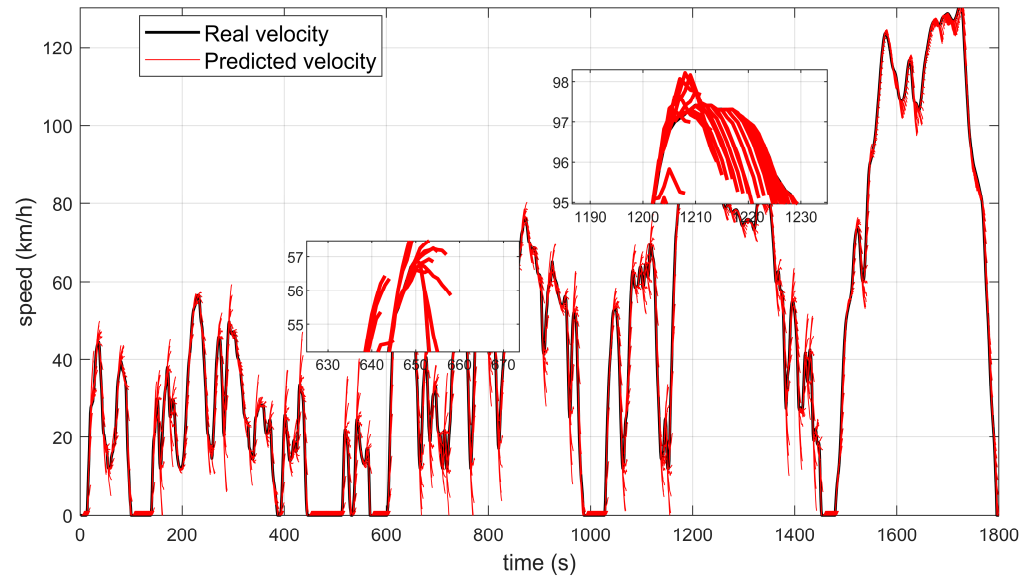


Figure 8. Prediction results.

The above results demonstrate that the proposed method, including the driving pattern recognition and Markov chain model, can significantly improve the prediction accuracy.

### 3. MPC-Based Energy Management Strategy

This section uses the model predictive control method to solve the optimization problem with constraints. First, the predicted vehicle speed is converted into demand power, and then mathematical models and optimization problems are established for the research object. Finally, the interior point method is used to solve the problem.

#### 3.1. Demanded Power Calculation

The demanding power of the vehicle can be calculated based on the longitudinal dynamics [28].

$$P_{dmd} = \frac{1}{3600\eta_m} \left( \delta m V \frac{dv}{dt} + mgfV + \frac{C_D A}{21.15} V^3 \right) \quad (3)$$

where  $V$  is the speed of the vehicle (km/h),  $\eta_m$  is the efficiency,  $m$  is the mass of the vehicle,  $f$  is the resistance coefficient,  $\delta$  is the vehicle rotational mass coefficient,  $C_D$  is the air resistance coefficient, and  $A$  is the windward area ( $m^2$ ).

#### 3.2. System Model

The state–space equation for the energy management strategy of the system can be obtained based on power balance and Kirchhoff’s voltage law as follows [19]:

$$\dot{x} = - \frac{V_{oc} - \sqrt{V_{oc}^2 - \frac{4R}{\eta_b} \left( P_m - \frac{T_g n_e \eta_g}{9549} \right)}}{2RC_b} \quad (4)$$

$$\dot{x} = f(x, u, v)$$

$$x = [soc], u = \begin{bmatrix} T_g \\ n_e \end{bmatrix}, v = [P_{dmd}] \quad (5)$$

where  $P_m$  is motor power (kW),  $C_b$  represents the capacity of the battery (aH),  $V_{oc}$  is the open circuit voltage of the battery (V),  $R$  is battery interior resistance ( $\Omega$ ),  $\eta_b$  is the efficiency of the battery,  $T_g$  is the torque of the generator (Nm),  $n_e$  is the rotational speed of the engine-generator set (rpm), and  $\eta_g$  is the efficiency of the generator.

### 3.3. Linearizing Predictive Model

The system model of vehicles is highly nonlinear, and dealing with this type of problem is more complicated. Therefore, in practical applications, a simpler and more effective linear model is often used, as follows.

$$\dot{x} = \tilde{A}x + \tilde{B}u + \tilde{C}v + \tilde{D} \tag{6}$$

Among them,

$$\begin{aligned} \tilde{A} &= \left. \frac{\partial f}{\partial x} \right|_{x=x_0, u=u_0, v=v_0}, \\ \tilde{B} &= \left. \frac{\partial f}{\partial u} \right|_{x=x_0, u=u_0, v=v_0}, \\ \tilde{C} &= \left. \frac{\partial f}{\partial v} \right|_{x=x_0, u=u_0, v=v_0}, \\ \tilde{D} &= f(x_0, u_0, v_0) - \tilde{A}x_0 - \tilde{B}u_0 - \tilde{C}v_0 \end{aligned}$$

Additionally, the terminal state can be expressed as

$$x(k+T) = Ax(k) + \varphi u(k|k) + \phi v(k|k) + \psi \bar{D}(k|k) \tag{7}$$

Among them,

$$\begin{aligned} u(k|k) &= [u(k); u(k+1); \dots; u(k+T-1)] \\ A &= 1 \\ v(k|k) &= [v(k), v(k+1), \dots, v(k+T-1)]^T \\ \varphi &= [A^{T-1}\tilde{B} \ A^{T-2}\tilde{B} \ \dots \ A^0\tilde{B}] \\ \phi &= [A^{T-1}\tilde{C} \ A^{T-2}\tilde{C} \ \dots \ A^0\tilde{C}] \\ \psi &= [A^{T-1} \ A^{T-2} \ A^{T-3} \ \dots \ A^0] \\ \bar{D}(k|k) &= [\tilde{D} \ \tilde{D} \ \dots \ \tilde{D}]^T \end{aligned}$$

$T$  is the prediction horizon.

### 3.4. Optimization Process

The primary objective of this study is to satisfy the need for power, which is mostly supplied by the engine generator set. Additionally, SOC maintenance has a significant impact on battery life for hybrid electric vehicles that are not plugged in. Thus, the cost function that was constructed is as follows:

$$\begin{aligned} J &= \left\| \frac{T_g n_e \eta_g}{9549} - v(k|k) \right\|_R^2 + Q * \text{sign}([x(k+T) - x_{opt}])[x(k+T) - x_{opt}] \\ \text{s.t. } x(k+T) &= A^T x(k) + \varphi u(k|k) + \phi v(k|k) \\ x_{\min} &\leq x \leq x_{\max} \\ u_{\min} &\leq u \leq u_{\max} \end{aligned} \tag{8}$$

$\left\| \frac{T_g n_e \eta_g}{9549} - v(k|k) \right\|_R^2$  penalize the difference between the power provided of the EGS and the demanded power,  $R$  and  $Q$  are the weighting coefficients, and  $Q * \text{sign}([x(k+T) - x_{opt}])[x(k+T) - x_{opt}]$  is the terminal punishment of the SOC where  $x_{opt}$  is set to 0.65.

Convert (8) to a quadratic programming form:

$$\begin{aligned} J &= u(k|k)^T H u(k|k) + c^T u(k|k) + d \\ \text{s.t. } \Omega u &\geq \omega \end{aligned} \tag{9}$$

where

$$\begin{aligned}
 H &= \text{diag}(R) \\
 c &= -\frac{2n_0\eta_g}{9549} [R_1v(k) \ R_2v(k+1) \ \dots \ R_Tv(k+T-1)]^T + Q\bar{B}^T \\
 d &= v(k|k)^T * \text{diag}(R) * v(k|k) + Q * e \\
 e &= A^T x(k) + \phi v^T(k|k) + \psi \bar{D}^T(k|k) + -soc_{opt} \\
 \Omega &= [I_{5 \times 5}, -I_{5 \times 5}], \omega = [u_{\min} \ u_{\max}]^T
 \end{aligned}$$

### 3.5. Interior Point Method

To balance the optimization effect and real-time algorithm as much as possible, an interior point method is employed when solving the above QP problem, and the result can be obtained by solving the KKT condition iteratively, as shown below [29]:

$$\begin{bmatrix} H & 0 & -\Omega^T \\ \Omega & -I & 0 \\ 0 & \Lambda & S \end{bmatrix} \begin{bmatrix} \Delta u \\ \Delta s \\ \Delta \lambda \end{bmatrix} = \begin{bmatrix} -r_d \\ -r_p \\ -S\Lambda e \end{bmatrix} \tag{10}$$

where  $r_d = \Omega u - \Omega^T \lambda + c$ ,  $r_p = \Omega u - s - \omega$ ,  $S = \text{diag}(s_1, s_2, \dots, s_{m_c})$ ,  $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_{m_c})$ ,  $e = (1, 1, \dots, 1)^T$ , Dual gap is  $\delta = \frac{s^T \lambda}{m_c}$ ,  $s$  is a slack variable,  $\lambda$  is a Lagrange multiplier, and  $m_c$  is the number of inequality constraints. Additionally, the control variables can be obtained by solving the above equation iteratively.

### 3.6. Simulation Results

The simulation was conducted under the specified cycle circumstances to assess the efficacy of the control method. The parameter of the vehicle is shown in Table 4. The aforementioned rule-based method and a model predictive control method without pattern recognition are employed for comparison. The WVUCITY driving cycle is utilized for analysis, as shown in Figure 9. The simulation results are shown in Figures 10–13, in which the abbreviation PR means pattern recognition.

**Table 4.** The primary parameters of the HEV.

Parameter	Value	Unit
Vehicle mass $m$	8000	kg
Radius of wheels $r_w$	0.38	m
Windward area $A$	3.24	m <sup>2</sup>
Air resistance coefficient $C_D$	0.38	-
rolling resistance coefficient $f$	0.015	-
Capacity of battery pack $C_{max}$	20	Ah
Voltage of battery pack $V_{oc}$	360	V
Rated power of the engine	120	kW
Rated power of the generator	120	kW
Rated power of the motor	160	kW

From Figure 10, it can be seen that all the three methods can regulate the SOC of the battery near the optimal state, which is 0.65 for the battery in this paper. However, the maximum deviation of the SOC with the rule-based strategy is more pronounced than those with the model predictive control-based strategies. Specifically, the MPC strategy with pattern recognition outperforms the MPC-based strategy without pattern recognition in terms of the SOC regulation, which illustrates the effectiveness of the driving pattern recognition mechanism.

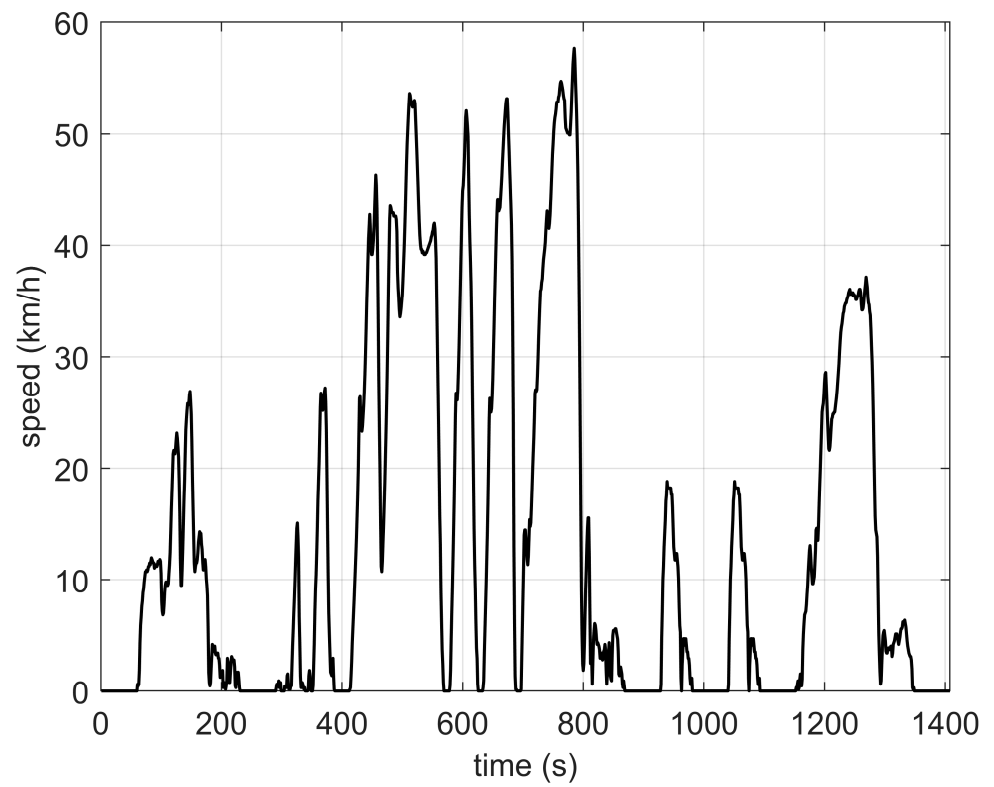


Figure 9. The speed profile of the vehicle.

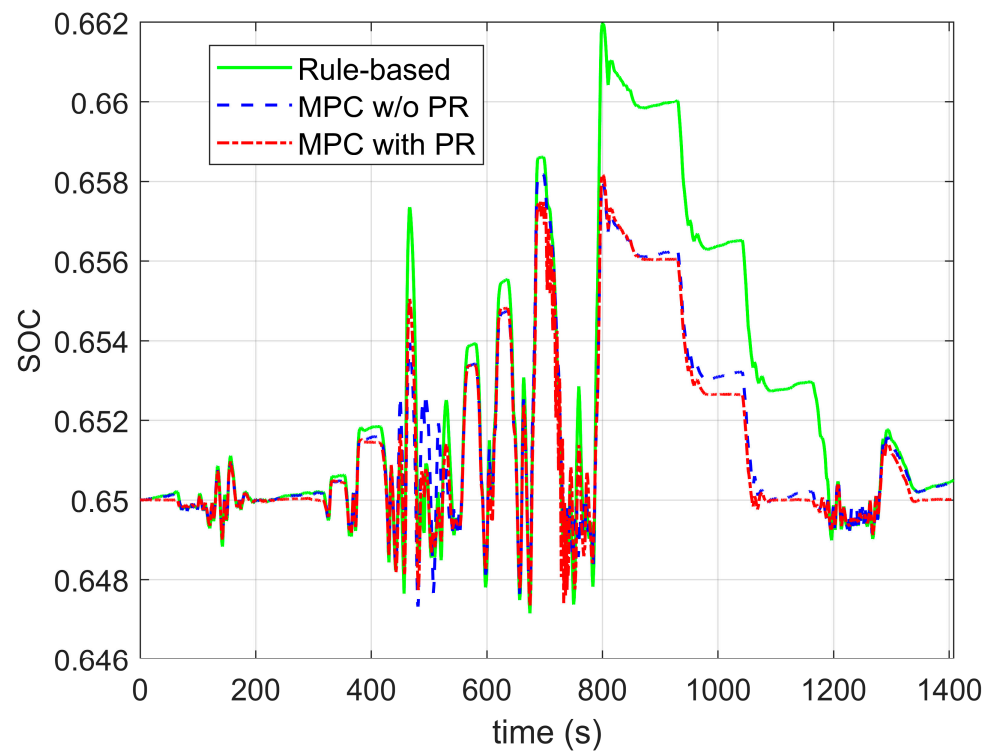


Figure 10. The SOC profile.

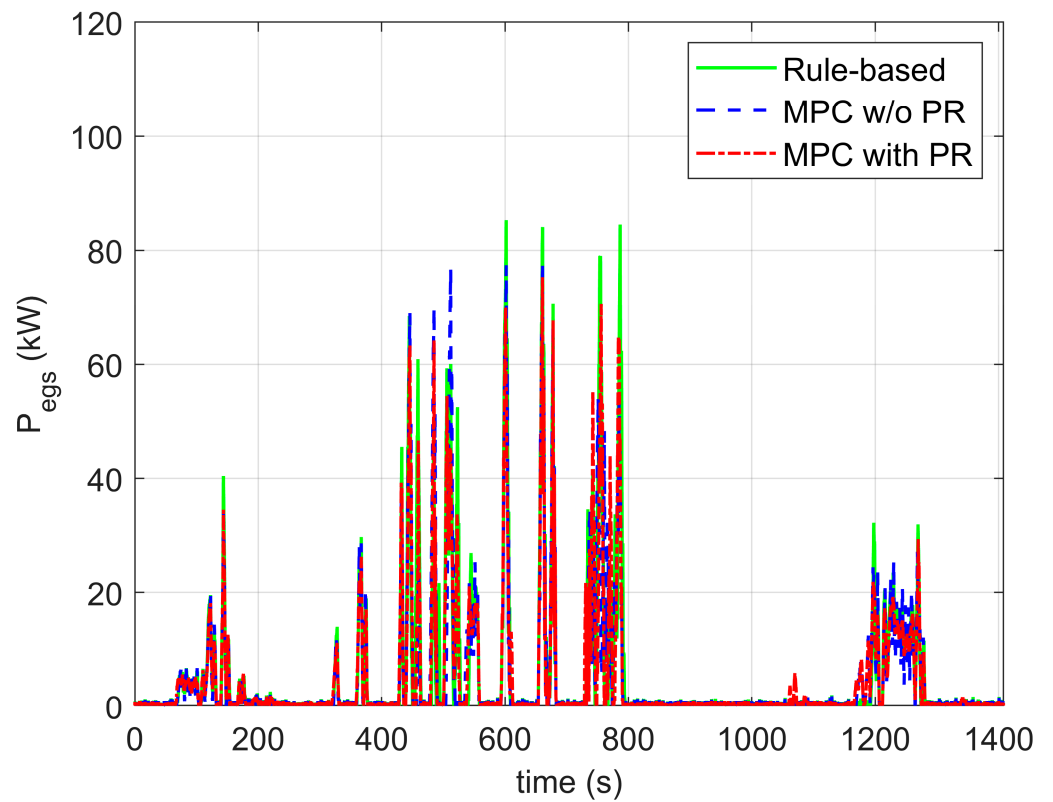


Figure 11. The power of the engine-generator set.

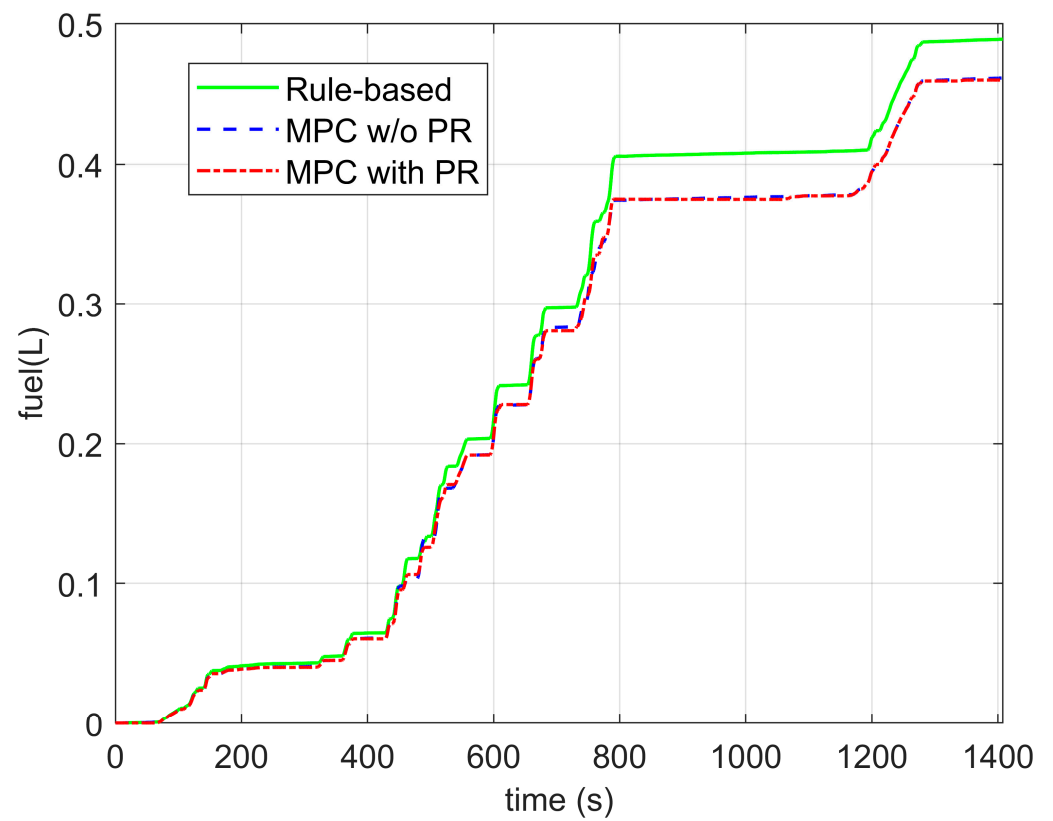
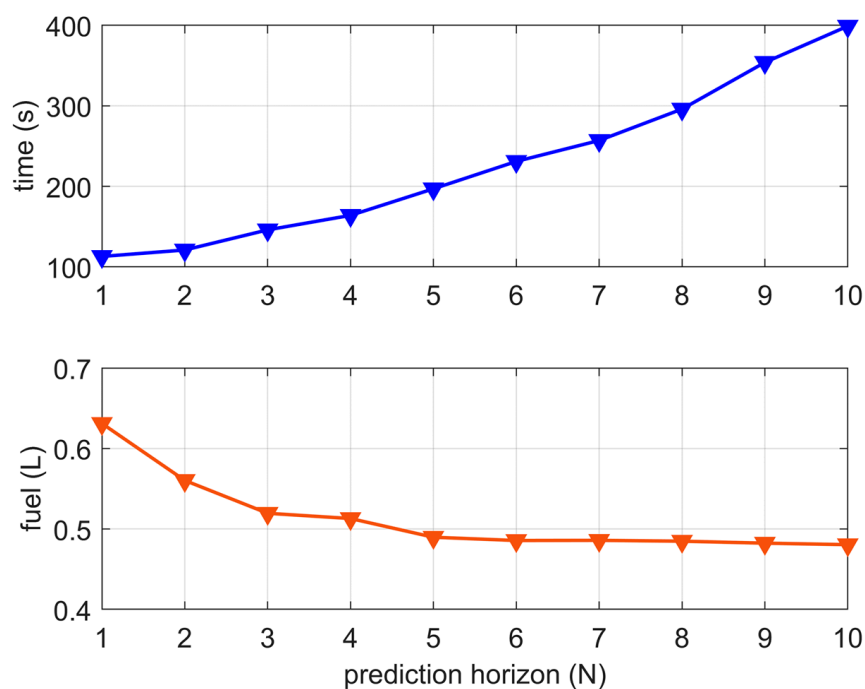


Figure 12. The fuel consumption profile.



**Figure 13.** The computation time and the fuel consumption with different prediction horizon.

The power of the engine–generator set is shown in Figure 11. It can be seen that, under some conditions with rapid acceleration, the rule-based strategy demands more power than the other two strategies. The fuel consumption results are depicted in Figure 12. The final fuel volumes for the whole cycle of the rule-based strategy, MPC-based strategy without pattern recognition, and MPC-based strategy with pattern recognition are 0.49, 0.47, and 0.45 L. It can be concluded that, compared with the rule-based strategy, MPC-based strategy performs well in terms of the SOC maintenance and fuel efficiency improvement. Additionally, the driving pattern recognition mechanism can help the control algorithm for better performance.

To evaluate the computational burden under different prediction horizon of the MPC, numerous simulations are conducted, and the results are illustrated in Figure 13. For the driving cycle with 1400 s, the computational time is acceptable and to balance the computational burden and the fuel efficiency, and the prediction horizon is set to 5 in this paper.

#### 4. Conclusions

In this study, the driving pattern is recognized using the expectation maximization algorithm, and the future demanded power of the HEV was then forecast using a Markov chain model. It was discovered that pattern recognition significantly improves prediction outcomes, and by comparison, pattern recognition reduces the predictive error significantly. Using the predicted speed, the model predictive control-based energy management strategy is developed in which maintaining the state of charge of the battery while reducing the energy consumption of the engine is set to the objective of the algorithm. The MPC is transferred into a quadratic programming solved with the interior point method.

Simulations are carried out, and the results illustrate that, compared with the rule-based EMS and the MPC-based EMS without pattern recognition, the MPC-based EMS with pattern recognition performs better in terms of reducing fuel consumption, as well as the fluctuation of the SOC.

Since the model used in this paper ignores the time-variance of system parameters due to continuous operation of the vehicle, improving the accuracy of the model used in this paper, while improving the computational efficiency, are left to future work.

**Author Contributions:** Conceptualization, Methodology, Software, Writing—Original draft preparation, J.H.; Formal analysis, Investigation, Data Curation, Writing—Review & Editing, S.R.; Formal analysis, W.W. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research received no external funding.

**Data Availability Statement:** Data available on request due to restrictions, e.g. privacy or ethical.

**Conflicts of Interest:** The authors declare no conflict of interest.

## Nomenclature

HEV	hybrid electric vehicle
EMS	energy management strategy
EM	expectation maximization
SOC	state of charge
MPC	model predictive control
ECMS	equivalent consumption minimization strategy
DP	dynamic programming
PR	pattern recognition
EGS	engine generator set
DB	Davies-Bouldin index

## References

- Peng, J.; He, H.; Xiong, R. Rule based energy management strategy for a series-parallel plug-in hybrid electric bus optimized by dynamic programming. *Appl. Energy* **2017**, *185*, 1633–1643. [[CrossRef](#)]
- Ruan, S.; Ma, Y. Real-Time Energy Management Strategy Based on Driver-Action-Impact MPC for Series Hybrid Electric Vehicles. *Complexity* **2020**, *2020*, 8843168. [[CrossRef](#)]
- Sorrentino, M.R.G.; Arsie, I. Analysis of a rule-based control strategy for on-board energy management of series hybrid vehicles. *Control. Eng. Pract.* **2011**, *19*, 1433–1441. [[CrossRef](#)]
- Li, L.; Coskun, S.; Zhang, F.; Langari, R.; Xi, J. Energy management of hybrid electric vehicle using vehicle lateral dynamic in velocity prediction. *IEEE Trans. Veh. Technol.* **2019**, *68*, 3279–3293. [[CrossRef](#)]
- Liu, K.; Asher, Z.; Gong, X.; Huang, M.; Kolmanovsky, I. *Vehicle Velocity Prediction and Energy Management Strategy Part 1: Deterministic and Stochastic Vehicle Velocity Prediction Using Machine Learning*; 0148-7191; SAE Technical Paper: Warrendale, PA, USA, 2019.
- Frambach, T.; Liedtke, R.; Dechent, P.; Sauer, D.U.; Figgemeier, E. A Review on Aging-Aware System Simulation for Plug-In Hybrids. *IEEE Trans. Transp. Electrification* **2022**, *8*, 1524–1540. [[CrossRef](#)]
- Biswas, A.; Emadi, A. Energy Management Systems for Electrified Powertrains: State-of-The-Art Review and Future Trends. *IEEE Trans. Veh. Technol.* **2019**, *68*, 6453–6467. [[CrossRef](#)]
- Huang, Y.; Wang, H.; Khajepour, A.; Li, B.; Hu, C. A review of power management strategies and component sizing methods for hybrid vehicles. *Renew. Sustain. Energy Rev.* **2018**, *96*, 132–144. [[CrossRef](#)]
- Silvas, E.; Hofman, T.; Murgovski, N.; Etman, L.F.P.; Steinbuch, M. Review of Optimization Strategies for System-Level Design in Hybrid Electric Vehicles. *IEEE Trans. Veh. Technol.* **2017**, *66*, 57–70. [[CrossRef](#)]
- Martinez, C.M.; Hu, X.; Cao, D.; Velenis, E.; Gao, B.; Wellers, M. Energy Management in Plug-in Hybrid Electric Vehicles: Recent Progress and a Connected Vehicles Perspective. *IEEE Trans. Veh. Technol.* **2017**, *66*, 4534–4549. [[CrossRef](#)]
- Pérez, L.V.; Bossio, G.R.; Moitre, D.; García, G.O. Optimization of power management in an hybrid electric vehicle using dynamic programming. *Math. Comput. Simul.* **2006**, *73*, 244–254. [[CrossRef](#)]
- Bertsekas, D.P. *Dynamic Programming and Optimal Control*, 3rd ed.; Athena Scientific: Belmont, MA, USA, 2011; Volume II.
- Bellman, R. Dynamic programming. *Science* **1966**, *153*, 34–37. [[CrossRef](#)]
- Serrao, S.O.a.G.R.L. ECMS as a realization of Pontryagin’s minimum principle for HEV control. In Proceedings of the 2009 American Control Conference, St. Louis, MO, USA, 10–12 June 2009; pp. 3964–3969.
- Musardo, C.; Rizzoni, G.; Guezennec, Y.; Staccia, B. A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management. In Proceedings of the 44th IEEE Conference on Decision and Control, Seville, Spain, 15 December 2005; pp. 1816–1823.
- Huang, Y.; Wang, H.; Khajepour, A.; He, H.; Ji, J. Model predictive control power management strategies for HEVs: A review. *J. Power Sources* **2017**, *341*, 91–106. [[CrossRef](#)]
- Capata, R. Urban and Extra-Urban Hybrid Vehicles: A Technological Review. *Energies* **2018**, *11*, 2924. [[CrossRef](#)]
- Meng, J.; Yue, M.; Diallo, D. Nonlinear extension of battery constrained predictive charging control with transmission of Jacobian matrix. *Int. J. Electr. Power Energy Syst.* **2023**, *146*, 108762. [[CrossRef](#)]
- Xiang, C.L.; Ding, F.; Wang, W.D.; He, W. Energy management of a dual-mode power-split hybrid electric vehicle based on velocity prediction and nonlinear model predictive control. *Appl. Energy* **2017**, *189*, 640–653. [[CrossRef](#)]



20. Doff-Sotta, M.; Cannon, M.; Bacic, M. Predictive Energy Management for Hybrid Electric Aircraft Propulsion Systems. *IEEE Trans. Control. Syst. Technol.* **2022**, *31*, 602–614. [[CrossRef](#)]
21. Guo, N.; Zhang, X.; Zou, Y.; Guo, L.; Du, G. Real-time predictive energy management of plug-in hybrid electric vehicles for coordination of fuel economy and battery degradation. *Energy* **2021**, *214*, 119070. [[CrossRef](#)]
22. Wang, H.; Huang, Y.; Khajepour, A.; Song, Q. Model predictive control-based energy management strategy for a series hybrid electric tracked vehicle. *Appl. Energy* **2016**, *182*, 105–114. [[CrossRef](#)]
23. Wang, W.; Guo, X.; Yang, C.; Zhang, Y.; Zhao, Y.; Huang, D.; Xiang, C. A multi-objective optimization energy management strategy for power split HEV based on velocity prediction. *Energy* **2021**, *238*, 121714. [[CrossRef](#)]
24. Schmid, R.; Buerger, J.; Bajcinca, N. Energy Management Strategy for Plug-in-Hybrid Electric Vehicles Based on Predictive PMP. *IEEE Trans. Control. Syst. Technol.* **2021**, *29*, 2548–2560. [[CrossRef](#)]
25. Ruan, S.; Ma, Y.; Yang, N.; Xiang, C.; Li, X. Real-time energy-saving control for HEVs in car-following scenario with a double explicit MPC approach. *Energy* **2022**, *247*, 123265. [[CrossRef](#)]
26. Xiao, J.; Lu, J.; Li, X. Davies Bouldin Index based hierarchical initialization K-means. *Intell. Data Anal.* **2017**, *21*, 1327–1338. [[CrossRef](#)]
27. Jain, S. Markov chain model and its application. *Comput. Biomed. Res.* **1986**, *19*, 374–378. [[CrossRef](#)]
28. Mitschke, M.; Wallentowitz, H. *Dynamik der Kraftfahrzeuge*; Springer: Berlin/Heidelberg, Germany, 1972; Volume 4.
29. Boyd, S.; Boyd, S.P.; Vandenberghe, L. *Convex Optimization*; Cambridge University Press: Cambridge, UK, 2004.

**Disclaimer/Publisher’s Note:** The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.