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Research on Electric Vehicle Parameter Identification Method Based on Battery and Ultracapacitor

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Abstract: The accuracy of the model relies heavily on parameter identification. In order to accurately identify the model parameters of batteries and ultracapacitors, three representative intelligent optimization algorithms: Grey Wolf Optimization Algorithm (GWO), Particle Swarm Optimization Algorithm (PSO), and Genetic Algorithm (GA) are selected in this study to identify the parameters of battery and ultracapacitor models, respectively. The results of the study show that the Grey Wolf optimization algorithm demonstrates significant advantages in improving the overall prediction accuracy of the battery and supercapacitor models. Specifically, the Grey Wolf optimization algorithm reduces the root mean square error (RMS), an evaluation metric, by at least 7.4% and 13.8% compared to the particle swarm optimization algorithm and the genetic algorithm, respectively. Therefore, the parameter identification of battery and supercapacitor models using the Grey Wolf optimization algorithm not only has better accuracy and reliability but also provides strong support for the subsequent research of electric vehicle energy storage systems.

Keywords: Electric vehicle; Battery; Ultracapacitor; Parameter identification; Intelligent optimization algorithm.

1. Introduction

In recent years, with the rapid development of electrified transport around the world, there has been a growing concern about air pollution and energy crisis issues[1]. To proactively address the challenge of climate change, China has proposed a 'dual-carbon' strategy to promote the widespread use of clean energy. Against this background, new energy vehicles have gradually become a substitute for traditional fuel vehicles[2,3]. Among them, lithium-ion batteries have been widely used in the field of new energy vehicles due to their advantages of high safety and low cost[4]. However, as a single power source, lithium-ion batteries have shortcomings such as limited service life and poor low-temperature performance[5,6]. In contrast, ultracapacitors exhibit superior charge/discharge rates, longer service life, and higher cycling stability[7,8]. Given the respective characteristics and limitations of lithium-ion batteries and ultracapacitors, hybrid energy storage systems have become a hot topic in current research.

The accuracy of the battery and ultracapacitor models is highly dependent on the parameter identification methods used[9,10]. This study focuses on the parameter identification of battery and ultracapacitor models, and three representative intelligent optimization algorithms, namely Grey Wolf Optimisation Algorithm (GWO), Particle Swarm Optimisation Algorithm (PSO), and Genetic Algorithm (GA), are selected to provide in-depth identification of the parameters of the battery and ultracapacitor models, respectively[11–13]. The results show that GWO exhibits more excellent performance in the parameter identification process. Compared to the other two algorithms, its recognition is more superior and more accurate.

2. Battery and Ultracapacitor Testing

2.1. Experimental Platform Construction

The core components of the experimental platform for this study include the host computer, an ARBIN-branded BT-5HC high-performance power test system, and an RGD-500 thermal chamber for maintaining a constant temperature. The overall layout is shown in Figure 1. In this architecture, the host computer plays a crucial role, which not only monitors the operation of the experimental device in real time but also is responsible for the development of the experimental management application, which ensures the efficient transmission and safe storage of experimental data.

In order to explore the target characteristics, the BT-5HC power test system provided by ARBIN was selected for this study, which is known for its multi-channel independent design and advanced voltage clamping safety mechanism. The data sampling frequency of the system was set to 1Hz in the experiment to capture the key information accurately during the experiment. In addition, the voltage range of the test system is set to [0v~5v] and the current range is set to [100A~100A], which fully meets the diversity and accuracy of the experimental requirements. As the key components of the experiment, we chose a high-performance supercapacitor with a rated operating voltage of 2.7V and a capacity of 1500F and a lithium ternary battery with a rated voltage of 3.6V and a rated capacity of 2Ah. To ensure the consistency of the experimental conditions, the battery and ultracapacitor were placed in the RGD-500 thermal chamber, which can effectively maintain the constant temperature of the experimental environment and eliminate the interference of temperature fluctuations on the experimental results.

Figure 1. Experimental Platforms

2.2. Results of The Experiment

This study aims to build a comprehensive experimental database integrating data from hybrid pulse power characteristics testing and urban road cycle conditions testing. The experimental data obtained enable a more in-depth evaluation of the performance of batteries and ultracapacitors.

Table 1. Detailed Experimental Steps

Step 1	Maintain a constant current charge of 1A to bring the battery or supercapacitor voltages to their respective upper cut-off voltages;
Step 2	Stand for 8 h until the supercapacitor reaches a steady state;
Step 3	Pulse test First, discharge with a 1A constant current for 7 s; stand for 10 s; charge with 1A constant current for 7 s; and stand for 18 s. Second, discharge with a 3A constant current for 7 s; stand for 18 s; charge with a 3A constant current for 7 s; and stand for 18 s. Finally, discharge with a 8A constant current for 7 s; stand for 18 s; charge with a 8A constant current for 7 s; and stand for 18 s;
Step 4	Maintain a constant current of 1A until the depth of discharge of the battery or supercapacitor is reduced by 10 percent;
Step 5	Return to step 4 until 10 cycles are complete:
Step 6	End of test.

The dynamic characteristics of ultracapacitors and batteries at different states of charge (SOC) were systematically explored in the HPPC test. This test procedure was executed with the preset steps, and the detailed experimental steps are shown in Table 1. The experimental results provide valuable data support for subsequent offline parameter identification. In order to further simulate the power demand of EVs in a real driving environment, the UDDS test was introduced.

3. Parameter Identification

3.1. Battery and Ultracapacitor Modeling

The electrochemical model can accurately reflect the dynamic characteristics of the battery by describing the electrochemical reaction mechanism inside the battery, but its structure is complex and the computational volume is large; the neural network model establishes a nonlinear mapping relationship between input and output through the data-driven way, which has high flexibility, but it is highly dependent on the training data and has poor interpretability. In contrast, equivalent circuits are widely used in electric vehicle energy management systems for their advantages of fewer model parameters and higher computational efficiency. Compared with other traditional equivalent circuit models, the Thevenin model was chosen as the battery model for this study due to its simple structure, computational efficiency, and ability to obtain the required data quickly and accurately. For ultracapacitors in energy storage devices, a more concise Rint model is used in this study. This model effectively balances computational complexity while ensuring model accuracy.

Figure 2 visualizes the circuit architecture of the Thevenin and Rint models.

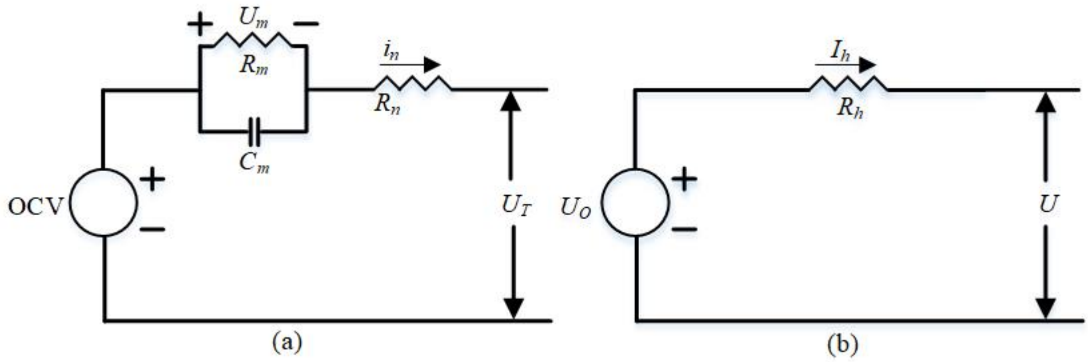


Figure 2. Equivalent Circuit Models Of (a) Thevenin And (b) Rint

In the Thevenin model, an RC network composed of polarization resistance Rm and polarization capacitance Cm is cleverly introduced to accurately describe the polarization effect of the battery. This design allows the model to more accurately capture the dynamic behavior of the battery during charging and discharging. For the Rint model, the model contains only an internal resistance Rh, which is used to represent the internal resistance loss of the ultracapacitor. Although the Rint model is more simplified compared to the Thevenin model, it can provide sufficient accuracy for energy storage elements such as ultracapacitors, which have fast charging and discharging characteristics. The operating equations of Thevenin and Rint models are shown in Eqs. (1) and (2).

$$\begin{cases} \dot{U}_T = \dfrac{i_n}{C_m} - \dfrac{U_m}{R_m C_m} \\ U_t = \mathrm{OCV} - U_T - i_n R_n \end{cases} \tag{0}$$

$$U = U_O - I_h R_h \tag{1}$$

To fully describe the two models, four key parameters need to be identified: the R_n、R_m and tau of the battery (where $\tau = R_m \times C_m$ is the time constant), and the Rh of the ultracapacitor.

3.2. Intelligent Optimization Algorithm

3.2.1. Principles of the Grey Wolf Optimizer

Grey Wolf Optimizer (GWO) is a group intelligence optimization algorithm that simulates the hunting behavior of a group of grey wolves. Grey wolves have a high degree of collaboration and a complex social structure to find food and hunt through group cooperation. The core idea of the grey wolf optimization algorithm is to perform global optimization by simulating the cooperation and competition mechanism of the grey wolf group in the process of finding prey. In order to accurately depict the social hierarchy of grey wolves in the GWO in the mathematical model, the top three best-performing wolves were named α, β, and δ, which played the role of leaders and led the rest of the pack in searching towards the target area. The remaining wolf pack members, on the other hand, are uniformly categorized as ω, and they update their positions based on α, β, or δ positional information to enable more efficient exploration of the search space. After each iteration, each wolf in the pack calculates its fitness function value and compares it to the current optimal solution. In the process of EV parameter identification, the GWO can effectively adjust and optimize the model parameters of the battery and ultracapacitor to improve the performance and accuracy of the EV system. The distance between each wolf and the current optimal wolf position is shown in Eq. (3):

$$\vec{D}_i = \left| \vec{C} \bullet \vec{X}_p(t) - \vec{X}_i(t) \right| \tag{2}$$

where $\vec{D}_i$ represents the current displacement vector of the ith wolf. $\vec{C}$ is an adjustment factor that controls the direction of the search. $\vec{X}_p(t)$ is the location information of the optimal solution in the current iteration. $\vec{X}_i(t)$ is the current location information of the ith wolf.

Based on the above distance calculation, the grey wolf's position update formula is shown in Eq. (4):

$$\vec{X}_i(t+1) = \vec{X}_i(t) - \vec{A} \cdot \vec{D} \tag{3}$$

Where $\vec{X}_i(t+1)$ denote the position of the ith wolf in the t+1st iteration. $\vec{X}_i(t)$ represent the position of the ith wolf in the t iteration. The two coefficients, $\vec{A}$ and $\vec{D}$, are used to regulate the behavior of the grey wolf and the search process, as defined in Eqs. (5) and (6):

$$\vec{A} = 2 \cdot \vec{a} \cdot \vec{r}_1 - \vec{a} \tag{4}$$

$$\vec{C} = 2 \cdot \vec{r}_2 \tag{5}$$

Where $\vec{r}_1$ and $\vec{r}_2$ are randomly generated numbers in the interval [0, 1]. $\vec{a}$ denote a constant that decays linearly from

2, decreasing with the number of iterations, and controls the transition between the exploration and development phases.

3.2.2. Principles of Particle Swarm Algorithm

As a collective intelligence optimization strategy, the core concept of the Particle Swarm Optimization (PSO) algorithm originates from a profound observation and simulation of birds' foraging behavior in nature. Within the framework of this algorithm, each potential solution is cleverly compared as a "particle" or a "bird" soaring in the search space. These particles fly freely over a vast search field, collaboratively exploring and converging toward globally optimal solutions by exchanging and sharing information. During the iterative process, each particle dynamically adjusts its own flight speed and spatial position based on its individual historical best position (p^{Best}) and the global best position (g^{Best}) discovered by the entire swarm to date. While the individual extreme value pBest reflects the accumulated experience of a single particle, the global extreme value gBest is the culmination of group wisdom. The particles can efficiently utilize their collective intelligence to accelerate the convergence process of the optimal solution through this information-sharing mechanism. The formulas for updating the velocity and position of the particles are shown in Eqs. (7) and (8), which enable the particles to navigate flexibly in the complex search space and approach the optimal solution step by step.

$$v_i = v_i w + c_1 r_1 (p^{Best(i)} - x_i) + c_2 r_2 (g^{Best(i)} - x_i) \tag{6}$$

$$x(i) = x(i) + v(i) \tag{7}$$

where v_i denotes the current velocity of particle i. r_1 and r_2 are two random numbers in the range [0, 1] used to increase the randomness of the search; c_1 and c_2 are the individual particle learning factors, also known as acceleration constants, which reflect the extent to a particle learns from its own and the population's historically optimal positions, respectively; $g^{Best(i)}$ denotes the individual historical optimal position of particle i; $x(i)$ represents the current position of particle i; $x(i)$ represents the updated velocity of particle i. w is the inertia factor, representing the degree of influence that a particle's previous velocity has on its current velocity, and also reflecting the inertia of the particle.

The particle swarm algorithm proceeds as follows:

Step 1: Define the parameter space for the rule switching threshold in the rule energy management strategy. These parameters are coded and designed, and the particles' maximum velocity and search range are determined.

Step 2: Initialize the particle population. Each particle represents a set of potential optimization parameters, and these initialization parameters should cover the entire parameter space to ensure comprehensive search.

Step 3: Set the particle speed and position update rules. Update the velocity of the particle based on Eqs. (3) update the position of particles according to Eqs. (4).

Step 4: Decode the parameters of each particle and apply them to the rule-based energy management strategy. By evaluating the performance of these parameters in different SOC states, update the individual best (p^{Best}) and global best (g^{Best}) for each particle.

Step 5: Determine whether the termination condition is satisfied, i.e., the maximum number of iterations or the optimal fitness value is reached. If it is not satisfied then enter the loop from Step 3, if it is satisfied then stop the iteration and output the optimal solution.

3.2.3. Principles of Genetic Algorithms

Genetic Algorithm (GA) is an optimization method that mimics the principles of natural selection and genetics and is one of the classical representatives of evolutionary algorithms. The core idea of the genetic algorithm is to optimize the objective function step by step by simulating the evolutionary process of species in nature, continuously selecting individuals (solutions) with higher fitness, and generating new solutions through crossover and mutation operations. The basic process of a genetic algorithm includes initializing the population, calculating fitness, selection operation, crossover operation, mutation operation, and iterative updating, and finally obtaining the global optimal solution through several iterations. The fitness function $f(x)$ is used to evaluate the performance of each individual in a population. The function is usually defined on a problem-specific basis and its objective is to maximize the value of $f(x)$. An individual x is represented as a vector encoding the solution characteristics. The probability of an individual being selected for reproduction is proportional to its fitness and is calculated as shown in Equation (9).

$$p_i = \frac{f(x_i)}{\sum_{j-1}^{N} f(x_j)} \tag{8}$$

where $f(x_i)$ denotes the fitness of the ith individual and N is the total number of individuals in the population.

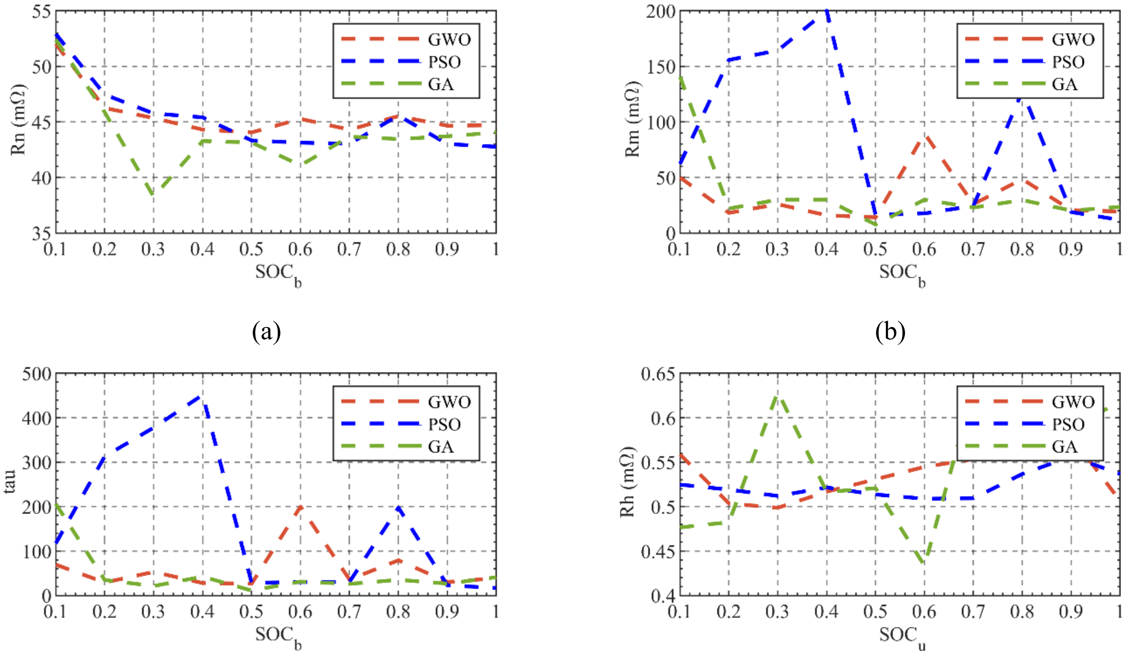
The crossover operation generates new offspring by exchanging some of the genes of two individuals. Assuming that the crossover point is k, for two individuals x_{ik} and x_{jn}, the generation of the offspring x_{new} can be expressed as equation (10).

$$x_{new} = (x_{i1}, x_{i2}, ..., x_{ik}, x_{j(k+1)}, ..., x_{jn}) \tag{9}$$

Where x_{ik} and x_{jn} denote the genes of individuals x_i and x_j before and after the crossing point k, respectively.

3.3. Parameter Identification Results

In the electric vehicle parameter identification study, three intelligent optimization algorithms were used to identify the model parameters Rn, Rm, τand Rh of the battery and ultracapacitor under different state of charge (SOC) conditions, respectively. The identification results are shown in Fig. 3, in which the identified values of the parameters of the battery are mainly concentrated in the interval [40mΩ, 50mΩ], [0mΩ, 80mΩ], [0, 200], while the identified values of the parameters of the supercapacitor are mainly located in the interval [0.45mΩ, 0.55mΩ]. Further analysis reveals that GWO demonstrates superior applicability compared to the other two algorithms over the entire SOC range.



(a) (b) (c) (d)

Figure 3. Offline Recognition Results Of Three Intelligent Optimization Algorithms: (a) R_n Offline Recognition Results, (b) R_m Offline Recognition Results, (c)τ Offline Recognition Results, (d) R_h Offline Recognition Results

4. Result Comparison and Discussion

In order to verify the advantages of the GWO algorithm in model construction, the model was validated using the UDDS working condition as the experimental driving condition. The results of voltage comparison as well as error analysis are shown in Fig. 4. The average absolute errors for GWO, PSO, and GA cells are 3.1mV, 14.1mV, and 15.4mV, respectively; and for ultracapacitors are 1.7mV, 2.0mV, and 2.0mV, respectively.

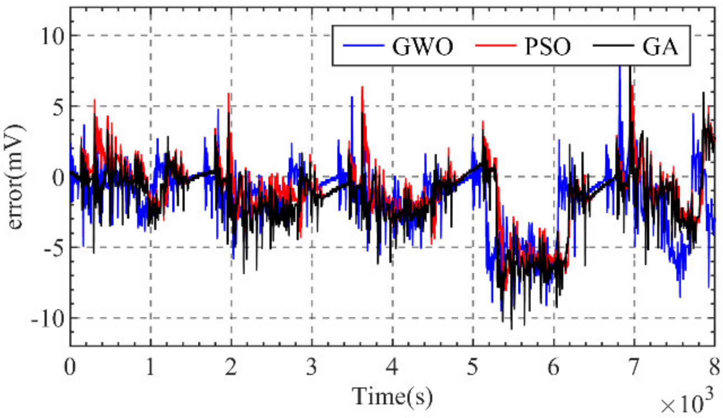


Figure 3. Voltage Errors Of Different Algorithms Under UDDS Conditions

Table 2. Specific Voltage Error Values Of Different Algorithm Models

Categorization	Parameter	GWO	PSO	GA
battery	MAE error (mV)	3.1	14.1	15.4
	RMSE error (mV)	5.1	18.1	19.6
ultracapacitor	MAE error (mV)	1.7	2.0	2.0
	RMSE error (mV)	2.5	2.7	2.9

5. Conclusion

This paper takes batteries and ultracapacitors as the research core. To address the problem of accurate identification of model parameters of batteries and supercapacitors, based on the full consideration of the operating characteristics of the two and past research experience. Three intelligent optimization algorithms applicable to parameter identification are first identified, and the corresponding algorithm parameters and evaluation criteria are set. Subsequently, a systematic parameter identification process was designed based on these three selected intelligent optimisation algorithms - Grey Wolf Optimisation (GWO), Particle Swarm Optimisation (PSO) and Genetic Algorithms (GA). The identification results of the algorithms are discussed and analysed in depth under uniform UDDS working conditions. Simulation results show that the designed parameter identification process can accurately identify the model parameters of the battery and ultracapacitor. In addition, while ensuring the stability and efficiency of the recognition process, the GWO algorithm demonstrates superior recognition accuracy compared to PSO and GA. Specifically, GWO reduces the average absolute error by 15% compared with PSO and GA on the ultracapacitor model; the root mean square error is reduced by 7.4% and 13.8%, respectively. The higher accuracy and the stability of the identification results are also more prominent, thus verifying the significant advantages of the GWO algorithm in the field of battery and ultracapacitor model parameter identification.

CONFLICTS OF INTEREST

The authors declare that they have no conflict of interest.

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