Machine learning and whale optimization algorithm based design of energy management strategy for plug-in hybrid electric vehicle

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Abstract

In this paper, a novel energy management strategy with the improved adaptability to various conditions for plug-in hybrid electric vehicle (PHEV) is proposed. The control parameters, derived from the benchmark test, are optimized offline for different driving conditions. The optimized parameters are implemented according to different driving behaviours identified online. The offline and online cooperation improves performance of energy management strategy in different driving conditions. Three main efforts have been made: Firstly, the valuable features that describe different driving conditions are extracted by random forest (RF) and the features are used for determining driving condition categories, utilized for online driving condition identification by support vector machine (SVM). Secondly, the control thresholds in the developed control strategy are optimized by whale optimization algorithm (WOA) under different driving conditions. The optimal control thresholds for different driving conditions will be called online after certain traffic condition is categorized. At last, simulation-based evaluation is performed, validating the enhanced performance of the proposed methods in energy-saving in different driving conditions.

1 | INTRODUCTION

The retention of conventional vehicles has roared following the rapid development of automobile industry in the 21st century. Despite the huge conveniences, automobiles have caused energy crisis and environmental pollution that gradually become public concerns [1–3]. Automobile engineers and researchers are expected to make a breakthrough to alleviate the existing crisis. The emergence of hybrid electric vehicles (HEVs) has brought bright prospects. Among the existing configurations of hybrid electric vehicles, plug-in hybrid electric vehicles (PHEVs) are considered as one of effective solutions that carry high-capacity electric batteries and efficient fuel engines. Owing to the mechanical merits, PHEVs have more ideal driving ranges than pure electric vehicles, and achieve less fuel consumption and exhaust emissions than oil-fuelled vehicles [4]. To guarantee the satisfying performance, energy management strategies of PHEVs should be carefully developed. The adaptabilities to various driving conditions and capacities in real-time application are the key issues in strategy design currently. For these reasons, this study focuses on developing a novel cooperative energy management strategy to enhance the robustness to various traffic conditions and the ability in real-time implementation.

A myriad of energy management strategies have come up within recent years. The presented energy management strategies can be divided into two categories: rule-based strategies, and optimization-based strategies [5, 6]. The rule-based strategies are formulated according to the characteristics of the power components and specific driving conditions. The simple control frameworks make this kind of energy management strategies...
easily applied in engineering practice [7, 8]. Peng et al. proposed a rule-based energy management strategy based on optimal working areas of the engine for PHEV, the simulation results proved that the PHEV achieved better fuel economy with the presented methods. [7]. However, the expert-knowledge based strategies cannot achieve optimal control effect with poor adaptabilities in various driving conditions [9]. Although parameter optimization methods such as genetic algorithm (GA) [10] and particle swarm algorithm (PSO) [11] have been successfully applied to improve the control effect of the rule-based energy management strategies, parameter optimization at specific driving conditions is still insatiately for the self-adaptive application under vary driving conditions. The optimization-based strategies can be divided into global optimization-based methods [12, 13] and instantaneous optimization-based methods [14, 15]. In the terms of global optimization-based methods, the most preferred methods include dynamic programming (DP) [13], Pontryagin's minimum principle (PMP) [14]. Peng et al. used the DP to locate the optimal actions for the engine in PHEVs and proposed a recalibration method through the results calculated by DP algorithm [16]. Onori et al. designed an energy management optimization of a PHEV based on PMP. The SOC curve with minimum equality fuel consumption was solved, and the economic optimization was realized [17]. Though global optimization-based methods can obtain the optimal solutions, the requirement on the pre-knowledge of whole driving cycles and burdensome calculation prevent them from instant application. Referring to the instantaneous based methods, equivalent consumption minimization strategy (ECMS) [18], model predictive control (MPC) [19] have shown huge potential in instant application. As for instantaneous optimization, Liu et al. employed ECMS to optimize the performance of fuel consumption of PHEV [20]. Guo et al. used MPC to establish an adaptive energy management strategy in PHEVs, achieving an improved fuel economy compared with the benchmark [21]. Even with the huge capacity in real-time application, the instantaneous optimization-based strategies are still partially dependent on the knowledge of future driving. The inner parameters in these methods, i.e. equivalent factor (EF) in ECMS, are requested to be tuned according to future driving information. Accordingly, the raised methods in literature all present close dependence on driving conditions that deteriorates the real-time application effect.

To solve the summarized drawbacks of the existing methods, some solutions have been raised to improve the adaptabilities of energy management strategies to different driving conditions. The appeared methods can be divided into velocity prediction and driving condition recognition. Velocity prediction can obtain the future driving condition. Combined with energy management strategy, velocity prediction method can guide the torque distribution of power components in the future period, improving the vehicle's adaptability to driving conditions [8, 22]. The methods of velocity prediction include Markov method [23], establishing vehicle dynamics equation [24] and machine learning method [25]. Shen et al. proposed a velocity prediction method by employing Markov Chain and backpropagation neural network, and integrated this method into MPC to optimize the fuel consumption rate of PHEVs [22]. The acquisition of future driving information through velocity prediction can moderately reduce the impact on the control process from future driving. The prediction accuracy, however, cannot be guaranteed by the existing methods in all conditions. In the aspect of driving condition recognition, the combination of driving condition recognition and energy management strategy can effectively improve the driving condition adaptability of energy management strategy. Wang et al. integrated driving condition recognition realized by learning vector quantization neural network into the PMP based energy management to optimize the fuel economy of PHEVs, and significant optimization effect was achieved [26]. Generally, the process of driving condition recognition can be divided into two steps: the determination of condition category [27] and category classification [28]. The methods to determine condition categories include principal component analysis (PCA) [29, 30] and cluster analysis [30, 31]. Hu et al. used fuzzy C-means clustering to divide the driving cycles into three types, and the distance between the value of features of actual driving conditions and the clustering centre was calculated to complete the condition recognition [30]. The recognition methods are mainly derived from machine learning [29, 32]. Zhang et al. divided the actual driving conditions into five types according to the NEDC driving cycle and realized the recognition of the driving conditions through the BP neural network which achieving high accuracy of condition recognition [33]. Despite some research achievements in classifying driving condition, the existed methods employ many input features to identify driving conditions, impressing huge computation that is not favoured in real-time application. Besides, accuracy of driving condition classification can still be improved. To prompt application effect of driving condition identification in real time, the accuracy of driving condition identification must be improved by using powerful identifiers with filtered valuable input features.

According to the literature review, the adaptability of energy management strategy in PHEV can be prompted remarkably by integrating valuable information of driving conditions. Even for the simple rule-based control strategies, performance in real-time control can be superiorly improved by adjusting control thresholds based on the corresponding traffic conditions. Accordingly, we design a novel energy management by integrally employing machine learning methods and whale optimization algorithm (WOA) in this paper. Particularly, WOA optimizes control thresholds in the strategy for different driving conditions offline. Then a machine learning based classifier is employed to complete the driving condition recognition with promising accuracy. In the online application, the optimized control thresholds, suitable for certain conditions, are called according to the identification results from classifier. The method can remarkably improve the real-time application effect of the rule-based energy management strategy and effectively reduce computing load of onboard controller. Three contributions are added in the literature:

1. Support vector machine (SVM), a supervised learning method, is employed to identify various driving conditions.
The SVM-based classifier has high classification precision even with small scale of training set.

2. To provide the most appropriate inputs for the SVM-based classifier and representative driving cycles for control strategy optimization, random forest (RF) based economical feature selection is applied to screen out the valuable features.

3. A whale optimization algorithm (WOA) is used to optimize control thresholds in energy management strategy. WOA is outstanding with fast convergence speed and strong global searching ability in parameter optimization, effectively avoiding the convergence to local optimal.

This study is organized as follows: Section 2 presents the introduction into PHEV models. Section 3 elaborates the developed novel energy management strategy for the studied PHEV. Section 4 lists the comparative analysis of simulations. Section 5 presents the conclusions and future expectations.

## 2 MODELS

### 2.1 The studied PHEV

A four-wheel drive (4WD) PHEV is preferred in this paper, the configuration of which is shown in Figure 1. The 4WD PHEV is loaded with a 2.0L internal combustion engine and a 12 kWh lithium-ion battery. Two electric motors are installed at the front and rear shafts respectively, responsible for driving the vehicle and recycling braking energy. Besides, the vehicle is equipped with a generator to adjust the operating point of the engine and to charge battery in serial mode. Depending on the engagement status of clutch, vehicle can operate in serial or parallel mode. The detailed parameters of the studied 4WD PHEV are shown in Table 1.

### 2.2 Vehicle dynamic model

At the wheel end, tractive torque from the cooperative work between engine and motors overcomes the driving resistance.

### 2.3 Engine model

An engine model is established by neglecting the transient dynamic performance. The function to express the static
FIGURE 2  Engine fuel consumption map

performance of engine can be expressed as:

$$flow_{con} = be_{ur} \cdot P_{eng} \cdot T_{eng} / 3600 \quad (3)$$

where $flow_{con}$ is the fuel consumption, $be_{ur}$ is the instantaneous fuel consumption rate, which is determined by engine torque $T_{eng}$ and engine rotating speed $N_{eng}$. In real application, fuel consumption can be acquired by interpolating an engine fuel consumption map, which is obtained via benchmark test. The preferred engine efficiency map is shown in Figure 2.

### 2.4 Motor/generator model

The motors and generator in the 4WD PHEV are all permanent magnet synchronous motors (PMSMs). Considering main target in this paper, the dynamic performance and thermal behaviours of PMSMs are all neglected in this paper. The relationship of output torque $T_{out}$, rotating speed $N_{f}$ and load $L_{f}$ is shown in Equation (4):

$$T_{out} = f \left( N_{f}, L_{f} \right) \quad (4)$$

For the motor model and generator model, the power of the motor and generator can be expressed as follows:

$$\begin{cases} P_{mot} = \frac{T_{mot} \omega_{mot}}{\eta_{mot}} \\ P_{gen} = \frac{T_{gen} \omega_{gen}}{\eta_{gen}} \end{cases} \quad (5)$$

where $P_{mot}$ is the power of the motor, $T_{mot}$ is the torque of the motor, $\omega_{mot}$ is the angular speed of motor, $\eta_{mot}$ is the efficiency of the motor, $P_{gen}$ is the power of the generator, $T_{gen}$ is the torque of the generator, $\omega_{gen}$ is the angular speed of generator, $\eta_{gen}$ is the efficiency of the generator. The efficiencies of motors and generator are also can be obtained by interpolating 2D efficiency maps, which are shown in Figure 3.

### 2.5 Battery model

In the study, the electrochemical properties and temperature rise impact are ignored. Hence, a first-order RC model is adopted to describe the battery performance. The first-order RC model consists of an ideal voltage source and an internal resistance, which are in series connection. The output current $I$ of the battery can be written as:

$$I = \frac{V_{bat} - \sqrt{V_{bat}^2 - 4R_{int}P_{bat}}}{2R_{int}} \quad (6)$$

where $V_{bat}$ is the battery voltage; $R_{int}$ denotes the internal resistance; $P_{bat}$ expresses the power.

The relationship of battery SOC with battery voltage and internal resistance can be expressed as:

$$\dot{SOC} = -\frac{V_{bat} - \sqrt{4R_{int}P_{bat}}}{2R_{int}Q_{bat}} \quad (7)$$

where $Q_{bat}$ is the battery capacity.

### 3 NOVEL ENERGY MANAGEMENT STRATEGY FOR THE 4WD PHEV

The proposed energy management strategy, generally, consists of two parts: offline parameter optimization and online driving condition based on control thresholds updating. The framework of the proposed energy management strategy is briefly illustrated in the Figure 4. As is shown in Figure 4, in the terms of offline task, to prepare valuable training data for the
SVM-based identifier, RF-based economical feature selection is performed. The selected features, tightly connected with fuel economy, can also be applied in the K-means based cluster to generate effective driving cycles for control threshold optimization. The logic thresholds for different driving conditions are optimized by WOA. In the terms of online task, according to the identified driving condition instantaneously, corresponding optimized control thresholds for the rule-based strategy is adaptively implemented. The optimized control thresholds for different driving conditions are obtained via WOA offline.

3.1 Driving condition recognition

Driving condition recognition is a supervisory classification. To accomplish the categorization, a two-step work must be done, which include classification category determination and driving condition identification. The process of driving condition is illustrated in Figure 5. In order to improve the real-time application ability of condition recognition, we identify driving condition every 10 s. According to the properly designed driving condition identification process, methods to accomplish the task will be described minutely in the following sections.
3.1.1 SVM-based driving condition identification

SVM is one of efficient machine learning methods that can achieve good classification accuracy with small training sets [34, 35, 41]. Therefore, we adopt this method to classify different driving conditions.

The establishment of SVM recognizer is actually the process of establishing the classification hyperplane. For the purpose of improving the classification accuracy, the distance between the output data of the training set and the hyperplane needs to be maximized, so as the optimization objective of the SVM maximum interval classifier is defined as:

$$\max \tilde{\gamma} = \frac{1}{\|\omega\|}$$  \hspace{1cm} (8)

where $\|\omega\|$ is the 2-norm of $\omega$ and $\tilde{\gamma}$ is the geometrical interval between data points.
To accomplish the optimization in Equation (8), some constraints should be met. The required constraints can be briefly described, as:

\[ y_i (\omega^T x_i + b) = \hat{y}_i \geq \bar{y}, i = 1, 2, \ldots, n \]

(9)

where \( y \) is the classification label, \( x \) is the input set sample, \( \omega \) is the coefficient matrix of the hyperplane and \( b \) is the constant term of the hyperplane.

Solving the described problem in Equation (8) is equivalent to solving the following problem:

\[ \max \bar{y} = \frac{1}{\|\omega\|^2} = \min \frac{1}{2} \|\omega\|^2 \]

(10)

To complete the calculation of Equation (10), we can rewrite Equation (10) into following manners, as:

\[
\begin{cases}
\min \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{n} \varepsilon_i \\
\text{s.t. } y_i (\omega^T x_i + b) \geq 1 - \varepsilon_i, \quad i = 1, 2, \ldots, n \\
\varepsilon_i \geq 0, \quad i = 1, 2, \ldots, n
\end{cases}
\]

(11)

where \( C \) is penalty parameter, which indicates the tendency between overfitting and underfitting.

Because the driving condition recognition is non-linear classification, the Lagrangian duality is applied to create a generalized Lagrangian operator, as:

\[
L (\omega, b, a, \varepsilon) = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^{n} \varepsilon_i - \sum_{i=1}^{n} a_i (y_i (\omega^T x_i + b) - 1 + \varepsilon_i) - \sum_{i=1}^{n} r \varepsilon_i
\]

(12)

It can be seen from Equation (12) that the process of classification can be transformed into solving the parameters \( a, \omega, b \) and \( \varepsilon \). Combining Lagrangian operator and original objective function, the specific optimization object for classification problem is converted to:

\[
\min \theta (\omega) = \min_{\omega, b, a \geq 0} \max \{ L (\omega, b, a) = p \}
\]

(13)

where \( p \) is the optimal value of this function.

After solving \( a, \omega \) and \( b \), the corresponding types \( j = (j_1, j_2, \ldots, j_n) \) of input condition features \( x=(x_1, x_2, \ldots, x_n) \) are classified, and thus a condition recognizer is set up.

Because the hyperparameters in SVM affect the classification accuracy, in order to realize higher accuracy identification, this paper uses cross validation to solve the SVM hyperparameters. In the terms of \( C \) which is one of hyperparameters, the optimized \( C \) is 18.6.

3.1.2 | Random forest based economical feature selection

As is mentioned, feature selection is incorporated into the novel energy management strategy. The feature selection can simply the SVM-based driving condition classifier and support the preparing of valuable training data. By the feature selection, most representative features that dominate description of driving conditions can be extracted, reducing the complex of SVM based classifier. Actually, a target-oriented feature selection, called economical feature selection is performed in this paper. Except focusing on connection between features and accurately sculpturing driving conditions, the economical feature selection also considers the relationship between features and fuel economy of vehicle. Therefore, representational driving cycles that are corresponding to various driving conditions can be acquired on the basis of the extracted features either, proving solid foundation for control threshold optimization.

The economical feature selection is realized by RF, which is an efficient ensemble learning method. The essence of RF is to optimize the effect of decision tree by combining bagging repeat sampling with random subspace method [37, 38, 42]. The basic of random forest is the establishment of cart regression tree and bagging repeat sampling. There are two parameters that affect the accuracy of random forest regression: number of regression trees \( M \) and number of randomly selected root nodes \( M_{tr} \).

Parameters of RF are defined as follows: the dependent variable \( Y \) of RF and corresponding input value \( X \) are randomly sampled by bagging; the data point set of regression tree building is defined as \( a_n \); on the split node of each tree, data are randomly selected from \( p \) original data, and data are split in accordance with the classification and regression tree (CART) criterion [37].

The classification and regression tree (CART) criterion is showed as:

\[
L_{\text{obs}} (j, z) = \frac{1}{N_n (A)} \sum_{i=1}^{n} (Y_i - \bar{Y}_A)^2 \prod_{X \in A} \bigg( \frac{1}{N_n (A)} \sum_{i=1}^{n} \left( Y_i - \bar{Y}_A \right) \prod_{X' \subset A, X' \neq 2A} \left( Y_i - \bar{Y}_{A'} \right) \prod_{X \in A} \bigg)^2
\]

(14)

where \( (j, z) \in C_{AB}, C_{AB} \) is the set of all possible of establishing of regression tree, \( A_{L} = \{ x \in A : x^{(j)} \leq z \}, A_{R} = \{ x \in A : x^{(j)} \geq z \}, \), and \( \bar{Y}_A \) (resp. \( \bar{Y}_{A_{L}}, \bar{Y}_{A_{R}} \)) means the average of \( Y_i \).

The pseudocodes of the RF are shown in Table 2:

During the economical feature selection, the RF is used to build a mapping relationship between features and fuel consumption rate. Hence, the input set \( X_n \) of RF is the candidate features, and the output set \( Y_n \) is the fuel consumption results. If a feature significantly affects fuel consumption, the precision of RF regression without this feature in the training set is lower than that of RF regression involving all features in the training set. The fuel consumption data used in regression comes from the simulation results under different driving cycles.
Accordingly, the weight of the influence of different features on fuel economy can be determined by RF. According to the literature study, the candidate features for the SVM-based recognizer includes: average velocity, maximum velocity, standard deviation of velocity, percent of velocity 0–30 km/h, percent of velocity 30–70 km/h, percent of velocity > 120 km/h, average acceleration, maximum acceleration, standard deviation of acceleration, percent of acceleration 0–1 m/s², percent of acceleration 1–2.5 m/s², percent of acceleration > 2.5 m/s², average deceleration, maximum deceleration, standard deviation of deceleration, percent of deceleration −1 to 0 m/s², percent of deceleration −2.5 to −1 m/s², percent of deceleration > −2.5 m/s², travel distance, times of stop, times of stop per kilometre, and time ratio of idle speed [36]. Based on the described method, the extracted features for SVM-based recognizer can be: average velocity, standard deviation of velocity, velocity range 30–70 km/h percentage, percent of velocity range 0–30 km/h, and percent of velocity range 0–30 km/h. In addition, to extract valuable inputs for the recognizer, 30 driving cycles are utilized. The chosen driving cycles are listed in Table 3.

3.1.3 Driving cycle clustering

Based on the extracted features, the driving cycles can be clustered into several different conditions. According to engineering experience, the preferred driving cycles can be clustered into 3 types, as: urban-area congestion conditions, urban suburb conditions, and high-speed driving conditions. K-means based method is preferred to accomplish the cluster.

In the K-means based cluster, the input set is the value that is corresponding to the screened features in the last section, and the output are the clustered three types of driving conditions. Figure 6 illustrates the cluster results. The clustering results show that the K-means cluster 30 driving cycles into 3 types based on 5 features. Type 1, marked in Figure 6, represents the urban-area congestion conditions, which is characterized by low average speed and frequently start and stop times. Type 2 represents urban suburb conditions, which is characterized by the fact that vehicles travel at moderate speed. Type 3 represents the high-speed driving conditions, which is characterized by high average speed with less starting and stopping times than other types.

On basis of these 3 types, 6 typical driving cycles are selected and used to optimize thresholds in energy management strategy of the studied 4WD PHEV. The method to select the typical driving cycles that are corresponding to different driving conditions can be described as:

1. Calculating the Euclidean distance between the candidate driving cycles and clustering centre.
2. Choosing the driving cycle that results the minimum Euclidean distance as the typical driving cycle for certain driving condition.

The Euclidean norm is calculated in Equation (15).

\[
\text{norm}(x_{\text{feas}}, x_{\text{cen}}) = \sqrt{\sum_{j=1}^{n} (x_{\text{feas},ij} - x_{\text{cen},j})^2}
\] (15)

where \(x_{\text{feas},ij}\) is the high-dimensional distribution of the driving condition features of the i-th driving cycle. \(x_{\text{cen}}\) is the centre of the high-dimensional features of driving cycle under a category to which the i-th driving cycle belongs. \(j\) is the serial number of the driving condition features.

**TABLE 2** The pseudo code of RF algorithm

| No. | Condition          | No. | Condition          |
|-----|--------------------|-----|--------------------|
| 1   | 1015               | 16  | HWFET              |
| 2   | WLTC               | 17  | IM240              |
| 3   | ARB02              | 18  | INDIYA_HWT_SAMPLE |
| 4   | ARTERIAL           | 19  | LA92               |
| 5   | BUSRTE             | 20  | MANHATTAN          |
| 6   | CBD14              | 21  | NewYorkBus         |
| 7   | US06               | 22  | NurebergR36        |
| 8   | CLEVELAND          | 23  | NYCC               |
| 9   | COMMUTER           | 24  | NYGTC              |
| 10  | CHINA              | 25  | REP05              |
| 11  | CSHVR_Vehicle      | 26  | SC03               |
| 12  | ECE                | 27  | UDDS               |
| 13  | EUDC               | 28  | UKBUS6             |
| 14  | NEDC               | 29  | UNIF01             |
| 15  | HL07               | 30  | US06_HWY           |

**TABLE 3** Condition name and driving condition serial number
The chosen typical driving cycles are shown in Table 4.

### Table 4: The chosen typical driving cycles

| No. of driving cycle | Name of driving cycle | Type of driving condition          |
|----------------------|-----------------------|------------------------------------|
| 6                    | CBD14                 | urban-area congestion conditions   |
| 5                    | BUSRTE                | urban-area congestion conditions   |
| 14                   | NEDC                  | urban suburb conditions            |
| 10                   | China                 | urban suburb conditions            |
| 16                   | HWFET                 | high-speed driving conditions      |
| 30                   | US06_HWY              | high-speed driving conditions      |

### 3.2 WOA-based multi-objective optimization of driving mode switch logic threshold

#### 3.2.1 Basic WOA-based optimization

The control threshold optimization of the rule-based energy management strategy is a multi-objective optimization problem. Among the existed optimization methods, heuristic algorithms have the fast convergence speed and small interference between optimization targets. Therefore, this paper chooses one of heuristic algorithms, WOA, to optimize the control thresholds. In the optimization, WOA obtains the optimal solutions by simulating the process of whale swarm prey [39, 40].

The process of WOA consists of three parts: prey searching (iterate updating), prey encircling (global search) and bubble attack (local search). The goal of prey searching is to update the location of individual whales. The purpose of prey encircling is to enable individual whales to complete a global search for optimized targets. Bubble attack is designed to accomplish local optimization.

Firstly, the whale population quantity should be initialized and the number of iterations be optimized. Let the whale population quantity be $N$, the optimized parameter dimension be $D$, and the optimized number of iterations be $M$.

In WOA, each whale position represents a candidate solution of the optimization problem. Let the number of individual whales be $i$. Then position of the $i$-th individual in the whale population is $X_i = (x_i^1, x_i^2, ..., x_i^D)$, where $i = 1, 2, ..., N$. Moreover, the whale at the optimal preying position is the global optimal solution. The pseudocodes of WOA are shown in Table 5.

### Table 5: The pseudo code of WOA

1. Parameter Initialization.
2. while $t < M$ do
3. for $i = 1, ..., N$ do
4. Update the convergence factor coefficient $a$, convergence factor $A$, swing factor $C$, random number $l$ and random number $p$.
5. if $(1)p > 0.5$ do
6. Update the positions of whale individuals by using spiral encircling hunt.
7. else if $(1)p \leq 0.5$ do
8. if $(2)|A| < 1$ do
9. Update the positions of whale individuals by using contraction encircling hunt.
10. else if $(2)|A| \geq 1$ do
11. Update the positions of whale individuals by using global searching.
12. end if (2)
13. end if (1)
14. Substitute the positions of whale individuals into the modelling to solve the fuel consumption quantity. Update the group adaptability and the optimal individual position.
15. $t = t + 1$
16. end for
17. end while

#### 3.2.2 Control thresholds optimization by WOA

In this paper, the updated whale individual represents the control thresholds that governs the working mode switch. The
fitness value \( f(x) \) is fuel consumption of the vehicle, which can be formulated as:

\[
f(x) = \sum_{t=1}^{N} \left( b_{\text{fuel}}(X) + \omega \cdot \frac{P_{\text{bat}}(X)}{Q_{\text{fuel}}} \right)
\]  

(16)

where \( Q_{\text{fuel}} \) is the fuel low heat value, \( \omega \) is the conversion rate of energy consumption, and \( t \) is the time step.

During the optimization, some constraints related to the powertrain performance and vehicle dynamic should be set, which ensure that different components can operate within limits. The corresponding constraints can be written as:

\[
\begin{align*}
P_{\text{c}, \min} &< P_{\text{c}} < P_{\text{c}, \max} \\
T_{\text{e}, \min} &< T_{\text{e}} < T_{\text{e}, \max} \\
N_{\text{e}, \min} &< N_{\text{e}} < N_{\text{e}, \max} \\
P_{\text{m}, \min} &< P_{\text{m}} < P_{\text{m}, \max} \\
T_{\text{m}, \min} &< T_{\text{m}} < T_{\text{m}, \max} \\
N_{\text{m}, \min} &< N_{\text{m}} < N_{\text{m}, \max} \\
P_{\text{g}, \min} &< P_{\text{g}} < P_{\text{g}, \max} \\
T_{\text{g}, \min} &< T_{\text{g}} < T_{\text{g}, \max} \\
N_{\text{g}, \min} &< N_{\text{g}} < N_{\text{g}, \max}
\end{align*}
\]  

(17)

where the superscripts \( \text{max} \) and \( \text{min} \) represent the maximum and minimum value of each variable, respectively. \( P_{\text{e}}, P_{\text{m}, \text{f}}, P_{\text{m}, \text{r}}, P_{\text{g}, \text{f}}, P_{\text{g}, \text{r}} \) represent the power of internal combustion engine (ICE), front motor, rear motor, and generator, respectively; \( N_{\text{e}}, N_{\text{m}, \text{f}}, N_{\text{m}, \text{r}}, N_{\text{g}, \text{f}} \) and \( N_{\text{g}, \text{r}} \) represent the rotating speed of internal combustion engine (ICE), front motor, rear motor, and generator; respectively. \( T_{\text{e}}, T_{\text{m}, \text{f}}, T_{\text{m}, \text{r}}, \) and \( T_{\text{g}} \) represent the torque of internal combustion engine (ICE), front motor, rear motor, and generator.

4 | COMPARISON OF SIMULATION RESULTS

In this section, we take advantage over simulation analysis to validate performance of the raised methods. The evaluation tries to assess the effectiveness from the perspective of general energy consumption and component operation behaviours. In this section, the two simulating driving cycles are obtained from real driving data which are from taxis. And the real driving cycles used in simulating is convincing in assessing operation behaviours. In the simulation, CR-EMS denotes the raised energy management strategy with driving condition in each segment. OL-EMS represents the original rule-based energy management strategy. BO-EMS denotes the raised energy management strategy with driving condition only in whole driving cycle. The simulation is performed on two driving cycles which are derived from real traffic data. The velocity profiles of the chosen driving cycles are presented in Figures 7 and 8. For better illustrate the performance of the strategy with driving condition recognition, we design an initial battery SOC formed by 90%.

4.1 | Comparison on energy consumption by different methods

Because the condition recognizer in online simulation is trained off-line and the optimized logic threshold is also generated off-line, the calculation load in online process is small. Under different execution modes, the simulation time of online process is close. Among different execution modes, simulation of OL-EMS takes 532 s, BO-EMS takes 536 s, CR-EMS takes 561 s.

The fuel consumption by different methods is shown in Figures 7–8. By comparing the fuel consumption curves of BO-EMS and OL-EMS, it can be seen that BO-EMS achieves lower fuel consumption at the end of simulation. By comparing CR-EMS and BO-EMS, the fuel consumption by CR-EMS is lower than that by BO-EMS in two driving cycles. The fuel consumption curves can reflect the working state of the ICE. The reason of dispersive performance owns to the integration of driving condition identifier. Based on the identified driving condition, the most appropriate control thresholds are implemented, ensuring engine operate in high-efficiency zone. In the terms of the fuel consumption by different methods in driving cycle 1, as shown in Figure 7 and Table 6, CR-EMS contributes to a reduction of 17.6% in the fuel consumption than OL-EMS and a reduction of 8.8% than BO-EMS. Similarly, results in Figure 8 and Table 7 reveal that CR-EMS contributes to a reduction of 6.3% in the fuel consumption than OL-EMS and a reduction of 2.8% than BO-EMS. From the perspective of fuel consumption, the proposed method can more effectively match the optimized logical threshold parameters in real-time by referring to the identified driving condition, so it has better adaptability to driving environment.

The battery SOC curves by different methods are shown in Figures 9 and 10. By comparing the battery SOC curves of BO-EMS and OL-EMS, it can be seen that BO-EMS achieves lower final SOC of battery in both two driving cycles. By comparing CR-EMS and BO-EMS, the final SOC of battery by CR-EMS is lower than that by BO-EMS in two driving cycles. The battery SOC curves can reflect the consumption of electricity. In the terms of driving cycle 1 in Figure 9, the holding fuel consumption by using CR-EMS is accompanied by the decreased battery SOC obviously from 5800 to 10,000 s. The reason of dispersive performance owns to the integration of driving condition identifier. Based on the identified driving condition, the most appropriate control thresholds are implemented by CR-EMS, ensuring pure driving mode operate in urban-area congestion condition and avoid the ICE working inefficiently. Because the BO-EMS and OL-EMS do not perform driving condition identification in each segment, the battery SOC discharge capacity is not fully utilized in the control process, so the downward trend of SOC curves is relatively gentle. In the terms of driving cycle 2 in Figure 10, from 8800 to 9000 s, the battery SOC decreased obviously by using CR-EMS. The reason of the performance
FIGURE 7  Comparison of fuel consumption by three different strategies in driving cycle 1

FIGURE 8  Comparison of fuel consumption by three different strategies in driving cycle 2

TABLE 6  Comparison in energy consumption by different methods in driving cycle 1

| EMS | Fuel consumption (g) | Final SOC of the battery (%) | Engine operating time (s) | Reduced fuel consumption (%) | Reduced equivalent fuel consumption (%) |
|-----|----------------------|------------------------------|---------------------------|-----------------------------|-----------------------------------------|
| DP  | 980                  | 28.35                        | 771                       | 14.5                        | 12.3                                    |
| CR  | 1086                 | 30.06                        | 778                       | 17.6                        | 8.9                                     |
| BO  | 1202                 | 31.99                        | 1146                      | 8.8                         | 4.6                                     |
| OL  | 1318                 | 35.42                        | 1417                      |                             |                                         |

TABLE 7  Comparison in energy consumption by different methods in driving cycle 2

| EMS | Fuel consumption (g) | Final SOC of the battery (%) | Engine operating time (s) | Reduced fuel consumption (%) | Reduced equivalent fuel consumption (%) |
|-----|----------------------|------------------------------|---------------------------|-----------------------------|-----------------------------------------|
| DP  | 1310                 | 27.92                        | 1350                      | 8.6                         | 11.4                                    |
| CR  | 1367                 | 31.92                        | 1415                      | 6.3                         | 8.2                                     |
| BO  | 1416                 | 33.78                        | 1388                      | 2.8                         | 4.3                                     |
| OL  | 1458                 | 33.81                        | 1630                      |                             |                                         |
owes to the stronger charging of battery by operating the ICE during the vehicle driving in high-speed driving condition from 7800 to 8000 s. Reasonable distribution of battery charge and discharge state benefits from driving condition recognition.

The fuel consumption and battery SOC are included in the economic indicators of the vehicle. It is not comprehensive to only use one of each indicator, so equivalent fuel consumption should be introduced to compare the economy of each control strategy. Equivalent fuel consumption is defined as the sum of the fuel quality converted from electricity consumption and the real fuel consumption. Reduced equivalent fuel consumption represents the proportion of the reduction in equivalent fuel consumption of the vehicle by using CR-EMS with the other control strategies. As shown in Table 6, CR-EMS contributes to a reduction of 8.9% in the equivalent fuel consumption than OL-EMS and a reduction of 4.6% than BO-EMS in driving cycle 1. Similarly, results in Table 7 reveals that CR-EMS contributes to a reduction of 8.2% in the equivalent fuel consumption than OL-EMS and a reduction of 4.3% than BO-EMS in driving cycle 2. Through the comparison in energy consumption, driving condition identification endows control strategy with better adaptability to driving environment, strengthening fuel economy of the 4WD PHEV.

4.2 Comparison on performance of components by different methods

In order to further analyse the energy saving mechanism of CR-EMS, this section compares the dynamic behaviours of power components in 4WD PHEV. The illustrations on ICE torques by different methods in driving cycle 1 and 2 are shown in Figures 11 and 12. The comparison on motor torques by different methods are shown in Figures 13 and 14. The generator torques resulted from three solutions are shown in Figures 15 and 16.

Figures 11–16 reveal the performance of different strategies from the perspective of component operation status. Further, the comparison on each section only includes the performance of the front motor as the power distribution rate of the rear motor is a fixed value of 0.8.
**FIGURE 11** Illustration on ICE torque by different methods in driving cycle 1

**FIGURE 12** Illustration on ICE torque by different methods in driving cycle 2

**FIGURE 13** Illustration on motor torque by different methods in driving cycle 1
FIGURE 14  Illustration on motor torque by different methods in driving cycle 2

FIGURE 15  Illustration on generator torque by different methods in driving cycle 1

FIGURE 16  Illustration on generator torque by different methods in driving cycle 2
Three periods in driving cycle 1 are selected to demonstrate the performance of different strategies. From 8800 to 10,500s in Figures 11, 13 and 15, the driving conditions mainly about urban-area congestion condition. The CR-EMS try to hold the fuel consumption by letting vehicle operate in pure electric driving mode, implying that CR-EMS encourages battery discharge when vehicle driving at low speed. When the vehicle is in urban-area congestion condition, the fuel consumption in serial driving mode by OL-EMS and OB-EMS forces engine to start, adverse to fuel consumption saving. From 10,800 to 11,100 s, vehicle operates on high-speed driving condition. The CR-EMS with driving condition identification seizes the opportunity to increase the battery SOC by changing the driving mode in parallel driving mode in high speed for efficient working state of ICE. Comparing with the performance of CR-EMS, BO-EMS operates the vehicle driving in parallel from 10,900 to 11,000 s and the OL-EMS totally drives the vehicle in pure electric driving mode, not giving full operate to the working ability of ICE. Then in urban-area congestion condition from 11,100 s to the end, the charged electricity is used to avoid over consumed fuel for operating in inefficient working state of ICE by using CR-EMS. Comparing with the performance of CR-EMS, because of driving condition recognition is not used, OL-EMS is impossible to operate the ICE adaptively, OL-EMS requires the ICE to operate in urban-area congestion condition frequently, increasing the fuel consumption. Similarly, CR-EMS still has the ability to adjust the driving mode by invoking adaptive logic thresholds at high-speed driving condition from 6200 to 6300 s in driving cycle 2 in Figures 12, 14 and 16. At this period, the strategy grasps the opportunity to increase the battery SOC in high-speed driving condition by governing ICE work in efficient working state. Comparing the torque curves of ICE and generator by using CR-EMS with other strategies, using driving condition recognition avoids the frequent start and stop of the ICE.

In reference to the CR-EMS with driving condition recognition, the strategy can grasp opportunity to invoke the optimized logic thresholds with higher adaptability to driving conditions by condition recognition, adaptively managing energy flow within powertrains effectively. Through the simulation analysis, it can be seen that the logic threshold optimization combined with driving condition recognition has strong robustness to various driving conditions.

5 | CONCLUSIONS

In this paper, a novel energy management strategy for plug-in hybrid electric vehicle is proposed with the enhanced capacity in energy saving after endowed superior adaptability to driving conditions. The support vector machine is utilized to identify driving behaviours online based on the specially extracted inputs by random forest. The cooperation by support vector machine and random forest provides the precise classification of driving conditions online, furnishing the adaptability of energy management strategy to environment. The whale optimization algorithm optimizes control thresholds for different driving conditions. The optimized control thresholds will be implemented online according to the identified traffic conditions. The simulation results validate that the proposed energy management strategy can improve fuel economy of the studied plug-in hybrid electric vehicles significantly. Compared with the original strategy, the raised method can save 8.9% energy at most in the simulation.

In the future, more efforts will be made to develop novel methods to further improve the adaptability of energy management strategy to environment. The driving condition identifiers can classify driving conditions based on multi-source information from Internet of Vehicles (IoVs). Besides, methods to precisely forecast velocity profiles will also be carefully investigated.

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REFERENCES

1. Lu, J., Chen X., Zhang Y.: Research on Governmental incentive mechanism of new-energy-vehicle industrialization based on purchasing allowance. J. Comput. Inf. Syst. 8(22), 9433–9440 (2012)
2. Xibo, W.: Spatial distribution evolvement characteristics and influencing factors of automobile manufacturing industry under the guidance of foreign investment: A case study of Guangzhou. Econ. Geogr. 39(07), 119–128 (2015)
3. Feng K., Li J.: Challenges in reshaping the sectoral innovation system of the Chinese automobile industry. In: Liu, K.C., Racherla, U. (eds) Innovation, Economic Development, and Intellectual Property in India and China, pp. 415–438. Springer, Singapore (2019)
4. Melo, P., Araujo R.E., Castro R.D.: Overview on energy management strategies for electric vehicles - Modelling, trends and research perspectives. In: Proceedings of the 2011 3rd International Youth Conference on Energetics (IYCE). Leiria, Portugal (2011)
5. Hafiz, F., Fajri P., Husain I.: Effect of brake power distribution on dynamic programming technique in plug-in series hybrid electric vehicle control strategy. In: Energy Conversion Congress and Exposition (ECCE). Montreal, Canada (2015)
6. Borhan, H., et al.: MPC-based energy management of a power-split hybrid electric vehicle. IEEE Trans. Control Syst. Technol. 20(3), 593–603 (2012)
7. Li, P., et al.: An intelligent logic rule-based energy management strategy for power-split plug-in hybrid electric vehicle. In: 37th Chinese Control Conference. Wuhan, China, pp. 7668–7672 (2018)
8. Johannesson, L., Asbogard M., Egardt B.: Assessing the potential of predictive control for hybrid vehicle powertrains using stochastic dynamic programming. IEEE Trans. Intell. Transp. Syst. 8, 71–83 (2007)
9. Shankar, R., Marco J., Assadian F.: The novel application of optimization and charge blended energy management control for component downsizing within a plug-in hybrid electric vehicle. Energies 5(12), 4892–4923 (2012)
10. Tizhao, W., et al.: Optimization of HESS power allocation for electric vehicle based on genetic algorithm. Electr. Drive 49(02), 49–55 (2019)
11. Xiaolan, W., et al.: Optimization design of fuzzy energy management for plug-in hybrid electric vehicles. J. Syst. Simul. 30(01), 242–248 (2018)
12. Xie, S., et al.: Pontryagin's minimum principle based model predictive control of energy management for a plug-in hybrid electric bus. Appl. Energy 236, 893–905 (2019)
13. Yang Y., et al.: Fuel economy optimization of power split hybrid vehicles: A rapid dynamic programming approach. Energy 166, 929–938 (2019)
14. Zhang, Y., et al.: Energy management strategy for plug-in hybrid electric vehicle integrated with vehicle-environment cooperation control. Energy 197, 117192 (2020)
15. Zhang, Y., et al.: A cyber-physical system-based velocity-profile prediction method and case study of application in plug-in hybrid electric vehicle. IEEE Trans. Cybern. 51(1), 40–51 (2019)
16. 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 185(pt.2), 1633–1643 (2016)
17. Simona, et al.: Adaptive Pontryagin's minimum principle supervisory controller design for the plug-in hybrid GM Chevrolet Volt. Appl. Energy 147, 224–234 (2015)
18. Vafaeipour, M., et al.: An ECMS-based approach for energy management of a HEV equipped with an electrical variable transmission. In: 2019 Fourteenth International Conference on Ecological Vehicles and Renewable Energies (EVER), Monaco (2019)
19. Hou, J., Song Z.: A hierarchical energy management strategy for hybrid energy storage via vehicle-to-cloud connectivity. Appl. Energy 257, 113900.1–113900.9 (2020)
20. Liu X., et al.: Minimum energy management strategy of equivalent fuel consumption of hybrid electric vehicle based on improved global optimization equivalent factor. Energies 12(11), 2076 (2019)
21. Guo, J., et al.: A novel MPC-based adaptive energy management strategy in plug-in hybrid electric vehicles. Energy 175, 378–392 (2019)
22. Shen, P., et al.: Optimal energy management strategy for a plug-in hybrid electric commercial vehicle based on velocity prediction. Energy S0360544218308843 155, 838–852 (2018)
23. Shin, J., Sunwoo M.: Vehicle speed prediction using a Markov chain with speed constraints. IEEE Trans. Intell. Transp. Syst. 20(9), 3201–3211 (2018)
24. Li, L., et al.: Energy management of hybrid electric vehicle using vehicle lateral dynamic in velocity prediction. IEEE Trans. Veh. Technol. 68(4), 3279–3293 (2019)
25. Yeon, K., et al.: Ego-vehicle speed prediction using a long short-term memory based recurrent neural network. Int. J. Automot. Technol. 20(4), 713–722 (2019)
26. Wang W., et al.: Driving Condition Recognition and Optimization-based Energy Management Strategy for Power-split Hybrid Electric Vehicles. Annual conference papers of China Society of Automotive Engineers,398(2019).
27. Xie, H., et al.: A hybrid method combining markov prediction and fuzzy classification for driving condition recognition. IEEE Trans. Veh. Technol. 67(11),10411–10424 (2018)
28. Kang, X., et al.: Analysis of vehicle maneuverability and driving characteristics on a curved road condition. KSCE J. Civ. Eng. 23(1), 420–432 (2019)
29. Liu, T., et al.: Online energy management for multimode plug-in hybrid electric vehicles. IEEE Trans. Ind. Inf. 15, 4352–4361 (2018)
30. Hu, J., et al.: Intelligent energy management strategy of hybrid energy storage system for electric vehicle based on driving pattern recognition. Energy 198, 117298.1–117298.17 (2020)
31. Shirmohammadi, H., Hadadi F., Saeedian M.: Clustering analysis of drivers based on behavioral characteristics regarding road safety. Int. J. Civ. Eng. 17(8), 1327–1340 (2019)
32. Song, K., et al.: Multi-mode energy management strategy for fuel cell electric vehicles based on driving pattern identification using learning vector quantization neural network algorithm. J. Power Sources 389, 230–239 (2018)
33. Wu, J., Zhang C.H., Cui N.X.: Fuzzy energy management strategy for a hybrid electric vehicle based on driving cycle recognition. Int. J. Automot. Technol. 15(7), 1159–1167 (2012)
34. Liang L., et al.: Scaling up Kernel SVM on limited resources: A low-rank linearization approach. IEEE Trans. Neural Networks Learn. Syst. 30(2), 369–378 (2019)
35. MengNa, Z., et al.: Image hybrid denoising algorithm based on improved SVM classification and sparse representation. J. Chin. Comput. Syst. 40(07), 1544–1547 (2019)
36. Safaei, A., et al.: Design of a fuzzy driving cycle identification unit for intelligent control strategy of hybrid vehicles. Modares Mech. Eng. 13(12), 134–143 (2014)
37. Breiman, L.: Random forest. Mach. Learn. 45, 5–32 (2001)
38. Liaw, A., Wiener M.: Classification and regression with random forest. R News 23(23), 18–22 (2002)
39. Mirjalili, S., Lewis A.: The whale optimization algorithm. Adv. Eng. Software. 95, 51–67 (2016)
40. Horng M., et al.: A Multi-Objective Optimal Vehicle Fuel Consumption Based on Whale Optimization Algorithm. In: Pan, J.S., Tsai, P.W., Huang, H.C. (eds) Advances in Intelligent Information Hiding and Multimedia Signal Processing. Smart Innovation, Systems and Technologies, vol 64. Springer, Cham (2017)
41. Shankar, K., et al.: Optimal feature-based multi-kernel SVM approach for thyroid disease classification. J. Supercomput. 76(28), 1–16 (2020)
42. Mistry, P., et al.: Using random forest and decision tree models for a new vehicle prediction approach in computational toxicology. Soft Comput. 20(8), 2967–2979 (2016)

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