Optimization of fuzzy control energy management strategy for fuel cell vehicle power system using a multi-island genetic algorithm

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Abstract
Energy storage system can be used to increase the fuel economy of fuel cell system (FCS). In this study, a new method was introduced for optimizing the energy management strategy (EMS) for fuel cell vehicle (FCV) to reduce fuel consumption. The membership function (MF) in fuzzy control is subjective; thus, 12 design variables in the input-output MFs were selected using sensitivity analysis, and elliptical basis function neural network method was used to establish a high-precision approximate model of FCV. Multi-island genetic algorithm was used to optimize the MFs. The effectiveness of the optimized fuzzy control EMS and the proposed optimization method were demonstrated in simulations of two EMSs under four driving cycles. The simulation results confirmed that the optimized fuzzy control EMS provided smoother and more stable output power from FCS reducing hydrogen consumption by 8.4\%, 1.1\%, 5.1\%, and 7.6\%, respectively, compared to the original fuzzy control EMS; and hydrogen saved by the optimized EMS provided extra range of 9.15, 1.10, 5.37, and 8.25 km per 100 km in the four driving cycles, respectively. The optimized EMS can reduce hydrogen consumption to increase fuel economy and extend the life span of the fuel cell.

\textbf{KEYWORDS}
elliptical basis function neural network, energy management strategy, fuel cell vehicle, fuzzy control, multi-island genetic algorithm

1 | INTRODUCTION

Energy crises and environmental pollution, such as oil shortage and air pollution, have brought great challenges to the automotive industry.\textsuperscript{1} To combat those problems, hydrogen fuel cells have been produced as alternatives to conventional internal combustion vehicles due to their efficient energy conversion and environmental cleanliness characteristics.\textsuperscript{2,5}

Hydrogen fuel cells are considered to be an ideal alternative energy source for electric vehicles.\textsuperscript{6-9} However, the output characteristic of the fuel cell is relatively soft. Its dynamic response ability is weak, and a single fuel cell may not provide sufficient power when the vehicle is accelerating.\textsuperscript{10,11} Fuel cell also cannot recover energy from motor braking feedback, providing lower power density and slower power response.\textsuperscript{12-15} Therefore, hydrogen-powered
vehicles need batteries or large capacitors as part of an energy storage system (ESS).\textsuperscript{16,17} Compared to most conventional power systems, batteries and capacitors can be used to better control energy flow and often help increase vehicle efficiency.\textsuperscript{18}

An ESS prevents oxygen starvation problem in fuel cell in order to achieve the potential of higher performance and better fuel economy. A battery or a supercapacitor combined with a fuel cell forms a smaller vehicle power system. Incorporation of an ESS to form a hybrid power system can improve the vehicle's response to abrupt load changes during acceleration, and fuel economy can be increased by restricting the operation of the fuel cell system (FCS) in high-efficiency operating points, as well as through the use of regenerative braking.\textsuperscript{19} Fuel cell vehicle (FCV) combines the benefits of fuel cell stack and ESS to achieve fuel economy and zero emission. The power system of FCV needs energy management strategy (EMS) to distribute energy between two sources, and to achieve the purpose of regulating power flow from FCS and ESS.\textsuperscript{20,21}

EMS has received considerable critical attention, serves as an essential function in determining, which power source should be activated or drawn, and focuses on the issue of how to allocate the power between fuel cell and power battery.\textsuperscript{22,23} An excellent EMS can not only guarantee the vehicle running normally; but also provide better performance of various power sources, meet the physical constraints of power sources, and improve the economy, durability, and reliability of power sources.\textsuperscript{24}

At present, the following three energy management methods are commonly used: fuzzy rule control, deterministic rule control, and global optimization.\textsuperscript{25,26} Stiffness coefficient model, dynamic programming, operation mode control, neural network and wavelet transform approaches, and optimal control and fuzzy logic control are some of these applied methods.\textsuperscript{8} Fuzzy rule management system is a rule-based method composed of fuzzy logic.\textsuperscript{27} Fuzzy logic refers to the process of judging and reasoning that imitates the concept of uncertainty in the human brain. Fuzzy control can be used to design a powertrain system, because it can adjust the fuzzy logic at any time, according to the degrees of freedom in the system.

Many research groups have developed several types of fuzzy controllers. An online fuzzy EMS was used to control a DC/DC converter in a literature study.\textsuperscript{28} Experimental results showed that online fuzzy control strategy could make full use of battery energy and reduce hydrogen consumption. Fuzzy logic has a suitable structure for hybrid system. Fuzzy logic control (FLC) can be used in a hydrogen-powered vehicle to improve the performance and service life of hybrid or battery system. The input to FLC system usually includes load power, power error, and the battery's state of charge (SOC), and the appropriate output current from the fuel cells is determined.\textsuperscript{29} The power demand between fuel cells and battery in a vehicle was determined by using a proposed optimized fuzzy control EMS.\textsuperscript{30} By determining the optimal degree of hybridization and power management strategy, the overall efficiency of the system could be maximized. Their simulation results showed that using FLC for power management can lead to decrease in fuel consumption and increase in overall system efficiency.

However, the disadvantages of FLC are also apparent. Fuzzy rules mainly come from expert knowledge or control experience, and there are inevitable defects in the parameters or rules when the rules are set manually. They are subjective and do not use prior information to optimize the entire cycle, which cannot guarantee optimum power distribution. Therefore, researchers usually apply intelligent methods in fuzzy control to optimize fuzzy rules.

Researchers have published some optimum power control strategies, where dynamic programming, stochastic dynamic programming, equivalent consumption minimization strategy, or an optimized fuzzy controller was used in a genetic algorithm (GA).\textsuperscript{31-34} GAs have become a popular class of optimization algorithms, attributed to their global search performance and low algorithm complexity in evolutionary computing. GAs have been widely used in discrete optimization, adaptive optimization, data processing, and other fields. Offspring generated in a GA is automatically updated, and global searching can be directed or randomized. Moreover, GAs have the advantage of service life prediction by using large data, which plays a vital role in predicting the lifetime of a fuel cell.\textsuperscript{35} GA has been used to optimize the discrete speed ratio, which was found to prevent energy loss and increase the energy efficiency of the system.\textsuperscript{36} To minimize hydrogen consumption in a pre-defined driving cycle, an FLC of the power flow of an FCV should be presented, and GA should be used to online optimize the controller's gains.\textsuperscript{37} A novel fuzzy controller with an adaptive MF was used to optimize power management in a fuel cell-powered vehicle.\textsuperscript{38} A power control strategy, which can be used to modulate current output from fuel cell, was developed and implemented using a fuzzy control algorithm. Then, to minimize fuel consumption and maintain the battery's SOC, the MF in the fuzzy controller was optimized.

Genetic algorithms still have undesirable local search ability, and they suffer from premature or slow convergence.\textsuperscript{39} An alternative is multi-island genetic algorithm (MIGA), which does not tend to get stuck in a local optimum. Instead, migration between different islands in the solution space occurs, which greatly expands the search range without sacrificing convergence speed.\textsuperscript{40} The development of computer technology allows engineering technicians to solve a large number of practical engineering problems through computer simulation. However, with increasing requirements for model accuracy, simulation model is becoming progressively more complex, and the later simulation optimization time is getting increasingly longer. It poses a huge challenge to the performance of the computer. In order to solve this problem, researchers have proposed the
use of approximate model instead of complex physical model for simulation and optimization, which can significantly improve the optimization efficiency and speed up the design process.

Therefore, MIGA was used to optimize a fuzzy control EMS for a vehicle power system in this study. A total of 12 design variables were selected for use in the input-output MFs using sensitivity analysis, and a high-precision approximate model of FCV was established by elliptical basis function neural network (EBFNN) method. MIGA was used to optimize a fuzzy control EMS, and the equivalent hydrogen consumption of the vehicle was reduced throughout China Heavy-duty Commercial Vehicle Test Cycle-truck (CHTC-HT) driving cycle as objective function, providing reduced fuel consumption and improved overall performance. In order to verify the effectiveness of the optimization method, Highway Fuel Economy Test (HWFET), optional air conditioning test (SFTP-SC03), and Urban Dynamometer Driving Schedule (UDDS) tests were simulated with a Chinese heavy-duty commercial vehicle.

The structure of the remaining part of this paper is as follows: Section 2 presents the power system architecture and models of power components. In Section 3, design power following EMS and fuzzy control EMS is presented. Section 4 describes the use of MIGA for optimization of the fuzzy control EMS. Section 5 presents the simulation results from the optimized fuzzy control EMS, and also the comparative analysis of these results with those from the original fuzzy control EMS. Conclusions are presented in Section 6.

2 | POWER SYSTEM STRUCTURE AND MODELING

2.1 | Power system structure

Figure 1 exhibits the structure of fuel cell power system. Fuel cell is the primary energy source, and ESS consisting of lithium battery provides supplemental power.

Fuel cell system is indirectly connected in parallel with the lithium battery through a unidirectional boost DC/DC converter, and the drive motor is directly connected to the transmission shaft. To supply appropriate voltage to the motor, a unidirectional DC/DC converter is connected to the fuel cell and DC bus to increase the output voltage of the fuel cell. The unidirectional DC/DC converter can prevent electrical energy from being recovered from the braking system on the fuel cell. A lithium battery is used to store excess power and smooth fluctuations in the power supply. According to the vehicle power demand $P_{load}$, the EMS distributes power between the two energy sources and decides whether to turn the fuel cell on or off. These energy sources provide power for the motor, which drives the wheels via a final drive and differential. Tables 1 and 2 list the design parameters and performance index of the vehicle, respectively.

2.2 | Vehicle model

In order to design a sized power unit, the maximum power required by a typical electric machine should be calculated first. This power is limited by acceleration, maximum speed, grade, and other parameters related to the vehicle characteristics. The required power is defined in terms of Equation (1) as follows:

$$P_{load} = \frac{u}{\eta_t} \left( mg \cos \alpha + 0.5 C_D A u^2 + m g \sin \alpha + \delta m \frac{du}{dt} \right)$$

where $\eta_t$ is the efficiency of the powertrain, $u$ is the vehicle speed, $g$ is gravitational acceleration, and other parameters of the vehicle model are listed in Tables 1 and 2.

2.3 | Fuel cell model

According to the vehicle parameters and design performance indexes presented in Tables 1 and 2, the parameter matching,
selection, and modeling of fuel cell, power battery, and motor are completed. Fuel cell is a device consisting of hydrogen and oxygen as fuel, and through electrode reaction, it directly converts chemical energy into electrical energy, and it is the main energy source of FCV. Detail parameters of the PEMFC are listed in Table 3. The fuel cell output voltage can be expressed as follows:

\[
V_{\text{FC}} = N_{\text{cell}} \times (E_{\text{cell}} - V_{\text{act}} - V_{\text{ohm}} - V_{\text{con}})
\]

where \(E_{\text{cell}}\) is reversible voltage, \(V_{\text{act}}\) is activation loss, \(V_{\text{ohm}}\) is ohmic loss, \(V_{\text{con}}\) is concentration loss, and \(N_{\text{cell}}\) is the number of cells in the stack.

In order to minimize hydrogen consumption, it is necessary to make the fuel cell run in the high-efficiency range; thus, it is necessary to study the fuel cell efficiency model. The theoretical efficiency of a fuel cell is defined as the ratio of the power produced by the fuel cell to the hydrogen supplied, as shown in Equation (3):

\[
\eta_{LHV} = \frac{\frac{V_{\text{FC}}I_{\text{FC}}}{2F} - \Delta H_{\text{LHV}}}{\Delta H_{\text{LHV}}}
\]

where \(\eta_{LHV}\) is the theoretical efficiency of the fuel cell, \(I_{\text{FC}}\) is the fuel cell output current, \(\Delta H_{\text{LHV}}\) is the caloric value of hydrogen, and \(F\) is Faraday's constant.

In order to ensure regular operation of the FCS, some auxiliary systems, such as cooling systems, and air compressors are required. Therefore, the efficiency of FCS is determined by using the theoretical efficiency of the fuel cell and the efficiency of actual accessories, as shown in Equation (4):

\[
\eta_{\text{FCS}} = \frac{V_{\text{FC}}}{1.254} \left( \frac{P_{\text{FC}} - P_{\text{AUX}}}{P_{\text{FC}}} \right)
\]

where \(\eta_{\text{FCS}}\) is the efficiency of FCS, \(P_{\text{FC}}\) is the fuel cell output power, and \(P_{\text{AUX}}\) is the fuel cell auxiliary system power consumption.

Noteworthy, the DC/DC converter is directly connected to the fuel cell; thus, the DC/DC converter efficiency should also be included in the FCS. Figure 2 exhibits the output power-efficiency curve of the FCS, and these data were obtained by fuel cell manufacturers through bench tests. In this figure, panels (A–C) show the high-efficiency interval of the FCS, and the efficiency of the FCS exceeds 42% in this range. Panels (A) and (B) show the desired efficiency interval of the FCS, where the efficiency of the FCS exceeds 45% in this range. The highest efficiency appears at around 17.5 kW, and the highest efficiency approaches 49%. In order to minimize hydrogen consumption, the FCS should be operated in the highest efficiency interval as far as possible.

The vehicle simulation focuses on calculating fuel cell energy consumption; therefore, an FCS consumption model should be based on the efficiency curve. Hydrogen consumption can be calculated from the fuel cell efficiency as follows:

\[
m_{\text{H}_2}^{\text{FC}} = \int \frac{P_{\text{FC}}}{\eta_{\text{FCS}}} \Delta H_{\text{LHV}}
\]

### 2.4 Battery model

As a secondary energy source, the battery mainly provides supplemental power for a long period. Detailed parameters of the battery are listed in Table 4. In order to maintain the DC bus voltage and recycle braking energy, the battery’s SOC should be kept within an appropriate range.

The internal current of the battery can be obtained by solving the following power balance relationship:
where both $V_{oc}$ and $R_{bat}$ are functions of the battery’s SOC, that is, $V_{oc} = f(SOC)$ and $R_{bat} = f(SOC)$. The battery current $I_{bat}$ can be described as follows:

$$I_{bat} = \frac{V_{oc} - \sqrt{V_{oc}^2 - 4R_{bat}P_{bat}}}{2R_{bat}} \quad (7)$$

The SOC is one of the most important parameters of the vehicle and the battery EMS41:

$$SOC = SOC_0 - \frac{\int I_{bat}dt}{Q} \quad (8)$$

where $SOC_0$ is the initial value of the SOC, and $Q$ is the rated capacity (the capacity of the battery in standard conditions).

### 2.5 Motor model

Motor is the only power source that provides the driving force for the entire vehicle. It can also be used as a generator to recover braking energy and complete mutual conversion of mechanical energy into electrical energy. Detailed parameters of the motor are listed in Table 5.

Motor power requirement in driving state is represented as follows:

$$T_{md} = \epsilon T_{max}(n_m) \quad (9)$$

$$P_{mec} = \frac{T_{md}n_m}{9550} \quad (10)$$

$$P_{eleb} = P_{mec}n_{mb}(T_{mb}, n_m) \quad (11)$$

where $T_{md}$ is the motor output torque while driving, $\epsilon$ is the driving signal from the driver model, $T_{max}(n_m)$ is the external characteristics of the motor drive, $P_{mec}$ is the motor’s output mechanical power, $P_{eleb}$ is the electrical power required by the motor, and $n_{mb}(T_{mb}, n_m)$ is the conversion efficiency of the motor.

While braking, the required motor power is similar to that while driving; only the input and output of the motor are interchanged. The motor converts mechanical energy of the vehicle into electrical energy and stores it in the battery. The electric power generated during braking can be calculated as follows:

$$P_{eleb} = P_{mec}n_{mb}(T_{mb}, n_m) \quad (13)$$

where $T_{mb}$ is the electric braking torque, $n_{mb}(T_{mb}, n_m)$ is the conversion efficiency of the motor as a generator, and $P_{eleb}$ is the electrical power generated while braking.

The actual output speed of the motor is determined by the motor’s maximum speed and the required speed, while the
actual output torque of the motor is determined by the motor drive torque and inertia torque, as shown in the following equations:

\[ n_m = \min(n, n_{\max}) \]  
\[ T_m = T + J\dot{\theta} \]

where \( J \) is the motor's inertia and \( \dot{\theta} \) is the angular acceleration of the motor.

### 3  |  ENERGY MANAGEMENT STRATEGY

An EMS can improve the dynamic response of the vehicle and increase its efficiency without increasing fuel consumption. An EMS operates by following several rules that are built based on different conditions such as the power behavior of the hybrid system (fuel cell, battery, and the vehicle's required power) and the battery's SOC. The vehicle's power system and energy control strategy should be designed by using the following principles:

1. The FCS and battery must be able to provide the power demanded by the vehicle.
2. The battery's SOC must be kept within a set range and in shallow charging/discharging states to prolong its life span. Recovered braking energy should be used to reduce hydrogen consumption.
3. The fuel cell should be selected so that the FCS can operate in the high-efficiency region as much as possible.

#### 3.1  |  Power following energy management strategy

The goal of a power following EMS is to maintain the SOC, and the output power from the FCS should be adjusted according to the current SOC such that the system operates in the high-efficiency region. The power balance relationship is as follows \(42\):

1. Battery works alone

When \( SOC < SOC^* \), FCS in the high-efficiency interval, fuel cell works alone. While \( P_{FC} \) meets the \( P_{load} \), it also requires charging of the battery.

\[ P_{bat} = \beta \frac{SOC^* - SOC}{SOC_{\text{max}} - SOC_{\text{min}}} \]  
\[ P_{FC} = P_{load} + P_{bat} \]

\[ SOC^* = \frac{SOC_{\text{max}} + SOC_{\text{min}}}{2} \]

\[ P_{FC_{\text{min}}} < P_{FC} < P_{FC_{\text{max}}} \]  

1. Fuel cell and battery work together

When \( SOC > SOC^* \), \( P_{load} \) is larger. Battery is the main power supply; FCS supplements the remaining required power.

\[ P_{bat} = \beta \frac{SOC - SOC^*}{SOC_{\text{max}} - SOC_{\text{min}}} \]  
\[ P_{FC} = P_{load} - P_{bat} \]

\[ P_{FC_{\text{min}}} < P_{FC} < P_{FC_{\text{max}}} \]

When \( SOC < SOC^* \), \( P_{load} > P_{FC_{\text{max}}} \) FCS outputs maximum power \( P_{FC_{\text{max}}} \), battery supplements the remaining required power.

\[ P_{FC} = P_{FC_{\text{max}}} \]

\[ P_{bat} = P_{load} - P_{FC_{\text{max}}} \]

where \( P_{load} \) is the vehicle's required power, \( P_{FC} \) is the load power generated by the vehicle's driving resistance, \( P_{bat} \) is the output power from the battery, \( \beta \) is cardinal of battery charging and discharging, \( SOC^* \) is average SOC value, \( SOC_{\text{max}} = 0.7 \) and \( SOC_{\text{min}} = 0.4 \) are respectively the maximum and minimum SOC values, \( P_{FC} \) is the output power of the FCS, and \( P_{FC_{\text{max}}} \) and \( P_{FC_{\text{min}}} \) are the maximum and minimum output power of the FCS, respectively.

In an EMS, the battery works in a favorable area at all times such that it experiences shallow charging and discharging near the set SOC value. Therefore, the life span of the battery can be prolonged on the premise that the output power from the FCS is stable and in the high-efficiency region.
Moreover, a slight change in the \( SOC \) value leads to the reduction in the design capacity of the battery, thereby allowing the weight and cost of the entire vehicle to be reduced.

### 3.2 Fuzzy control energy management strategy

Fuzzy control is an intelligent control method based on fuzzy sets, fuzzy language, and fuzzy reasoning, which can be used to adaptively adjust the output power of the FCS based on driving conditions. Fuzzy control has already been successfully used to control the powertrain, engine, and transmission. In this study, a double-input single-output Mamdani fuzzy controller was established based on a fuzzy control strategy and power following control strategy.

#### 3.2.1 Design of input and output variables

In order to maintain the \( SOC \) in the steady state while meeting the power demand, \( P_{load} \) and \( \Delta SOC \) are taken as the two input variables, and \( P_{FC} \) is taken as the output variable of the fuzzy controller. The input and output variables are constrained as follows: \( P_{load} \in [-130, 130] \) kW, \( \Delta SOC \in [-0.55, 0.45] \), and \( P_{FC} \in [0,42.5] \) kW. The MFs and fuzzy distributions of the input and output variables are shown in Figure 3(A-C).

\( P_{load} \) is divided into six fuzzy subsets, expressed as \{NH, NM, NL, PL, PM, PN\}, and the MF is a combination of triangle and trapezoid. \( P_{FC} \in [0,42.5] \) kW; therefore, \( P_{load} \) adopts a triangular MF within this range, and the division is tight to improve the sensitivity of control. According to the appropriate range of \( SOC \), \( \Delta SOC \) is divided into five fuzzy subsets, denoted as \{NB, NS, Z, PS, PB\}, and its MF also adopts the combination of triangle and trapezoid. \( P_{FC} \) is divided into six fuzzy subsets, expressed as \{L0, L1, L2, L3, L4, L5\}, and its MF adopts a trapezoid.

#### 3.2.2 Formulation of fuzzy control rules

Fuzzy control rules can be formulated according to the control logic of a power following EMS, formulation principles of EMS, and actual operation experience. The fuzzy control rules should meet the following requirements:

1. The sum of the output power from the FCS and the battery must satisfy the vehicle’s power demand to ensure the normal driving.
2. Stability of FCS operation should be ensured, the large fluctuation of output power should be avoided, and FCS should work as efficiently as possible.

3. \( SOC \) should lie within the set range, the power battery should always be in the state of shallow charging and discharging, and the power battery should be fully used to recover the braking energy.

The rule base of fuzzy control is presented in Table 6. Using the center-of-gravity method as the clearness method, the three-dimensional surface formed by the input and output variables of the fuzzy controller was obtained as shown in Figure 4.
4 | OPTIMIZATION OF FUZZY CONTROL ENERGY MANAGEMENT STRATEGY

4.1 | Design of experiment and sensitivity analysis

There are 22 variables in the input-output MFs that can be used for optimization. Therefore, the fuzzy control EMS has 23 variables to be optimized. Different parameters have different contributions to equivalent hydrogen consumption; therefore, optimization variables can be screened by calculating the sensitivity of different variables to reduce the number of design variables, and decrease convergence time of the optimization.

4.1.1 | Design of experiment

A sampling method is used in the design of variable space, which can be used to limit the amount of sampling data. The Latin hypercube method is a stratified sampling approach to obtain the parameter value. The method has an effective space filling capability, and it can be used to obtain the greatest factor level with the least number of sample points. Therefore, it is often used to fit second-order or higher-order nonlinear relationships. However, the process of generating sample points in a Latin hypercube design is random; this method is irreproducible and yields an uneven distribution of test points. In order to solve this problem, an optimized Latin hypercube design is proposed. This method uses an optimization algorithm to improve the random Latin hypercube design, which makes the distribution of sampling points in the design space more uniform and makes the fitting of factors and responses more accurate. In this study, equivalent hydrogen consumption was taken as the response value, and the 23 variables were sampled by the optimized Latin hypercube method to complete the simulation design.

4.1.2 | Sensitivity analysis

A multiple quadratic regression model can be used to model the sample points and their response values as follows:

\[ y = \beta_0 + \sum \beta_i x_i + \sum \beta_i x_i^2 + \sum \beta_{ij} x_i x_j \]  

First, the ranges of the input variables are normalized to [-1,1]. Second, the least square method is used for fitting, where the model coefficients are \( S_i \). Finally, \( S_i \) is converted to the percentage of contribution to equivalent hydrogen consumption, which can more fairly reflect the contribution from each input variable to the response. Considering the response and the characteristics of power system components, design variables \( X_{05}, X_{07}, X_{08}, X_{10}, X_{11}, X_{12}, X_{14}, X_{17}, X_{18}, X_{19}, X_{22}, \) and \( SOC^* \) are selected as the optimization variables for use in the fuzzy control EMS. The initial values and design space are presented in Table 7. The results indicate that these variables are all in critical areas of fuzzy control and the selection of optimization variables conforms to engineering experience.

4.2 | Elliptical basis neural network approximate model

Approximate model technology is a design optimization method that includes experimental design and approximation methods. It uses a mathematical model to replace the original simulation analysis module in the system to achieve a computing framework and integration of simulation analysis modules. Moreover, it makes the design optimization of complex systems practical and feasible.

The essence of the approximate model is to approximate the corresponding relationship between the input and output through interpolation and fitting. The objective is to fit the discrete experimental data to form a simpler mathematical model to replace a complex simulation model composed of simulation software or physical experiments, and to realize the test results of predicting unknown points.
There are many nonlinear modules in the vehicle model that require long simulation time. Owing to a large number of design variables, the calculation time required for optimization is too long. In order to decrease the calculation time, an approximate model can be established to optimize the fuzzy control strategy for the vehicle while providing sufficient fitting accuracy. Common approximate model methods mainly include polynomial models, response surface models, neural networks, and Kriging models. Among them, a neural network is useful for modeling complex nonlinear functions and can be used as a “black box” model. The vehicle model is a highly nonlinear system; thus, an EBFNN method can be used for approximation. It is a feedforward neural network composed of an input layer, hidden layer, and output layer, as shown in Figure 5. Where $x_1, x_2, \ldots, x_m$ represent the $m$-dimensional vectors of the input layer, and $y_1, y_2, \ldots, y_R$ represent the $R$-dimensional vector of the output layer. Each node of the input layer uses two weights to connect with each node of the hidden layer, representing the center and semi-axis length of the ellipsoidal neuron to the input unit, respectively. The output layer node and the hidden layer node are fully connected, and the decision space is divided by a hyper-ellipsoid to form a closed and bound computing decision area.

The optimized Latin hypercube method was used to sample the 12 selected design variables, and the EBFNN was trained with sample data obtained from the simulation to build the approximate model. In order to verify the accuracy of the model, 20 sampling points in the design space were randomly selected. The simulated values of these sampling points and the observed values in the approximate model were used to evaluate the credibility of the approximate model. The checked error values are listed in Table 8. The results show that the various error test values are within the allowable range of the project, and the accuracy of the approximate model based on the EBFNN meets the engineering requirements. Thus, it can replace the original nonlinear model for the optimization of fuzzy control EMS.

### 4.3 Parameter optimization using a multi-island genetic algorithm

Multi-island genetic algorithm is a parallel GA. It can jump out of a local optimal solution through migration between islands in the solution space, which significantly expands the search range and increases the convergence speed of the algorithm. A flowchart for MIGA used in this study is shown in Figure 6.
Owing to the large number of design variables in the fuzzy control EMS, the design space may contain multiple local optima. MIGA is used to prevent premature convergence.

1. Objective function

\[ m_{H_2}(X) = m_{H_2}^{FC}(X) + m_{H_2}^b(X) \]  

\[ m_{H_2}^{FC}(X) = \frac{P_b \eta_{dis} \Delta H_{LHV}}{\eta_{FCS} \Delta H_{LHV}} P_b \geq 0 \]

\[ m_{H_2}^b = \frac{P_b \eta_{chg} \Delta H_{LHV}}{\eta_{FCS} \Delta H_{LHV}} P_b < 0 \]

where \( \eta_{dis} \) and \( \eta_{chg} \) are charging and discharging efficiencies of the battery, respectively.

1. Constraints

In addition to limiting the parameter range of design variables, it is also necessary to ensure the power demand of vehicle and the response speed of FCS, which can be expressed as follows:

\[ P_{load}(t) = P_{FC}(t) + P_{bat}(t) \]  

\[ -P_{FCscope} \leq \frac{dP_{FC}(t)}{dt} \leq P_{FCscope} \]

where \( P_{FCscope} \) is the maximum fluctuation in the FCS output power.

1. Optimization results

An approximate model is used in optimization; therefore, the number of iterations in the GA can be increased. The number of initial populations, islands, and generations are set to 10, 10, and 50, respectively, giving a total of 5000 iterations. The other parameters are presented in Table 9, and the optimization process is shown in Figure 7, exhibiting that the equivalent hydrogen consumption is minimized.

The optimization results are presented in Table 10. The inputs MFs and output MF in the optimized fuzzy control EMS are shown in Figure 8, where the SOC* is set to 0.578.

### TABLE 9 Operating parameters in MIGA

| Crossover probability | Mutation probability | Interisland mobility | Migration interval algebra | Proportion of race | Elite retention number |
|-----------------------|----------------------|----------------------|---------------------------|------------------|----------------------|
| 0.9                   | 0.01                 | 0.01                 | 5                         | 0.5              | 1                    |

5 | SIMULATION RESULTS AND DISCUSSION

5.1 | Driving cycle

The standard China Automotive Test Cycle was officially started in 2017 and released on 18 October 2019. It was planned to be formally implemented on 1 May 2020. It mainly includes light-duty vehicles and heavy-duty commercial vehicles. CHTC-HT is the driving cycle of trucks with a total mass of more than 5500 kg, which lasts for 1800 seconds in total. The test is split between an urban area (342 seconds), suburban area (988 seconds), and high-speed area (470 seconds), all with different speeds (88.5 km/h maximum, 34.65 km/h average speed, 13.72% idle speed ratio). The driving cycle diagram is shown in Figure 9(A).

Through the simulation analysis under the HWFET driving cycle, the output power from the FCS and the SOC of the battery when the vehicle is driving at high speed in the suburban area are described. This driving cycle represents operating conditions on suburban highways in the United States. Under this driving cycle, the range of speed variations...
is smaller, the average speed is higher, the acceleration range is smaller, braking happens less often, and the vehicle demands more power. The simulation under SFTP-SC03 driving cycle reflects the vehicle’s required power and hydrogen consumption related to air conditioning. The UDDS driving cycle represents an urban driving cycle in the United States, and the simulation results under this driving cycle are used as a supplement to the CHTC-HT simulation results.

5.2 Simulation results and discussion

The mathematical and electrical models of the FCV were developed in detail and simulated by using MATLAB and Simulink environments. The simulation results obtained from the original fuzzy control EMS and optimized fuzzy control EMS could be obtained based on the four drive cycles shown in Figures 10 and 11, as well as Table 11. Figure 10(A) shows the required vehicle power and the output power from the FCS with three EMSs. The optimized fuzzy control EMS ensures that the output power from the FCS in the first two portions of the CHTC-HT driving cycle is more extensive than that under the other EMSs. Figure 10(E) shows how the system efficiency varies over time with the optimized fuzzy control EMS; and the FCS has the highest efficiency, reaching 49%. It is found that the output power varies between 17.5 and 30 kW, which ensures that the FCS operates in the high-efficiency region.

Figures 10(A) and 11(A, E, I) show the required vehicle power and the output power from the fuel cell in four typical driving cycles. Comparative analysis of fuel cell powers between the optimized fuzzy control EMS and original fuzzy control EMS is presented in these figures. Clearly, with the original EMS, the fuel cell output power fluctuates significantly when the vehicle accelerates and decelerates, especially in the UDDS driving cycle. With the optimized EMS, the output power from the fuel cell is relatively more stable and smoother compared to the original EMS. The stable output power of the FCS can reduce adverse effects on its internal chemical structure; therefore, it can extend the service life of the fuel cell.

The power distribution of the fuel cell and battery for four typical driving cycles with the optimized EMS are shown in Figures 10(B) and 11(B, F, J). With the optimized EMS, battery rapidly supplies peak power to respond to increased power demand, in particular, when the required power fluctuates. The fuel cell provides a base portion of power, ensuring stable operation.

**TABLE 10** Design variables optimization results

| Design variable | $x_{05}$ | $x_{07}$ | $x_{08}$ | $x_{10}$ | $x_{11}$ | $x_{12}$ |
|-----------------|---------|---------|---------|---------|---------|---------|
| Original        | 0       | 40      | 60      | -0.15   | 0       | 0.15    |
| Optimized       | -33.4   | 44.0    | 57.8    | -0.115  | -0.0648 | 0.221   |

**FIGURE 8** Inputs MFs for (A) $P_{load}$ and (B) $\Delta SOC$. (C) Output MF $P_{FC}$
the required power such that its transient power is the major energy source and the battery helps the fuel cell supply the required steady state power. The battery can completely absorb braking energy, and the absorbed braking energy can be used to drive the vehicle, which reduces hydrogen consumption.

A comparison of the battery $SOC$ in the two control strategies is shown in Figures 10(C) and 11(C, G, K). Under the same driving cycle, the trends for the two battery $SOC$ curves are the same. Both control strategies can maintain the battery $SOC$ between 0.4 and 0.7, which guarantees that the battery has high charging and discharging efficiency. HWFET contains the high-speed driving cycle with average speed of 77.57 km/h. The required vehicle power is higher in this cycle, which simultaneously requires the FCS and battery supply power. The overall battery SOC shows a decreasing trend, mainly because the battery continuously outputs power, which is used to balance the lack of output power from the FCS relative to the required power of the vehicle. Thus, the FCS is not required to provide power when the vehicle is decelerating and braking. Moreover, the output power from the FCS is lower or nearing the off state. The SOC of the battery also increases in a small range, mainly due to the higher driving speed and higher braking energy during the HWFET driving cycle. The energy recovered by the braking energy recovery system is stored in the battery, which increases the $SOC$ of the battery.

In order to further demonstrate the advantages of the optimized fuzzy control EMS in reducing FCS output power fluctuations (variation in FCS output power per second) and prolonging fuel cell life span, Figures 10(D) and 11(D, H, L) show a comparison of fluctuations in the FCS output power. Compared to the original EMS, the optimized EMS can ensure that the FCS output power fluctuation ranges from $-200$ to $200$ W/s, and the percentage increases to $81.5\%$, $73.2\%$, $71.2\%$, and $76.8\%$. The optimized EMS reduces the number of power fluctuation points with 400 to 600 W/s and $-1200$ to $-800$ W/s significantly; the number of points approaches zero for the CHTC-HT driving cycle.

Furthermore, to verify the advantages and effectiveness of the optimized fuzzy control EMS for increasing fuel economy and extending the vehicle’s mileage, comparative analysis of hydrogen consumption results and range in four driving cycles was carried out and the results are presented in Table 11. Obviously, the optimized EMS led to the reduction in hydrogen consumption by $8.4\%$, $1.1\%$, $5.1\%$, and $7.6\%$, respectively, compared to the original EMS. Moreover, compared to the original EMS, hydrogen saved by the optimized EMS provided extra range of $9.15$, $1.10$, $5.37$, and $8.25$ km per 100 km in the four driving cycles, respectively. Therefore, the optimized EMS can reduce hydrogen consumption to increase fuel cell economy.

## 6 | CONCLUSIONS

In this study, a fuzzy control EMS was proposed for an FCV, considering the vehicle’s required power and $\Delta SOC$ as input variables, and the FCS output power as output variable.
However, the fuzzy rules in the fuzzy control EMS mainly come from expert knowledge or control experience, and have certain limitations. Therefore, an innovative method for optimizing the fuzzy control EMS was proposed. Sensitivity analysis was used to select 12 optimization variables from input-output MFs in the original fuzzy control EMS, and a high-precision approximate model of the FCV was established by EBFNN method. Finally, MIGA was used to optimize the original fuzzy control EMS.

The effectiveness of the optimized fuzzy control EMS and proposed optimization method was demonstrated by conducting simulations with the original fuzzy control EMS and optimized fuzzy control EMS for the CHTC-HT, HWFET, SFTP-SC03, and UDDS driving cycles.
The results revealed that the optimized EMS reduced hydrogen consumption by approximately 8.4%, 1.1%, 5.1%, and 7.6% compared to the original EMS, which provided range increases of 9.15, 1.10, 5.37, and 8.25 km per 100 km in the four driving cycles, respectively.

The optimized EMS ensures that the output power from the FCS is more stable and smoother. The percentage of power fluctuation points from −200 to 200 W/s increased to 81.5%, 73.2%, 71.2%, and 76.8% in the four driving cycles, respectively. The stable output power of fuel cell reduces the adverse effect on its internal chemical structure and further leads to a longer life span of the fuel cell.

For a given driving cycle, the battery’s SOC curves are the same. Both control strategies can maintain the battery SOC between 0.4 and 0.7, which guarantees that the battery has high charging and discharging efficiency.

The optimized EMS can reduce hydrogen consumption to improve the economic and overall efficiency of the vehicle and extend the life span of the fuel cell. However, in this study, optimized fuzzy control EMS and simulations were conducted under assumptions. Undeniably, more experiments and research are further needed to validate the benefits of the optimized EMS.

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