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A Neural Network Fuzzy Energy Management Strategy for Hybrid Electric Vehicles Based on Driving Cycle Recognition

Qi Zhang [1,2,*] and Xiaoling Fu [3,*]

1 State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun 130025, China
2 School of Control Science and Engineering, Shandong University, Jinan 250061, China
3 Department of Physics, Changji College, Changji 831100, China
* Correspondence: zhangqi2013@sdu.edu.cn (Q.Z.); fxl@sdu.edu.cn (X.F.)

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Abstract: Aiming at the problems inherent in the traditional fuzzy energy management strategy (F-EMS), such as poor adaptive ability and lack of self-learning, a neural network fuzzy energy management strategy (NNF-EMS) for hybrid electric vehicles (HEVs) based on driving cycle recognition (DCR) is designed. The DCR was realized by the method of neural network sample learning and characteristic parameter analysis, and the recognition results were considered as the reference input of the fuzzy controller with further optimization of the membership function, resulting in improvement in the poor pertinence of F-EMS driving cycles. The research results show that the proposed NNF-EMS can realize the adaptive optimization of fuzzy membership function and fuzzy rules under different driving cycles. Therefore, the proposed NNF-EMS has strong robustness and practicability under different driving cycles.

Keywords: hybrid electric vehicle; energy management strategy; driving cycle recognition; neural network fuzzy

1. Introduction

Hybrid electric vehicles (HEVs) combine the advantages of traditional fuel vehicles with battery electric vehicles (BEVs). However, unlike BEVs, HEVs have a more complex structure. According to the structure and energy flow of the powertrain, HEVs are mainly divided into series HEVs (SHEVs), parallel HEVs (PHEVs), and series–parallel HEVs (SPHEVs). Meanwhile, HEVs are also divided into plug-in HEVs and non-plug-in HEVs, depending on whether the battery can be charged externally. Apparently, higher requirements are imposed on the energy management strategy (EMS) of the vehicle [1,2]. The EMSs of HEVs are responsible for distributing the energy flow between the engine, the motor, and the battery under the premise of satisfying the vehicle's power demand, so as to achieve the optimal overall fuel consumption and emission performance [3,4]. At present, the EMSs applied to HEVs are mainly rule-based, including deterministic rule-based EMSs and fuzzy rule-based EMSs (F-EMSs) [5,6]. Among them, the deterministic rule-based EMSs are widely used in HEVs because of their simplicity, small computation, and strong practicability, but their disadvantages are also obvious. The logical threshold control strategy must be determined in advance, and the adaptability to different driving cycles is poor. Although F-EMSs cannot achieve global optimal energy management, fuzzy control itself has strong robustness and good real-time performance, and it can describe control rules that are difficult to quantify. Therefore, the application prospect is very good [6,7].

Up to now, many research results were achieved through the use of fuzzy control in the energy management of electric vehicles. The F-EMSs of parallel hybrid electric vehicles (PHEVs) were studied in References [8–11], which achieved good control performance. Aiming at the problem whereby fuzzy control cannot realize self-learning and poor self-adaptability, the particle swarm optimization (PSO) algorithm was used to optimize the parameters of fuzzy control rules and membership function, and the state of charge (SOC) changes of the battery were well controlled in Reference [6]. In Reference [12], pointing to the complexity of the quantization factor tuning process, a PSO algorithm with the compression factor was introduced to optimize and improve the robustness and accuracy of the fuzzy controller. The above studies improved the adaptability of F-EMSs to some extent by optimizing fuzzy control rules and membership functions, but they did not consider the impact of driving cycles. Recent studies showed that driving cycles have a significant impact on the fuel consumption and emission performance of HEVs. Therefore, many researchers carried out studies on driving cycle recognition (DCR) technology and incorporated it into EMSs [13–23]. Fotouhi et al. [14] summarized the application of traffic information and driving data in the field of automobile energy conservation and environmental protection. Zhu et al. [15] studied the self-learning method of urban road driving cycles for electric vehicles, and, in Reference [16], the F-EMS for HEVs based on DCR was optimized. Through the analysis and recognition of driving cycles of HEVs, a hybrid control strategy based on real-time changes of driving cycles was proposed in Reference [17]. A novel EMS for a plug-in HEV was proposed based on the driving cycle model and a dynamic programming algorithm [18], while an F-EMS based on DCR was proposed in Reference [19] to improve the fuel economy of a PHEV, which consisted of DCR and a fuzzy torque distribution controller. Researchers such as Montazeri et al. used intelligent control methods such as clustering to study the identification of traffic conditions and driving segments, and they studied the most effective energy-saving control methods of HEV through driving pattern recognition [20–22]. Zhang et al. studied a fuzzy neural network energy management strategy for PHEV based on the adaptive neuro-fuzzy inference system (ANFIS) optimization algorithm on the ADVISOR software platform [23]. Based on the above recent researches, the traditional rule-based energy management strategy is not ideal. Fuzzy control is easy to understand and easy to implement in the control chip. Considering the implementation of the algorithm in vehicles and practical applications, the energy management strategy using fuzzy control combined with intelligent algorithm optimization has broad prospects in energy management systems of electric vehicles.

Unlike the previous control methods, a neural network fuzzy energy management strategy (NNF-EMS) for HEVs is designed based on DCR, with the objective of addressing the inherent problems of traditional F-EMS, such as poor adaptability and lack of self-learning. The methods of neural network sample learning and characteristic parameter analysis are used to realize the recognition of driving cycles, and the recognition results are considered as the reference input of the fuzzy controller. Research shows that the proposed NNF-EMS can perform adaptive optimization of the fuzzy membership function and control rules under different driving cycles. Consequently, the proposed NNF-EMS has strong robustness and practicability under different driving cycles.

In this paper, a novel NNF-EMS based on DCR for HEVs is designed to improve the adaptability of EMS to different driving cycles. The research ideas and arrangement for the rest of this paper are as follows: Section 2 introduces the traditional F-EMS of HEVs. Then, the driving cycle block and its definition are introduced, and the design method of NNF-EMS based on DCR is proposed in Section 3. In Section 4, the simulation verification of an HEV is designed and performed using different methods. Finally, the results and analysis are compared and illustrated in Section 4, followed by the conclusion and discussion in Section 5.

2. Fuzzy Energy Management Strategy (F-EMS) of HEVs

Unlike the control strategy based on deterministic rules, fuzzy control does not describe the controlled system from the perspective of a precise mathematical expression, but rather determines some fuzzy control rules based on experience, experimental data analysis, and cognitive reasoning of the process, as well as obtaining the control parameters by controlling the output error of the system and the reasoning of the fuzzy rules, thereby not depending on the mathematical model of the controlled object, but realizing the complex control object with uncertainty. Therefore, for high-order complex systems that are difficult to implement with traditional control methods, the advantages of fuzzy control are very evident. Fuzzy control has strong robustness and adaptability to uncertain factors, such as electric vehicle parameters and driving conditions. The control rules that are difficult to accurately quantify in the EMS of HEV can be realized by fuzzy logic [12,23,24].

The core of fuzzy control is the fuzzy control rules, which are expressed in the form of human language. For example, if an electric vehicle requires more power, the output power of the battery and engine is greater. Rules are easily accepted and understood; in addition, fuzzy control algorithms are easy to implement digitally. These distinctive features allowed fuzzy control theory to develop rapidly in recent decades and become an active field in intelligent control [8,9,25,26].

In the fuzzy system, there are two main representations of the fuzzy model: one is that the latter part of the fuzzy rule is a fuzzy set of outputs, called the standard model of the fuzzy system or the Mamdani model; the other is that the latter part of the fuzzy rule is a function of the input linguistic variable, called the Takagi–Sugeno model of the fuzzy system. Obviously, the Mamdani model should be used for the energy management or torque distribution control strategy of HEVs. The principle of the Mamdani fuzzy logic system, which is based on the standard model, is shown in Figure 1. In the process of realizing fuzzy control, a fuzzy controller is the carrier of a fuzzy control algorithm, which is mainly composed of the rule base, input fuzzification, fuzzy reasoning, and clear output [10,11].

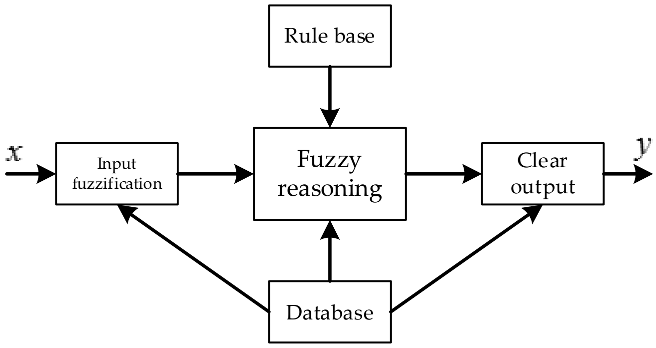


Figure 1. Composition of the fuzzy controller.

The fuzzy control rules of the Mamdani fuzzy controller are represented by a series of fuzzy conditional statement with "if . . . , then . . . ". The basic form of the fuzzy rule language of the fuzzy controller is as follows:

$$\text{If } x_1 \text{ is } A_1 \text{ and } x_2 \text{ is } A_2 \text{ and} \ldots \text{and } x_n \text{ is } A_n, \text{ then } y \text{ is } B, \tag{1}$$

where x_i and A_i (i = 1, 2, . . . n) are the input fuzzy linguistic variables and their values, respectively, whereas y and B are the output linguistic variables and their values.

In this paper, the fuzzy control strategy selects the SOC of the power battery and the total demand torque as the reference input of the fuzzy controller; that is, the state signals (such as SOC and demand torque) are converted into a set of fuzzy quantities expressed by membership degree, and the switching state of the engine and the magnitude of the output torque are determined by fuzzy rules according to the operating efficiency curve of the engine. The design ideas of the fuzzy EMS are described below.

(1) When the battery is fully charged and the demand torque is large, the HEV operates in the hybrid drive mode. At this point, the engine works near the optimal efficiency curve, and the residual torque is provided by the motor; when the demand torque is relatively large and less than the optimal efficiency torque of the engine, the HEV is separately driven by the engine, and the motor does not work;

(2) When the battery is relatively full and the demand torque is large, the HEV operates in engine drive mode or hybrid drive mode. At this point, the engine works at optimum efficiency, and the residual torque is supplemented by the motor or used to charge the battery;

(3) When the battery is low, the motor works as much as possible in the generator state. At this point, the vehicle is driven primarily only by the engine, the engine works near the optimal efficiency curve, and the remaining battery is charged.

In summary, the fuzzy rules of the F-EMS of HEVs consist of a series of "if ... , then ... " fuzzy conditional statements in the following form:

$$\begin{cases} \text{Rule 1 : If } X_{in} \text{ is } A_1 \text{ and } Y_{in} \text{ is } B_1, \text{ then } Z \text{ is } C_1, \\ \ldots \\ \text{Rule } i : \text{If } X_{in} \text{ is } A_i \text{ and } Y_{in} \text{ is } B_i, \text{ then } Z \text{ is } C_i, \\ \ldots \\ \text{Rule } m : \text{If } X_{in} \text{ is } A_m \text{ and } Y_{in} \text{ is } B_m, \text{then } Z \text{ is } C_m. \end{cases}, \tag{2}$$

where Rule i represents the i-th rule, m is the total number of fuzzy rule, Z is the rule output linguistic variable, here referring to the actual given engine output torque T_e, X_{in} and Y_{in} represent the regular input linguistic variables, here referring to the SOC of power battery and the total demand torque T_r, and A_i and B_i are the fuzzy sets SOC {VL, L, N, H, VH} and T_r {VS, S, RS, M, RB, B, VB}, corresponding to the input variables X_{in} and Y_{in}, respectively. C_i is the fuzzy set corresponding to the output variable T_e {VS, S, RS, RM, M, VM, RB, B, VB}, wherein VL, L, N, H, and VH respectively indicate battery SOC from low to high: very low, low, normal, high, very high, while VS, S, RS, RM, M, VM, RB, B, and VB respectively represent the demand torque and engine output torque from small to a large extent: very small, small, relatively small, medium–small, medium, medium–large, relatively large, large, very large. In summary, the control rules of the fuzzy controller for HEV are shown in Table 1.

Table 1. Control rules set by the fuzzy controller.

SOC \ Tr	VS	S	RS	M	RB	B	VB
VL	VS	VS	S	RS	RM	M	VM
L	VS	S	RS	RM	M	VM	RB
N	S	RS	RM	M	VM	RB	B
H	RS	RM	M	VM	RB	B	VB
VH	RM	M	VM	RB	B	VB	VB

In the F-EMS, the membership function settings of the demand torque, the battery SOC, and the given torque signal of the engine are respectively shown in Figures 2–4. According to the basic principle of fuzzy control, as more experience is learned, the division of the control rules becomes finer, and the membership function become narrower and thinner, such that the scope of control can be divided more finely and the control be more sensitive; otherwise, the control will be rougher and more stable. In the F-EMS of HEVs, if different driving cycles can be identified online and the fuzzy control rules or membership functions can be adjusted and optimized accordingly, the control effect of the F-EMS can be improved. According to the fuzzy rules, the fuzzy output rules of the HEV fuzzy controller are shown in Figure 5 through fuzzy reasoning.

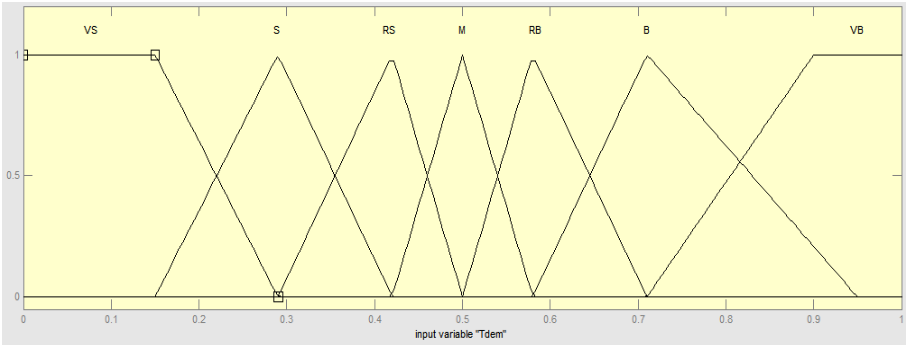


Figure 2. Demand torque membership function.

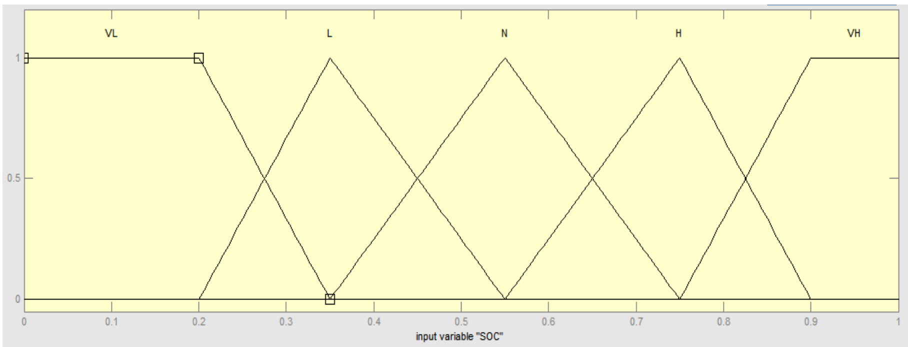


Figure 3. Battery state-of-charge (SOC) membership function.

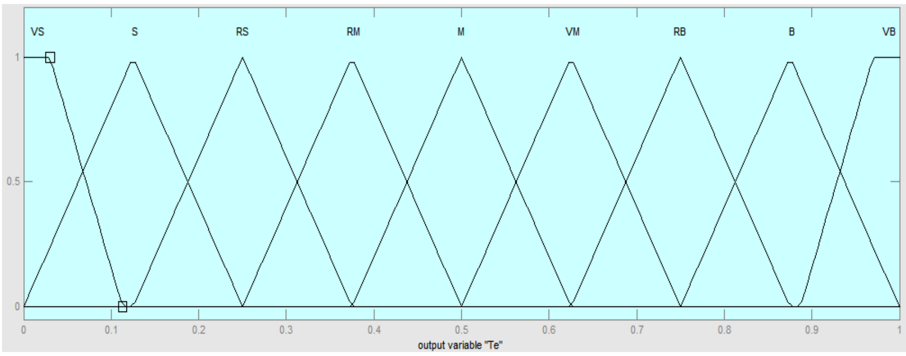


Figure 4. Engine output torque membership function.

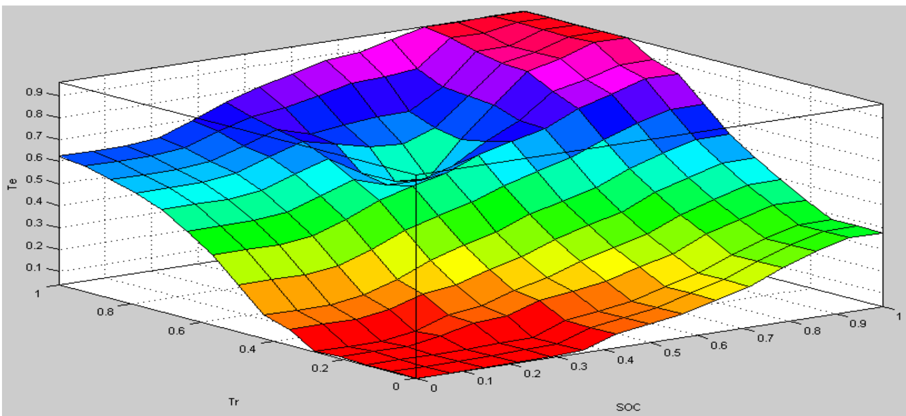


Figure 5. Fuzzy inference input–output map.

3. Neural Network Fuzzy EMS Based on DCR

The fuzzy control system relies on experience to reason, but its speed is slow, precision is low, self-learning ability is poor, and membership function and fuzzy rules are difficult to determine. In addition, the neural network uses expert knowledge to simulate the thinking function of the human brain structure, which has strong self-learning ability and less manual intervention, but cannot make full use of empirical knowledge to deal with fuzzy information. It can be seen that it is necessary to use a combination of fuzzy logic and neural networks to learn from others in order to achieve complementarity [27,28].

The fuzzy control can analyze the driving intention based on experience, and then distribute the output torque of the motor and the engine. However, in reality, the driver's driving mode is determined based on the actual driving conditions, which vary greatly and significantly affect the fuel economy and emissions of HEV. The traditional HEV fuzzy control strategy apparently does not adjust the control strategy according to the change in driving conditions, which seriously affects the control effect and the popularization application of F-EMS. If the sample information of the neural network training condition can be used, then the neural network can be used to learn the online recognition of the driving cycle category, and the recognition result and the SOC, demand torque, and other signals become blurred, which are then used together as a reference input to the fuzzy controller, whereby the membership function and fuzzy rules of the fuzzy controller can be adjusted online based on the driving cycle information to improve the fuel economy and emissions of the HEV vehicle.

3.1. Basic Test Conditions and Characteristics

Different countries and regions have different standard driving cycles for vehicle emission tests. The representative driving cycles are the Federal Test Procedure, commonly known as FTP-75 for the city driving cycle, defined by the United States (US) Environmental Protection Agency (EPA), and the New European Driving Cycle (NEDC) of the Economic Commission of Europe (ECE). They are both a series of tests for measuring tailpipe emissions and fuel economy of passenger cars (excluding light trucks and heavy-duty vehicles); however, FTP75 is mainly used in the United States, Canada, South America, etc., while NEDC is mainly used in Europe, China, Australia, etc. [29,30]. The local driving velocity in NEDC is set to a constant value, as shown in Figure 6. The NEDC consists of two parts: Urban Driving Cycle ECE-15 (or simply UDC), repeated four times, is plotted from 0 s to 780 s; Extra-Urban Driving Cycle ECE R101 (or simply EUDC) cycle is plotted from 780 s to 1180 s. FTP75 is a mandatory dynamometer test on tailpipe emissions of a car that represents the driving conditions of the city, which was developed from the Urban Dynamometer Driving Schedule (UDDS, also known as FTP-72). As shown in Figure 7, FTP75 is identical to UDDS plus the first 505 s of an additional UDDS cycle.

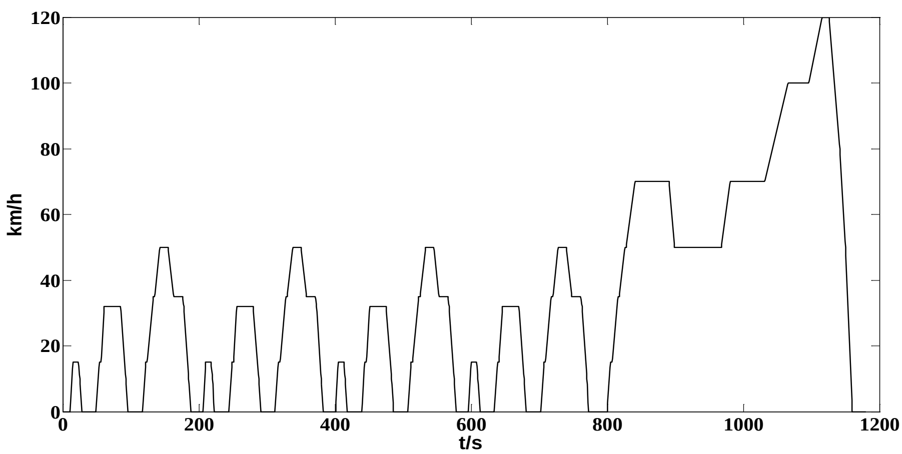


Figure 6. Driving cycle of New European Driving Cycle (NEDC).

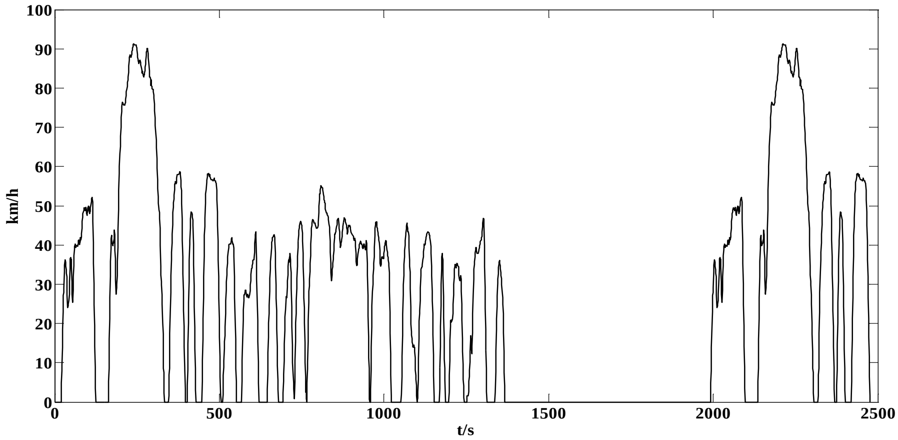


Figure 7. Driving cycle of Federal Test Procedure (FTP75).

The comparison and driving cycles of NEDC and FTP75 are shown in Table 2. Obviously, their basic characteristic parameters are different; in particular, the NEDC and the FTP75 that are steady-state and transient driving cycles, respectively, with an obvious characteristic difference. Under different driving cycles, it is apparently not appropriate to adopt a constant EMS. According to the characteristic parameters of different driving cycles, a small section of the driving cycle that runs continuously between the start and stop of the vehicle is defined as a "driving cycle block". In this way, no matter how complicated the driving cycles are, they can be divided into specific small driving cycle blocks.

Table 2. Comparison of the New European Driving Cycle (NEDC) and Federal Test Procedure (FTP75) driving cycles.

Cycle Name	Cycle Time	Total Distance	Maximum Velocity	Average Velocity	Ambient Temperature	Ambient Relative Humidity
	(s)	(km)	(km/h)	(km/h)	(°C)	(RH)
NEDC	1180	11.00	120	33.6	25 ± 5	50%
FTP75	2474	17.86	91.2	34.1	25 ± 5	50%

3.2. Driving Cycle Block and Its Definition

Driving cycle blocks can be distinguished according to different operating parameters, such as maximum velocity, maximum acceleration, maximum deceleration, average driving velocity, and driving distance, thereby effectively reducing the complexity of driving cycle analysis. In addition, the driving cycle blocks are independent of each other, and any complicated actual driving conditions can be divided into a plurality of different driving cycle blocks, which improves the reuse rate of the blocks [15,17]. The driving cycle blocks are used for the recognition of driving conditions, and the block recognition library of different scales and different levels of complexity can be established according to the control requirements, thereby designing an EMS that is highly targeted [31,32]. For example, a driving cycle library for different cities and different road sections can be established separately.

Taking NEDC as an example, driving cycle blocks can be divided into five basic categories [17].

(1) Block ① is defined for the driving condition in the city center, where the vehicle runs and stops frequently with heavy traffic;

(2) Block ② is defined for driving conditions in urban areas, where the vehicle runs at low velocity;

(3) Block ③ is defined for the driving condition in the suburbs, where the vehicle runs at medium and low velocity;

(4) Block ④ is defined for the driving condition in the suburbs, where the vehicle runs at medium and high velocity;

(5) Block ⑤ is defined for the driving condition on the highway between cities and suburbs, where the vehicle runs at high velocity.

In fact, the NEDC basically consists of the above five basic driving conditions. The "driving cycle block" for NEDC defined in this paper is shown in Figure 8. Of course, these blocks are divided by different characteristic parameters of the driving conditions, which are closely related to complicated driving conditions. The block division of FTP75 is much more complicated than that of NEDC.

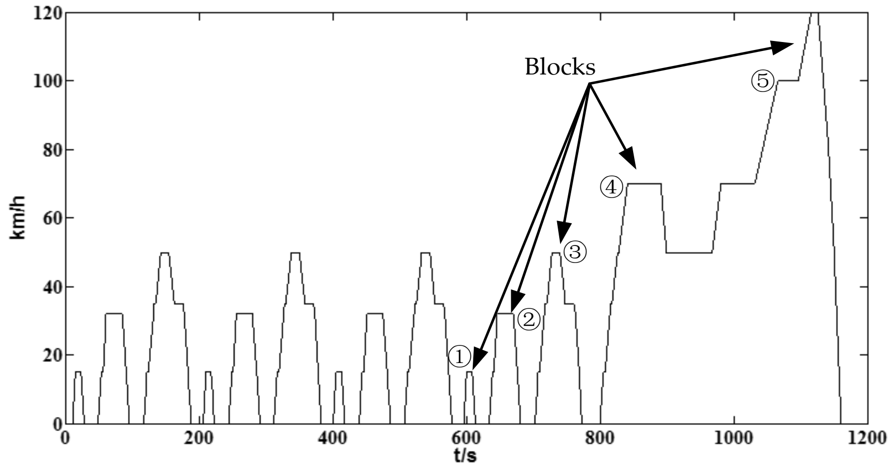


Figure 8. Division of "driving cycle blocks" in NEDC.

3.3. Neural Network Fuzzy EMS (NNF-EMS) Design Based on DCR

In this paper, the backpropagation (BP) neural network is used for DCR. The BP neural network is a multi-layer feed-forward network trained based on the error backpropagation algorithm. It can store and learn a large number of input–output mappings without having to mathematically describe these mappings. It embodies a nonlinear functional relationship between the input and output of the network. The BP neural network generally consists of an input layer, a hidden layer, and an output layer. The basic structure of the network is shown in Figure 9, which has M input nodes, L output nodes, and q neurons, wherein the actual input of the network is $x_1, x_2, \ldots, x_M$, and the actual output is $y_1, y_2, \ldots, y_M$. In the calculation process, learning and training are continuously performed according to the input sample network, and the response values of the neurons are transmitted from the input layer to the output layer through the hidden layer. According to the obtained network response, the output layer continuously adjusts the connection weights and thresholds of the network in the direction of the greatest reduction of error; the square of the error of the network is minimized by backpropagation, thereby improving the accuracy of the network output [27,28].

BP neural networks are used for pattern recognition and classification, but are not suitable for expressing rule-based knowledge. In the fuzzy system, knowledge extraction and rule expression are more convenient and suitable for fuzzy or qualitative knowledge, but lack the capacity for self-learning and self-adaptation. It can be seen that the neural network fuzzy EMS (NNF-EMS) of HEV combines the neural network-based cycle recognition and F-EMS, and their advantages complement each other to realize the DCR-based fuzzy control reasoning process. Although the actual driving conditions are random and undeterminable, if there are sufficient circulating conditions, the driving cycle blocks with similar characteristics can be found, and the control parameters can be adjusted or the corresponding control strategies can be found to improve control performance through real-time analysis.

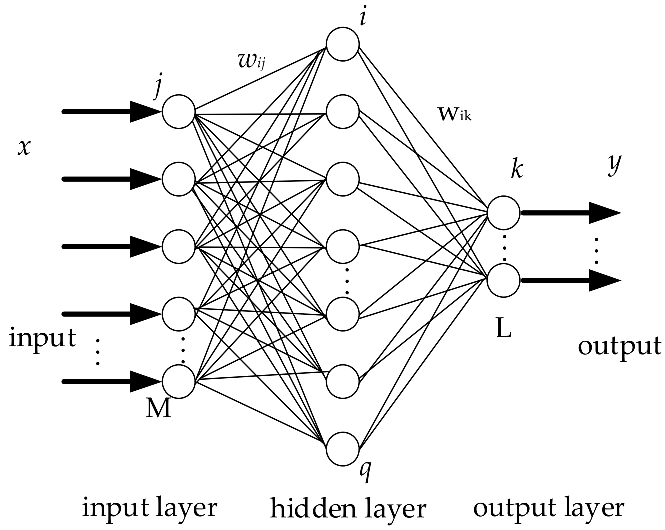


Figure 9. Schematic diagram of backpropagation (BP) neural network structure.

The main advantage of a neural network for DCR is that the sample data can adapt to the driving conditions, and the neural network can also function normally even when the acquired driving condition data contain noise. In addition, the neural network provides simple tools for automatic feature selection, generates useful data representations, and can also serve as a front-end preprocessor for fuzzy controllers. Therefore, this paper uses a neural network to realize DCR, and the recognition result is combined with the input signals such as SOC and demand torque, and then used as input to the fuzzy controller to optimize the fuzzy membership function and fuzzy rules in overcoming the poorly targeted shortcomings of the F-EMS of HEVs.

The BP neural network algorithm is used as the training algorithm, and the number of training times is 50. The input node of the neural network selects the relevant characteristic parameters of the current driving velocity, average vehicle velocity, average acceleration, average deceleration, maximum vehicle velocity, maximum acceleration, maximum deceleration, traveled distance, and the travel time as the input nodes of the BP network. By adjusting the connection weighting coefficient, the role of different characteristic parameters in the identification of the working cycle can be adjusted, and the output value of the network node can be obtained by the weighted sum [16]. In this paper, the graphical interface editor (Anfis editor) of the adaptive neuro-fuzzy inference system was used provided by MATLAB Fuzzy Logic Toolbox to train and test the driving conditions of NEDC, and we selected parameters such as BP algorithm, error accuracy, and training times to train the neural network system. It can be seen that the error accuracy of the test data was reduced to a certain degree after a certain number of trainings. Figure 10 displays the training data and test data for training NEDC. After 50 training sessions, the error curve is shown in Figure 11.

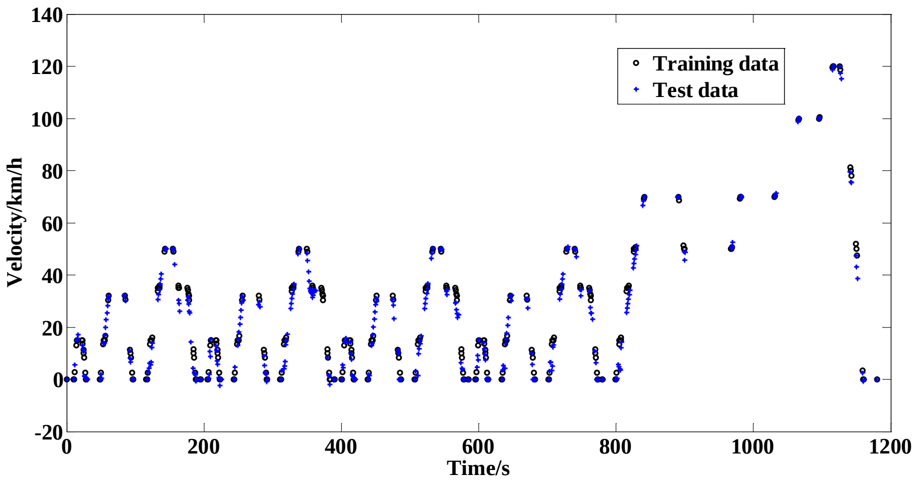


Figure 10. Training data of neural network and test data of NEDC.

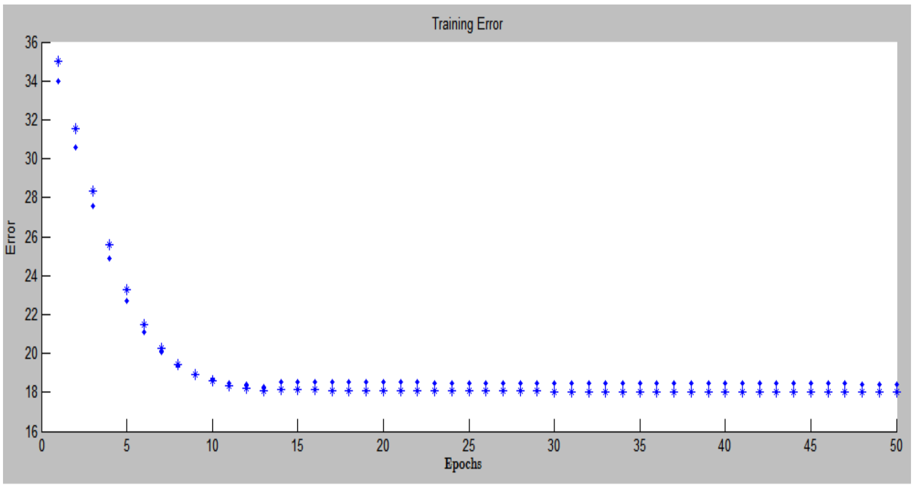
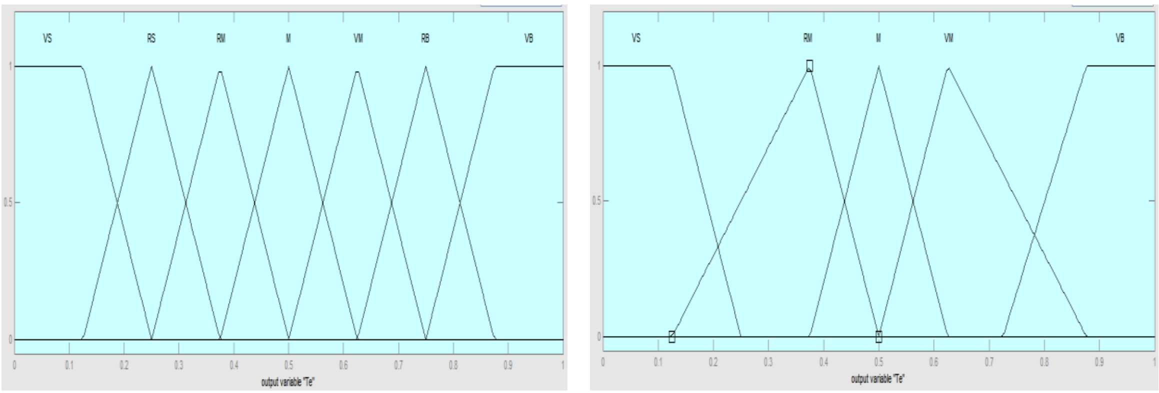


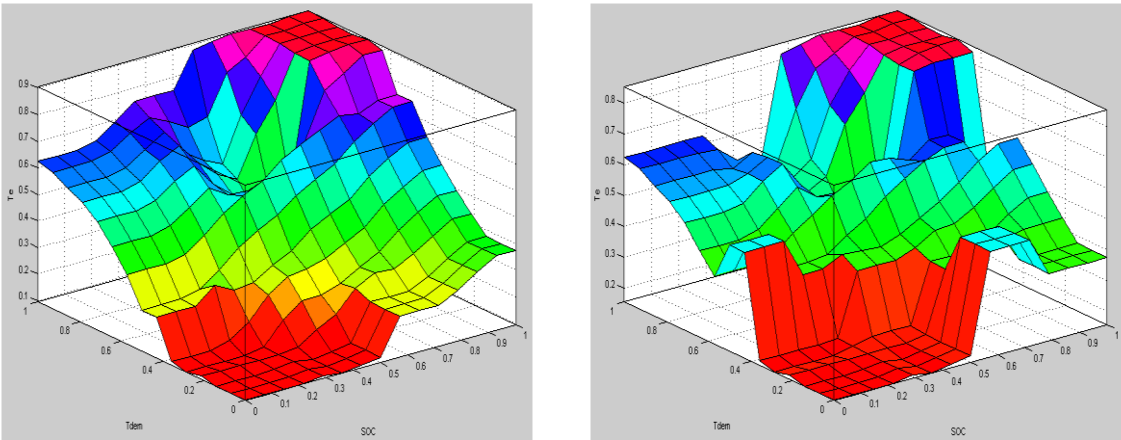
Figure 11. Error curve after system training.

The neural network is used to train the driving cycle samples and solve the DCR problem by learning and extracting characteristic parameters of driving cycles. Then, the recognition results are used as control parameters to optimize the fuzzy membership function and fuzzy rules of the fuzzy controller. Taking the recognition process of the driving cycle blocks ② and ④ as an example, when the vehicle is recognized to be driving in the urban area (block ②), the traffic is relatively smooth and the vehicle runs at a low velocity. Therefore, as shown in Figures 12a and 13a, the membership function of the engine output torque signal is optimized to be relatively narrow and thin, the control scope is finely divided, and the control accuracy is high. When it is recognized that the vehicle is driving in the suburb (block ④), the traffic is smooth, and the vehicle drives at medium and high velocity. At this time, as shown in Figures 12b and 13b, the membership function of the engine output torque signal is optimized to be relatively wide and fat, and the control is relatively rough and stable.



(**a**) (**b**)

Figure 12. Optimized engine torque membership function for driving condition blocks: (**a**) Block ②; (**b**) Block ④.



(**a**) (**b**)

Figure 13. Optimized fuzzy input–output map for driving condition blocks: (**a**) Block ②; (**b**) Block ④.

4. Simulation Results and Analysis

The designed PHEV model in AVL Cruise is shown in Figure 14. Models of motors, engines, and power batteries are mainly built based on the look-up tables, which can greatly improve the calculation speed. In practice, the data in the look-up tables of these components can be obtained experimentally. According to the configuration, the drive and powertrain structure of the HEV is a parallel drive system, which is a torque-coupled, single-shaft hybrid drive system whose transmission is located behind the motor. The engine and the motor are required to have the same speed range, because the torque and speed transmitted by them to the drive axle are adjusted by the continuously variable transmission (CVT). The motor performs multiple functions, such as driving the vehicle, starting the engine, and generating regenerative braking.

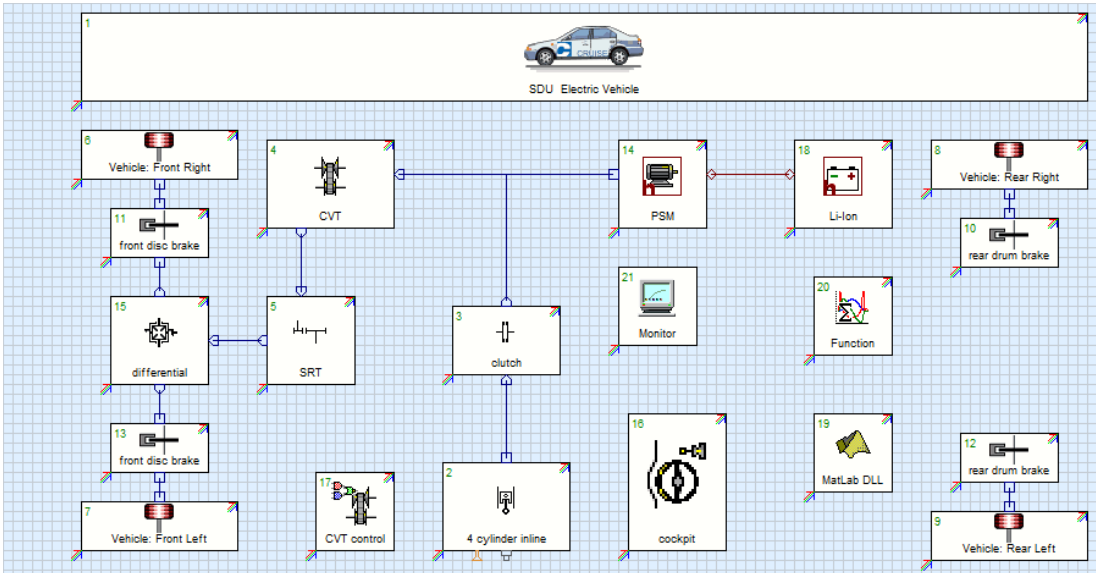


Figure 14. The designed parallel hybrid electric vehicle (PHEV) model in AVL Cruise.

The driving cycles of NEDC and FTP75 were selected correspondingly to test the fuel consumption, CO, NOx, and hydrocarbon (HC) emission performance of the vehicle. The fuzzy rule-based F-EMS and the cycle recognition-based NNF-EMS were established through the co-simulation of AVL Cruise and Matlab/Simulink. Additionally, the co-simulation was implemented in the form of a dynamic link library called the Matlab DLL.

4.1. Results Analysis of Power Performance

The vehicle velocity performance shows the dynamic response of the actual vehicle velocity following the driver's given velocity, which is also the most basic condition for judging whether EMS is feasible. From the vehicle velocity conditions shown in Figures 15 and 16, it can be seen that, during the entire cycle of NEDC and FTP75, the vehicle had good dynamic performance and could respond quickly to a given vehicle velocity, indicating that the vehicle model is rationally modeled and the control strategy is feasible. It can be seen from the following situation after enlargement in Figures 17 and 18 that the NNF-EMS based on DCR has the best performance, whose dynamic response time is the fastest with no overshoot. In addition, it can be seen from the following situation that it is obviously better in the steady-state driving cycle NEDC than in the transient driving cycle FTP75, which is close to the actual operation.

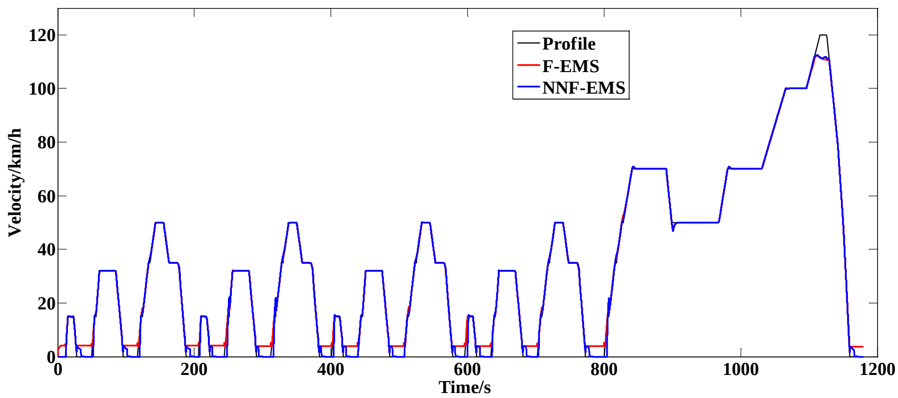


Figure 15. Vehicle velocity following under NEDC cycle.

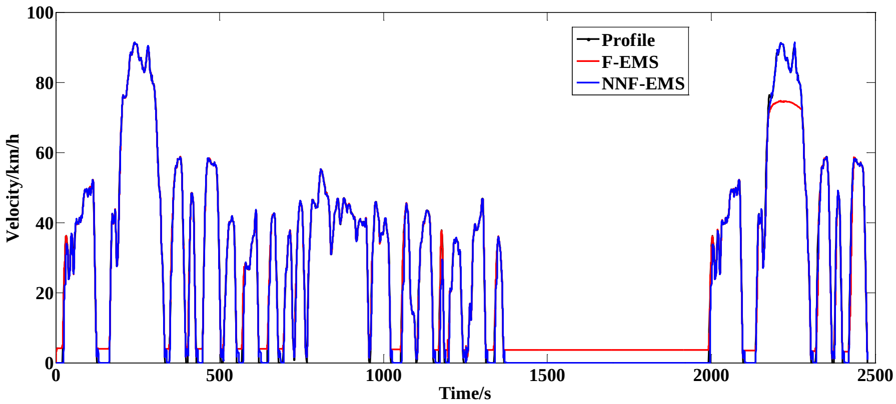


Figure 16. Vehicle velocity following under FTP75 cycle.

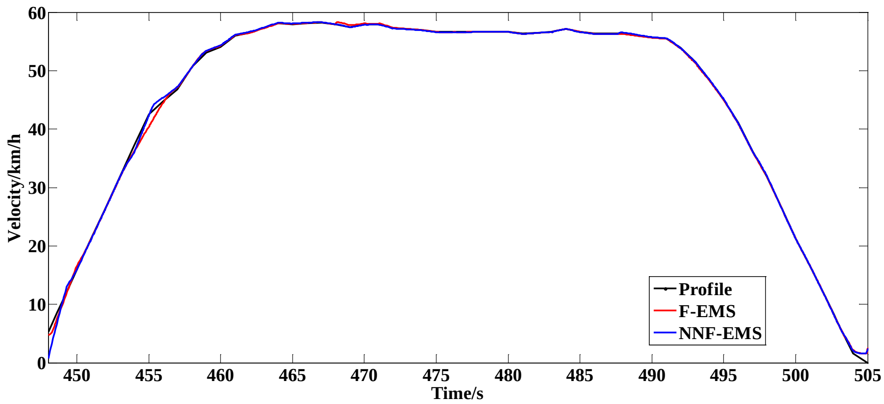


Figure 17. Vehicle velocity following under FTP75 cycle (partial enlargement).

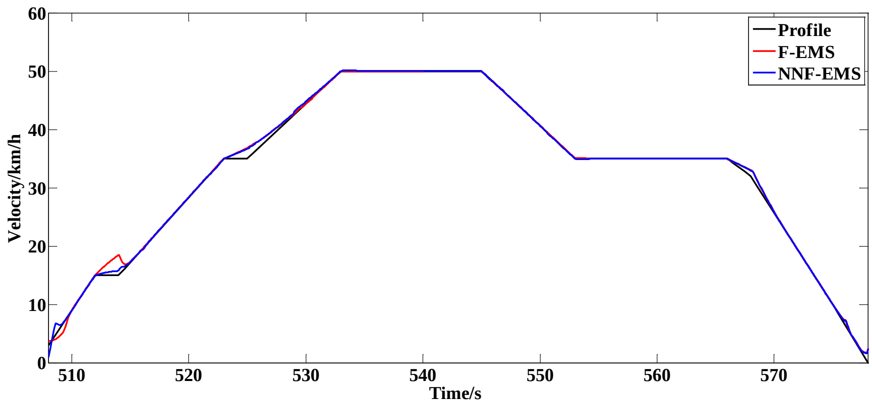


Figure 18. Vehicle velocity following under NEDC cycle (partial enlargement).

4.2. Results Analysis of Fuel Economy and Emission Performance

Cycle economy tests of vehicle fuel economy and emission performance under NEDC and FTP75 were carried out through AVL Cruise. The experimental results are compared in Table 3. In comparison with the F-EMS, the NNF-EMS considers that the DCR is more sensitive to the driving conditions and the control fuzzy rules are more detailed; hence, the control is more sensitive and the vehicle performance of the HEV is further improved. Specifically, compared to the F-EMS, the fuel consumption of the NNF-EMS based on the cycle recognition under the NEDC cycle was reduced from 7.093 L/100 km to 5.576 L/100 km, and the fuel optimization rate reached 21.39%; CO emissions decreased from 5.362 g/km to 4.419 g/km, a 17.59% reduction; NOx emissions decreased from 1.910 g/km to 1.524 g/km, a 20.21% reduction; HC emissions decreased from 0.5702 g/km to 0.4054 g/km, a 28.90% reduction. In addition, the reduction in fuel consumption and the improvement in emission performance did not occur at the expense of consuming more battery power. The power consumption only increased from 6.0488 kWh to 6.0645 kWh. This shows that the NNF-EMS based on DCR better optimizes the working zone of the engine, improves fuel efficiency, and reduces emissions. The simulation output results of NNF-EMS in AVL Cruise under NEDC cycles are shown in Figure 19.

Table 3. Comparison of fuel economy and emission performance under NEDC cycles.

Performance	F-EMS	NNF-EMS	Optimization Rate
Actual travel distance (m)	11,312.29	11,002.79	/
Total power consumption (kWh)	6.0488	6.0645	/
Battery SOC variation (%)	22.39	23.87	/
Total fuel consumption (kg)	0.6010	0.4595	/
Fuel consumption (L/100 km)	7.093	5.576	21.39%
CO emission (g/km)	5.362	4.419	17.59%
NOx emission (g/km)	1.910	1.524	20.21%
HC emission (g/km)	0.5702	0.4054	28.90%

Cycle	Fault-time [s]	Vehicle - mass [kg]	Calculation	Slip	DISTANCE [m]	CONSUMPTION [l/100km]	EMISSIONS NOx [g]	CO [g]	HC [g]	SOOT [g]
NEDC_man	150.05	1550.0	Simulatio*	Off	11002.79	5.58	16.77	48.62	4.46	0.00

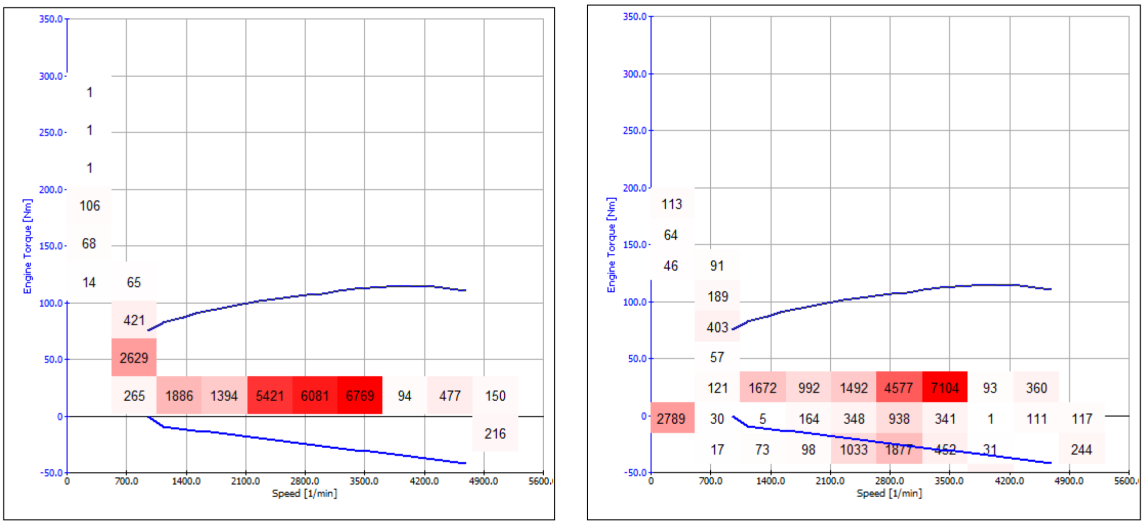
```
Overall Fuel Consumption:            0.4595   [kg]
Idle Fuel Consumption:               0.0000   [kg]
Acceleration Fuel Consumption:       0.1195   [kg]
Constant Drive Fuel Consumption:     0.2371   [kg]
Deceleration Fuel Consumption:       0.1029   [kg]
Overall Energy Consumption:          6.0645   [kWh]

TRANSPORT EFFICIENCY RESULTS:

Fuel Consumption:         5.576 (l/100km)
```

Figure 19. Simulation results of neural network fuzzy energy management strategy (NNF-EMS) under NEDC cycles in AVL Cruise.

Fuel consumption is ultimately caused by differences in engine operating points. Figure 20 shows the distribution of key operating points of the engine under the NEDC cycle. According to the comparison, in Figure 20a,b, under the F-EMS, the engine can work closer to the rated torque, with higher fuel efficiency, thereby significantly improving fuel economy and emissions. NNF-EMS further optimizes the engine operating points, thereby further reducing fuel consumption and improving emission performance.

Table 4 shows the simulation results of fuel economy and emissions comparison under the FTP75 cycle. It can be seen that the performance is quite different under NEDC and FTP cycles, indicating that the driving conditions have a great impact, and the control strategy should be adjusted based on the driving conditions. The fuel economy and emission performance of the F-EMS are relatively stable under different NEDC and FTP75 cycles, indicating that the fuzzy control itself is robust to changes in driving conditions. The NNF-EMS performance of DCR-based HEV is always the best under different driving conditions, indicating that the impact changes in driving conditions on the EMS optimization of HEVs cannot be ignored.

Simultaneously, it can be seen from Tables 3 and 4 that, compared to NEDC driving conditions, DCR-based NNF-BMS improves the fuel consumption and emission performance of the vehicle by more than 30% under the FTP75 driving cycles, but not the power consumption, which was reduced from 9.6751 kWh to 9.3127 kWh. It shows that the application of DCR-based NNF-EMS is more obvious under real transient conditions.



(**a**) (**b**)

Figure 20. Comparison of engine optimized operating points in NEDC cycles: (**a**) F-EMS; (**b**) NNF-EMS.

Table 4. Comparison of fuel economy and emission performance under FTP75 cycles.

Performance	F-EMS	NNF-EMS	Optimization Ratio
Actual travel distance (m)	18,513.22	17,613.76	/
Total power consumption (kWh)	9.6751	9.3127	/
Battery SOC variation (%)	43.57	43.89	/
Total fuel consumption (kg)	1.2404	0.8042	/
fuel consumption (L/100 km)	8.945	6.096	31.85%
CO emission (g/km)	8.003	5.100	36.27%
NOx emission (g/km)	2.777	1.673	39.76%
HC emission (g/km)	0.8421	0.4496	46.61%

5. Conclusions

The driving pattern recognition results affect the EMS directly, and the driving condition is complex in NEDC, UDDS, etc. Some results are now shown in Figures 10 and 11, because the "driving cycle block" is defined differently under different conditions, as shown in Figure 8 for the definition of NEDC; however, the NNF-EMS is still efficient for other conditions. Although there are other existing EMS techniques in the literature that were not designed in this paper in comparison with our proposed method, such as dynamic programming, it can be used as a benchmark for evaluating the proposed method; however, it is not useable in real-time, and the focus of this article is how to improve current fuzzy control methods with high availability. This paper does not excessively emphasize and compare global and real-time optimization methods of energy management.

Looking at the literature, the concept of using driving data and traffic information in an adaptive fuzzy inference system for energy management of HEV is not new. In this paper, by analyzing the characteristic parameters of the driving cycles and learning using neural network samples, the DCR is realized, and the recognition results are used as the reference input for the fuzzy control strategy. Therefore, the membership function in the fuzzy controller is optimized to solve the problem of poorly targeted driving cycles. The proposed method can adopt the optimized control strategy in different driving cycles, and its robust substitution and performance are better than the traditional fuzzy control strategy. The proposed NNF-EMS can realize the adaptive optimization of fuzzy membership function and fuzzy rules under different driving cycles. Different from intelligent algorithms such as global optimization and real-time optimization, from the perspective of real vehicle application, fuzzy control is more practical. Thus, it will have good practical application value in improving the fuel economy of hybrid electric vehicles.

For electric vehicles, especially battery electric vehicles with limited energy, the optimization of energy management is crucial. With the vigorous development of electric vehicles toward unmanned vehicles and connected vehicles, on-board electronic devices such as sensors and high-performance computers that consume large power put forward higher requirements for vehicle energy management. Road condition information not only affects driving safety but also directly affects fuel and/or electricity consumption. Intelligent energy management strategies that take into account information prediction of road/operating condition will become a hot research topic in the area of vehicle energy management in the future. Artificial intelligence methods are also widely applied, such as deep learning, reinforcement learning, and convolutional neural networks, and further research is urgently needed.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

EMS	energy management strategy
F-EMS	fuzzy rule-based energy management strategy
NNF-EMS	neural network fuzzy energy management strategy
DCR	driving cycle recognition
HEV	hybrid electric vehicle
BEV	battery electric vehicle
PHEV	parallel hybrid electric vehicle
SHEV	series hybrid electric vehicle
SPHEV	series-parallel hybrid electric vehicle
PSO	particle swarm optimization
SOC	state of charge
FTP75	Federal Test Procedure 75
UDDS	Urban Dynamometer Driving Schedule
EPA	Environmental Protection Agency
NEDC	New European Driving Cycle
ECE	Economic Commission of Europe
UDC	Urban Driving Cycle
EUDC	Extra-urban driving Cycle
BP	Back Propagation
ANFIS	adaptive Neuro-fuzzy inference system

References

1. Chen, Z.; Mi, C.; Xia, B.; You, C. A novel energy management method for series plug-in hybrid electric vehicles. *Appl. Energy* **2015**, *145*, 172–179. [CrossRef]
2. Zhang, Q.; Cui, N.; Li, K.; Shang, Y.; Zhang, C. Co-Simulation of Energy Management Strategy for Hybrid Electric Vehicle in AVL InMotion. In Proceedings of the Chinese Automation Congress, Jinan, China, 20–22 October 2017; pp. 4932–4937.
3. Lei, Z.; Cheng, D.; Liu, Y.; Qin, D.; Zhang, Y.; Xie, Q. A dynamic control strategy for hybrid electric vehicles based on parameter optimization for multiple driving cycles and driving pattern recognition. *Energies* **2017**, *10*, 54. [CrossRef]

4. Sun, J.; Xing, G.; Zhang, C. Data-driven predictive torque coordination control during mode transition process of hybrid electric vehicles. *Energies* **2017**, *10*, 441. [CrossRef]
5. Liu, Y.; Gao, J.; Qin, D.; Zhang, Y.; Lei, Z. Rule-corrected energy management strategy for hybrid electric VEHICLES based on operation-mode prediction. *J. Clean. Prod.* **2018**, *188*, 796–806. [CrossRef]
6. Wu, J.; Zhang, C.; Cui, N. Fuzzy energy management strategy of parallel hybrid electric vehicle based on particle swarm optimization. *Contr. Decis.* **2008**, *23*, 46–50.
7. Yang, L.; He, H.; Sun, F.; Shi, S.; Li, Y.; Liu, L. Research of Fuzzy Logic control STRATEGY for Engine Start/Stop in Dual-Clutch Hybrid Electric Vehicle. In Proceedings of the International Conference on Fuzzy Systems and Knowledge Discovery, Yantai, Shandong, China, 10–12 August 2010; pp. 912–917.
8. Zhang, D.; Zhou, Y.; Liu, K.; Chen, Q. A Study on Fuzzy Control of Energy Management System in Hybrid Electric Vehicle. In Proceedings of the IEEE Asia-pacific Power & Energy Engineering Conference, Wuhan, Hubei, China, 27–31 March 2009; pp. 1–4.
9. Pei, J.; Su, Y.; Zhang, D. Fuzzy energy management strategy for parallel HEV based on pigeon-inspired optimization algorithm. *Sci. China Technol. Sci.* **2017**, *60*, 425–433. [CrossRef]
10. Fu, Z.; Wang, B.; Song, X.; Liu, L.; Wang, X. Power-split hybrid electric vehicle energy management based on improved logic threshold approach. *Math. Probl. Eng.* **2013**, *2013*, 840648. [CrossRef]
11. Fu, Z.; Wang, B.; Gao, A.; Zhou, P. Fuzzy control strategy of battery management for PHEV during regenerative braking. *Res. J. Appl. Sci. Eng. Technol.* **2014**, *7*, 30–36. [CrossRef]
12. Zhou, M.; Zhang, Y.; Yang, Z.; Kang, D. Fuzzy energy management strategy for HEV based on particle swarm optimization with compressibility factor. *Electr. Mach. Control* **2011**, *15*, 67–72.
13. Huang, D.; Xie, H.; Xiong, S.; Shen, T.; Qiang, S.; Zhang, R. Optimization Energy Management Strategy of Plug-In Hybrid Electric City Bus Based on Driving Cycle Prediction. In Proceedings of the SAE World Congress & Exhibition, Detroit, MS, USA, 12–14 April 2016; p. 9.
14. Fotouhi, A.; Yusof, R.; Rahmani, R.; Mekhilef, S.; Shateri, N. A review on the applications of driving data and Traffic information for vehicles' energy conservation. *Renew. Sustain. Energy Rev.* **2014**, *37*, 822–833. [CrossRef]
15. Zhu, D.; Xie, H.; Yan, Y.; Song, Z. Control strategy Dynamic optimization of the hybrid electric bus based on driving cycle self-learning. *J. Mech. Eng.* **2010**, *46*, 33–38. [CrossRef]
16. Tian, Y.; Zhang, X.; Zhang, L.; Zhang, Y. Fuzzy control strategy for hybrid electric vehicle based on neural network identification of driving conditions. *Contr. Theory Appl.* **2011**, *28*, 363–369.
17. Luo, Y.; Hu, H.; Shen, J. Analysis and recognition of running cycles of hybrid electric vehicle. *J. South China Univ. Technol. (Nat. Sci. Ed.)* **2007**, *36*, 8–13.
18. Fu, X.; Wang, H.; Cui, N.; Zhang, C. Energy management strategy based on the driving cycle model for plugin hybrid electric vehicles. *Abstr. Appl. Anal.* **2014**, *2014*, 341096. [CrossRef]
19. Wu, J.; Zhang, C.; Cui, N. Fuzzy energy management strategy for a hybrid electric vehicle based on driving cycle recognition. *Int. J. Autom. Technol.* **2012**, *13*, 1159–1167. [CrossRef]
20. Montazeri, M.; Fotouhi, A.; Naderpour, A. Driving segment simulation for determination of the most effective driving features for HEV intelligent control. *Veh. Syst. Dyn.* **2012**, *50*, 229–246. [CrossRef]
21. Montazeri, M.; Fotouhi, A.; Naderpour, A. Driving patterns clustering based on driving feature analysis. *Proc. Inst. Mech. Eng. Part C J. Mech. Eng. Sci.* **2011**, *225*, 1301–1317. [CrossRef]
22. Montazeri, M.; Fotouhi, A. Traffic condition recognition using the K-means clustering method. *Sci. Iran.* **2011**, *18*, 930–937. [CrossRef]
23. Zhang, X.; Liu, Y.; Zhang, J.; Dai, W.; Liu, Z. A fuzzy NEURAL Network Energy Management Strategy for Parallel Hybrid Electric Vehicle. In Proceedings of the 9th International Conference on Modelling, Identification and Control (ICMIC), Kunming, Yunnan, China, 10–12 July 2017; pp. 342–347.
24. Wang, J.; Wang, Q.; Liu, J.; Zeng, X. Forward Simulation Model Precision Study for Hybrid Electric Vehicle. In Proceedings of the IEEE International Conference on Mechatronics and Automation, Changchun, Jilin, China, 9–12 August 2009; pp. 2457–2461.
25. Jin, L.Q.; Cai, W.B. Study on Fuzzy Control for Starting Torque of Vehicle with Motorized Wheels. In Proceedings of the IEEE International Power Electronics and Motion Control Conference-ECCE Asia, Harbin, Heilongjiang, China, 2–5 June 2012; pp. 2557–2560.
26. Jang, J.S.R.; Sun, C.T.; Mizutani, E. Neuro-fuzzy and soft computing: A computational approach to learning and machine intelligence. *IEEE Trans. Automat. Contr.* **1997**, *42*, 1482–1484. [CrossRef]

27. Li, H.; Xu, D.; Wang, L. Application of Fuzzy Algorithms Based on Neural Networks to the Hybrid Energy Management Systems of Future Combat Vehicles. In Proceedings of the IEEE International Conference on Sensor Networks and Signal Processing, Shanxi, Xian, China, 28–31 October 2018; pp. 475–481.
28. Chen, R.; Li, C.; Meng, X.; Yu, Y. The Application of Fuzzy-neural Network on Control Strategy of Hybrid Vehicles. In Proceedings of the Chinese Control Conference, Kunming, Yunnan, China, 16–18 July 2008; pp. 281–284.
29. Fu, X.; Zhang, Q.; Wang, C.; Tang, J. Torque coordination control of hybrid electric vehicles based on hybrid dynamical system theory. *Electronics* **2019**, *8*, 712. [CrossRef]
30. Chen, Z.; Mi, C.; Xu, J.; Gong, X.; You, C. Energy management for a power-split plug-in hybrid electric vehicle based on dynamic programming and neural networks. *IEEE Trans. Veh. Technol.* **2014**, *63*, 1567–1580. [CrossRef]
31. Ericsson, E. Variability in urban driving patterns. *Int. J. Transport. Res. Part. D* **2000**, *5*, 337–354. [CrossRef]
32. Ericsson, E. Independent driving pattern factors and their influence on fuel-use and exhaust emission factors. *Int. J. Transp. Res. Part. D* **2001**, *6*, 325–341. [CrossRef]