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Coordinated Control of Multiple Wayside Energy Storage Systems Based on Fuzzy Logic Algorithm

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Abstract

With the rapid development of urban rail transit, installing multiple wayside energy storage systems for regenerative braking energy recovery has become a hotspot. This paper analyses the energy flow in urban rail transit installing multiple energy storage systems in both short-time and long-time scales. Furthermore, a coordinated control strategy of multiple energy storage systems based on fuzzy logic algorithm is proposed to realize the adaptive adjustment of charging/discharging thresholds according to the traction network voltage and ESS operation state. Finally, a case study is conducted to verify the effectiveness of the proposed coordinated control strategy.

Keywords: urban rail transit, regenerative braking energy recovery, multiple energy storage systems, fuzzy control, energy management strategy, energy flow

1 Introduction

Energy storage technology plays a crucial role in urban rail transit. The energy storage system stores the regenerative energy generated during train braking for future use during train traction, thereby reducing energy waste. In addition, it also supports energy backup in emergency situations, enabling emergency rescue and enhancing system stability and reliability. Therefore, energy storage technology not only enhances the economy and environmental friendliness of rail transit but also provides critical support for sustainable operation of modern urban rail systems. Installing multiple energy storage devices on a rail transit line brings significant benefits. Firstly, it can enhance the overall energy recovery rate of the line. When a train brakes, multiple energy storage devices can recover energy simultaneously at different stations, reducing energy losses on braking resistors. By coordinating control between multiple energy storage devices, the capacity of energy storage configuration can be reduced, achieving better recovery of regenerated braking energy.

A significant amount of literature has been devoted to studying control strategies for supercapacitor energy storage systems. References [1,2] dynamically adjust the discharge commands based on the variation of the no-load voltage to maintain a constant energy output ratio between the energy storage device and the rectifier unit, ensuring that the energy released during discharge does not fluctuate with the variation of the open-circuit voltage. Some literature adopts intelligent algorithms to optimize energy management strategies. Reference [3] proposes a novel optimization method that combines genetic algorithms with a simulation platform for urban rail power supply systems, enabling simultaneous optimization of the optimal energy management strategy, location, and scale. Reference [4] proposed a regenerative energy prediction method based on the BP neural network model to determine whether the energy storage system will be fully charged during the charging process. In cases where the energy storage system cannot fully absorb the regenerative energy, appropriately raising the charging threshold and reducing the output energy of the substation can achieve certain energy-saving effects. Reference [5] proposed a mixed energy storage system operation optimization strategy based on dynamic programming. However, due to the real-time changes in the traction power supply system's topology as the train moves, dynamic programming cannot achieve online optimal control. Reference [6], based on an analysis of the train's operating status, proposed a braking voltage-following energy management strategy to adjust the charging and discharging threshold voltages, thereby maximizing the utilization of the energy storage system. Based on similar principles, Reference [7] proposed an energy storage device control strategy that considers the train's operating status. This control strategy dynamically adjusts the charging voltage command of the energy storage device based on real-time train power and position data, keeping the train in a state where the braking resistance is not activated, ensuring that the energy storage device operates in an optimal state. Reference [8] takes into account the changes in no-load voltage and departure interval and proposes an adaptive energy management strategy based on fuzzy rule control for hybrid energy storage systems, which improves energy efficiency and voltage stabilization. Reference [9], based on a model of urban rail dual supercapacitor energy storage systems, aims to minimize line loss between two stations as the objective function and uses grasshopper algorithm to optimize the energy management parameters of the supercapacitor energy storage system. Compared with the particle swarm optimization algorithm (PSO), line loss is significantly reduced, achieving energy-saving effects. However, although the above references may consider multiple energy storage systems during modeling and simulation, coordination between multiple energy storage systems is not considered in the control of energy storage charging and discharging. Currently, some literature has proposed multi-energy storage control strategies. References [10,11] propose a multi-agent deep reinforcement learning-based coordinated control strategy for multiple energy storage systems. This method represents the decision-making process of multiple ESS agents as a fully cooperative Markov game. Compared with traditional GA optimization algorithms, the energy-saving effect is improved. However, the above methods rely on objective functions and optimization algorithms, requiring a large amount of real-time substation information, energy storage information, and train information. They have high communication requirements and are difficult to implement in practical engineering

In this paper, the energy flow characteristics of multi-energy storage systems are analysed firstly, which indicates the advantages of coordinated charging and discharging of multiple energy storage systems. Furthermore, a multi-energy storage coordinated energy management strategy based on fuzzy logic control is proposed and simulated to verify its effectiveness.

2 Energy Flow Analysis of Urban Rail Transit with Multiple ESSs

This section analyses the energy flow in urban rail transit when the regenerative braking energy of a train is recovered by multiple ESSs. The system studied in this paper contains five substations with two ESSs installed at substation 2 and 4 respectively, as depicted in Figure 1. The distance between substations is shown in Table 1.

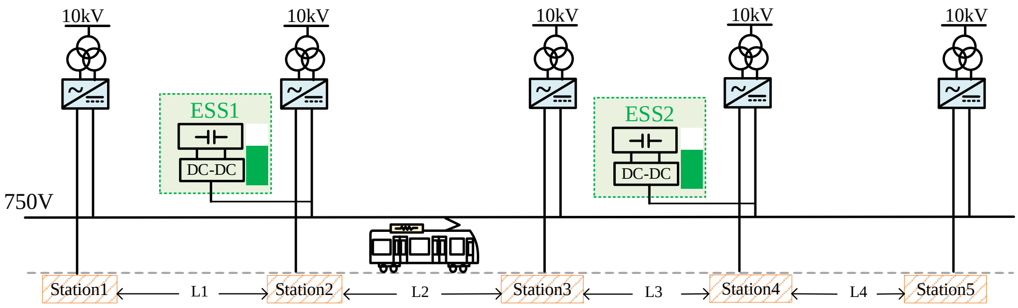


Figure 1: Schematic diagram of urban rail transit.

L1/km	1.86
L2/km	1.7
L3/km	1.64
L4/km	1.41
L1/km	1.86
L2/km	1.7
L3/km	1.64

Table 1: The distance between substations.

2.1 Energy flow in short-time scale

We take the scenario as an example where a train brakes at a distance of 1km from substation 2 with a braking power of 2MW. The corresponding equivalent circuit model of the system at this moment is illustrated in Figure 2. The related parameters of substations are shown in Table 2. The unit line resistance is 0.0429Ω/km. By multiplying it with the distances between stations shown in Table 1, we can obtain the line resistance r1~r4.

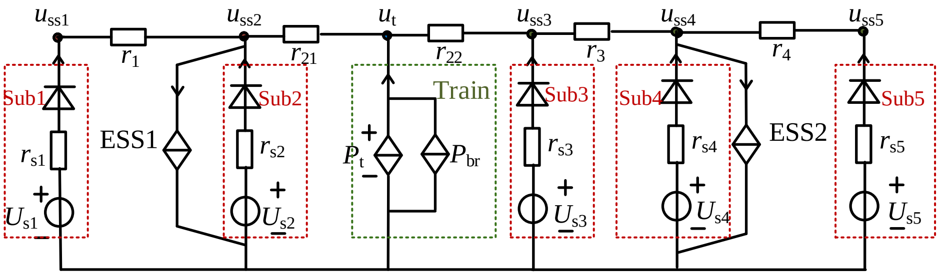


Figure 2: Equivalent circuit model of urban rail transit.

U_{s1}/V	830	r_{s1}/Ω	0.0119
U_{s2}/V	822	r_{s2}/Ω	0.0119
U_{s3}/V	833	r_{s3}/Ω	0.0149
U_{s4}/V	859	r_{s4}/Ω	0.0149
U_{s5}/V	867	r_{s5}/Ω	0.0119

Table 2: Parameters of substations.

(1) Regenerative braking energy recovery by single ESS

Assuming that all the regenerative braking energy of the train is absorbed by ESS1 which is closer to the train, it is obvious that the larger the braking current absorbed by ESS, the greater the voltage drop in the line. When Equation (1) is satisfied, substation 1 begins to output power and when Equation (2) is satisfied, substation 2 begins to output power. P_{t1} denotes the regenerative power absorbed by the traction power supply system located on the left side of the train. Therefore, it is very likely to occur that the regenerative braking energy recovered by energy storage system partially comes from substations.

$$u_t - \frac{P_{t1}}{u_t} \cdot r_{21} < U_{s1} \tag{1}$$

$$u_t - \frac{P_{t1}}{u_t} \cdot r_{21} < U_{s2} \tag{2}$$

The status of left substations is shown in Table 3, where 1 represents the substation on and 0 represents the substation off. Therefore, if the braking power is 2MW and all absorbed by ESS1, both substation 1 and substation 2 will output power. By solving the node voltage equations, we can obtain the energy flow in traction power supply system, as shown in Figure 3. ESS1 needs to provide 3.18MW to fully absorb the 2MW train braking power. Specifically, the 3.18MW charging power of ESS1 not only includes the train's braking power but also includes the output power of substation 1 (0.236MW) and substation 2 (1.164MW). The output power of substations not only increases their energy consumption but also occupies the capacity of ESSs.

scenario	substation 1	substation 2
P_{t1}<1.47MW	0	0
1.47MW<P_{t1}<1.64MW	1	0
P_{t1}<1.64MW	1	1

Table 3: Status of left substations.

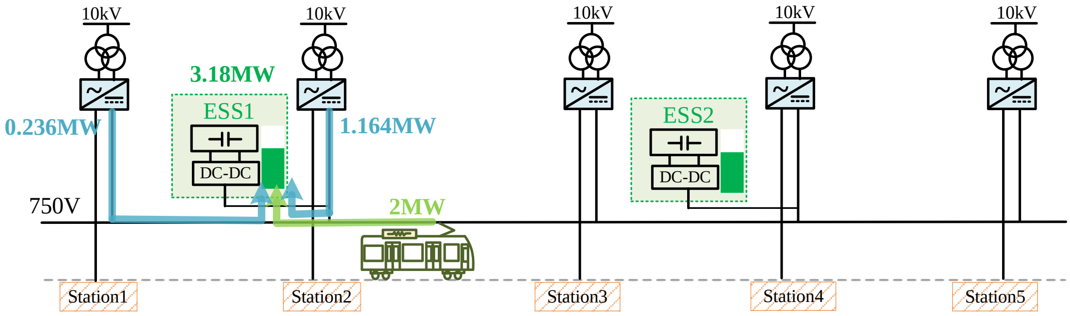


Figure 3: Energy flow in urban rail transit.

(2) Regenerative braking energy recovery by dual ESSs

Assuming that the regenerative braking energy of the train is absorbed by both ESS1 and ESS2, ESS1 on the left is limited by its own maximum power and can only provide a charging power of 1.5MW, i.e., P_{char}=1.5MW. Taking into account the line losses and the output power of substation 1, the power balance equation at this time is shown in Equation (3). Therefore, we can obtain that the regenerative braking power absorbed by the left part P_{t1} is 1.59MW. Therefore, the remaining 0.41MW needs to be absorbed by ESS2 on the right side.

$$\begin{aligned} P_{char} &= P_{t1} - I_{t1}{}^2 r_{21} + u_{ss2} \cdot I_{sub1} \\ &= P_{t1} - \left(\frac{P_{t1}}{u_t}\right)^2 \cdot r_{21} + u_{ss2} \cdot \frac{U_{s1} - u_{ss2}}{r_{s1} + r_1} \end{aligned} \tag{3}$$

When the braking power of the train flows to the right, substation 3 starts to output power if Equation (4) is satisfied, substation 4 starts to output power if Equation (5) is satisfied, and substation 5 starts to output power if Equation (6) satisfied. P_{t2} denotes the regenerative power absorbed by the traction power supply system located on the right side of the train.

$$u_t - \frac{P_{t2}}{u_t} \cdot r_{22} < U_{s3} \tag{4}$$

$$u_t - \frac{P_{t2}}{u_t} \cdot \left(r_{22} + r_3\right) < U_{s4} \tag{5}$$

$$u_t - \frac{P_{t2}}{u_t} \cdot \left(r_{22} + r_3\right) < U_{s5} \tag{6}$$

The status of right substations is shown in Table 4. Therefore, when the remaining 0.41 MW of train braking power needs to be absorbed by ESS2, substation 4 and substation 5 will output power at the same time. According to the nodal voltage equation, we can obtain the energy flow of the traction power supply system, as shown in Figure 4. The charging power of ESS1 is 1.5 MW, the charging power of ESS2 is 0.82 MW, the output power of substation 1 is 0.05 MW, the output power of substation 4 is 0.28 MW, and the output power of substation 5 is 0.15 MW. Compared with the above case where ESS1 needs 3.81MW to recover the 2MW regenerative braking power of the train, in this case ESS1 and ESS2 only need to provide a total power of 2.32 MW for regenerative braking energy recovery. This not only helps to reduce the investment cost of ESSs, but contributes to the reduction of energy consumption of substations.

scenario	substation3	substation4	substation5
P_{t2}<0.3MW	0	0	0
0.3MW<P_{t2}<0.36MW	0	0	1
0.36MW<P_{t2}<2.02MW	0	1	1
P_{t2}>2.02MW	1	1	1

Table 4: Status of left substations.

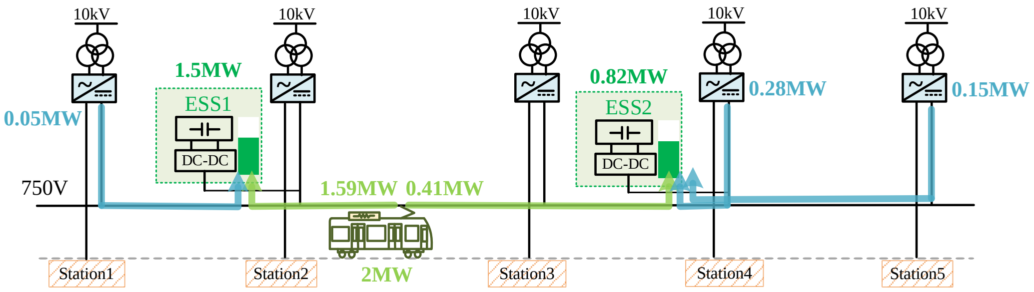
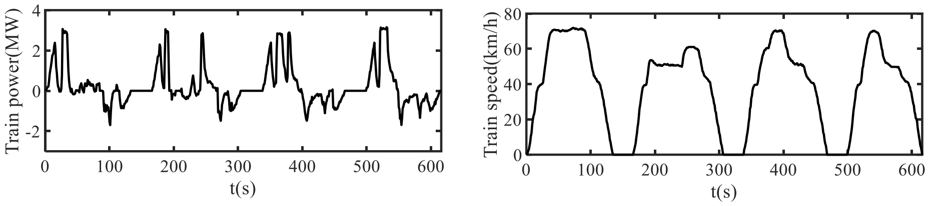


Figure 4: Energy flow in urban rail transit.

2.2 Energy flow in long time scale

In this section we will analyse the effect of coordinated control of ESSs in long time scale. The power and speed profile of the train from substation 1 to substation 5 are shown in Figure 5. The charging and discharging threshold for ESS1 are set as 840V and 820V and the charging and discharging threshold for ESS2 are set as 860V and 840V. The range of state of energy (SOE) for ESSs is set to be 0.2~0.9. The simulation duration is 20min with a headway of 2min. The corresponding SOE of two ESSs during this period is shown in Fig 6.



(a) (b)

Figure 5: Speed and power profile of the train.

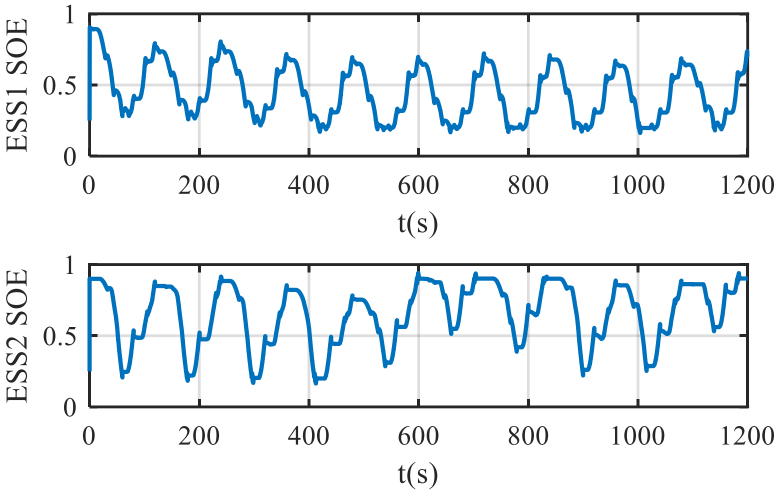


Figure 6: SOE of ESS1 and ESS2.

Taking the time interval of 600s~720s as an example, the comparison between the actual power output and the power command of the two ESSs is shown in Figure 7. The overlapping parts indicate that ESS can meet the power command, while the non-overlapping parts occur when the actual power output of ESS cannot satisfy the power demand due to constraints on its power or energy. It can be observed that during 655s~672s, ESS1 cannot meet the discharging power requirement because it is in a low state of charge at this time. Similarly, ESS2 cannot meet the charging power requirement during 705s~720s due to its high state of charge. Therefore, it is necessary to adjust the charging and discharging thresholds of ESSs flexibly.

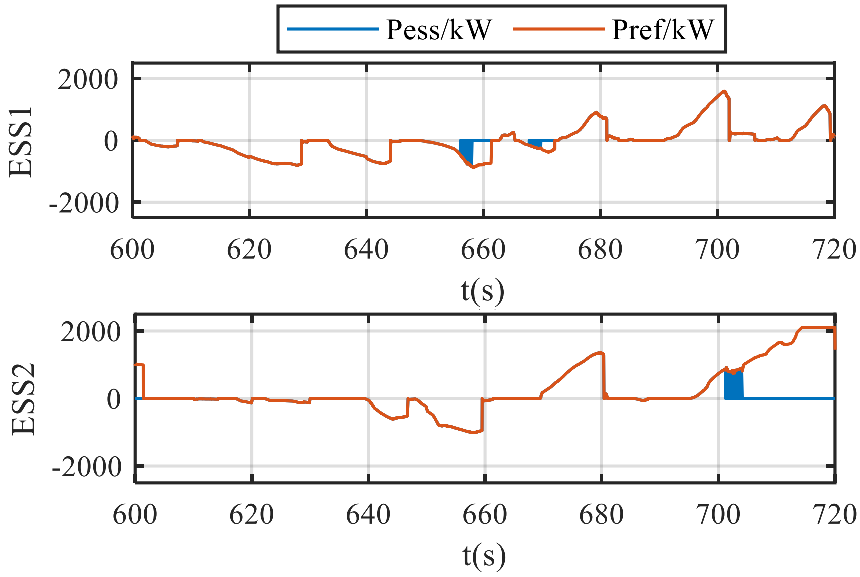


Figure 7: Power output of ESS1 and ESS2.

3 Coordinated control of multiple ESSs based on fuzzy logic algorithm

According to the energy flow analysis in the previous section, coordinated charge and discharge of multiple ESSs can help to recover more regenerative braking energy. Therefore, this paper proposes coordinated control of multiple ESSs based on fuzzy logic algorithm to realize the adaptive adjustment of charging/discharging thresholds according to the traction network voltage and ESS operation state.

3.1 Energy flow in long time scale

A hierarchical energy management framework is proposed in this paper for coordinated control of ESSs, as shown in Figure 8. The main responsibility of central level EMS is to issue appropriate dynamic threshold commands based on SOE of ESSs and traction network voltage Red uploaded from each substation. The station level EMS is responsible for calculating the SOE and Red uploaded to central level, setting the current charging and discharging thresholds according to the environmental changes and the central level commands, and controlling the operation mode switching and regulating the power output of ESSs.

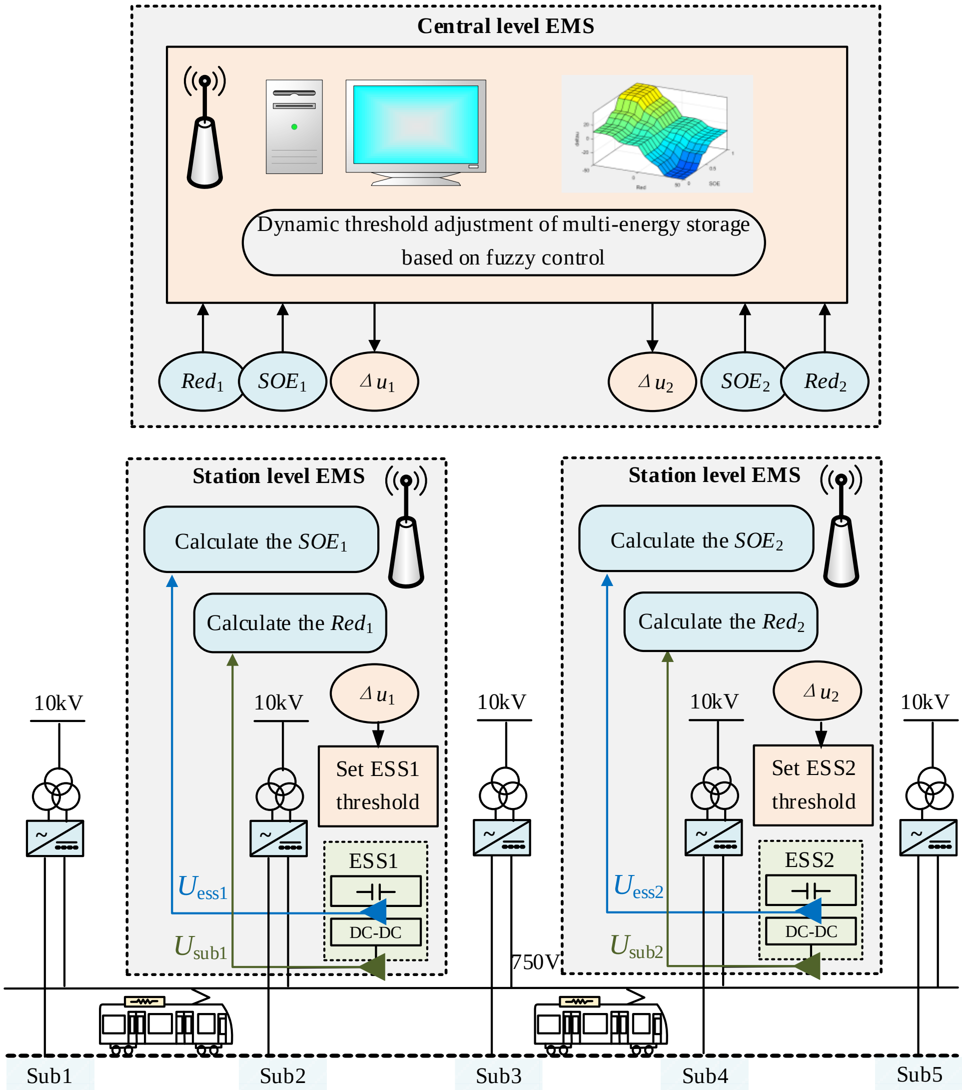


Figure 8: Hierarchical energy management framework.

The calculation of SOE and Red is shown in Equation (7) and (8), where U_{ess} denotes the current voltage of ESS, $U_{\mathrm{ess,max}}$ denotes the maximum voltage of ESS, U_{dc} denotes the traction network voltage, U_{char0} and U_{dis0} denote the original charging and discharging threshold of ESS.

$$SOE = \frac{U_{ess}^2}{U_{ess,\max}^2} \tag{7}$$

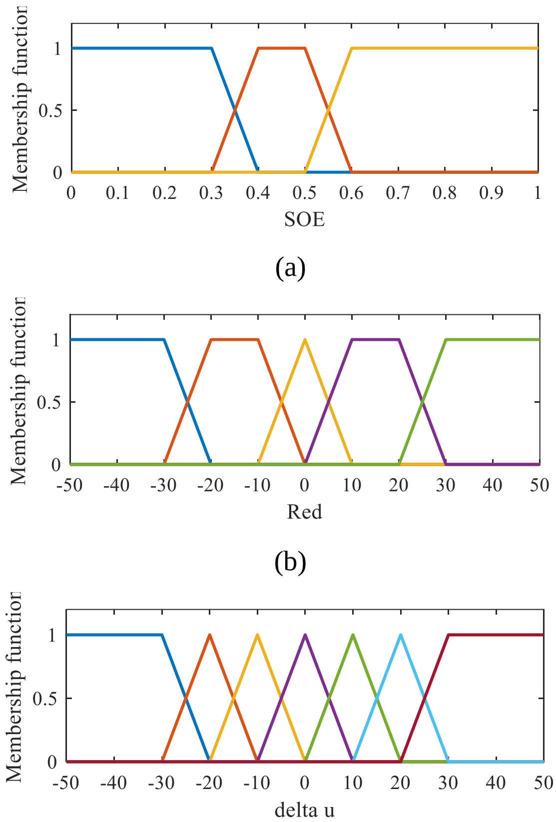
$$\begin{cases} U_{\mathrm{dc}} > U_{\mathrm{char0}}, \mathrm{Red} = U_{\mathrm{dc}} - U_{\mathrm{char0}} \\ U_{\mathrm{dc}} < U_{\mathrm{dis0}}, \mathrm{Red} = U_{\mathrm{dc}} - U_{\mathrm{dis0}} \end{cases} \tag{8}$$

The adjusted charging and discharging threshold of ESS is shown in Equation (9), which adds the dynamic threshold adjustment Δu to the original threshold. So next we aim to get an optimal Δu by applying fuzzy logic algorithm.

$$\begin{cases} U_{\text{char}} = U_{\text{char0}} + \Delta u \\ U_{\text{dis}} = U_{\text{dis0}} + \Delta u \end{cases} \tag{9}$$

3.2 Design of affinity function

The inputs to the fuzzy logic algorithm includes SOE of ESSs and traction network voltage information Red. For SOE, the logic languages "VS, M, VB" are used to represent their states as "very small, medium, very large" respectively, as shown in Figure 9(a). "NB, NS, O, PS, PB" is used to represent the state of "negative big, negative small, zero, positive small, positive big" for RED, as shown in Figure 9(b). The outputs Δu also use the logic language NB, NS, O, PS, PB to describe their states, as shown in Figure 9(c).



(a)

(b)

(c)

Figure 9: Affinity function.

3.3 Design of fuzzy rule

Under the control mode of voltage outer loop and current inner loop, the traction network voltage can be stabilized at the charging and discharging thresholds if ESS is not constrained by its energy, power, response speed, and so on. When the traction network voltage at a certain substation is higher or lower than the charging and discharging thresholds, it means that ESS at this substation needs to be coordinated with ESS at other stations. The fuzzy rule for coordinated control of ESSs is given in Table 5.

	Red1 \ SOE2	VS	M	VB
coordinated discharging	NB	PS	PM	PB
	NS	O	PS	PM
independent operation	O	O	O	O
coordinated discharging	PS	NM	NS	O
	PB	NB	NM	NS

Table 5: Fuzzy rule for coordinated control of ESSs.

(1) Coordinated discharging of ESSs

When the traction network at the substation where ESS1 is located is lower than the discharge threshold, ESS2 needs to increase the charge and discharge threshold to assist discharge. The larger the difference between the voltage and the discharge threshold of the traction network where ESS1 is located, the more the corresponding threshold of ESS2 increases. At the same time, the larger the current SOE of ESS2, the larger the remaining discharge power and energy, and the higher the corresponding threshold of ESS2.

(2) Coordinated charging of ESSs

When the traction network voltage of the substation where ESS1 is located is higher than the charging threshold, ESS2 needs to lower the charging and discharging threshold to assist in charging. The greater the difference between the traction network voltage and the charging threshold at the substation where ESS1 is located, the more the threshold value corresponding to ESS2 is reduced. In addition, the smaller the current SOE of ESS2, the larger the remaining charging capacity, and the lower the threshold of ESS2.

3.4 Case study

Applying the above coordinated control strategy to the scenario described in Section 2.2, we can obtain the adjusted charging/discharging thresholds of ESSs, as shown in Figure 10. The discharge threshold of ESS2 is increased within 640~660s to assist ESS1 discharge. What's more, the charging threshold of ESS1 is lowered within 690~700s for coordinated charging of ESS2. The corresponding SOE change curve is shown in Figure 11.

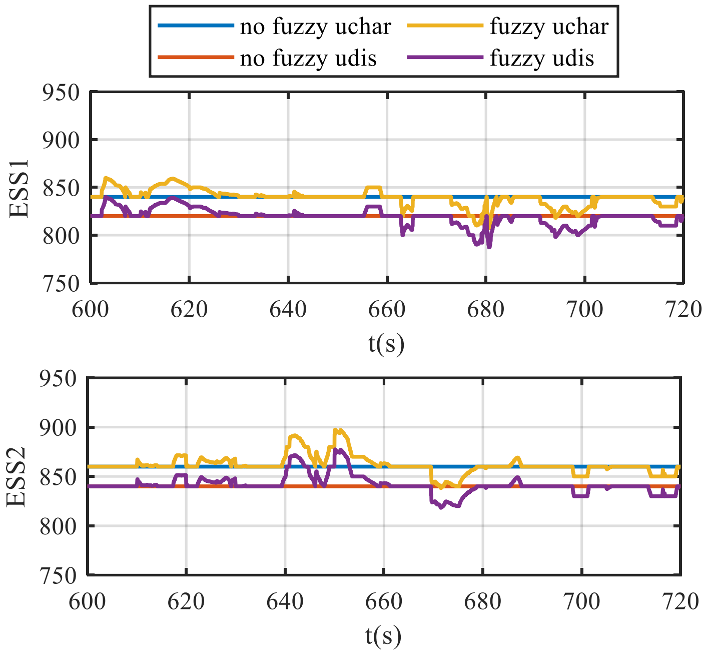


Figure 10: Comparison of charging/discharging thresholds of ESSs.

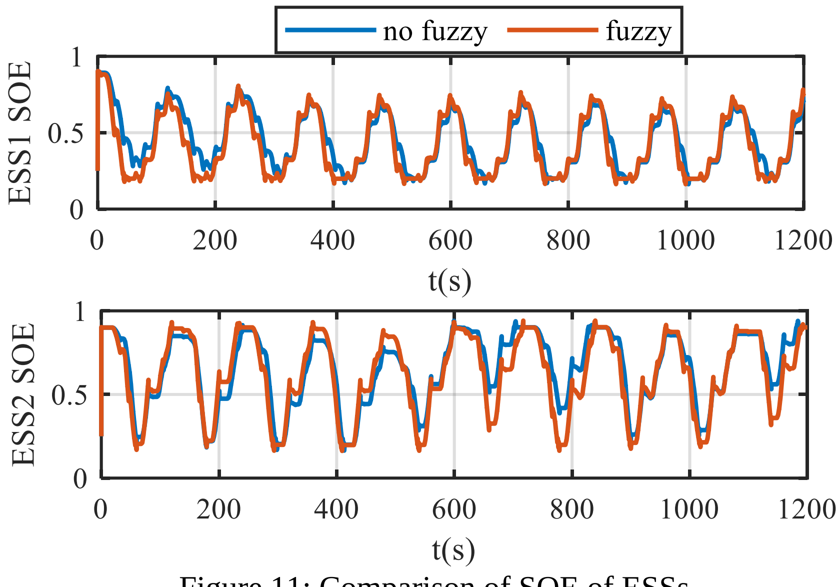


Figure 11: Comparison of SOE of ESSs.

4 Conclusions and Contributions

This paper proposed coordinated control of multiple energy storage systems based on fuzzy logic algorithm. It can realize the adaptive adjustment of charging/discharging thresholds of ESSs according to the traction network voltage and ESS operation state. A case study indicates that it not only can help to reduce the investment cost of energy storage systems, but also contributes to reducing the energy consumption of substations.

References

[1] L. Ye, K. Zou and L. Song, " Control strategy for super capacitor energy storage device of urban rail transit," Urban rapid rail transit, 30, pp. 118-122+127, 2017.

[2] Y. Zhao, H. Xia, J. Wang et al, " Control strategy of ultracapacitor storage system in urban mass transit system based on dynamic voltage threshold," Journal of Electrotechnical Technology, 30, pp. 427-433, 2015.

[3] H. Xia, H. Chen, Z. Yang, F. Lin, and B. Wang, "Optimal Energy Management, Location and Size for Stationary Energy Storage System in a Metro Line Based on Genetic Algorithm," Energies, 8, pp. 11618-11640, 2015.

[4] H. Bao, "Energy management strategy of ground-mounted supercapacitor energy storage system based on energy prediction of BP neural network,". Beijing Jiaotong University,2020, p94.

[5] X. Chen, Y. Wang and Q. Wu, "A Bio-Fuel Power Generation System With Hybrid Energy Storage Under a Dynamic Programming Operation Strategy," IEEE Access, 7, pp. 64966-64977, 2019.

[6] Z. Yang, Z. Yang, H. Xia, and F. Lin, "Brake Voltage Following Control of Supercapacitor-Based Energy Storage Systems in Metro Considering Train Operation State," IEEE Transactions on Industrial Electronics., 65, pp. 6751-6761, 2018.

[7] H. Xia, Z. Yang, Z. Yang , " Control strategy of urban rail supercapacitor energy storage device based on train running state," Chinese Journal of Electrotechnical Technology, 32, pp. 16-23, 2017.

[8] Y. Liu, Z. Yang, X. Wu, D. Sha, F. Lin, and X. Fang, "An Adaptive Energy Management Strategy of Stationary Hybrid Energy Storage System," IEEE Transactions on Transportation Electrification, 8, pp. 2261-2272, 2022.

[9] S. Lin, X. Wang, B. Qin, "Optimization of energy management parameters of urban rail supercapacitor energy storage system based on locust algorithm," New Industrialization, 12, pp. 82-86, 2022.

[10] F. Zhu, Z. Yang, F. Lin, and Y. Xin, "Decentralized Cooperative Control of Multiple Energy Storage Systems in Urban Railway Based on Multiagent Deep Reinforcement Learning," IEEE Transactions on Power Electronics, 35, pp. 9368-9379, 2020.

[11] Z. Yang, F. Zhu and F. Lin, "Deep-Reinforcement-Learning-Based Energy Management Strategy for Supercapacitor Energy Storage Systems in Urban Rail Transit," IEEE Transactions on Intelligent Transportation Systems, 22, pp. 1150-1160, 2021.