Multi-objective Energy Storage Power Allocation Strategy based on GA-APSO Algorithm

Hongyan Li, Jiajing Wu, Long Zhao, Weifeng Wang, Jing Sun

***Abstract*—In order to address the challenge of grid stability posed by the integration of renewable energy sources such as wind and photovoltaic, a multi-objective fusion energy storage power allocation strategy based on the GA-APSO algorithm is proposed as a potential solution. The initial step is to construct a multi-objective fusion model that incorporates the total profit of the energy storage system, the loss rate, and the consistency of the battery charge state. Subsequently, the GA-APSO algorithm is employed to resolve the multi-objective fusion model, with the objective of enhancing the operational efficiency of the energy storage system. Finally, the enhanced allocation strategy is implemented in two arithmetic scenarios for simulation, and the power allocation strategy under the traditional algorithm is evaluated. The results of the simulation demonstrate that the strategy is an effective means of reducing the loss of energy in the VRB energy storage system, reducing the number of charging and discharging cycles of the system, and improving the overall operational efficiency of the system.**

***Index Terms*—Vanadium redox battery, GA-APSO algorithm, Power allocation strategy, Multi-objective optimization**

I. Introduction

As an emerging dispatchable energy source, energy storage technology has the potential to effectively address the challenges of intermittency, volatility and stochasticity inherent in renewable energy generation, and facilitate the transition from a traditional fossil energy structure to a cleaner one. Among the various types of energy storage batteries, liquid current batteries are regarded as one of the most promising large-scale energy storage technologies due to their extended operational lifetime, high flexibility, and straightforward scalability, particularly in the case of all-vanadium liquid current batteries (Vanadium Redox Battery, VRB). However, the voltage of a single battery as an energy storage unit is insufficient and its capacity is restricted. Therefore, individual batteries must be connected in series and then in parallel to expand their capacity before they can be connected to the grid for unified management and control. It is therefore imperative that the safe operation of the Vanadium Redox Battery storage of energy system is guaranteed, and that its power distribution is optimised and operating efficiency improved, when the current storage of energy system is linked to the grid.

In the field of energy storage systems, scholars from both domestic and international academic institutions have put forth a series of proposed solutions to the issue of power allocation following extensive research. Initially, pioneering scholars put forth conventional power allocation methodologies, as evidenced in the literature [1]-[3]. These strategies typically apportion the storage of energy system's power in conformity with the battery's state of charge or remaining energy, with a unified control objective. The control strategy is straightforward and readily implementable.

The present study proposes the use of intelligent algorithms to solve the distribution of electricity model of an established storage of energy system. The literature [4] suggests a control algorithm based on dynamic programming and genetic algorithms, which combines spectrum analysis, dynamic programming and genetic algorithms to optimize the model. Literature [5] proposes a particle swarm optimization algorithm to solve the model. Literature [6] suggests a capacity allocation method combining variational modal decomposition (VMD) and an adaptive particle swarm algorithm (APSO). However, the majority of the aforementioned literature only considers the operating cost of the energy storage system, without taking into account the loss of energy storage system capacity following its operational deployment. Furthermore, the control objective is overly simplistic. Accordingly, the literature [7] proposes a power dynamic allocation strategy, establishes a model with the total life decay discounted cost and tracking performance of the hybrid storage of energy system as the comprehensive optimisation objective, and solves the problem by using the particle swarm algorithm to realise the dynamic allocation of power; The existing literature [8] establishes a multi-objective power allocation optimisation model that includes the depreciation cost, loss rate and the consistency

Manuscript received June 25, 2024; revised March 29, 2025.

This work was supported in part by the National Key R & D Program (2021YFE0105000), Natural Science Foundation of China (52074213), Xi'an Science and Technology Plan Project of Science and Technology Personnel from Colleges and Institutes to Serve Enterprises （22GXFW0110）.

Hongyan Li is a Senior Engineer of Electrical and Control Engineering, Xi'an University of Science and Technology, Xi'an 710054, China (e-mail: lihongyan@xust.edu.cn).

Jiajing Wu is a postgraduate student in Electrical and Control Engineering, Xi'an University of Science and Technology, Xi'an 710054, China (e-mail: 984285878@qq.com).

Long Zhao is a postgraduate student in Electrical and Control Engineering, Xi'an University of Science and Technology, Xi'an 710054, China (e-mail: 383423811@qq.com).

Weifeng Wang is a Professor of Electrical and Control Engineering, Xi'an University of Science and Technology, Xi'an 710054, China (e-mail: wangwf03@126.com).

Jing Sun is a teacher of School of Mechanical and Material Engineering, Xi'an University, Xi'an, 710065, China (e-mail: 2035730535@qq.com).

of the battery's current state of charge (SOC). Furthermore, it proposes the use of a particle swarm algorithm with adaptive weighting, which considers the priority of solving the model. In literature [9], a loss-accounted power allocation model is proposed, which establishes a power allocation model with the system loss and state of charge (SOC) balance as the objective function. The power demand and SOC higher and lower limits are set as constraints, and the model is solved by a virtual particle-adaptive difference evolution algorithm (VP-ADE). In literature [10], the state of charge and power balance are established as constraints, with the lowest total cost of the storage of energy system, the average loss rate and the best SOC balance serving as the power optimization objective function. The whale algorithm, according to adaptable weights and an approach to simulated annealing, is employed to solve the model, while a simulated annealing strategy-based whale optimization algorithm is used to optimize the objective model.

The existing multi-objective model for storage of energy power allocation introduces both economic and loss objectives. However, the economic objective often consists of cost only, whereas the economic benefit of the storage of energy system in grid-connected operation is more intuitive than cost as the final objective. This paper therefore establishes a multi-objective model that takes into account the maximization of the economic benefit, the lowest system loss and the best SOC consistency. In order to solve the multi-objective model and maximize the power allocation of a VRB energy storage system, it then suggests a hybrid approach that combines Genetic approach (GA) and Adaptive Particle Swarm Optimization (APSO).

II. All-vanadium liquid current battery energy storage system

A. *All*-vanadium Flow Battery Structure

The all-vanadium liquid current battery represents a pivotal component of the VRB storage of energy system, serving as the nucleus of the entire storage of energy apparatus and enabling the system. The system is comprised of three primary units: an electric stack (power unit), an electrolyte and storage tank (energy storage unit), and electrolyte pipelines and pumps and valves (electrolyte delivery unit). For the purpose of facilitate the real-time monitoring of battery status, a VRB battery is typically equipped with a battery management system (BMS) that enables communication with the upper level. The structure of this system is illustrated in Fig. 1. The operational principle of the VRB battery is based on the transfer of electrons between vanadium ions of four distinct valence states within the electrolyte. The vanadium ions present in the positive electrode are in the VO_2^+/VO^{2+} state, while those in the negative electrode are in the V^{3+}/V^{2+} state. The aforementioned vanadium ions flow through the electrolyte and circulating pump, and ultimately undergo a redox reaction on the electrode surface.

B. *Grid*-connected *Structure* of All-vanadium Liquid Current Battery Energy Storage System

An all-vanadium liquid current battery energy storage system

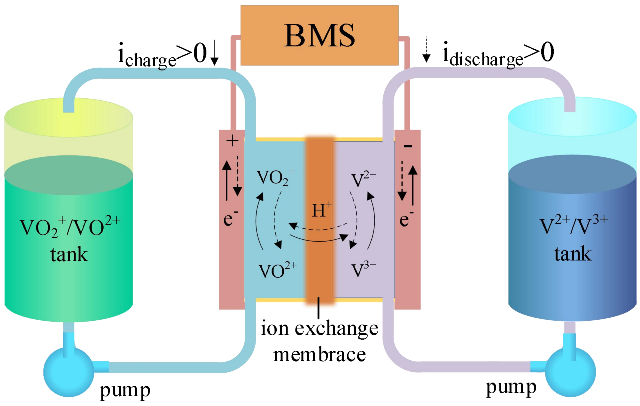

Fig.1 Diagram of vanadium liquid battery

is a system directly connected to the grid that is capable of storing and releasing energy. It comprises an all-vanadium liquid current battery, an inverter and an upper-level energy management system. The system comprises an all-vanadium liquid current battery, an inverter and an upper-level energy management system. The all-vanadium liquid current battery energy storage system is capable of realising pre-set operation modes and functions under the scheduling and management of the energy management system. The structure of the all-vanadium liquid current battery energy storage system is illustrated in Fig. 2.

The all-vanadium flow battery storage system comprises multiple sets of battery storage modules, a battery management system, a DC/DC converter, and other components, contingent on the power and capacity configuration. The battery storage module represents the smallest unit in the all-vanadium flow battery storage system that can be dispatched independently. As the smallest unit in the all-vanadium liquid current battery energy storage system that can be dispatched independently, the battery storage module is capable of being started, stopped, charged and discharged by a single unit. The operational state of the unit battery energy storage module is subject to regulation by the battery management system (BMS), while the scheduling of the entire energy storage system is overseen by the energy management system.

The BMS and EMS engage in communication in order to facilitate the transfer of operational state information, and the EMS also interacts with the BMS to obtain updates on the status of the batteries. From the EMS, which accepts remote instructions and schedules the entire energy storage system in accordance with grid operational requirements. This ultimately serves to enhance the stability of the power system and economy. Furthermore, the EMS can be utilized as a backup power source, providing power for critical loads in extreme circumstances, thereby improving the reliability of the power supply.

III. Multi-objective fusion modelling of VRB energy storage systems

A. *Objective Function*

Objective 1: Maximize profits from VRB energy storage

The economic benefit of the energy storage system, which is

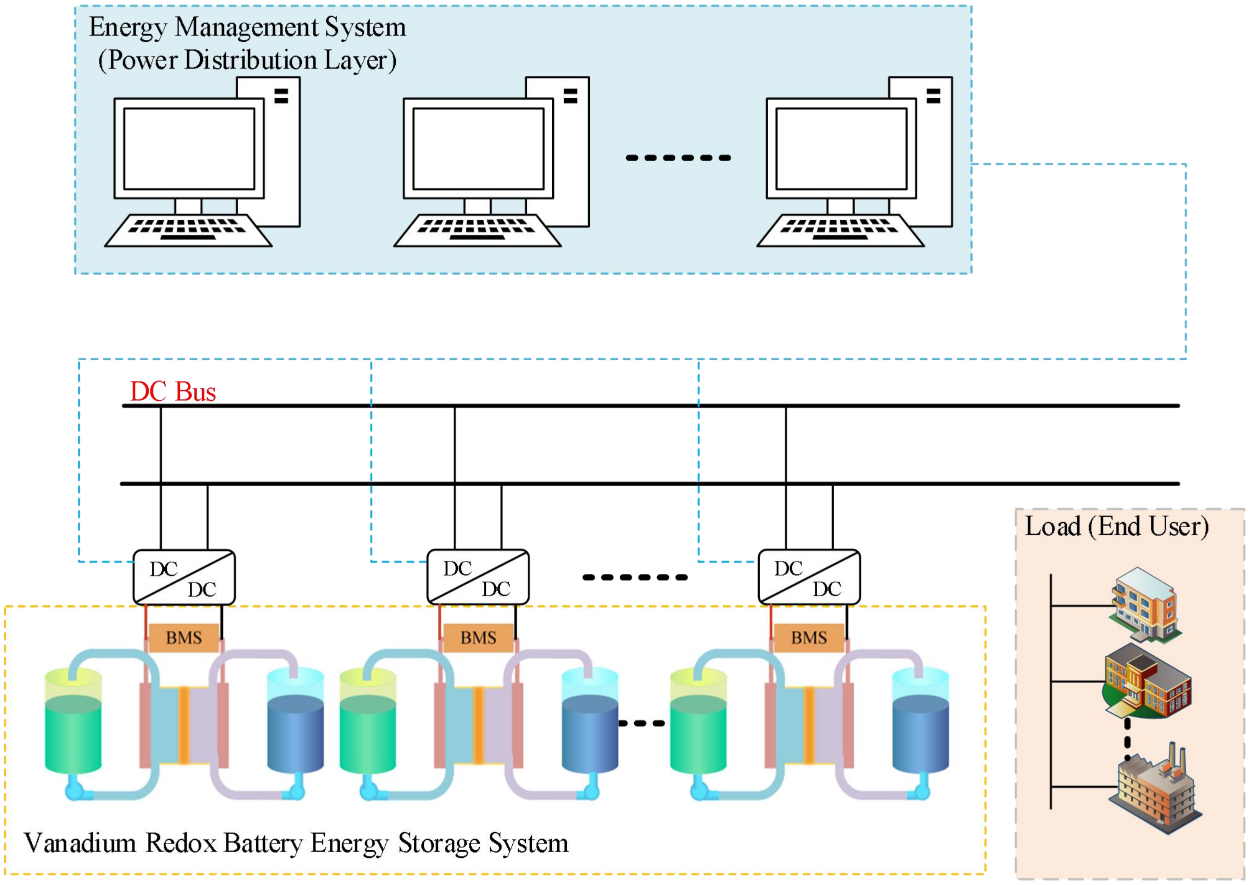

Fig.2 Diagram of vanadium liquid battery for energy storage systems[11]

is computed by deducting the system's cost from its economic value, is the main factor that determines the system's profitability. The economic gain of the energy storage system can be classified into four principal categories:

a. Peak and valley tariff arbitrage

The utilization of the discrepancy between peak and valley tariffs within the power system enables the generation of revenue through the storage of electricity during periods of lower tariffs and its subsequent release during periods of higher tariffs:

$$W_A = P_{peak} E \tag{1}$$

Where: P_{peak} is the peak hour tariff of the grid, E is the amount of extra electricity accepted by the grid.

b. Ancillary services market

Energy storage systems are capable of providing a range of ancillary services, including frequency regulation, peaking, standby, and black start, for which they receive service fees from the power system operator. At present, the objective is to streamline the calculation and the policies pertaining to the market revenue of auxiliary services provided by energy storage systems in each province. Consequently, the revenue generated from auxiliary services is calculated as follows:

$$W_B = hS \tag{2}$$

Where: h is the number of annual peaking hours, S is the compensation for peaking (including tax).

c. Energy storage system leasing services

Energy storage system owners may lease energy storage capacity to customers or other market participants who require the regulation of electricity demand. The guideline prices for leasing energy storage systems in various parts of China are predominantly expressed in kWh per year, with a typical range of RMB 150-337/(kWh-year) and an average value of RMB 243.5/(kWh-year).

d. Policy subsidies and incentives

Energy storage systems represent a significant technology with the potential to enhance the regulatory capability, comprehensive efficiency and security of the power system. Consequently, they have received considerable attention from national and local governments. In order to facilitate the advancement of the energy storage industry, governments at all levels have implemented a range of policy subsidies and incentives. The latest policy in Jiangsu Province is a subsidy of RMB 0.3/kWh from 2023 to 2024 and RMB 0.25/kWh from 2025 to January 2026. The subsidy funds will be derived from the incremental funds allocated to the peak tariff and disbursed by the provincial power company in accordance with the pertinent regulations pertaining to metering and settlement.

The principal investment costs associated with the energy storage system[12] are as follows:

$$C = C_{battery} + C_{DC/DC} + C_{other} \tag{3}$$

Where: $C_{battery}$ is the price of the battery body, $C_{DC/DC}$ the price of the DC/DC converter, and C_{other} the total price of other equipment.

In conclusion, the maximum profit of a VRB energy storage system can be calculated as follows:

$$\max(F_1) = \frac{1}{n}\sum(W_A + W_B + W_C + W_D - C) \tag{4}$$

Where: W_C is the energy storage system lease revenue, W_D is the government subsidy and incentive revenue.

Objective 2: Minimization of power loss of VRB energy storage system

As illustrated in Fig. 2, the power loss of the VRB energy storage system can be attributed to two primary sources: the power loss of the VRB energy storage battery and the power loss of the DC/DC converter.

a. Power loss of VRB energy storage battery

As illustrated in Fig. 3, the equivalent circuit model indicates that the power loss of the VRB battery can be attributed to two distinct categories: internal loss and parasitic loss.

$$P_{BL} = P_{IL} + P_{PL} \tag{5}$$

which:

$$\begin{aligned} P_{IL} &= (I_d - \frac{U_d}{R_{fixed}} - I_{pump})^2 R_{resistive} \\ &+ \frac{[U_d - (I_d - \frac{U_d}{R_{fixed}} - I_{pump})R_{resistive} - V_{stack}]^2}{R_{reaction}} \end{aligned} \tag{6}$$

$$P_{PL} = U_d^2 R_{fixed} + U_d I_{pump} \tag{7}$$

Eqs. (5)-(7) in: P_{IL} and P_{PL} represent the battery's internal loss and parasitic loss, respectively, internal loss is generated by the equivalent internal resistance and generated by the former, the latter generated by the loss ratio of about 3:2, parasitic loss is generated by the parasitic resistance and pumping loss current, for the charging and discharging currents, for the voltage of the electric stack.

b. DC/DC converter loss

In the VRB energy storage system, the primary function of the DC/DC converter is to regulate the voltage through the frequent on/off operation of the main switching device during the battery charging and discharging process. This is the primary source of operating losses. It should be noted that even when the battery is not undergoing charging or discharging, the control and auxiliary circuits of the DC/DC converter still require a certain level of power in order to maintain their fundamental functions. These functions include, but are not limited to, monitoring the battery status, preparing to respond to charging or discharging commands, and so forth. Accordingly, the loss of the DC/DC converter can be classified into two principal categories: working loss and standby loss:

$$P_{DC/DC} = \lambda_n P_{work} + (1-\lambda_n) P_{suspend} \tag{8}$$

Where: λ_n is similar to a state indication, $\lambda_n = 1$ indicating that the DC/DC converter of the VRB energy storage unit is in the working state, and its loss is shown in equation (9); $\lambda_n = 0$ indicating that the DC/DC converter of the VRB energy storage unit is in the standby state, and its loss is shown in equation (10):

$$P_{work} = (1-\eta) P_n \tag{9}$$

$$P_{suspend} = 0.5\% P_{DCN} \tag{10}$$

Where: η indicates the working efficiency of the DC/DC converter, according to the national standard of the People's Republic of China[14], the value is taken as 95%, and the standby loss of the DC/DC converter should be no more than 0.5% of the rated power; P_n is the allocated power of the first energy storage unit.

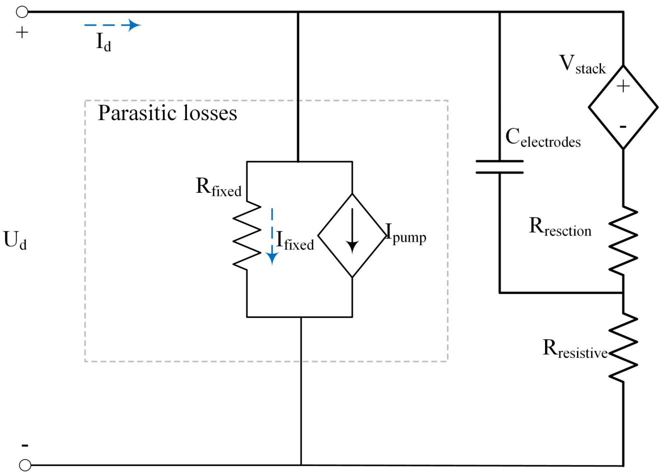

Fig.3 VRB equivalent circuit loss model

In conclusion, the power loss of the VRB energy storage system can be expressed as follows:

$$\min(F_2) = \frac{1}{n} \sum (P_{BL} + P_{DC/DC}) \tag{11}$$

Objective 3: Optimization of SOC Balance Degree

The term 'variance' is employed as a quantitative metric to measure the degree of dispersion of a set of data. A smaller value of variance indicates a more optimal SOC balance:

$$\min(F_3) = \frac{1}{n} \sum (S(t) - \frac{1}{n} \sum S(t))^2 \tag{12}$$

Where: $S(t)$ denotes the SOC value of the VRB energy storage unit near the time.

B. Constraints

In order to guarantee the stable operation and performance optimization of the VRB energy storage system (an all-vanadium liquid current battery energy storage system), it is essential to take a variety of constraints into account during the design and operational phases. The following constraints are considered in this paper:

a. Technical performance constraint: creep rate

The term 'climbing rate constraint' is typically used to describe the maximum rate of change in energy storage system power per unit of time. This concept is closely linked to the responsiveness of the energy storage system to fluctuations in the grid and the overall health of the battery:

$$R(t) = \frac{P(t) - P(t - \Delta t)}{\Delta t} \tag{13}$$

Where: $R(t)$ denotes the climbing rate at the time, $P(t)$ denotes the power at the time, $P(t-\Delta t)$ denotes the power at the time, Δt denotes the unit time.

b. Technical performance constraints: power

In the context of energy storage systems, the term 'power constraint' typically denotes the maximum charge/discharge rate that the system is capable of providing. The power constraint serves to guarantee that the energy storage system does not exceed its designed maximum charge/discharge capacity at any given time:

$$P(t) = \sum \lambda_n P_n(t) \tag{14}$$

$$P_{\min} < P_{VRB} < P_{\max} \tag{15}$$

Where: $P(t)$ denotes the total power demand of the VRB energy storage system at the time.

c. Battery Management Constraints: State of Charge

The state of charge (SOC) is an indicator of the current stored energy of a battery, typically expressed as a percentage. The upper and lower limits of SOC serve to constrain the depth of charge and discharge of a battery, thereby preventing overcharging or over-discharging and thus prolonging the battery's lifespan:

$$S_{\min} < S < S_{\max} \tag{16}$$

d. Operating condition constraints: temperature

The operational temperature range of VRB energy storage systems is typically defined to prevent damage to the battery from overheating or overcooling:

$$T_{\min} < T < T_{\max} \tag{17}$$

In this paper, the Augmented Lagrangian Method (ALM)[15] is adopted for the constraints Eqs. (13)-(17).

C. Evaluation indexes

In this paper, we make reference to the content of the document entitled "Operation indexes and evaluation of electrochemical energy storage power station"[16], and proceed to summarise the following evaluation indexes, which are to be employed in a quantitative analysis of the VRB energy storage system's power distribution:

a. Charge-discharge energy conversion efficiency

The ratio of the energy storage unit's net discharging volume to its charging volume, plus the total of the auxiliary energy used during the charging process throughout the evaluation cycle, is the measure of the energy conversion process' efficiency during both charging and discharging:

$$\eta = \frac{E_{sD} - W_{sD}}{E_{sC} + W_{sC}} \times 100\% \tag{18}$$

Where: E_{sD} , E_{sC} respectively, represents the VRB energy storage unit's overall charge and discharge throughout the assessment cycle, W_{sD} , W_{sC} respectively, represents the consumption of auxiliary equipment in the VRB energy storage unit's charging and discharging procedures throughout the assessment cycle.

b. Utilization factor

The utilization factor of the VRB energy storage unit is defined as the ratio of the operating time to the statistical time during the evaluation cycle:

$$UTF = \frac{UTH}{PH} \times 100\% \tag{19}$$

Where: UTH indicates the number of hours of operation in the evaluation cycle; PH indicates the number of hours of statistical time in the rating cycle, and when the evaluation cycle is 1 year, it is $8760\,h$.

c. VRB energy storage unit battery stack relative failure times

The relative number of battery stack failures will be determined by dividing the number of battery stack failures in the energy storage unit by the total number of battery stacks in the unit throughout the evaluation cycle:

$$RTOP = \frac{FTOP}{BPN} \times 100\% \tag{20}$$

Where: $FTOP$ indicates the number of battery stack failures; BPN is the total number of battery stacks in the energy storage unit.

D. Multi-objective fusion

In this paper, the GA-APSO algorithm objective function is employed for the resolution of the multi-objective function, which necessitates the preprocessing of said function as outlined in Section A.

a. In order to eliminate the discrepancies between the magnitudes and numerical ranges of the various objective functions, this paper employs the method of Max-Min Normalization (Min-Max Normalization) to normalize the aforementioned objective functions:

$$\overline{F_i} = \frac{F_i - F_i^{\min}}{F_i^{\max} - F_i^{\min}} \tag{21}$$

Where: $F_i^{\min}$ and $F_i^{\max}$ are the minimum and maximum values respectively; $\overline{F_i}$ are the normalized variables.

b. Following the aforementioned normalisation, the objective function of profit maximisation is initially minimised through the introduction of a negative sign. Subsequently, the particle swarm algorithm with adaptive weights assigns distinct weights to the three objective functions. Finally, a single objective function is obtained through summation:

$$\min(F_{VRB}) = w_1(-F_1) + w_2F_2 + w_3F_3 \tag{22}$$

$$\begin{cases} w_1 + w_2 + w_3 = 1 \\ w_i \geq 0 \end{cases} \tag{23}$$

Where: w_i is the weight coefficient of each objective function, F_{VRB} is the total objective function.

IV. Power allocation strategy of all-vanadium liquid current energy storage system

A. Power allocation strategy

The layered control strategy of the energy storage system has the potential to enhance the flexibility and reliability of the energy storage system. Furthermore, it allows for the consideration of varying demands and constraints across different time scales. The main modules of the system are divided into three main sections, as shown in Fig. 4: the grid information layer, which responds to grid scheduling; the power allocation layer, which allocates power in real-time; and the in-situ control layer, which tracks the state of the energy storage units.

This paper employs the GA-APSO algorithm to address the power allocation challenge inherent to energy storage systems. The block diagram of the power allocation process is presented as follows. The power allocation layer receives the total power demand instructions and the operational constraints transmitted by the grid information layer and employs the enhanced algorithm to address the issue in accordance with the established multi-objective optimization model.

B. Algorithm solving

This paper employs the GA-APSO algorithm to address the aforementioned objective function. The GA-APSO algorithm, as detailed in reference [17], is a hybrid optimization algorithm that integrates the Genetic Algorithm (GA) with Adaptive

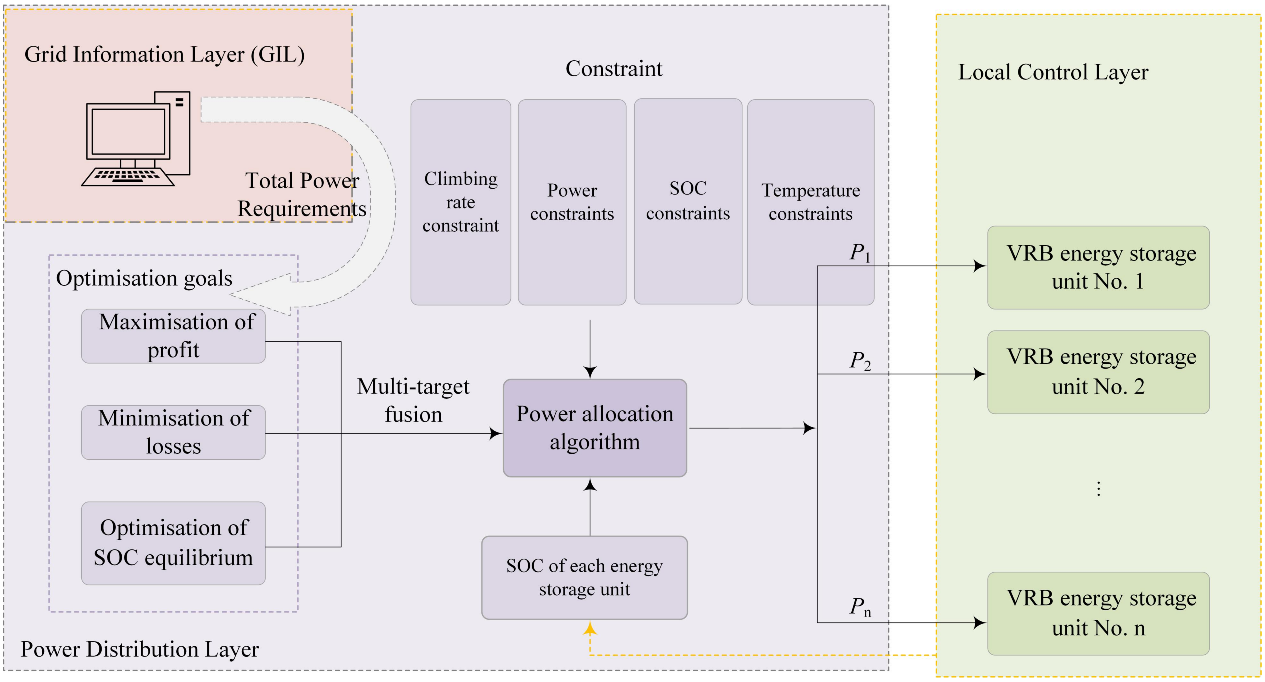

Fig.4 Power distribution strategy for energy storage system

Particle Swarm Optimisation (APSO). The objective of this algorithm is to combine the global search capability of GA with the fast convergence property of APSO in order to solve complex optimisation problems. The solution process is illustrated in Fig. 5.

Prior to solving the objective function using the GA-APSO algorithm, it is essential to obtain the scheduling information instruction of the grid information layer, i.e. $P_{\max}(t)$, specifically the total power demand, as well as the SOC values and the maximum allowable outputs of each storage unit in the local control layer, and if $P(t) > \sum P_{\max}(t)$, all the storage units are operated with the maximum power, and if $P(t) < \sum P_{\max}(t)$, then it is crucial for prioritize the SOC values of the various storage units, and to turn on the selected storage units participating in the power allocation. DC/DC i.e. $\lambda_k = 1$.

Once the energy-storage devices to be included in the power allocation process have been selected, the optimisation of the latter is conducted in accordance with the following steps:

a. Parameter initialization. Establish the starting values for the settings for optimization, which includes the population size M, the quantity of iterations S, the highest and lowest factors of hysteresis $w_{\max}$ and $w_{\min}$, the acceleration factors c_1 and c_2, the highest and lowest selection probabilities $\eta_{\max}$ and $\eta_{\min}$, the crossover probabilities p_c, the higher and lower bounds of each particle's position x_i^u and x_i^l.

$$x_i(0) = x_i^l + rand(x_i^u - x_i^l), i = 1, 2, \ldots, M \tag{24}$$

Generate a random population of size by Eq. (24) and give the starting location of every particle in the population.

b. Evaluate the fitness value. Based on the multi-objective fusion function of the optimization problem, the fitness value of each initially generated particle is evaluated and its position is ranked. Then, determine the initial best particle position of the particle swarm as well as the initial global best position and the worst position, respectively.

c. Update the particle swarm. Update the current positions and velocities of the particles according to Eqs. (25)-(28).

$$x_i(\lambda+1) = x_i(\lambda) + v_i(\lambda) \tag{25}$$

$$\begin{aligned} v_i(\lambda+1) = {} & w_i(\lambda)\cdot v_i(\lambda) + c_1 r_1 (P_i(\lambda) - x_i(\lambda)) \\ & + c_2 r_2 (P_g(\lambda) - x_i(\lambda)) \end{aligned} \tag{26}$$

Where.

$$w_i(\lambda) = w_{\min} + (w_{\max} - w_{\min})\sin(\frac{\beta_i(\lambda)\pi}{2}) \in [w_{\min}, w_{\max}] \tag{27}$$

$$\beta_i(\lambda) = \frac{f_i(\lambda) - f_g(\lambda)}{f_w(\lambda) - f_g(\lambda)} \in [0,1], i = 1, 2, \ldots, N \tag{28}$$

Where: $f(\lambda)$ is the threshold value of the first particle in this iteration; $f_g(\lambda)$ and $f_w(\lambda)$ are t the optimal and suboptimal crowd values for fitness in this iteration, respectively. From Eq. (27) and Eq. (28), the inertia factor is adaptively modified within the specified range during the iteration process.

(4) Update the best population. Assess the present wellness rating of each particle, revise the optimal particle location, and update the top-notch and global dirtiest positions of the population.

(5) Genetic algorithm operation. Produce novel particles (offspring) in accordance with the genetic algorithm to enhance population diversity. Upon satisfying the GA selection criteria in Eq. (29), both pointwise randomization and the overlap operator variation operator are used to modify the locations of the chosen particles and produce new particles.

$$0 < \left| \frac{f_i(\lambda) - f_g(\lambda)}{f_g(\lambda)} \right| < \eta \tag{29}$$

Where: $f_i(\lambda)$ is the current fitness value of the first particle at the next iteration; $f_g(\lambda)$ is the optimal fitness value of the

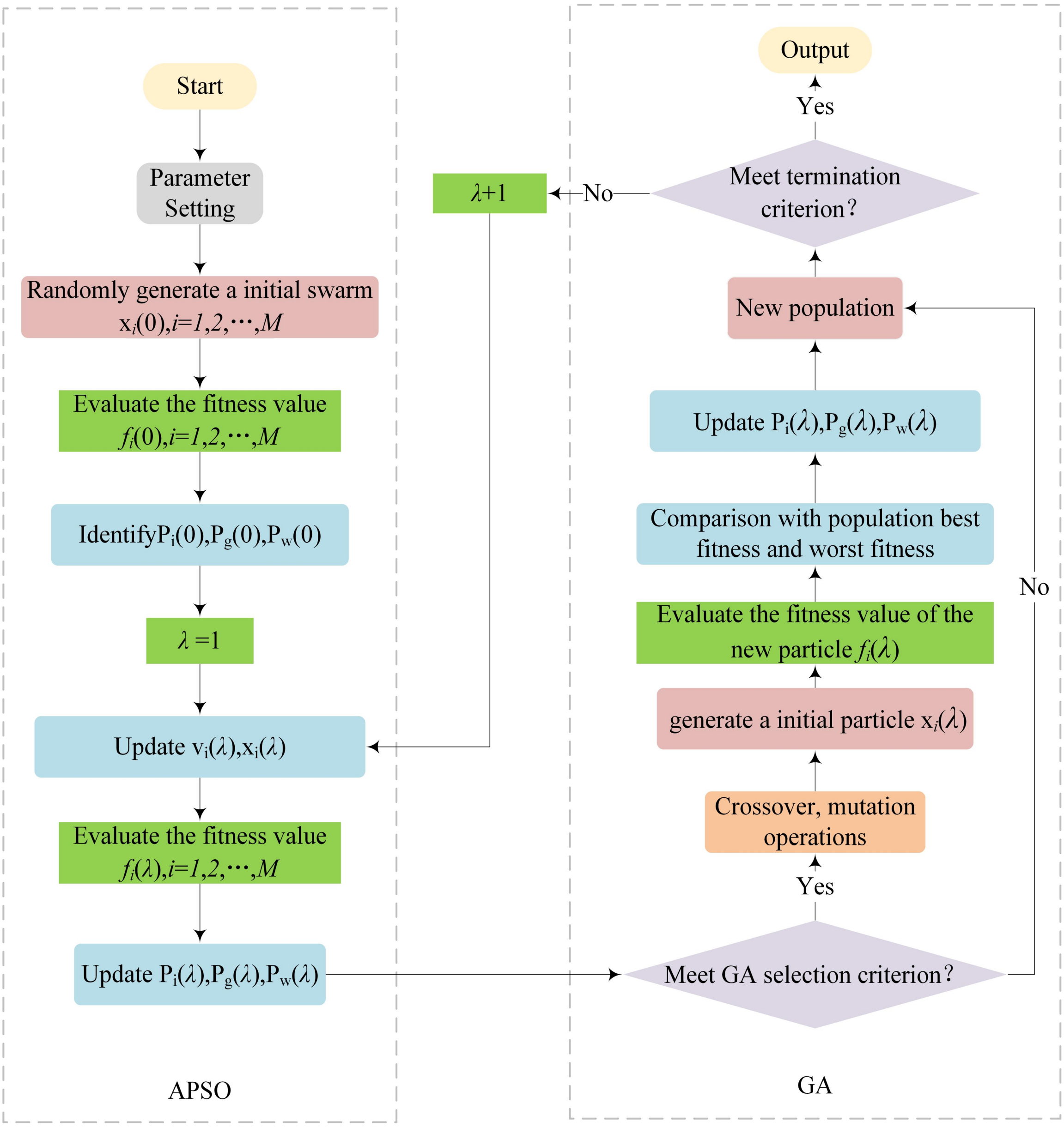

Fig.5 Flowchart of the GA-APSO

population at its global optimal position; and η is the time-varying selection probability from $\eta_{\max}$ down to $\eta_{\min}$ during the iteration process.

(6) Re-evaluation of fitness. Assess the lifetime score of the fresh particle $\overline{f_i}(\lambda)$ and juxtapose it with the optimal and suboptimal metrics for fitness of the population, respectively. If $\overline{f_i}(\lambda) < f_g(\lambda)$, replace the particle. Update the optimal particle location $P_i(\lambda)$ and the optimal and suboptimal places of the world population $P_g(\lambda)$ and $P_w(\lambda)$.

(7)Repeat the preceding stages (4)-(7) until the termination condition is satisfied, i.e., the predefined number of iterations, and output the optimal result after satisfying the update criteria.

V. Case Analysis

In order to verify the effectiveness of the power allocation strategy proposed in this paper, two arithmetic cases are used to simulate different application scenarios during the operation of the energy storage system. The first case (Case 1) compares the allocation effect of GA-APSO with GA and PSO by fixing the total output demand and improving the grid's dispatching capability. The second case (Case 2) intercepts the new energy generation and the total load demand in a regional power grid as test data, and solves the multi-objective fusion model through GA-APSO algorithm to optimise the power allocation of the storage of energy system.

A. Case 1

The energy storage method for all-vanadium liquid current batteries in Case 1 is constituted by five energy storage units, with the initial settings of each energy storage unit set out in Table 1 below. The detailed settings are defined as follows: the population scale of the particle swarm is 50, the quantity of iterations is 100, the acceleration constants $c_1 = c_2 = 2.05$, $w_{\max}$ and $w_{\min}$ are 0.9 and 0.4, respectively, the adaptive weights w are updated as shown in Eq. (27), the crossover probability pc is 0.7, and the variance probability pm is 0.2.

TABLE I
INITIAL PARAMETERS OF THE VRB ENERGY STORAGE UNIT

Parameters	No. 1	No. 2	No. 3	No. 4	No. 5
SOC	0.40	0.50	0.60	0.38	0.80
Rating/kW	50	50	50	50	50
Priority	Ⅳ	Ⅲ	Ⅱ	Ⅴ	Ⅰ

When the overall power demand of the VRB storage of energy system is 190 kW, the comparative analysis of GA-APSO with PSO and GA for optimised power allocation is presented in Table 2 below.

In order to ascertain the veracity of the prioritisation algorithm in consideration of the SOC, the total power demand is set at 260 kW and 180 kW, respectively. The resulting power allocation of the units that store energy is presented in Table 3 for the reader's convenience.

TABLE II
VRB STORAGE UNIT POWER ALLOCATION RESULTS

Algorithm	No. 1	No. 2	No. 3	No. 4	No. 5
GA	39.88	38.91	38.05	40.29	33.38
PSO	40.21	39.83	39.91	39.02	36.10
GA-APSO	38.91	37.69	37.50	39.52	36.90

TABLE III
CONSIDERING THE RESULTS OF POWER ALLOCATION IN TERMS OF PRIORITY

Total Power Requirement	No. 1	No. 2	No. 3	No. 4	No. 5
260	50.00	50.00	50.00	50.00	50.00
180	45.97	45.00	44.04	46.19	0.00

The final evolution curve of the fitness function, which was obtained by applying the three algorithms to the multi-objective fusion model for solving, is shown in Fig. 6. It illustrates that the GA algorithm is capable of maintaining diversity throughout the search space and gradually approaching the optimal solution. However, it is not particularly adept at precisely locking onto the optimal solution. The PSO algorithm typically exhibits a faster convergence speed during the initial phase but may prematurely converge on a local optimal solution. The GA-APSO algorithm effectively harnesses the rapid convergence of the PSO algorithm during the initial phase and then employs the GA algorithm's capacity to search globally during the subsequent phase, enabling it to escape from Locally optimal outcomes and enhance the overall optimization search process.

B. Case 2

From the power allocation block diagram, it can be seen that the total power demand of the VRB storage of energy system originates from the scheduling centre at the grid information layer. This paper employs the total power demand for the purpose of stabilising the fluctuations of photovoltaic and wind power, as documented in literature [18], to have to assess the efficacy of the improved algorithm in terms of power allocation. The total power demand is illustrated in Fig. 7, comprising 60 scheduling cycles (06: The time interval is set to 15 minutes, with the remaining time set to the same interval. The remaining parameter setting are identical to those described in Section *A,* with the interval set to 15 minutes.

Fig. 9 illustrates the histogram of power distribution utili-

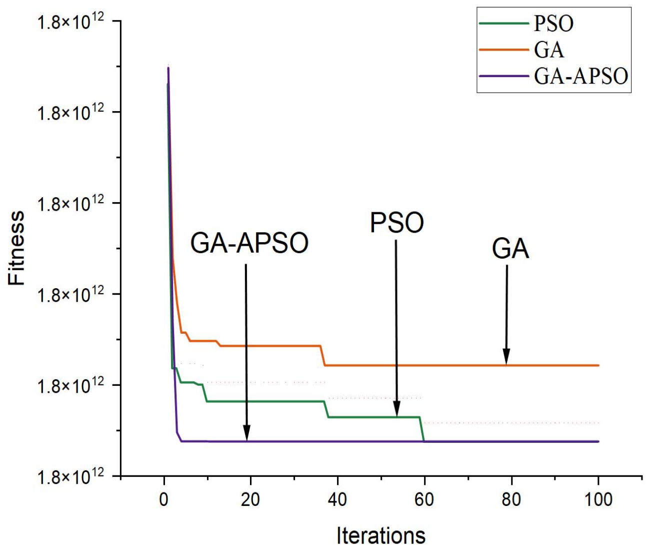

Fig.6 Algorithm objective function evolution curve

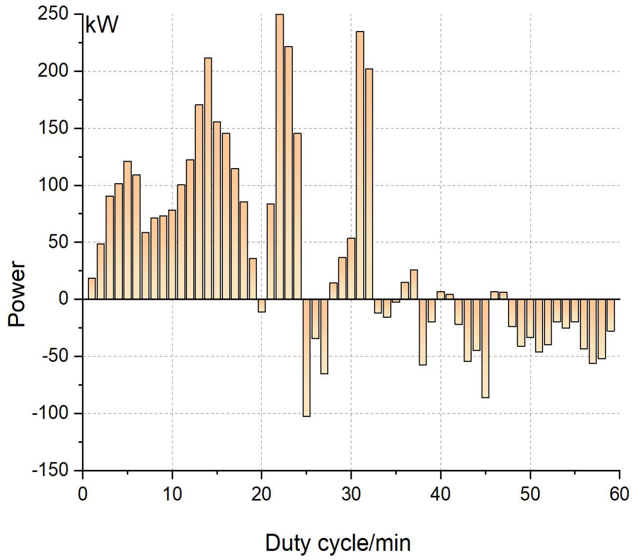

Fig.7 Total power demand for energy storage systems

sing the conventional PSO algorithm. A comparison of Fig. 8 and Fig. 9 reveals that the traditional PSO algorithm prioritises meeting the total power demand when solving, for instance, in the initial scheduling cycle, the five VRB storage units are activated, ultimately satisfying the total power demand (i.e. It can be observed that during grid-connected operation, the DC/DC converter will repeatedly commence and then cease operation. This not only results in a loss of energy from the VRB energy storage system, but also affects the overall efficiency of the energy storage system due to the significant discrepancy in the state of charge (SOC) values of each energy storage unit after 60 scheduling cycles.

The optimization process is conducted using the highest total profit of the energy storage battery unit as the goal function, and the power allocation results are computed by substituting them into the total profit function. As shown in Fig. 10, the comparative results of the total profit of the VRB energy storage cell under the conventional strategy and the GA-APSO method were obtained after the total profit of the VRB energy storage cell was finally used as the objective value.

Substituting the results of power allocation during the scheduling cycle between the traditional strategy and the GA-APSO strategy into the established loss mathematical model, the loss objective function is used to further calculate the loss rate target value of the VRB energy storage unit. The parameter settings of the equivalent circuit model in the optimisation objective are shown in Table 2 in the Appendix, and the comparison outcomes of the loss rate target values under the traditional strategy and the GA-APSO strategy are shown in Fig. 11.

An analysis of the SOC simulation curves obtained by different algorithms in Fig. 12 and Fig. 13 reveals that when the method for storing energy is operated in grid-connected mode, each VRB energy storage unit is involved in the solution process using the PSO algorithm. However, the value of SOC does not converge after 60 scheduling cycles. Conversely, when the GA-APSO algorithm is employed, the value of SOC converges.

VI. CONCLUSION

In order to solve the power allocation issue of a VRB energy storage system, this research suggests a power allocation approach based on the GA-APSO algorithm. Through a case study of several scenarios, the efficacy of the suggested approach is confirmed, and the primary findings are as follows:

a. The power allocation issue of a VRB energy storage system is addressed in this study using a multi-objective fusion model that takes profit, loss, and SOC consistency into account;

b. A method for allocating electricity depending on the GA-APSO algorithm is proposed as a means of effectively improving the solution speed of power allocation and improving the SOC balance;

c. The algorithm presented in this paper offers a valuable reference point for the allocation of power in all liquid-flow storage battery energy storage systems;

d. The VRB battery model presented in this paper employs a basic equivalent approach that does not account for the impact of voltage and current fluctuations resulting from particle diffusion within the battery. This limitation can be addressed through the development of a more precise real-time VRB equivalent battery model and the utilisation of actual numerical values to construct a multi-objective fusion model.

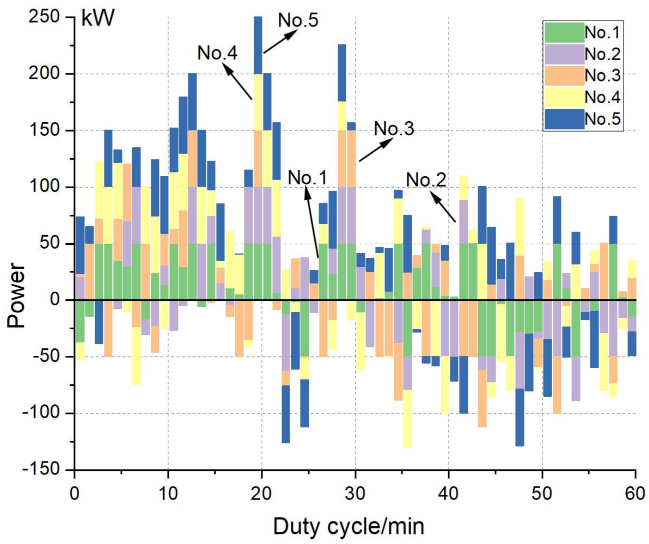

Fig.8 Power distribution histogram(PSO)

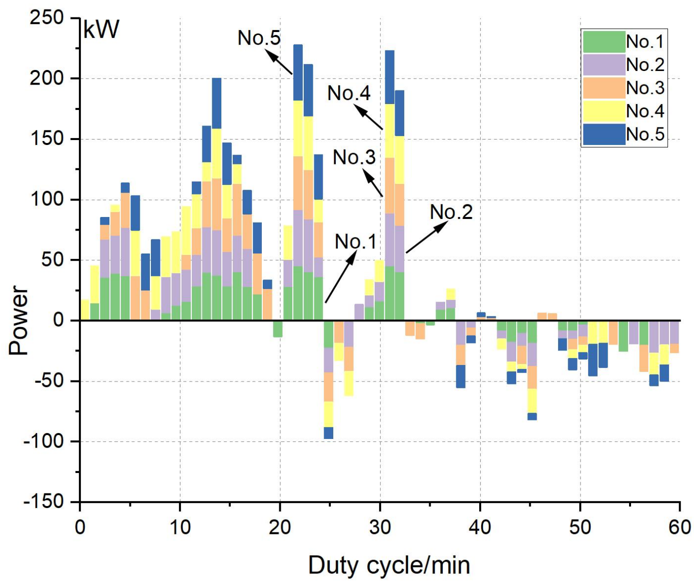

Fig.9 Power distribution histogram(GA-APSO)

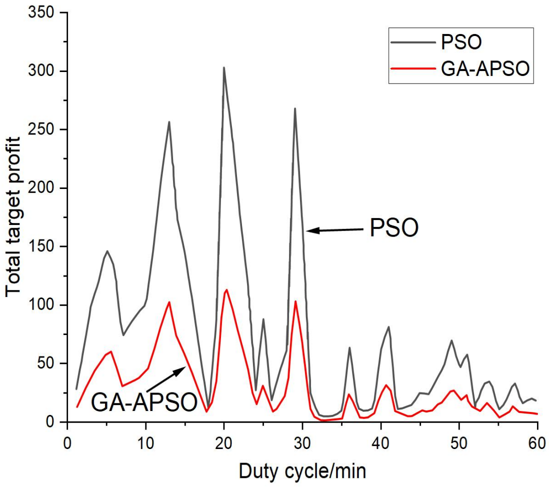

Fig.10 Total VRB Storage Battery Profit under PSO and GA-APSO Strategies

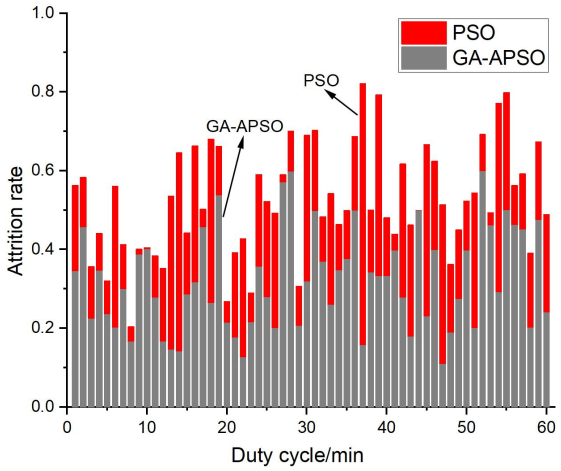

Fig.11 Comparison diagram of VRB energy storage unit loss rate

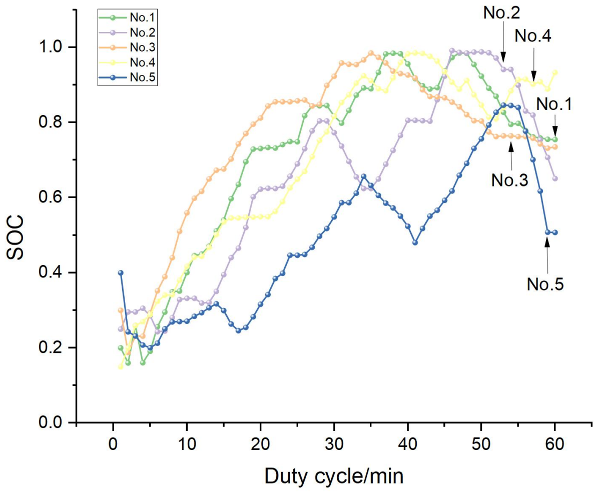

Fig.12 SOC curve of VRB energy storage unit(PSO)

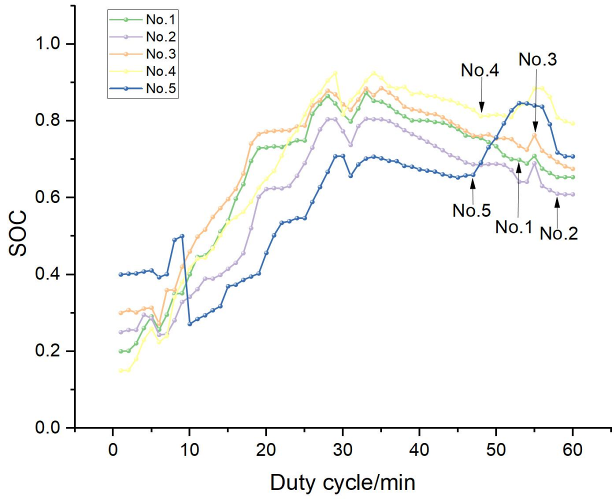

Fig.13 SOC curve of VRB energy storage unit(GA-APSO)

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