ABSTRACT The energy saving of Plug-in hybrid electric bus (PHEB) can be maximized by co-design method (integrated design of topology, component sizing and energy management). In many cases, the components have been manufactured, so it is a shortcut to realize the co-design with existing components. Motivated by this, a Taguchi robust design (TRD) method is proposed for the robust co-design of the PHEB. The main innovation is that the noises of driving cycles and stochastic vehicle mass are considered in the TRD, and the TRD is formulated as a smaller-the-better (STB) problem. Moreover, the signal-to-noise ratio (SNR) is taken as the analysis index, where the fuel economy together with its robustness can be simultaneously enhanced. In specific, the dynamic programming (DP) is firstly taking as the fuel consumption calculation module of the TRD. Then, a series of historical driving cycles and the stochastic vehicle mass are designed as noise factors; the components are designed as control factors. Finally, a receding horizon control (RHC) strategy is deployed to realize adaptive energy management control using the robust component match and the same DP. The TRD results demonstrate that the proposed co-design method is applicable and reasonable; the simulation results show that the RHC strategy can realize adaptive control, and averagely improve the fuel economy by 10.85% compared to a rule-based control strategy.

INDEX TERMS Plug-in hybrid electric bus, co-design, Taguchi robust design, receding horizon control, energy management.

NOMENCLATURE

- $m_e$ the instantaneous fuel consumption of every engine
- $P_e$ the power of every engine
- $T_e$ the torque of every engine
- $n_e$ the speed of every engine
- $b(T_e, n_e)$ the fuel consumption rate
- $P_m$ the power of every motor
- $n_m$ the speed of every motor
- $T_m$ the torque of every motor
- $\eta_m$ the efficiency of every motor in the motoring mode
- $\eta_g$ the efficiency of every motor in the generating mode
- $Q_b$ the battery capacity
- $I_b$ the current of the battery
- $R_0$ the internal resistance
- $V_{oc}$ the open-circuit voltage
- $P_b$ the power of the battery
- $F_f$ the rolling resistance
- $m$ the vehicle mass
- $g$ the gravity acceleration
- $f_r$ the rolling resistance coefficient
- $\beta$ the road angle
- $F_w$ the air resistance
- $C_D$ the aerodynamic drag coefficient
- $A$ the frontal area
- $v$ the velocity
- $F_a$ the acceleration resistance
- $\delta$ the rotating mass coefficient
- $a_v$ the acceleration
- $F_i$ the climbing resistance
- $P_T$ the required power
- $\eta_t$ the efficiency of the transmission system
- $SN_{STB}$ the SNR of the STB
- $n$ the number of experiment
- $y_i$ the response
- $L(y)$ the quality loss
- $k$ the coefficient of the quality loss
have strong coupling relationship and can simultaneously affect the fuel economy of the PHEV. So the co-design (integrated design of topology, component sizing and energy management) is an indispensable approach to tap the potential of energy saving [12]. The co-design can be categorized into three levels, including topology optimization, component sizing optimization and topology combined with component sizing optimization [13], [14]. Wherein, energy management is indispensable for any level of the co-design [15].

In terms of the first level, the investigations mainly focus on the topology optimization. F. Zhang et al. proposed a topology optimization method by employing a one-dimensional Equivalent Consumption Minimization Strategy (ECMS), based on China Bus Driving Cycle [3]. Because no equivalence factor identification method was proposed, the ECMS could not be directly used in real-world. M. Delkhosh et al. proposed a topology optimization method by employing an electric assist control strategy (EACS), based on a typical driving cycle [16]. Since the EACS was one of the rule-based energy managements, it could be directly used in real-world without any known driving conditions. However, the optimality could not be ensured. X. Zhou et al. proposed a multi-objective optimization method by deploying dynamic programming (DP)-based energy management, based on a fixed driving cycle [17]. Similar to the ECMS, it also could not be directly used in real-world.

In terms of the second level, the investigations mainly focus on the component sizing optimization. It can be further classified into indirect and direct methods. For the former, M. Kim proposed a method based on nonlinear programming (NLP) and DP [18]. M. Pourabdollah et al. proposed a combination method with convex optimization and DP [19]. F. Millo et al. proposed a combination method based on genetic algorithm (GA) and ECMS [20]. L. N. Azad et al. proposed a method based on Chaos oscillator differential search algorithm and Pontryagin’s Minimum Principle (PMP) [21]. For the latter, M. Pourabdollah et al. proposed a method using convex optimization to minimize the objective function of weighted sum of operational and component costs [22]. X. Hu et al. proposed a method to simultaneously design the battery sizing, charging, and on-road energy management, based on convex programming [23]. However, apart from the fuzzy logic control strategy in [24] and [25], the optimization-based energy managements were deployed and difficult to be directly used in real-world. Besides, fixed driving cycles were usually deployed in the above methods. This may not be feasible, because many investigations have demonstrated that the optimal component sizing has strong relationship with driving cycles [24]–[28]. In other words, the component sizing that is optimized by any fixed driving cycle cannot reflect the average level of the fuel economy. Therefore, the driving cycles should be taken as a noise.

In terms of the third level, the investigations mainly focus on the topology combined with component sizing optimization. For example, X. Zhang et al. proposed a
method to find the best co-design by employing 12 possible configurations and different component sizes [29]. A. E. Bayrak et al. proposed an all-in-one method by taking GA as the system-level optimization module and Sequential Quadratic Programming (SQP) as subsystem-level optimization module [30]. Z. Qin et al. proposed a method by deploying a meta-heuristic algorithm [31]. W. Zhuang et al. proposed a method by deploying a nested and enhanced iterative optimization algorithm [32]. More importantly, W. Zhuang et al. found that the noise of stochastic vehicle mass was also sensitive to the co-design [32]. However, seldom investigations consider this problem.

From the above analysis, it can be concluded that the co-design should consider two aspects. The first aspect is the direct energy management application problem, that is, the energy management deployed in the co-design should be further used in real-world. The second aspect is that the noises of driving cycles and stochastic vehicle mass should be considered in the co-design.

In many cases, the key components such as engines, motors, automated manual transmissions (AMTs) and final drives have been manufactured. Therefore, it is a shortcut to realize the co-design with the existing components. Then, the co-design becomes the robust component match together with energy management control problem, once the configuration is determined. In practice, Taguchi Robust Design (TRD) is favored by its excellent robust design performance in many product development fields, such as solar photovoltaic system [33], motor design [34], [35] and robotics [36], [37]. This paper proposes a TRD-based co-design method for plug-in hybrid electric bus (PHEB) with existing components. Since the configuration is determined, only the co-design with respect to the component match and energy management is investigated. Three innovations are made to distinguish our contributions from others.

1. A series of historical driving cycles are downloaded from remote monitor system (RMS) and taken as the first noise of the co-design. Meanwhile, the stochastic vehicle mass is designed as the other noise.
2. The co-design is formulated by a static TRD problem, and the fuel consumption extracted from DP is taken as response. Meanwhile, The TRD is formulated as a smaller-the-better (STB) problem, and the signal-to-noise ratio (SNR) is taken as the analysis index.
3. The direct energy management application problem is casted into a RHC strategy. Here, the same method in [38] is directly deployed. Because the same DP in the TRD will be employed in the RHC strategy, the RHC strategy is a feasible method to enhance the advantage of the co-design method. However, it is only a compromised method, because the RHC strategy is not directly used in the co-design.

The remainder of this paper is organized as follows. The models of the vehicle are introduced in Section 2. The TRD-based co-design is detailed in Section 3. The results and discussions are presented in Section 4, and the conclusions are drawn in Section 5.

**II. THE MODELS OF THE VEHICLE**

As shown in Fig. 1, the configuration of the PHEB is single-axle parallel. The torque of the engine and the motor can be coupled before the AMT. The motor is connected to the engine by the clutch. The working modes of the pure-engine and the hybrid driving with or without charging can be realized by engaging the clutch. On the contrary, the regenerative braking and electric vehicle modes can be realized by disengaging the clutch. The curb weight of the PHEB is assumed as 10500kg, the maximum passenger number is assumed as 50 and the average passenger mass is assumed as 70kg. The alternative components are listed in Table 1.

**TABLE 1. The alternative components of the PHEB.**

| Item        | Description                        |
|-------------|------------------------------------|
| AMT 1       | Speed ratios: 6.39, 3.97, 2.40, 1.48, 1, 0.73 |
| AMT 2       | Speed ratios: 6.43, 4.18, 2.53, 1.54, 1, 0.78 |
| AMT 3       | Speed ratios: 6.75, 3.87, 2.36, 1.47, 1, 0.83 |
| AMT 4       | Speed ratios: 7.03, 4.09, 2.45, 1.50, 1, 0.81 |
| Final drive 1| Speed ratio: 6.33                  |
| Final drive 2| Speed ratio: 5.57                  |
| Final drive 3| Speed ratio: 5.13                  |
| Engine 1    | Max torque (Nm): 801.5             |
|             | Max power (kW): 147.7              |
| Engine 2    | Max torque (Nm): 761               |
|             | Max power (kW): 148.4              |
| Motor 1     | Max torque (Nm): 607.8             |
|             | Max power (kW): 94.2               |
| Motor 2     | Max torque (Nm): 484.4             |
|             | Max power (kW): 66.8               |
| Battery     | Capacity (Ah): 50                  |

**A. MODELING THE ENGINES**

In terms of every engine, the fuel consumption rate MAP (Fig. 2) is formulated to look-up table. Because the instantaneous fuel consumption has relationship with the power and the fuel consumption rate, it can be calculated by

\[
m_e = P_e \cdot \frac{b_e(T_e, n_e)}{3600} \tag{1}
\]
where \( m_e \) denotes the instantaneous fuel consumption; \( h_e(T_e, n_e) \) denotes the fuel consumption rate, which can be interpolated by the look-up table of every engine. \( P_e \) denotes the power of every engine and can be obtained by

\[
P_e = \frac{T_e \cdot n_e}{9550}
\]

where \( T_e \) denotes the torque of every engine; \( n_e \) denotes the speed of every engine.

**B. MODELING THE MOTORS**

As shown in Fig. 3, 2 motors are deployed in the co-design. They are formulated by look-up tables based on the efficiency MAPs of the motors. The power of every motor from or to the battery can be described as

\[
P_m = \begin{cases} 
\frac{n_m \cdot T_m}{9550} \cdot \frac{1}{\eta_m}, & \text{if } T_m \geq 0 \\
\frac{n_m \cdot T_m}{9550} \cdot \eta_g, & \text{if } T_m < 0
\end{cases}
\]

where \( P_m \) denotes the power of every motor; \( n_m \) denotes the speed of every motor; \( T_m \) denotes the torque of every motor; \( \eta_m \) and \( \eta_g \) denote the efficiencies of every motor in the motoring and the generating modes, respectively.

**C. MODELING THE BATTERY**

As shown in Fig. 4, the Rint model is deployed. Then, the battery model can be described as

\[
\begin{align*}
S\hat{O}C &= -\frac{1}{Q_b}I_b \\
I_b &= \frac{1}{2R_0}(V_{oc} - \sqrt{V_{oc}^2 - 4R_0P_b})
\end{align*}
\]

where \( Q_b \) denotes the battery capacity; \( I_b \) denotes the current of the battery; \( R_0 \) denotes the internal resistance; \( V_{oc} \) denotes the open-circuit voltage; \( P_b \) denotes the power of battery.

**D. MODELING THE VEHICLE**

Since only the energy saving problem is focused in the co-design, only the longitudinal dynamics is considered in this paper. Therefore, the required power can be obtained by

\[
\begin{align*}
F_r &= m \cdot g \cdot f_r \cdot \cos \beta \\
F_w &= \frac{C_D \cdot A \cdot v^2}{21.15} \\
F_a &= \delta \cdot m \cdot a_v \\
F_i &= m \cdot g \cdot \sin \beta \\
P_r &= (F_r + F_w + F_a + F_i) \cdot \frac{v}{3600 \cdot \eta_t}
\end{align*}
\]

where \( F_r \) denotes the rolling resistance; \( m \) denotes the vehicle mass; \( g \) denotes the gravity acceleration; \( f_r \) denotes the rolling resistance coefficient; \( \beta \) denotes the road angle, which is designed to 0 without the influence of the climbing driving cycles; \( F_w \) denotes the air resistance; \( C_D \) denotes the aerodynamic drag coefficient; \( A \) denotes the frontal area.
area; \(v\) denotes the velocity; \(F_a\) denotes the acceleration resistance; \(\delta\) denotes the rotating mass coefficient; \(a_v\) denotes the acceleration; \(F_i\) denotes the climbing resistance, which is considered as 0 with ignoring the factor of road slope. \(P_r\) denotes the required power; \(\eta_t\) denotes the efficiency of the transmission system.

II. THE PHEB-BASED CO-DESIGN

A. THE FORMULATION OF THE PROBLEM

As stated above, the noises of driving cycles and stochastic vehicle mass can greatly affect the co-design. To clarify the problem, 6 combined driving cycles (the combination of driving cycles and stochastic distributions of passenger mass) named from No. 1 to No. 6 are designed. Moreover, three different cases are defined. Case 1: the combined driving cycles from No. 1 to No. 2 have different historical driving cycles and the same passenger mass. Case 2: the combined driving cycles from No. 3 to No. 4 have the same historical driving cycle and different stochastic distributions of passenger mass. Case 3: the combined driving cycles from No. 5 to No. 6 have different historical driving cycles and stochastic distributions of passenger mass. The stochastic vehicle mass is summed by the assumed curb weight of the PHEB mass and the stochastic distribution of passenger mass. To obtain the stochastic distribution of passenger mass, the passenger number in every road segment is assumed as stochastic variable and is sampled by optimal Latin hypercube design (Opt, LHD) method. The passenger mass is evaluated by passenger number multiplied by the average passenger mass. In addition, Full Factorial design method is deployed to find the best-found component match, by taking the components as factor and the minimum fuel consumption as response.

| Case | Combined driving cycle | Engine | Motor | AMT | Final drive |
|------|------------------------|--------|-------|-----|-------------|
| No. 1 | No. 1 | 2 | 1 | 2 | 1 |
| No. 2 | No. 2 | 2 | 1 | 4 | 1 |
| No. 3 | No. 3 | 2 | 1 | 3 | 1 |
| No. 4 | No. 4 | 2 | 1 | 2 | 1 |
| No. 5 | No. 5 | 2 | 1 | 4 | 1 |
| No. 6 | No. 6 | 2 | 1 | 3 | 1 |

B. THE BASIC PRINCIPLE OF THE CO-DESIGN

As shown in Fig. 8, the co-design of the PHEB is divided into two steps: the robust component matching design and the adaptive energy management control. In the first step, the components are designed as control factors; the stochastic vehicle mass (the stochastic passenger number) and historical driving cycles are designed as noise factors;
C. THE FORMULATION OF THE TRD

In practice, TRD is a powerfully robust design method, which can reduce the effect of the noises on the response, by taking the SNR as analysis index. In this paper, the main purpose of the co-design is to minimize the mean fuel consumption whilst reducing the corresponding quality loss. In other words, the component match should have high robust performance and counter the existing noises. Therefore, it can be taken as a static robust design problem. Moreover, the TRD problem can be changed into a STB problem based on the design objective. Then, the SNR can be described as

$$ SN_{STB} = -10 \log_{10} \left( \frac{1}{n} \sum_{i=1}^{n} y_i^2 \right) $$

where $SN_{STB}$ denotes SNR of the STB, in which the higher of the value is, the better performance will be; $y_i$ denotes the response, $n$ denotes the number of experiments. The quality loss function is designed as

$$ L(y) = k \cdot y^2 $$

where $L(y)$ denotes the quality loss; $k$ denotes the coefficient of the quality loss; $y$ denotes the quality value.

As shown in Table 3, the SNR can be calculated by an inner-outer table, which is also the most important issue of the TRD. Here, the inner table is constituted by control factors, where 48 experiments are designed by Full Factorial design method. The outer table is constituted by noise factors, where 100 experiments are designed by Opt, LHD method, using descriptive sampling method. Moreover, 100 energy management calculations will be executed for every control factor, based on the experiments of noise factors. Finally, the SNR and the quality loss can be calculated based on Eq. (7) and Eq. (8), respectively.

D. THE FORMULATION OF DP

Inspired by [32], the states are designed as SOC and the gear position of the AMT. The control vector is constituted by the throttle of the engine and the shift instruction of the AMT. Then the state equation can be described as

$$
\begin{align*}
SOC(k+1) &= SOC(k) - \frac{V_{oc}(k) - \sqrt{V_{oc}(k)^2 - 4R_0(k)P_b(k)}}{2R_0(k)Q_b} \\
gear(k+1) &= \begin{cases} 
1, & \text{gear}(k) + \text{sh}(k) < 1 \\
6, & \text{gear}(k) + \text{sh}(k) > 6 \\
gear(k) + \text{sh}(k), & \text{otherwise}
\end{cases} \\
x(k) &= \begin{bmatrix} SOC(k) \\
gear(k) \end{bmatrix} \\
u(k) &= \begin{bmatrix} \text{throt}(k) \\
\text{sh}(k) \end{bmatrix}
\end{align*}
$$

(9)
TABLE 3. The inner-outer table of the TRD.

| The experiments | The inner table | The outer table |
|------------------|-----------------|-----------------|
|                  | The control factor | The noise factor |
| $\Omega_1$ | $\Omega_2$ | $\Omega_3$ | $\ldots$ | $\text{cyc}_1$ | $m_1$ | $m_3$ | $\ldots$ |
| $\Omega_1$ | $\Omega_2$ | $\Omega_3$ | $\ldots$ | $\text{cyc}_2$ | $m_2$ | $m_3$ | $\ldots$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| $\Omega_1$ | $\Omega_2$ | $\Omega_3$ | $\ldots$ | $\text{cyc}_{100}$ | $m_{100}$ | $m_{100}$ | $\ldots$ |

The evaluation of the SNR and $L(x)$

| The experiments | SNR1 and $L_r(x)$ |
|------------------|-------------------|
|                  | $\text{cyc}_1$ | $m_1$ | $m_3$ | $\ldots$ |
|                  | $\text{cyc}_2$ | $m_2$ | $m_3$ | $\ldots$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| $\text{cyc}_{100}$ | $m_{100}$ | $m_{100}$ | $\ldots$ | $\ldots$ |

The evaluation of the SNR and $L_{48}(y)$

| The experiments | SNR48 and $L_{48}(y)$ |
|------------------|-------------------------|
| $\text{cyc}_1$ | $m_1$ | $m_3$ | $\ldots$ |
| $\text{cyc}_2$ | $m_2$ | $m_3$ | $\ldots$ |
| $\ldots$ | $\ldots$ | $\ldots$ | $\ldots$ |
| $\text{cyc}_{100}$ | $m_{100}$ | $m_{100}$ | $\ldots$ | $\ldots$ |

where $\text{gear}(k)$ denotes the gear position of every AMT; In fact, the value of the gear position used in the calculation is 2 to 6 without the influence of the climbing driving cycles; $\text{throt}(k)$ denotes the throttle of every engine, which is ranged from 0 to 1; $x(k)$ denotes the state vector; $u(k)$ denotes the control vector; $sh(k)$ denotes the shift instruction of every AMT, which is designed as 1, 0 and -1 to denote upshift, hold on and downshift, respectively. The objective function is designed as the weighed sum of the fuel consumption and the shift frequency. It can be described as

$$
\text{Min} \ J_{\pi} (x_0) = \sum_{k=0}^{N-1} \left[ m_e(k) + \eta \left| sh(k) \right| \right]
$$

where $J_{\pi} (x_0)$ denotes the objective function; $\eta$ denotes the weighted factor, which is designed to 0.01 to balance the two objectives; $n_{e_{\text{min}}}^{\text{min}}$ and $n_{e_{\text{max}}}^{\text{max}}$ denote the lower and upper boundaries of the speed of every engine; $n_{m_{\text{min}}}^{\text{min}}$ and $n_{m_{\text{max}}}^{\text{max}}$ denote the lower and upper boundaries of the speed of every motor; $T_{e_{\text{min}}}^{\text{min}}$ and $T_{e_{\text{max}}}^{\text{max}}$ denote the lower and upper torque boundaries of every engine, respectively; $T_{m_{\text{min}}}^{\text{min}}$ and $T_{m_{\text{max}}}^{\text{max}}$ denote the lower and upper torque boundaries of every motor, respectively; $SOC_{\text{f}}$ denotes the terminal SOC at the destination of the route, which is designed as a soft constraint to ensure the convergence of DP.

E. THE RHC CONTROL STRATEGY

As shown in Fig. 9, the RHC is constituted by the DP, the Markov chain and the predictive model of SOC terminal constraint. The Markov chain is generated by historical driving cycles [9]. The basic principle of the RHC is that, at every time step, the Markov chain will firstly predict the acceleration sequence in the next 60s, based on the current driving condition. Then the velocity sequence in the next 60 can be deduced, and the optimal control vector can be obtained by DP with predicted terminal SOC. Finally, the first control vector will be transmitted to the vehicle model to update the states of the SOC and the gear position.
Referenced by [38], a similar predictive model of terminal SOC is directly constructed based on Levenberg-Marquardt algorithm. As shown in Fig. 10, a series of combined driving cycles are designed to construct the predictive model.

\[
SOC_t(k) = a_1 \cdot e^{-a_2 D_d(k)} + a_3 \cdot e^{-a_4 D_d(k)} + a_5 \cdot e^{-a_6 D_d(k)}
\]

(11)
where $SOC_r(k)$ denotes the reference SOC of the predictive model, which will also be defined as a soft constraint at every time step in the RHC strategy; $D_d(k)$ denotes the normalized trip distance; $e$ denotes the Euler number, whose value is about 2.71828; $a_1 \sim a_8$ denote the fitting coefficients of the predictive model. The detailed coefficients are shown in Fig. 11.

![FIGURE 11. The SOC trajectories.](image1)

![FIGURE 12. The SNR.](image2)

### IV. THE RESULTS AND DISCUSSIONS

#### A. THE ROBUST COMPONENT MATCH

As shown in Fig. 12, the experiment 31 is the robust co-design point, because it has the maximum SNR. This is also demonstrated by the lowest quality loss in Fig. 13. Moreover, the mean fuel consumption of the experiment 31 also has the minimum value (Fig. 14). In short, the robust component match is constituted by the engine 2, the motor 1, the AMT 3 and the final drive 1 (Table 4).

![FIGURE 13. The quality loss.](image3)

![FIGURE 14. The mean fuel consumption.](image4)

**TABLE 4. The component match of the experiments.**

| The component | The experiment |
|---------------|----------------|
| Engine        | 1 1 2 2         |
| Motor         | 1 2 1 2         |
| AMT           | 1 2 3 2         |
| Final drive   | 3 3 1 3         |

To demonstrate the robustness of the experiment 31, other experiments of 3, 18 and 42 are also deployed (Table 4). Besides, eight combined driving cycles named from No. 16 to No. 23 are also designed (Fig. 15). As shown in Fig. 16, the mean fuel consumption of experiment 31 is the lowest, and the component match of experiment 31 can improve the fuel economy by 3.72%, 4.61%, 3.04%, respectively, compared to other experiments (Table 5).

![FIGURE 15. The combined driving cycles from No.16 to No.23.](image5)

#### B. THE REFERENCE SOC MODEL

As shown in Fig. 11, the coefficient of determination ($R^2$) of the predictive model is 0.995, which implies that it has high predictive precision. To demonstrate the conclusion, a series
of combined driving cycles named from No. 24 to No. 27 (Fig. 17) are designed. As shown in Fig. 18, most of the relative errors between the predicted SOC and the optimal SOC for the four combined driving cycles locate in the scope of [-5% 5%]. This implies that the designed reference SOC model is reasonable for the RHC strategy.

As shown in Fig. 19, the SOC trajectories of the RHC are close to the DP for all of the driving cycles. This implies that the feedback SOC of the RHCs can track the predicted SOC well. Specially, the SOC trajectories of the rule-based control strategy are different from others, where the PHEB will firstly work in CD mode, then work in CS mode once the feedback SOC is lower than 0.3. Furthermore, from the SOC trajectories of the DP and the RHC, it can be seen that the CD mode can be approximately realized, where the motor and the engine will coordinately work to provide the required power of the PHEB, and the CS mode will be avoided.

The initial SOCs of the combined driving cycles are the same, and the terminal SOCs are similar (Fig. 19). In this case, the fuel economy of the control strategies can be evaluated by fuel consumption. From this point of view, it can be seen from Table 6 that the DP is the best control strategy. However, it is difficult to be directly used in real-world. As an improved method, the fuel economy of the RHC is worse than the DP, while it has great promising for the practical application because no driving conditions should be known in a prior. Although the rule-based control strategy can be directly used in real-world, the worst fuel economy may restrict its application. In addition, the fuel economy of the RHC strategy can be averagely improved by 10.85%, compared to the rule-based control strategy. In addition,

C. THE RHC STRATEGY

To evaluate the RHC strategy, a rule-based control strategy which is characterized by charge depletion (CD) followed by charge sustain (CS) modes is deployed. Moreover, the DP is once deployed, assuming the combined driving cycles are known in a prior.
from Table 7, it can be seen that the computation time of the RHC is less than the whole time of the combined driving cycle in the simulation environment. However, the computation burden may be higher than the currently used vehicle controllers. Therefore, the strategy should be further improved for practical application.

V. CONCLUSION

This paper proposes a TRD-based co-design method for PHEB. The noises of the driving cycles and the stochastic vehicle mass are considered. The main conclusions are drawn as follows.

(1) The robust component match that has the lowest mean fuel consumption and quality loss can be found with TRD method, by taking the components as control factors, the driving cycles and the stochastic vehicle mass as noise factors and STB as design objective.

(2) Adaptive energy management control can be realized by the RHC strategy with the same DP in the TRD. Although DP is an off-line algorithm, the RHC strategy can realize adaptive control by combining the DP, the Markov chain and the predictive model of terminal SOC constraint. Moreover, the RHC strategy can averagely improve the fuel economy by 10.85%, compared to the on-line algorithm of rule-based control strategy.

The future work will mainly focus on the computation efficiency improvement of the strategy and the development of a controller that has high computation ability.

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