FUZZY CONTROL STRATEGY OF URBAN RAIL ENERGY BASED ON PARTICLE SWARM OPTIMIZATION ALGORITHM

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***Abstract*— The city rail train starts and brakes frequently in the process of operation, and the existing braking technology can not make full use of this part of energy. In this study, a lithium battery super capacitor composite energy storage system is proposed, which uses the fuzzy control of particle swarm optimization algorithm for energy optimization management. The fuzzy energy controller is established to optimize the system parameters by using particle swarm optimization (PSO) algorithm. Simulation results show that the strategy can not only optimize the energy management of urban rail trains, but also improve the stability, reliability and economic performance of train operation and reduce fuel consumption.**

***Keywords*— energy management; fuzzy control; particle swarm optimization; Urban Rail Transit.**

I. INTRODUCTION

In recent years, with the steady progress of urbanization construction and the sharp increase of population, urban rail train has developed rapidly (Cheng *et al*., 2015; Chang *et al*., 2015; Ding *et al*., 2015). It has the characteristics of fast operation speed, safety and stability, large passenger capacity, and basically not affected by the weather change, which brings great convenience to people's travel. However, the frequent start-up and braking state of urban rail train will lead to the fluctuation of traction network voltage, which is not conducive to the safe operation of the train, and will seriously affect the quality of power supply. In addition, the electric braking of the train will cause a lot of electric energy to be converted into heat energy loss, which will cause the temperature rise in the station, increase the construction cost and further electric energy loss. Therefore, some energy storage facilities are needed to solve these problems.

At present, there are many energy storage facilities applied to urban rail trains, which can be divided into two types (Chung *et al*., 2013; Su *et al*., 2019a; Fierro *et al*., 2013): energy type and power type. The energy density of the battery is relatively large, which can meet the requirements of the system for high energy, but the internal electrochemical reaction is carried out, so the power density is low and the response speed is slow. The inner part of the supercapacitor is changing physically, with high power density and fast response speed, but its energy density is relatively low. A single energy storage element can not meet the needs of the system for high power and high energy at the same time. Therefore, a hybrid energy storage system composed of battery and super capacitor is needed to give full play to their advantages and make up for their shortcomings.

In view of the distribution of energy and power between super capacitor and battery, many literatures have been studied. In reference (Wu *et al*., 2011), the low-pass filter method is used to distribute the power, that is, the super capacitor bears the variable high-frequency power, while the battery bears the corresponding low-frequency power, but the state of charge of the super capacitor and the power of the battery are not considered, and the mixed storage capacity ratio scheme and quantitative calculation are not studied in depth. In reference (Marinaki *et al*., 2011; Su *et al*., 2019b), based on the low-pass filtering method, the power of the battery is determined by the state of charge of the super capacitor, which can ensure that the state of charge of the super capacitor is in a safe range. In reference (Costa and Serra, 2015), the control of bi-directional converter is studied to reduce the loss of switch tube, but the energy exchange between super capacitor and battery is not introduced.

Based on the above analysis, it is of great significance to study the hybrid energy storage system of urban rail transit (Ma *et al*., 2019; Yuvaraj *et al*., 2019). Firstly, the hybrid energy storage system composed of super capacitor, battery and DC/DC converter is connected to the traction network to absorb or compensate the power difference. In the MATLAB/Simulink software, the whole vehicle model of the composite energy storage train is established. Combined with the multi input fuzzy control theory, the energy management strategy suitable for the working condition of the train is formulated. Particle swarm optimization algorithm is used for optimization. Finally, the effectiveness of the control strategy is proved by simulation.

II. COMPOSITE ENERGY STORAGE SYSTEM MODEL OF URBAN RAIL TRAIN

The structure of composite energy storage system of urban rail train is shown in Fig. 1, which is an energy structure with power battery as the main part and super capacitor as the auxiliary part (Haji and Monje, 2017; Jamin and Ghani, 2016; Costa and Serra, 2015; Pan and Das, 2016; Hashim *et al*., 2018). The power battery and super

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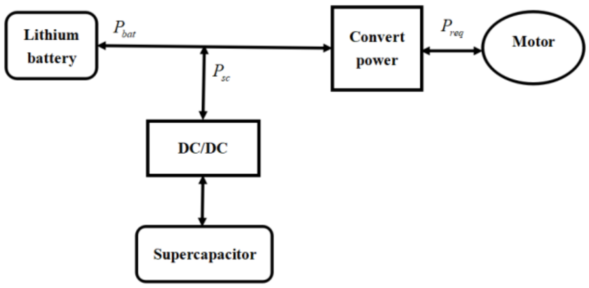

Fig. 1: Structure of composite energy storage system of urban rail train.

capacitor are connected in parallel to the structure of the urban rail train of the composite energy storage system to jointly provide the energy needed for train driving and recover the feedback energy during train braking. Super capacitor is mainly used to discharge large current when the train starts, accelerates and climbs, providing peak power to meet the dynamic performance of the train, while lithium battery is mainly used to meet the average power demand of the train under cruising condition, and both of them recover the braking energy of the train. At the same time, because the voltage of the lithium battery is relatively stable and easy to follow, the super capacitor is connected in series with the DC/DC converter, so that the super capacitor can easily follow the voltage change of the lithium battery and give full play to the characteristics of the high current discharge of the super capacitor.

The output power of the super capacitor is not only affected by its own characteristics, but also related to the power required by the motor. Due to the contradiction between the maximum output power and efficiency of the super capacitor, it is not allowed to work in the state of maximum power for a long time, so the ideal situation is that the super capacitor can output the optimal power to meet the load demand.

The state of charge of the battery not only affects the cycle life and charge discharge characteristics of the battery itself, but also affects the economy of the whole vehicle. It is reasonable to keep the state of charge value between 0.5-0.8. At this time, the internal resistance of the battery is the smallest. Combined with the limitation of the charging and discharging power, the life of the super capacitor can be prolonged. The energy management strategy is to coordinate the relationship between the power battery and the super capacitor to distribute the energy, that is, to distribute the bus power, let them cooperate with each other to complete the charging and discharging, meet the driving power demand of the train, and make the power system run safely and efficiently. The relationship between bus power, lithium battery power and super capacitor power is as follows:

$$P_{req} = P_{bat} + P_{sc} \tag{1}$$
$$P_{bat} = K_{bat} P_{req}$$
$$P_{sc} = K_{sc} P_{req}$$
$$K_{bat} + K_{sc} = 1$$

In which, P_{req} represents bus power; P_{bat} represents lithium battery power; P_{sc} represents supercapacitor power; K_{bat} represents the proportion of lithium battery power to bus power; K_{sc} represents the proportion of super capacitor power to bus power,

It can be seen that when the bus demand power is known, only the proportion of the lithium battery power K_{bat} can be obtained, and the power values of the lithium battery and the super capacitor can be obtained, thus completing the energy distribution.

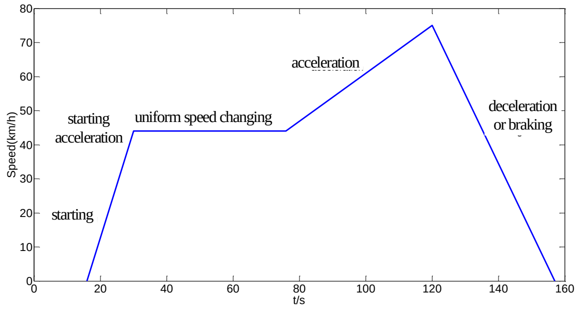

Fig. 2: Working state diagram of composite energy storage system.

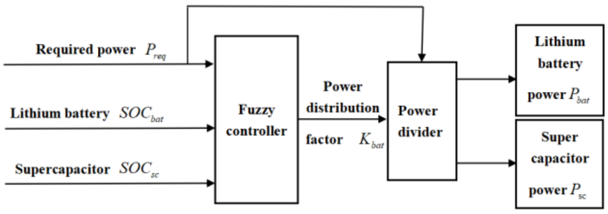

Fig. 3: Energy control structure of composite energy storage system.

III. ENERGY MANAGEMENT STRATEGY BASED ON FUZZY CONTROL

Energy management strategy is the key to improve vehicle performance. The control objective is to minimize the energy loss of the train operation system, ensure that the composite energy storage system works stably in a safe and efficient area, avoid large-scale movement of the working point (Arulkumar and Madhavasarma, 2017; Wang *et al.*, 2017; Mesloub *et al.*, 2017; Xing and Li, 2019; Sun *et al.*. 2019), and take into account the battery state of charge range, so as to extend the battery life and ensure energy recovery. The working state flow chart of the power system is shown in Fig. 2.

A. Fuzzy Control Structure Design

Using Matlab fuzzy logic toolbox to design the fuzzy inference system, as shown in Fig. 3, the fuzzy inputs are respectively: the difference between the vehicle demand power and the optimal power on the corresponding super capacitor optimal curve under the current working condition, and the SOC of the current battery. The fuzzy output is a proportional coefficient, which is multiplied by the power difference in front to get the regulated power that the battery should bear (Jamaluddin and Siringoringo, 2017). The power of the super capacitor engine is equal to the total demand power minus the regulated power of the battery.

The fuzzy input membership function is shown in Fig. 4, where negative indicates that the vehicle demand po-

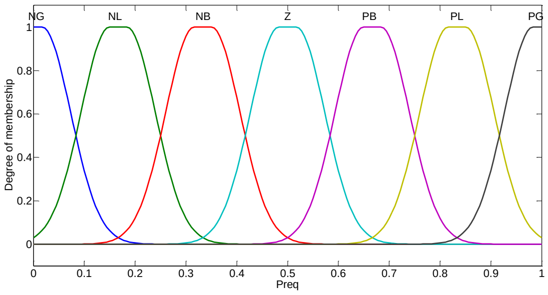

Fig. 4: Membership function of fuzzy input.

wer is much lower than the optimal power; zero indicates that the vehicle demand power is not much different from the optimal power; positive small indicates that the vehicle demand power is much higher than the optimal power but not much higher than its maximum power; positive large indicates that the vehicle demand power is large and has greatly exceeded the maximum output power of the super capacitor. The SOC of the battery remains within the normal range. The membership function of each variable is trapezoid, which is convenient for parameter adjustment.

Takagi Sugeno fuzzy inference is adopted, and the output membership type is constant (Ling *et al*., 2016). Single point fuzzy set is used for fuzzification, and weighted average method is used for clarity. The minimum operator is used in the "and" operation, and the not operation is used in the complement operation. The fuzzy output is reduced to [0,1] in the same proportion. See Table 1 for fuzzy rules.

It can be seen that when the power difference is zero, there is no need to adjust the power of the battery; when the power difference is large, use the battery to adjust the working point of the super capacitor to the economic zone or even the optimal curve. If the SOC deviates from the normal area, the charging or power consumption load shall be increased accordingly to restore the SOC to the normal area.

B. Optimization Control Strategy Based On Multi Particle Swarm Optimization

Particle swarm optimization (PSO) algorithm was proposed by Kennedy and Eberhart in 1995 when they used computers to simulate the simple social behavior of birds foraging, which was inspired and simplified (Jamaluddin and Siringoringo, 2017; Tsekouras *et al*., 2018; Li *et al*., 2019; Su *et al*., 2019c).

At the beginning of the algorithm, the position and velocity of the randomly initialized particles constitute the initial population, which is uniformly distributed in the solution space. It is an optimization tool based on iteration (Wu *et al*. 2016; Hannan *et al*., 2018). The system initializes a group of random solutions and searches for the optimal value through iteration. In PSO, the position X_i of each particle represents the candidate solution of the optimization problem. The particle flies at a certain speed in the search space, which dynamically adjusts its flight direction and speed according to its own flight experience and the flight experience of its companion.

Table 1: Fuzzy Rules

When P_{req} is L

Kbat \ SOCbat / SOCsc	NL	NB	M	PB	PL
NL	M	M	NL	NL	NL
NB	PL	M	M	NB	NL
M	PL	PB	M	NB	NL
PB	PL	PB	M	PB	M
PL	PL	PL	PL	PL	PB

When P_{req} is M

K_{bat} \ SOC_{bat} / SOC_{sc}	NL	NB	M	PB	PL
NL	M	NB	NB	NB	NL
NB	PL	PL	NB	NB	NL
M	PL	PL	PL	PB	M
PB	PL	PL	PL	PB	M
PL	PL	PL	PL	PL	M

When P_{req} is B

Kbat \ SOCbat / SOCsc	NL	NB	M	PB	PL
NL	NB	M	PB	PB	PL
NB	NB	M	M	M	PL
M	NL	NL	M	M	PL
PB	NL	NL	M	M	PB
PL	NL	NL	NL	NB	M

All particles have an fitness determined by the fitness function, and know their current position (current position X_i) and the best position (individual extremum P_i) found so far, as well as the best position (global extremum P_g) found by all particles in the whole population. The particles follow the current optimal particles to search in the solution space. Given a D-dimensional search space and m particles, the position and velocity of the i th particle are $X_i=(X_{i1},X_{i2},\cdots,X_{id})$ and $V_i=(V_{i1},V_{i2},\cdots,V_{id})$, in each iteration, the particle according to the individual extreme value $P_i=(P_{i1},P_{i2},\cdots,P_{id})$ and global extreme value $P_i=\left(P_{g1},P_{g2},\cdots,P_{gd}\right)$ to dynamically adjust its own speed vector to adjust its own position, the evolution equation of particle I's speed is

$$V_{ij}(t+1)=\omega V_{ij}(t)+c_1r_1\left(P_{ij}-X_{ij}(t)\right)+ c_2r_2\left(P_{gj}-V_{ij}(t)\right) \quad (2)$$

In which, ω is the inertia weight, c_1 and c_2 are the acceleration factors, r_1 and r_2 are the evenly distributed random number between 0 and 1.

In order to ensure the stability of the algorithm, the algorithm defines a maximum speed limit V_{max}, which is used to limit the particle moving speed

$$V_{ij}(t+1)\le V_{max} \quad (3)$$

The evolution equation of the particle i position is:

$$X_{ij}(t+1)=X_{ij}(t)+V_{ij}(t+1)\ (j=1,2,\dots,d) \quad (4)$$

The inertia weight ω in the speed update formula is linearly reduced from the maximum weighting factor to the minimum weighting factor by the linear decreasing weighting strategy proposed by Eberhart and Shi (2000). In each iteration, the inertia weight is:

$$\omega(j) = \omega_{min} + \frac{\omega_{max}-\omega_{min}}{n}(n-j) \tag{5}$$

In which, j is the current iterations number; ω_{max} is the maximum inertia factor; n is the maximum evolution number; ω_{min} is the minimum inertia factor.

In order to better balance the detection and development ability of particles in search space, the acceleration factor changes dynamically with iteration, c_1 decreases linearly, c_2 increases linearly, which ensures the global optimization ability of particles in each iteration. The acceleration factors c_1 and c_2 are:

$$\begin{cases} c_1(j) = (c_{1e} - c_{1j})\frac{j}{n} + c_{1j} \\ c_2(j) = (c_{2e} - c_{2j})\frac{j}{n} + c_{2j} \end{cases} \tag{6}$$

In the formula, c_{1j} is the initial value of c_1, c_{2j} is the initial value of c_2, c_{1e} is the final value of c_1, c_{2e} is the final value of c_2.

C. Fuzzy Controller Based on Particle Swarm Optimization

Considering the evaluation indexes of train operation stability and energy saving, the applicability function adopted in this paper is:

$$f = \lim_{t\to\infty}\int_0^T\left[Q\left(x_m(t) - x_g(t)\right)^2 + \ddot{x}_b^2(t)\right]dt \tag{7}$$

In which, Q is the weighting coefficient of train operation displacement.

Seven language variables {NG, NL, NB, Z, PB, PL, PG} are used in the input V_1, V_2 and the output K_{bat} of the fuzzy controller, and the corresponding membership function is Gauss type. The shape of the Gaussian curve is determined by two variables β and δ, namely

$$\mu(x) = \exp\left(-\left(\frac{x-\beta}{\delta}\right)^2\right) \tag{8}$$

In which, β is the central position value of Gaussian curve, δ is the width of Gaussian curve.

In this paper, particle swarm optimization is used to optimize membership function and fuzzy control rules to get the optimal fuzzy energy management strategy. The optimization process is shown in Fig. 5. The algorithm first generates a group of random particles and iteratively searches for the optimal solution. Particles constantly update themselves by comparing with two extreme values: one hand, the optimal solution found by the particles themselves, that is, the individual optimal location P_{best}; the other hand, the optimal solution found by the whole population to the current location, that is, the global optimal location g_{best}.

Figure 6 and Fig. 7 are the simulation results after optimization. Before optimization, the output power of the super capacitor follows the demand power of the motor. The result of power distribution is approximately equal to the result of steady-state distribution, and the maximum power that the super capacitor can provide. After optimization, the super capacitor slowly follows the motor demand power when loading, the super capacitor provides peak power, the battery power decreases, the super capacitor power slightly increases, making the super capacitor work in the optimal curve. In Fig. 6, the ordinate unit is w, the abscissa unit is min, and the battery has a negative value, which indicates that the battery is in charging state, so as to supplement the electric energy in case of insufficient output power of super capacitor. From Fig. 7, it can be seen that the SOC curve of the optimization algorithm is higher than that of the rule algorithm on average, which is controlled in a smaller range, thus improving the efficiency of the battery.

Table 2 shows the comparison of relevant parameters before and after optimization. Before optimization, the output power of the battery accounts for 29.8% of the total power, and after optimization, it increases to 18.9%. Before optimization, the energy utilization rate of fuzzy

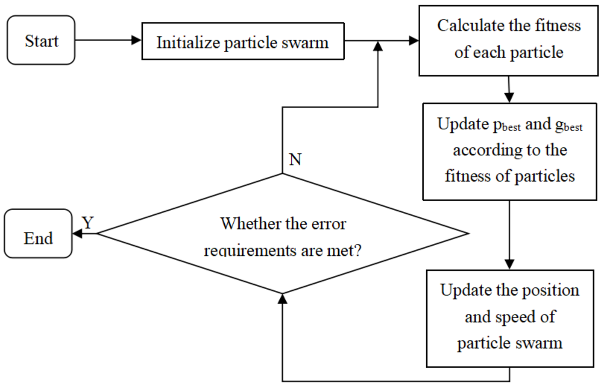

Fig. 5: Specific flow of particle swarm optimization algorithm.

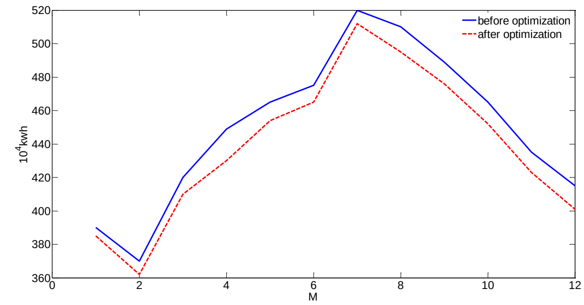

Fig. 6: Simulation results after optimization.

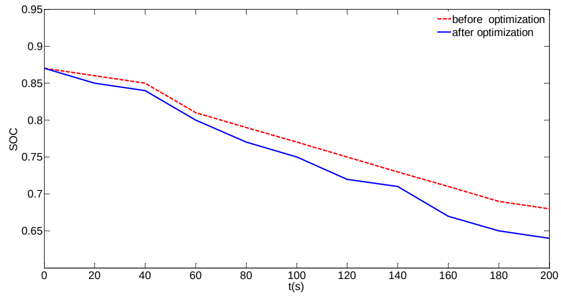

Fig. 7: SOC curve of battery before and after optimization.

Table 2: Comparison of parameters before and after optimization.

	Proportion of battery power	Overall energy utilization
Before optimization	29.8%	20.6%
After optimization	18.9%	32.4%

Table 3: Optimal objective function, economic efficiency and voltage improvement rate under different weight coefficients.

ω	0.3	0.4	0.5	0.6	0.7	0.8	0.9	1
Optimal objective function	0.2211	0.2032	0.1924	0.1845	0.1726	0.1637	0.1548	0.1324
Economic efficiency	0.0821	0.0901	0.0984	0.1021	0.1114	0.122	0.131	0.1331
Voltaje improvement rate	0.2724	0.2694	0.2621	0.2542	0.2435	0.2302	0.2124	0.1865

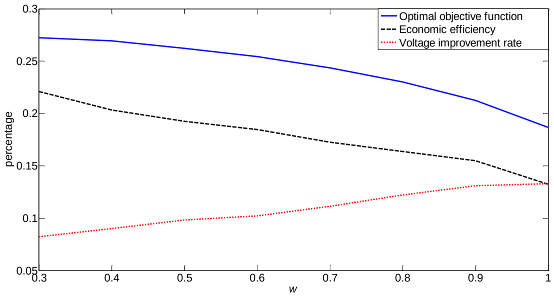

Figure 8: Optimal objective function, economic efficiency and voltage improvement rate under different weight coefficients

control is too high by 20.6%; after optimization, the energy utilization rate of train composite energy storage system is increased by 32.4%.

It can be seen from Table 2 that the proportion of the output power of the optimized battery in the total demand power decreases, that is, the proportion of the output power of the super capacitor in the total demand power increases, thus improving the utilization rate 13.5% of the train energy.

The optimal objective function, economic efficiency and voltage improvement rate of composite energy storage system under different weight coefficients ω are shown in Fig. 8 and Table 3. When the weight coefficient ω increases from 0.3 to 1, the economic efficiency of the composite energy storage system increases from 8.21% to 13.31%, but the voltage improvement rate decreases from 27.24% to 18.65%.

The optimization results in Figure 8 and table 3 can provide certain reference and help for different urban rail transit supply and chemical systems in improving the company's operation efficiency, improving network voltage drop and selecting appropriate weight coefficient. For example, for the metro power supply system, the more suitable selection range of ω is [0.7,1], which can better realize the recovery of train braking energy, reduce the power supply cost and improve the company's operation efficiency; for the tram power supply system, the more appropriate selection range of ω is [0.3,0.6], which can better improve the network voltage drop and ensure the reliable operation of DC power supply network.

V. CONCLUSIONS

(1) In order to achieve the effective energy management of the super capacitor hybrid electric train, this paper proposes a fuzzy control energy management strategy based on particle swarm optimization algorithm based on the existing fuzzy control strategy. The optimized strategy can not only achieve the energy management of the super capacitor hybrid electric locomotive, but also reduce the fuel consumption and improve the vehicle economy.

(2) The fuzzy hybrid controller is constructed by building the composite energy storage system model of urban rail train in MATLAB. The membership function and fuzzy control rules of the fuzzy hybrid controller are optimized simultaneously by using particle swarm optimization algorithm, and the particle swarm fuzzy hybrid control strategy is developed. The particle swarm optimization fuzzy hybrid control strategy is obviously superior to the traditional fuzzy control strategy, which can effectively improve the comprehensive performance of urban rail train operation system, and achieve better control effect under different road input excitation.

(3) The proposed strategy can not only ensure the stability of DC traction network voltage, but also distribute the power reasonably according to the actual operation state of urban rail train and the use of energy storage elements. At the same time, it can also avoid overcharge and over discharge of super capacitor and battery. The response of super capacitor to high frequency power can also avoid the battery from being impacted greatly and prolong the service life of battery.

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