INTRODUCTION

In our previous work, a novel distributed electric-wheel drive configuration applied in vehicles is proposed, which is called hierarchical coupled electric powertrain (HCEP).\(^1\) The HCEP is composed of the upper coupling layer (the torque coupling between the front and rear axles) and the lower coupling layer (the dual-motor rotation speed coupling in each wheel). The HCEP is promising because of the following two advantages: (1) it integrates the rotation speed coupling and torque coupling, which allows it to expand the efficient working range of distributed drive electric vehicles (DDEVs) in two dimensions of the vehicle speed and torque and to significantly improve the economy of DDEVs; (2) compared with peer powertrains proposed in\(^2\)-\(^3\) which arrange both the rotational speed coupling and torque coupling in each wheel, the HCEP is simpler in structure. The HCEP utilizes the independence and controllability between the output torque of the front axle and that of the rear axle in DDEVs and moves the torque coupling from inside of wheels to between the front and rear axles; thus, only the rotational speed coupling is arranged in each wheel. According to the previous research, the HCEP
could theoretically reduce the energy consumption of DDEVs by 5.6% to 10.6% under different driving cycles.

The HCEP is a multi-power sources drive system (MPSDS) that cannot exert its energy-saving potential without a suited energy management strategy (EMS). The energy management of the HCEP is much more complicated than that of common MPSDSs because the torque coupling and rotation speed coupling exist together in the HCEP and the rotation speed allocation is restricted by the torque allocation. Because of this, EMSs of common MPSDSs cannot be directly applied to the HCEP. However, fortunately, EMSs of common MPSDSs can provide a reference for the development of the EMS of the HCEP.

So far, there have been many reports on EMSs of common MPSDSs. Experience-based EMSs, for example, rules-based EMSs and fuzzy logic-based EMSs, are widely used because they do not require complex algorithms and are easily implemented. However, the economy and robustness of this type of EMSs is difficult to be guaranteed. The equivalent consumption minimum strategy is often utilized in the energy management of hybrid electric vehicles (HEVs), but it is not suitable for pure electric vehicles (PEVs).

Dynamic programming (DP) is an effective method to locate the global optimal EMS, but it requires large amount of calculation. Compared with the DP, the computation burden of the convex optimization is much lower. However, the convex optimization of complex systems can be arduous due to the excessive number of parameters that has to be taken into consideration and not all systems are suitable for linearization. Another usually used optimization algorithm is the Pontryagin’s Minimum Principle (PMP) that can locate the global optimal EMS by minimizing the Hamiltonian function. But PMP-based EMSs are difficult to be applied directly as the costates in the Hamiltonian function need to be determined with repeat iteration. A predominantly limiting factor for the online application of the above optimization algorithm-based EMSs is that they need to know the precise driving conditions in advance. Results obtained from optimization algorithm-based EMSs are usually used as the benchmark to improve or evaluate other EMSs. In addition, optimization algorithms such as the genetic algorithm and particle swarm optimization are also often used to optimize the parameters of EMSs to achieve better control effects.

In some researches, the model predictive control (MPC) is applied in the EMSs of MPSDSs. In MPC-based EMSs, the MPC is commonly used together with vehicle speed prediction. In other words, prediction algorithms, such as the Markov chain and neural network, are first used to predict the near future vehicle speed, and then, the MPC is adopted to realize the local optimal energy management of powertrains. Although the MPC is an instantaneous optimal control method, the real time is the biggest obstacle to its online application. When the vehicle speed prediction is integrated in an EMS, the EMS can adapt to the change of traffic conditions. However, ensuring the prediction accuracy of the vehicle speed is difficult. The near future traffic conditions can also be obtained through the global positioning system, geographic information system, Internet of vehicles, etc.

Another type of EMSs with adaptability to actual traffic conditions is based on the driving condition recognition. The idea of driving condition recognizer (DCR)-based EMSs is that different substategies are designed for different driving conditions, and then, the substrategy most suitable for the current driving condition is used. In DCR-based EMSs, the misrecognition of driving conditions is always unavoidable, which decreases the performance of this type of EMSs.

Recently, some scholars use reinforcement learning (RL) algorithms to build EMSs. According to their research, it can be concluded that RL algorithms, such as Q-learning, deep Q-learning, double deep Q-learning, deep deterministic policy gradient, and Dyna framework, can well deal with energy management of MPSDSs. However, RL algorithms are a learning process starting from scratch because no prior knowledge is involved, which leads to the fact that RL algorithm-based EMSs may require a long training time.

In MPSDSs, the improvement of energy efficiency usually leads to the increase of mode switching frequency, which may deteriorate the ride comfort. In Ref. 40, the method of delay mode switching is applied in the EMS of a dual-motor drive EV to suppress the mode switching frequency. The difficulty of this approach is how to find appropriate delay switching rules to better balance energy efficiency and mode switching frequency.

This paper aims to develop an online adaptive EMS for the promising HCEP to exert its energy-saving potential as much as possible while considering the adaptability to driving conditions and the suppression of mode switching frequency.

2 | CONFIGURATION AND PRINCIPLE OF THE HCEP

In the novel HCEP, all four wheels are capable of power output and their power output characteristics are the same. As shown in Figure 1, each wheel is integrated with two motors (ie, M1 and M2), two planetary gear trains (ie, PGT 1 and PGT 2), and two brakes (ie, B1 and B2). M1 and M2 are connected to the sun gear and ring gear of PGT 1, respectively. The carrier of PGT 1 is connected to the sun gear of PGT 2, the carrier of PGT 2 is fixed, and the ring gear of PGT 2 is connected to the tire. B1 and B2 are responsible for braking the sun gear and ring gear of PGT 1, respectively. In each front axle wheel, an additional synchronizer (SY) is fitted between PGT 1 and PGT 2 to disconnect the power transmission between the tire and M1 and M2 if needed.
driving conditions to be analyzed in this study are straight, subsequent analyses are conducted from the perspective of the front and rear axles instead of that of four wheels. The HCEP consists of two coupling layers. One is the upper coupling layer that denotes the torque coupling between the front and rear axles; the other is the lower coupling layer that denotes the dual-motor rotation speed coupling in each wheel.

In the upper coupling layer, there are two working modes, that is, single axle driving (SA) and torque coupling driving by the front and rear axles (TC). When the vehicle demand torque is small, the upper coupling layer adopts mode SA, that is, the rear axle wheels output impetus while the front axle wheels do not work. In this case, the power flow of the vehicle is shown in Figure 2A and its dynamic model is as follows:

\[ T_v = T_r = T_{rr} + T_{rl} \]  

where, \( T_v \) is the vehicle demand torque, \( T_r \) is the output torque of the rear axle, and \( T_{rr} \) and \( T_{rl} \) are the output torque of the right rear and left rear wheels, respectively. When the vehicle demand torque is large, the upper coupling layer adopts mode TC, that is, the front and rear axle wheels drive the vehicle in the form of torque coupling. In this case, the power flow of the vehicle is shown in Figure 2B and its dynamic model is as follows:

\[ T_v = T_r + T_f = T_{rr} + T_{rl} + T_{fr} + T_{fl} \]  

where, \( T_f \) is the output torque of the front axle, and \( T_{fr} \) and \( T_{fl} \) are the output torque of the right front and left front wheels, respectively.

In the lower coupling layer, that is, in each wheel, there are three working modes which are single M1 driving (SM1), single M2 driving (SM2), and dual-motor rotation speed coupling driving (SC), respectively. Mode SM1 will be selected when the desired output torque of a wheel is not large and the vehicle speed is low. The power flow of the wheel is shown in Figure 3A, and its dynamic model is as follows:

\[ n_w = \frac{n_1}{(1 + k_1)k_2} \]

\[ T_w = T_1(1 + k_1)k_2\eta_t \]  

where, \( n_w \) and \( T_w \) are the rotation speed and output torque of the wheel, respectively, \( n_1 \) and \( T_1 \) are the rotation speed and output torque of M1, respectively, \( k_1 \) and \( k_2 \) are the characteristic parameters of PGT 1 and PGT 2, respectively, \( \eta_t \) is the total transmission efficiency of PGT1 and PGT2. It should be noted that although in theory there is a small difference between the transmission efficiency when the power is input from the sun gear of PGT1 while is output from the carrier of PGT1 and the transmission efficiency when the power is input from the ring gear of PGT1 while is output from the carrier of PGT1, this small difference is ignored in this paper to facilitate the development
of the EMS. That is, we consider the transmission efficiency of PGT1 to be the same regardless of the power is input from the sun gear or ring gear. Thus, no matter which mode is adopted in the wheel, $\eta_t$ is the same. Mode SC will be selected when the desired output torque of a wheel is low and the vehicle speed is high. The power flow of the wheel is shown in Figure 3B, and its dynamic model is as follows:

$$n_w = \frac{n_1 + k_1 n_2}{(1 + k_1)k_2}$$

$$T_w = T_1 (1 + k_1)k_2 \eta_t$$

where, $n_2$ and $T_2$ are the rotation speed and output torque of M2, respectively. Mode SM2 will be selected regardless of the vehicle speed, as long as the desired output torque of a wheel is large. The power flow of the wheel is shown in Figure 3C, and its dynamic model is as follows:

$$n_w = \frac{k_1 n_2}{(1 + k_1)k_2}$$

$$T_w = \frac{T_2 (1 + k_1)k_2 \eta_t}{k_1}$$

The specifications of the vehicle are listed in Table 1. The specifications of parts of a wheel are listed in Table 2. Figures 4 and 5 are efficiency MAPs of M1 and M2, respectively.

### 3.1 Energy management issue of the HCEP

The energy management issue of the HCEP can be described using the following discrete dynamic system:

$$x_{i+1} = f(x_i, u_i) i = 0, 1, 2, \ldots, N - 1$$

$$u_i = [u_{i,1}, u_{i,2}, u_{i,3}]$$

where, $u_i$ is the action vector. $u_{i,1}$ is the target torque distribution ratio between the front and rear axles at the sampling time $i$, and it can be expressed as follows:

$$u_{i,1} = \frac{T_{f,i,\text{tar}}}{T_{f,i,\text{tar}} + T_{r,i,\text{tar}}}$$

here, $T_{f,i,\text{tar}}$ and $T_{r,i,\text{tar}}$ are the target output torque of the front and rear axles, respectively. $u_{i,2}$ is the target rotation speed distribution ratio in front axle wheels at the sampling time $i$, and it can be expressed as follows:

$$u_{i,2} = \frac{n_{f,M1,\text{tar}}}{n_{f,M1,\text{tar}} + k_1 n_{f,M2,\text{tar}}}$$
$u_{i, 3} = \frac{n_{r, M1, tar}}{n_{r, M1, tar} + k_{1}n_{r, M2, tar}}$ (12)

$u_{i, 1}$ and $u_{i, 2}$ are rotation speed ratios in front and rear axle wheels at sampling time $i+1$, respectively.

The mapping $f$ in Equation (9) can be described as follows: (1) If $u_{i, 1}$ is equal to 0, $x_{i+1, 1}$ is SA; if $u_{i, 1}$ is between 0 and 1, $x_{i+1, 1}$ is TC. (2) If $u_{i, 2}$ is equal to 0, $x_{i+1, 2}$ is SM2; if $u_{i, 2}$ is between 0 and 1, $x_{i+1, 2}$ is SC; if $u_{i, 2}$ is equal to 1, $x_{i+1, 2}$ is SM1. (3) If $u_{i, 3}$ is equal to 0, $x_{i+1, 3}$ is SM2; if $u_{i, 3}$ is between 0 and 1, $x_{i+1, 3}$ is SC; if $u_{i, 3}$ is equal to 1, $x_{i+1, 3}$ is SM1. (4) $x_{i+1, 4}$ is equal to $u_{i, 1}$, $x_{i+1, 5}$ is equal to $u_{i, 2}$, and $x_{i+1, 6}$ is equal to $u_{i, 3}$.

At any sampling time, the search range of $u_{i, 1}$ is [0, 1), but the search range of $u_{i, 2}$ and $u_{i, 3}$ is not always [0, 1]. Figure 6 shows the external characteristic curves (ECCs) of the rear axle when the rear axle wheels work in modes SM1, SM2, and SC, respectively. ECC of the vehicle is also drawn in Figure 6. Due to the ECCs of the front axle is completely consistent with that of the rear axle, it is not repeated to draw here. Assume that at the sampling time $i$, the target operating point of the vehicle is located at A. If $u_{i, 1}$ values 0, the
upper coupling layer works in mode SA, the front axle does not output power, the operating point of the rear axle is located at A, the rear axle wheels can work in mode SM2 or SC, and the rotation speed distribution range of M1 in the rear axle wheels is \([0, n_1]\); when the value of \(u_{i-1}\) is changed, such as 0.25, then the upper coupling layer will work in mode TC, the operating point of the front axle will locate at C, the front axle wheels can work in modes SM1, SM2, or SC, the rotation speed distribution range of M1 in the front axle wheels is \([0, n_3]\), the operating point of the rear axle will locate at B, the rear axle wheels can only work in mode SM2 or SC, and the rotation speed distribution range of M1 in the rear axle wheels is \([0, n_2]\). It can be seen that the rotation speed distribution range in front and rear axle wheels changes with the torque distribution between front and rear axles, that is, the search range of \(u_{i-2}\) and \(u_{i-3}\) varies with \(u_{i-1}\).

To sum up, the torque distribution exists together with the rotation speed distribution in the HCEP, and the rotation speed distribution is restricted by the torque distribution. The energy management of the HCEP is an optimization issue in the three-dimensional continuous space. It is not possible to solve the complex energy management issue online. In fact, even if the optimization algorithm such as DP is adopted to solve this issue offline, if the discrete lattice points are small, the calculation amount and solution time are also not to be underestimated. In fact, in order to ensure the optimization effect, the discrete lattice points of continuous variables are generally not too large. Therefore, it is necessary to simplify the energy management issue of the HCEP to reduce its calculation time.

### 3.2 Simplification of the issue

In order to decrease the complexity of the energy management issue of the HCEP, a simple power allocation method is introduced. The power allocation method includes two parts. One is the rotation speed distribution submethod, and the other is the torque distribution submethod.

1) Introduced simple rotation speed distribution submethod: the search of the optimal rotation speed allocation within the wheel is simplified to look up the table. For the working mode SM1 or SM2 of the lower coupling layer, that is, of each wheel, only M1 or M2 works, and there is no rotation speed allocation between M1 and M2. For the working mode SC, the optimal rotation speed distribution corresponding to each working point of the wheel can be obtained offline through traversal method and stored in the controller of the wheel in the form of a table. In the actual control, if a wheel works in mode SC, the optimal rotation speed distribution between M1 and M2 can be obtained directly by looking up the table. The optimal rotation speed of M1 under mode SC obtained offline is shown in Figure 7. Since the rotational speeds of the wheel, M1, and M2 satisfy the constraint of Equation (5), no matter what the rotational speed of the wheel is, as long as M1 works at the optimal assigned rotational speed, then M2 will naturally work at its assigned optimal rotation speed. Therefore, only the optimal rotation speed distribution table of M1 needs to be stored in the memory, as well as only the optimal rotation speed of M1 needs to be queried in the control.

2) Introduced simple torque distribution submethod: when the upper coupling layer works in mode TC, the required torque of the vehicle is evenly distributed to the front and rear axles. Thus, the search range of \(u_{i-1}\) is changed from \([0, 1)\) to the two values of 0 and 0.5.

If both of the introduced rotation speed and torque distribution submethods are reasonable, the energy management issue of the HCEP can be transformed from Equation (9) to

\[
X_{i+1} = \begin{bmatrix} U_i \\ X_i \\ \end{bmatrix}, i = 0, 1, 2, \ldots, N - 1
\]

\[
U_i = [u_{i-1}, u_{i-2}]
\]

\[
X_{i+1} = [X_{i+1,1}, X_{i+1,2}]
\]

![Figure 6](image1.png)  
**Figure 6** ECCs of the rear axle and vehicle when the vehicle is in drive

![Figure 7](image2.png)  
**Figure 7** Optimal rotation speed distribution of M1 under the mode SC
where, $X_{i+1}$ is the new state vector, $U_i$ is the new action vector, $U_{i,1}$ and $U_{i,2}$ are the target working modes of the upper and lower coupling layers at the sampling time $i$, respectively. $X_{i+1,1}$ and $X_{i+1,2}$ are the working modes of the upper and lower coupling layers at the sampling time $i+1$, respectively. It can be seen that the front axle wheels and rear axle wheels are no longer distinguished here, but are uniformly referred to by the lower coupling layer. This is because when the upper coupling layer works in mode TC, the power output of the front axle wheels and that of rear axle wheels is the same and the front and rear axle wheels can work in the same mode. In addition, when the upper coupling layer works in mode SA, we can also assume that the front axle wheels and rear axle wheels work in the same mode, but the front axle wheels does not output power. Thus, at any sampling time, $U_{i,1}$ has at most two values, that is, SA and TC, while $U_{i,2}$ has at most three values, that is, SM1, SM2, and SC. The energy management of the HCEP is transformed from the optimization in the three-dimensional continuous space to the optimization in the set listed in Table 3. The computational burden is greatly reduced.

For an electric wheel, it is possible to obtain and store its working characteristics, control parameters, and other information before leaving the factory. Therefore, it is feasible to simplify the search of the optimal rotation speed allocation in the lower coupling layer to look up the table. The rationality of the introduced torque distribution submethod can be evaluated by comparing the following two cases. In the first case, the torque distribution ratio between the front and rear axles traverses in $[0, 1)$. In the second case, the torque distribution ratio only traverses the two values of 0 and 0.5. As to the lower coupling layer, regardless of the case, modes SM1, SM2, and SC are traversed and the most efficient mode is adopted. The difference between vehicle efficiencies obtained from the two cases is shown in Figure 8, and the statistical analysis results of the difference are listed in Table 4. It can be seen that there is no significant distinction between the vehicle efficiencies obtained from the two cases. Therefore, when the upper coupling layer works in mode TC, it is reasonable to evenly assign the required torque of the vehicle to the front and rear axles.

### Table 3

| Action vector | $U_{i,1}$ | $U_{i,2}$ |
|---------------|-----------|-----------|
| 1             | SA        | SM1       |
| 2             | SA        | SM2       |
| 3             | SA        | SC        |
| 4             | TC        | SM1       |
| 5             | TC        | SM2       |
| 6             | TC        | SC        |

### Table 4

| State of vehicle | Mean (%) | Standard deviation (%) |
|------------------|----------|------------------------|
| Driving          | −0.01    | 0.40                   |
| Regenerative braking | −0.03   | 0.96                   |

### 3.3 Solution of the simplified issue

The DP can be used to solve the simplified energy management issue, so as to offline obtain the optimal working mode sequences of the HCEP. The idea of the DP is to divide the optimization issue into a series of minimization subissues backward from the terminal sampling time. These subissues can be expressed as follows:

At sampling time $N-1$:

$$J^*_N (X_{N-1}) = \min_{U_{N-1}} [L(X_{N-1}, U_{N-1})]$$  \hspace{0.5cm} (14)

At sampling time $i$, $0 \leq i < N-1$:

$$J^*_i (X_i) = \min_{U_i} \left[ L(X_i, U_i) + J^*_{i+1} (X_{i+1}) \right]$$  \hspace{0.5cm} (15)

where, $J^*_i (X_i)$ is the optimal accumulated cost function which represents the optimal cost that if at the sampling time $i$, the HCEP starts at state $X_i$ and follows the optimal control path thereafter until the final sampling time. $L(X, U)$ is the instantaneous cost function. Here, only energy consumption is considered. Thus, $L(X, U)$ denotes the total energy consumption
of all motors in the HCEP at the sampling time \( i \), and it can be expressed as follows:

\[
L(X_i, U_i) = \frac{2\Delta t}{9550} (n_{r1} T_{r1} \eta_{r1} \text{sign}(T_{r1}) + n_{r2} T_{r2} \eta_{r2} \text{sign}(T_{r2})) + n_{f1} T_{f1} \eta_{f1} \text{sign}(T_{f1}) + n_{f2} T_{f2} \eta_{f2} \text{sign}(T_{f2}))
\]  

(16)

where, \( \Delta t \) is the sampling interval. \( n_{r1} \) and \( T_{r1} \) are the rotation speed and output torque of M1 in the rear axle wheels, respectively. \( n_{r2} \) and \( T_{r2} \) are the rotation speed and output torque of M2 in the rear axle wheels, respectively. \( n_{f1} \) and \( T_{f1} \) are the rotation speed and output torque of M1 in the front axle wheels, respectively. \( n_{f2} \) and \( T_{f2} \) are the rotation speed and output torque of M2 in the front axle wheels, respectively. \( \eta_{r1} \) and \( \eta_{r2} \) are the efficiencies of M1 and M2 in the rear axle wheels, respectively. \( \eta_{f1} \) and \( \eta_{f2} \) are the efficiencies of M1 and M2 in the front axle wheels, respectively. The number 2 refers to two wheels, that is, the left and right wheels, on each axle.

In addition, the following constraints should be imposed to ensure reasonable operation of the HCEP. For each wheel:

\[
T_{1,\text{min}}(n_1(i)) \leq T_1(n_1(i)) \leq T_{1,\text{max}}(n_1(i))
\]

(17)

\[
n_{1,\text{min}} \leq n_1(i) \leq n_{1,\text{max}}
\]

(18)

\[
T_{2,\text{min}}(n_2(i)) \leq T_2(n_2(i)) \leq T_{2,\text{max}}(n_2(i))
\]

(19)

\[
n_{2,\text{min}} \leq n_2(i) \leq n_{2,\text{max}}
\]

(20)

\[
n_1(i) \cdot n_2(i) \geq 0
\]

(21)

The last constraint is to avoid the power cycling.

To fully consider the characteristics of actual traffic situations, 12 comprehensive driving cycles listed in Table 5 are used to solve the simplified energy management issue. These driving cycles simultaneously include the traffic characteristics of urban, suburban, and highway. After using the DP to solve the simplified energy management issue, the optimal working mode sequences of the HCEP are obtained, as shown in Figures 9 and 10.

### Table 5: Driving cycles used to solve the simplified energy management issue

| No. | Name       | No. | Name       |
|-----|------------|-----|------------|
| 1   | AQMDRTC2  | 7   | CUEDCMCE   |
| 2   | ARB02      | 8   | JC08       |
| 3   | INRETS     | 9   | NEDC       |
| 4   | REP05      | 10  | NRTC       |
| 5   | Viking     | 11  | RTS95      |
| 6   | WHM        | 12  | WLTC       |
The extracted basic working mode decision rules of the upper coupling layer are shown in Figure 11. An additional stipulation is added in the extraction of the basic working mode decision rules of the lower coupling layer. That is, when the vehicle speed exceeds the snapback speed of mode SM1, that is, 45 km/h, mode SM1 will be disabled. The snapback speed of mode SM1 is corresponding to the base rotation speed of M1. Thus, for the area in the dotted box in Figure 10, modes SM1 and SC can be separated only via a plumb line. The extracted basic working mode decision rules of the lower coupling layer are shown in Figure 12. The extracted basic working mode decision rules of the upper and lower coupling layers are, respectively, formulated as follows:

\[
T_v = 9.45207 \cdot v + 57.2367 \quad \text{B\_U1}
\]
\[
T_v = 1.39318 \cdot v + 289.074 \quad \text{B\_U2}
\]
\[
T_v = 440 \quad \text{B\_U3}
\]
\[
T_v = -11.4629 \cdot v - 63.3747 \quad \text{B\_U4}
\]
\[
T_v = -0.847 \cdot v - 461.464 \quad \text{B\_U5}
\]
\[
T_v = -525 \quad \text{B\_U6}
\]

and

\[
T_v = -0.588416 \cdot v + 895 \quad \text{B\_L1}
\]
\[
T_v = 8.84695 \cdot v + 255.877 \quad \text{B\_L2}
\]
\[
T_v = 880 \quad \text{B\_L3}
\]
\[
T_v = 7.34082 \cdot v - 179.615 \quad \text{B\_L4}
\]
\[
T_v = -1050 \quad \text{B\_L5}
\]
\[
T_v = 45 \quad \text{B\_L6}
\]
\[
T_v = -8.1243 \cdot v + 177.131 \quad \text{B\_L8}
\]

where, \( v \) is the vehicle speed and \( T_v \) is the torque.

4.2 | Construction of auxiliary working mode decision rules

If the working mode of the HCEP is determined only depends on basic decision rules, frequent mode switching is inevitable. Therefore, this paper draws lessons from the principle of delay shift of automatic mechanical transmissions. Concretely, the auxiliary working mode decision rules are constructed by translating the basic working mode decision rules, as shown in Figures 11 and 12. Herein, green arrows represent the translation directions. Thus, the area between the basic and auxiliary working mode decision rules forms the mode-hold-band that can avoid the mode switching when the working point bouncing around decision thresholds. And, the frequency of mode switching is significantly reduced. The auxiliary working mode decision rules of the upper and lower coupling layers can be, respectively, expressed as follows:

\[
T_v = 9.45207 \cdot (v - \Delta v) + 57.2367 - \Delta T_v \quad \text{D\_U1}
\]
\[
T_v = 1.39318 \cdot (v - \Delta v) + 289.074 - \Delta T_v \quad \text{D\_U2}
\]
\[
T_v = 440 - \Delta T_v \quad \text{D\_U3}
\]
\[
T_v = -11.4629 \cdot (v - \Delta v) - 63.3747 + \Delta T_v \quad \text{D\_U4}
\]
\[
T_v = -0.847 \cdot (v - \Delta v) - 461.464 + \Delta T_v \quad \text{D\_U5}
\]
\[
T_v = -525 + \Delta T_v \quad \text{D\_U6}
\]

and

\[
T_v = -0.588416 \cdot (v + \Delta v) + 895 - \Delta T_v \quad \text{D\_L1}
\]
\[
T_v = 8.84695 \cdot (v + \Delta v) + 255.877 - \Delta T_v \quad \text{D\_L2}
\]
\[
T_v = 880 - \Delta T_v \quad \text{D\_L3}
\]
\[
T_v = 7.34082 \cdot (v + \Delta v) - 179.615 + \Delta T_v \quad \text{D\_L4}
\]
\[
T_v = -1050 + \Delta T_v \quad \text{D\_L5}
\]
\[
T_v = 45 - \Delta T_v \quad \text{D\_L6}
\]
\[
T_v = -8.1243 \cdot (v + \Delta v) + 177.131 - \Delta T_v \quad \text{D\_L8}
\]
where, $\Delta v$ and $\Delta T_v$ are the translation quantities of the vehicle speed and torque, respectively.

### 4.3 Online decision logics of the working mode of the HCEP

The working mode decision logics of the upper coupling layer are shown in Figure 13. When the working mode of the last sampling time is SA, $B_{Us} 1-6$ are used as the decision thresholds of the current working mode; otherwise, $D_{Us} 1-6$ are used as the decision thresholds.

The working mode decision logics of the lower coupling layer are shown in Figure 14. When the working mode of the last sampling time is SM1, $B_{Ls} 1-8$ is used as the decision thresholds of the current working mode; when the working mode of the last sampling time is SM2, $D_{Ls} 1-8$ is used as the decision thresholds; and when the working mode of the last sampling time is SC, $B_{Ls} 1-3, 6$ and $D_{Ls} 4-5, 7-8$ are used as the decision thresholds.

**FIGURE 13** Working mode decision thresholds of the upper coupling layer: (A) Previous working mode is SA. (B) Previous working mode is TC

**FIGURE 14** Working mode decision thresholds of the lower coupling layer: (A) Previous working mode is SM1. (B) Previous working mode is SM2. (C) Previous working mode is SC

### 5 Optimization of the Auxiliary Working Mode Decision Rules

Although wide gaps between the basic and auxiliary working mode decision rules, that is, large $\Delta v$ and $\Delta T_v$, can greatly reduce the mode switching frequency, the energy-saving
effect will suffer deterioration. Moreover, an EMS usually has different optimal control parameters for different driving conditions.\textsuperscript{31,32} Therefore, it is necessary to optimize $\Delta v$ and $\Delta T_v$ for different driving conditions.

5.1 Classification of driving conditions

Actual traffic situations can be described by the combination of the following four types of representative driving conditions. The first type is the urban congestion condition, as shown in Figure 15A, in which the vehicle speed is almost always lower than 50km/h, while accompanied by frequent starting and stopping. The second type is the urban unimpeded condition, as shown in Figure 15B, in which both the peak and average vehicle speed are improved compared with the urban congestion condition. The third type is suburban condition, as shown in Figure 15C, in which the average vehicle speed is high and the peak vehicle speed is generally close to 100km/h. The last type is the highway condition, as shown in Figure 15D, in which the average vehicle speed is very high and the peak vehicle speed is generally larger than 100km/h.

In this study, four groups of driving cycles listed in Table 6 are selected to, respectively, express the above four types of representative driving conditions.

5.2 Optimization of $\Delta v$ AND $\Delta T_v$ for different driving conditions

The optimization of $\Delta v$ and $\Delta T_v$ can be regarded as a single-objective multi-constraint issue. The objective can be written as follows:

$$F = \min (N_{ms})$$

where, $N_{ms}$ denotes the mode switching times. The first constraint is that the increasing rate of the energy consumption cannot exceed 0.5%. That is

$$\frac{E_{\text{with}} - E_{\text{without}}}{E_{\text{without}}} \leq 0.5\%$$

where, $E_{\text{without}}$ is the energy consumption of the HCEP when the determination of working modes only relies on the basic decision rules. $E_{\text{with}}$ is the energy consumption of the HCEP when the determination of working modes relies on both the basic and auxiliary decision rules. The second constraint is that $\Delta v$ and $\Delta T_v$ obedient to

$$0 \leq \Delta T_v \leq 0.15T_{v,\text{max}}$$

$$0 \leq \Delta v \leq 0.15v_{\text{max}}$$

where, $T_{v,\text{max}}$ and $v_{\text{max}}$ are the maximum design output torque and maximum design speed of the vehicle, respectively.

In this paper, the enumeration method is used to search the best combinations of $\Delta v$ and $\Delta T_v$ for each type of representative driving condition. The search results are listed in Table 7.

6 ONLINE ADAPTIVE EMS OF THE HCEP

6.1 Driving condition recognizer

In order to get more samples to train the driving condition recognizer (DCR) used to identify the near future driving condition, the driving cycles listed in Table 6 are divided into 334 vehicle speed profile segments by the composite equipartition method shown in Figure 16. Each segment is a training sample. The characteristics and categories of the 334 training samples are, respectively, used as the input and output databases to train the DCR. The categories of training samples are known. The characteristics of training samples can be expressed by the 25 parameters listed in Table 8. It needs to be explained that the service coefficient of the vehicle power capability is the ratio between the vehicle demand power and the maximum design power of the vehicle.

If the 25 parameters are directly used to describe the characteristics of training samples, the input database is 25-dimensional. Such dimension is too large for the driving condition identification. In fact, the 25 parameters are not independent and the principal component analysis (PCA) can be used to treat them in dimension reduction. After PCA treatment, the original 25 parameters become 25 principal components.
components. Table 9 shows the top 10 principal components sorted from large to small and their cumulative variance contribution rates (CVCRs). As can be seen, the first seven principal components contain 85.85% of the information contained in the original 25 parameters. In other words, we can only use the first seven principal components to describe the characteristics of training samples. Thus, the dimension of the input database is reduced from 25 to 7.

Due to the generalized regression neural network (GRNN) has fast convergence speed and strong adaptability to data with poor accuracy, it is chosen to construct the DCR to on-line recognize the near future driving condition. The constructed GRNN-based DCR based on the seven principal components can be expressed as follows:

\[
X = [x_1, x_2, \ldots, x_7]^T
\]

\[
X_i = [x_{i1}, x_{i2}, \ldots, x_{i7}]^T \quad i = 1, 2, \ldots, 334
\]

\[
y = \frac{S_N}{S_D} = \sum_{i=1}^{334} y_i \exp\left[-\frac{(X - X_i)^T(X - X_i)}{2\sigma^2}\right]
\]

where, \(X\) and \(y\) are the characteristic vector and predictive category of a vehicle speed profile segment to be recognized, respectively. \(X_i\) and \(y_i\) are the characteristic vector and category of the \(i\)th training sample, respectively. \(\sigma\) is the smoothing factor.

In the GRNN-based DCR, \(\sigma\) is the only parameter that can be controlled and should be controlled. As shown in Figure 17, the prediction accuracy of the GRNN-based DCR roughly decreases with the increase of \(\sigma\), and the highest prediction accuracy reaches 95.45%. In general, the closer \(\sigma\) is to zero, the worse the generalization ability of the GRNN-based DCR is. Therefore, the optimal value of \(\sigma\) is determined to be 0.16.

In addition, we also train another GRNN-based DCR based on the original 25 parameters. For the sake of distinction, the GRNN-based DCR based on the original 25 parameters is called GRNN-based DCR1 here. The change of the prediction accuracy of the GRNN-based DCR1 with \(\sigma\) is also shown in Figure 17. It can be seen that the GRNN-based DCR and DCR1 have similar prediction accuracy, which indicates that the dimensionality reduction of the original 25 parameters is reasonable.
6.2 Online adaptive EMS of the HCEP

As shown in Figure 18, the developed online adaptive EMS includes three parts. They are GRNN-based DCR trained in Section 6.1, online working mode decision rules established in Sections 4 and 5, and simple power allocation method introduced in Section 3.2, respectively. In control, the developed EMS can be interpreted as the following steps. First, a period of vehicle speed profile is recorded. Second, the characteristics of the recorded vehicle speed profile are calculated. Then, the trained GRNN-based DCR is used to recognize the category of current driving condition. And, $\Delta v$ and $\Delta T_r$ are updated online according to the identified category. Subsequently, the working mode decision logics illustrated in Figures 13 and 14 are used to determine the target working modes of the upper and lower coupling layers, respectively. Finally, the introduced torque and rotation speed distribution submethods, as stated in Section 3.2, are, respectively, used to determine the target torque distribution of the upper coupling layer and target rotation speed distribution of the lower coupling layer.

7 VERIFICATION

Table 10 lists three groups of vehicle energy consumption under the 12 comprehensive driving conditions. The first group of energy consumption is obtained by traversing the torque and rotation speed allocations of the HCEP (referred to as traversal-based EMS). The second group of energy consumption is obtained according to the following way: First, the energy management issue of the HCEP is simplified as described in Section 3.2, and then, the simplified issue is solved by the DP and the energy consumption is
calculated (referred to as DP-based EMS). The third group of energy consumption is derived from the developed online adaptive EMS. Compared with the traversal-based EMS, the energy consumption caused by the DP-based EMS almost does not increase, which once again indicates that the introduced simple power allocation method does...
not destroy the energy-saving potential of the HCEP, and the simplification of the energy management issue of the HCEP is reasonable.

As expected, the energy consumption caused by the developed online adaptive EMS only has a slight increase compared to these caused by the traversal-based and DP-based EMSs. And, compared with the DP-based EMS, the mode switching times of the online adaptive EMS are greatly reduced, as shown in Table 11. These comparisons show that the developed online adaptive EMS can not only maintain the energy efficiency of the HCEP, but also can significantly reduce the mode switching frequency.

In order to further verify the effectiveness of the developed online adaptive EMS, a test driving cycle including traffic characteristics of the urban congestion, urban unimpeded, suburban, and highway is established, as shown in Figure 19. The recognition result of the GRNN-based DCR is also shown in Figure 19. The numbers 1, 2, 3, and 4 denote the conditions of the urban congestion, urban unimpeded, suburban, and highway, respectively. The recognition result shows that the constructed GRNN-based DCR can identify the driving condition accurately. In addition, the energy consumption curves of the traversal-based EMS, DP-based EMS, and online adaptive EMS are drawn in Figure 20. As expected, these energy consumption curves are almost overlap. Moreover, the working mode sequences of the upper and lower coupling layers determined by the developed EMS are shown in Figures 21 and 22, respectively. In Figure 21, the numbers 1 and 2 denote modes SA and TC, respectively. In Figure 22, the numbers 1, 2, and 3 denote modes SM1, SM2, and SC, respectively.

**TABLE 11** Comparison of mode switching times for different EMSs

| Cycle No. | DP-based EMS | Developed EMS | Decreasing rate (%) |
|-----------|--------------|---------------|---------------------|
| 1         | 310          | 157           | 49.35               |
| 2         | 288          | 192           | 33.33               |
| 3         | 284          | 186           | 34.51               |
| 4         | 172          | 105           | 38.95               |
| 5         | 58           | 24            | 58.62               |
| 6         | 162          | 89            | 45.06               |
| 7         | 567          | 269           | 52.56               |
| 8         | 188          | 69            | 63.30               |
| 9         | 99           | 54            | 45.45               |
| 10        | 453          | 315           | 30.46               |
| 11        | 262          | 166           | 36.64               |
| 12        | 248          | 149           | 39.92               |

**FIGURE 19** Test driving cycle and recognition result of the GRNN-based DCR

**FIGURE 20** Comparison of energy consumption for different EMSs

**FIGURE 21** Working mode sequences of the upper coupling layer
8 | CONCLUSION

In this paper, an online adaptive EMS is developed for the promising HCEP. The developed EMS can not only ensure the energy-saving effect of the HCEP, but also can effectively avoid frequent working mode switching, as well as has adaptive ability to different driving conditions. The research in this paper can provide reference for the development of EMSs for electric powertrains that simultaneously operates in the torque coupled mode and rotational speed coupled mode.

First, by introducing simple torque and rotation speed allocation submethods, the energy management of the HCEP is transformed from the optimization in a three-dimensional continuous space to the optimization in a set containing only six elements. After that, the DP is used to offline solve the simplified energy management issue, and the optimal working mode sequences of the HCEP are obtained.

Second, the online working mode decision rules of the HCEP are established according to the obtained optimal working mode sequences. And, the auxiliary rules in the working mode decision rules are optimized for different types of driving conditions.

Third, the PCA is utilized to reduce the dimension of the characteristic parameters used to express driving conditions. After that, the seven-dimensional GRNN-based DCR with the highest prediction accuracy of 95.45% is trained. On the basis of the trained DCR, established working mode decision rules, and introduced torque and rotation speed allocation submethods, an online adaptive EMS is developed for the HCEP.

Compared with the traversal-based EMS that is optimal in term of energy saving, the energy consumptions obtained from the developed online adaptive EMS increase only slightly, and the increasing rate is 0.07% to 1.57% under 12 comprehensive driving cycles. Compared with the DP-based EMS which has similar energy-saving effect with the traversal-based EMS, the mode switching times caused by the developed online adaptive EMS are greatly reduced, with a decreasing rate of 30.46% to 63.30%. These comparisons validate the effectiveness of the developed online adaptive EMS.

ACKNOWLEDGMENTS

This work was supported by the National Natural Science Foundation of China under Grant 51975069 and the Natural Science Foundation of Chongqing (China) under Grant cstc2018jcyjAX0077.

ORCID

Hongyu Shu https://orcid.org/0000-0001-8157-2892

REFERENCES

1. Chen X, Shu H, Song Y, et al. Configuration, parameter matching and energy efficiency analysis of the layered coupled electric drive applied for vehicles. J Mech Eng, 2019;55:21-32.
2. Hoang N, Yan H. On the design of in-wheel-hub motor transmission systems with six-link mechanisms for electric vehicles. Energies, 2018;11:2920.
3. Gunji D, Matsuda Y, Kimura G. Wheel hub motor. U.S. Patent 8,758,178. 2014-6-24.
4. Martinez CM, Hu X, Cao D, et al. Energy management in plug-in hybrid electric vehicles: recent progress and a connected vehicles perspective. IEEE Trans Veh Technol. 2017;66:4534-4549.
5. Trovão JP, Pereirinha PG, Jorge HM, et al. A multi-level energy management system for multi-source electric vehicles—an integrated rule-based meta-heuristic approach. Appl Energy. 2013;105:304-318.
6. Bagwe RM, Byerly A, dos Santos EC, et al. Adaptive rule-based energy management strategy for a parallel HEV. Energies. 2019;12:4472.
7. Ming LV, Ying Y, Liang L, et al. Energy management strategy of a plug-in parallel hybrid electric vehicle using fuzzy control. Energy Procedia. 2017;105:2660-2665.
8. Essoufi M, Hajji B, Rabhi A. Fuzzy logic based energy management strategy for fuel cell hybrid electric vehicle. In: 4th International Conference on Electrical and Information Technologies. Qingdao China, Oct; 2019.
9. Li H, Ravey A, N’Diaye A, et al. Online adaptive equivalent consumption minimization strategy for fuel cell hybrid electric vehicle considering power sources degradation. Energy Convers Manage. 2019;192:133-149.
10. Wang W, Zhang Z, Shi J, et al. Optimization of a dual-motor coupled powertrain energy management strategy for a battery electric bus based on dynamic programming method. IEEE Access. 2018;6:32899-32909.
11. Li H, Wei D, Fu B, et al. Energy management strategy for a CVT hybrid electric vehicle based on dynamic programming. In: 5th International Conference on Control, Automation and Robotics. Beijing China, Apr; 2019.
CHEN ET AL.

12. Hu X, Murgovski N, Johannesson LM, et al. Optimal dimensioning and power management of a fuel cell/battery hybrid bus via convex programming. IEEE/ASME Trans Mechatron. 2015;20:457-468.

13. Yavasoglu H, Tetik Y, Ozcan H. Neural network-based energy management of multi-source (battery/UC/FC) powered electric vehicle. Int J Energy Res. 2020;44:12416-12429.

14. Onori S, Tribioli L. Adaptive Pontryagin's Minimum Principle supervisory controller design for the plug-in hybrid GM Chevrolet Volt. Appl Energy. 2015;147:224-234.

15. Hemi H, Ghouli J, Cheriti A. Combination of markov chain and optimal control solved by Pontryagin’s Minimum Principle for a fuel cell/supercapacitor vehicle. Energy Convers Manage. 2015;91:387-393.

16. Xi L, Zhang X, Sun C, et al. Intelligent energy management control for extended range electric vehicles based on dynamic programming and neural network. Energies. 2017;10:1871-1888.

17. Zhao M, Shi J, Lin C, et al. Application-oriented optimal shift schedule extraction for a dual-motor electric bus with automated manual transmission. Energies. 2018;11:325.

18. Zhang S, Xiong R, Zhang C. Pontryagin’s Minimum Principle-based power management of a dual-motor-driven electric bus. Appl Energy. 2015;159:370-380.

19. Li P, Cui N, Kong Z, et al. Energy management of a parallel plug-in hybrid electric vehicle based on SA-PSO algorithm. In: 36th Chinese Control Conference. Chongqing, China, Jul; 2018.

20. Yu H. Fuzzy logic energy management strategy based on genetic algorithm for plug-in hybrid electric vehicles. In: 3rd Conference on Vehicle Control and Intelligence. Hefei, China, Sep; 2019.

21. Borhan H, Vahidi A, Phillips AM, et al. MPC-based energy management of a power-split hybrid electric vehicle. IEEE Trans Control Syst Technol. 2012;20:593-603.

22. Shen P, Zhao Z, Zhan X, et al. Optimal energy management strategy for a plug-in hybrid electric commercial vehicle based on velocity prediction. Energy. 2018;155:838-852.

23. Shen Z, Guo N, Shen J, et al. A hierarchical energy management strategy for power-split plug-in hybrid electric vehicles considering velocity prediction. IEEE Access. 2018;6:33261-33274.

24. Xiang C, Ding F, Wang W, et al. 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.

25. Li L, Coskun S, Zhang F, et al. Energy management of hybrid electric vehicle using vehicle lateral dynamic in velocity prediction. IEEE Trans Veh Technol. 2019;68:3279-3293.

26. Chen Z, Xiong R, Wang C, et al. An on-line predictive energy management strategy for plug-in hybrid electric vehicles to counter the uncertain prediction of the driving cycle. Appl Energy. 2017;185:1663-1672.

27. Zhang S, Luo Y, Wang J, et al. Predictive energy management strategy for fully electric vehicles based on preceding vehicle movement. IEEE Trans Intell Transp Syst. 2017;18:3049-3060.

28. Lei Z, Qin D, Zhao P, et al. A real-time blended energy management strategy of plug-in hybrid electric vehicles considering driving conditions. J Clean Prod. 2020;252:119735.

29. Yuan J, Yang L. Predictive energy management strategy for connected 48V hybrid electric vehicles. Energy. 2019;187:115952.

30. Kandidayeni M, Macias Fernandez AO, Khalatbarisoltani A, et al. An online energy management strategy for a fuel cell/battery vehicle considering the driving pattern and performance drift impacts. IEEE Trans Veh Technol. 2019;68:11427-11438.

31. Zhou Y, Ravey A, Péra M. Multi-mode predictive energy management for fuel cell hybrid electric vehicles using Markov driving pattern recognizer. Appl Energy. 2020;258:114057.

32. Hu J, Niu X, Jiang X, et al. Energy management strategy based on driving pattern recognition for a dual-motor battery electric vehicle. Int J Energy Res. 2019;43:3346-3364.

33. Yang YE, Zhang Y, Tian J, et al. Adaptive real-time optimal energy management strategy for extended range electric vehicle. Energy. 2020;195:117237.

34. Lee H, Kang C, Park Y-I, et al. Online data-driven energy management of a hybrid electric vehicle using model-based Q-learning. IEEE Access. 2020;8:84444-84454.

35. Sun H, Fu Z, Tao F, et al. Data-driven reinforcement-learning-based hierarchical energy management strategy for fuel cell/battery/ultracapacitor hybrid electric vehicles. J Power Sources. 2020;455:227964.

36. Du G, Zou Y, Zhang X, et al. Deep reinforcement learning based energy management for a hybrid electric vehicle. Energy. 2020;201:117591.

37. Han X, He H, Wu J, et al. Energy management based on reinforcement learning with double deep Q-learning for a hybrid electric tracked vehicle. Appl Energy. 2019;254:113708.

38. Li Y, He H, Khajepour A, et al. Energy management for a power-split hybrid electric bus via deep reinforcement learning with terrain information. Appl Energy. 2019;255:113762.

39. Liu T, Du G, Zou Y, et al. Fast learning-based control for energy management of hybrid electric vehicles. In: 5th Conference on Engine and Powertrain Control, Simulation and Modeling, Changchun, China, Jul, 2018.

40. Wang D, Wang B. Research on driving force optimal distribution and fuzzy decision control system for a dual-motor electric vehicle. In: Proceedings of the 34th Chinese Control Conference; 2015:8146-8153.

AUTHOR BIOGRAPHIES

Xianbao Chen graduated as a vehicle engineer from the School of Automotive Engineering, Chongqing University (2016), and is currently a Ph.D. student at the School of Automotive Engineering, Chongqing University. His interests include electric machines, electric powertrain, especially in-wheel motor powertrain.
Hongyu Shu received his Ph.D. in mechanical engineering from Chongqing University, Chongqing, China, in 1999. He is currently a professor of the State Key Laboratory of Mechanical Transmission, Chongqing University, China. His research interests include electric vehicles, mechatronics, vehicle noise, vibration and harshness, and vehicle system dynamics and control. He is currently a senior member of the Chinese Society of Mechanical Engineering.

Yitong Song graduated as a vehicle engineer from the College of Mechanical and Vehicle Engineering, Hunan University (2016), and is currently a Ph.D. student at the School of Automotive Engineering, Chongqing University. His main interests are integrated chassis control techniques for electric vehicles. He is currently working on integrated chassis control based on four-wheel steering and an active differential braking system of electric vehicles.

How to cite this article: Chen X, Shu H, Song Y. Development of an online adaptive energy management strategy for the novel hierarchical coupled electric powertrain. Energy Sci Eng. 2021;00:1–18. https://doi.org/10.1002/ese3.931