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Non-Pareto Genetic Algorithm for Optimal Planning of Multi-Type Energy Resources in Active Distribution Networks

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Based on summarizing and analyzing the typical applications of energy storage, the study established a model for an active distribution network, and analyzed the technical and economic benefits of its access to the distribution network. In addition, considering the economic and technical requirements of multiple types of energy, ensure the stable and continuous operation of multiple types of energy, and build an optimal configuration model for multiple types of energy. To achieve a reliable solution to the model, a non-Pareto genetic algorithm (NSGA-II) is designed to obtain the optimal Pareto solution set for multi-type energy location and volume schemes. The proposed solution algorithm has a rich individual update mechanism and an advanced Pareto solution set storage and screening mechanism, which can effectively solve the problem. Furthermore, idea point decision making (IPDM) has been designed to select the best compromise solution in Pareto non-dominated solution set. Finally, based on the IEEE-33 node standard test system, the input source-load uncertainty scenario set is used to construct the distribution network operation scenario, and the configuration model is solved. The results show that NSGA-II can obtain a Pareto front with better solution quality and a more uniform distribution. After accessing the battery energy storage systems (BESS), the annual total power fluctuation and peak-valley difference of daily maximum load have been reduced by 19.25% and 11.8% respectively.

Keywords: energy storage, multi-type energy resources, multi-objective optimization, non-Pareto genetic algorithm, Pareto front

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1 INTRODUCTION

Today, the energy structure has ushered in profound changes, and the energy industry urgently needs to seek new development space (Sepulveda Rangel et al., 2018). Facing the dual pressure of resources and environment, renewable energy with the advantages of rich reserves, and low carbon provides new opportunities for the transformation of energy structure (Yu et al., 2016; Liu et al., 2020; Peng et al., 2020; Sun et al., 2020). Therefore, promoting new energy is an important measure to promote the adjustment of global energy structure and the transformation of clean and low-carbon consumption side. However, the key to the high-quality development of new energy industry is to fully absorb it and ensure the safe, stable and efficient operation of power grid.

In addition, the role of energy storage in regulating the power grid and supporting new energy depends largely on the construction address and configuration capacity of large-scale energy storage, that is, the reasonable optimal configuration can not only reduce the cost but also maximize the role of multi-type energy storage systems (Wang et al., 2014). On the contrary, improper access location may cause voltage out of limit, line loss increases, and other problems, and even affect the safety of power grid operation (Kerdphol et al., 2016a). At the same time, the efficiency and service life of multi-type energy storage system components will be reduced due to the long-term insufficient charging state (Zhou et al., 2021). In addition, if the capacity allocation is too small, it cannot effectively absorb excess wind and photovoltaic power resources, and even affect voltage and frequency regulation (Gan et al., 2019). Therefore, the optimal allocation technology of BESS is to be solved in the design (Kerdphol et al., 2016b). With the continuous increase in new energy grid-connected capacity, the uncertainty of BESS operation is becoming more and more prominent (Hlal et al., 2019). At present, in the energy storage allocation model of the distribution network, some only consider a single economic index, and the technical index is often considered in the constraints (Chong et al., 2016). For example, Chong et al., 2018) established a two-stage energy storage location and volume optimization model for the whole life cycle, which reduced the investment cost.

Furthermore, many studies use multi-objective optimization methods to objectively select the weight, so as to achieve the best compromise between economic and technical objectives (Jia et al., 2017; Wu et al., 2019). In particular, we can make a trade-off between technology and economy, so as to make the final energy storage allocation scheme more reasonable (He et al., 2015). At present, there are mainly analytical methods, numerical methods, heuristic algorithms, neural network–based methods, and so on (He et al., 2021). However, most research models are single-objective models, which cannot reasonably coordinate the economy of energy storage and power grid stability. Meng et al. (2021) proposed a two-layer BESS planning scheme considering the uncertainty of new energy and load. However, they did not mention the screening scheme of Pareto's non-dominated solution and did not consider the influence of access to the BESS on power grid stability. Wu et al. (2014) established a multi-objective optimization model based on the minimum voltage fluctuation and load fluctuation of nodes and the total capacity of BESS. However, this model does not consider the cost of investment operation and maintenance of BESS and lacks practical engineering application. Liu et al. (2021) took BESS economic benefit and voltage quality as optimization objectives and established a multi-objective optimal allocation model. However, voltage quality cannot fully reflect the real operation of the power grid after access to the BESS.

The traditional analysis methods and numerical methods are difficult to solve accurately and quickly, and cannot guarantee the global nature of the solution. Meta-heuristic algorithms are popular because of their flexibility, model, and avoidance of local optimization (Oudalov et al., 2007; Li et al., 2018; Pang et al., 2019; Yang et al., 2020). However, the traditional meta-heuristic algorithm has the problems of strong search randomness, and low avoidance rate of local optimization, and is only suitable for a single objective solution.

In the study, BESS considering both economic and technical indicators is established. The main contributions are as follows:

1) A non-Pareto genetic algorithm (NSGA-II) with good optimization performance is designed based on Pareto theory.
2) The application design of the algorithm is carried out to apply the proposed algorithm to the solution of the battery energy storage system (BESS) multi-objective optimization allocation model. Different algorithms are used to solve the established BESS multi-objective optimal configuration model. It is verified that the proposed solution method can obtain the Pareto Frontier with better solution quality and a more uniform distribution.
3) Idea point decision making (IPDM) has been designed to select the best compromise solution in the Pareto non-dominated solution set.

The structure of this study is as follows: **Section 2** develops the location and capacity planning modeling of BESS. **Section 3** introduces NSGA-II based on IPDM. **Section 4** develops the case studies. In **Section 5**, the content of this study is summarized and the prospect of future research is proposed.

2 MODELING OF BESS LOCATION AND CAPACITY PLANNING

In BESS planning, it is necessary to comprehensively consider BESS investment cost-effectiveness and distribution network operation reliability (Wong et al., 2019). Therefore, the optimization model is as follows:

$$\begin{cases} \min\limits_{X} \boldsymbol{F}(\boldsymbol{X},\boldsymbol{x}) = [F_1(\boldsymbol{X},\boldsymbol{x}), \cdots, F_h(\boldsymbol{X},\boldsymbol{x})],\ h = 1,2,3, \\ \text{s.t. } \boldsymbol{G}(\boldsymbol{X},\boldsymbol{x}) \le 0, \end{cases} \tag{1}$$

where $F_h(\boldsymbol{X},\boldsymbol{x})$ is the hth objective function (Zakeri and Syri, 2015).

2.1 Objective Functions

In the planning of an energy storage power station, the investor often makes investment planning based on the principle of the minimum cost, while the operator optimizes the allocation based on the principle of maximizing the comprehensive benefits brought by the BESS (Harvey, 2020; Injeti and Thunuguntla, 2020).

Therefore, the total annual investment and operation cost of the system considered in the outer objective function is described as follows (Huang et al., 2020):

$$F_1 = C_{\mathrm{TCC}} + C_{\mathrm{OM}} + C_{\mathrm{cha}} - I_{\mathrm{dis}} - I_{\mathrm{sub}} + C_{\mathrm{cur}} + C_{\mathrm{Ploss}} + C_{\mathrm{ENV}}, \tag{2}$$

where C_{cur}, C_{Ploss}, and C_{ENV} represent the annual wind and light abandonment cost, network loss cost, and carbon emission cost caused by conventional power peak shaving of the distribution network, respectively. In addition, C_{cha}, I_{dis}, and I_{sub} represent government subsidies for BESS's annual power purchase expenses, power sales revenue, and power sales, respectively.

For C_{TCC}, it needs to satisfy the following equation.

$$\begin{cases} C_{\mathrm{TCC}} = \left[C_{\mathrm{inv}} \cdot N_{\mathrm{BESS}} + \sum_{n=1}^{N_{\mathrm{BESS}}} \left(a \cdot P_{\mathrm{BESS},n} + b \cdot E_{\mathrm{BESS},n}\right)\right] \cdot \mu_{\mathrm{CRF},} \\ \mu_{\mathrm{CRF}} = \dfrac{y \cdot (1+y)^{x}}{(1+y)^{x} - 1}, \end{cases} \tag{3}$$

where C_{inv} is the fixed investment and construction cost of an energy storage power station (Fonseca and Fleming, 1993), $E_{\mathrm{BESS},n}$ and $P_{\mathrm{BESS},n}$ represent the configured capacity and power of the nth BESS, respectively, a and b are the unit power and the unit capacity cost, respectively,μ_{CRF} is the annual capital recovery rate, and x is the service life of BESS, which is 10 years in this study (Zhang et al., 2017).

For C_{TCC} is expressed as:

$$C_{\mathrm{OM}} = \left[\sum_{n=1}^{N_{\mathrm{BESS}}} \left(a \cdot P_{\mathrm{BESS},n} + b \cdot E_{\mathrm{BESS},n}\right)\right] \cdot \rho_{\mathrm{om}}, \tag{4}$$

where ρ_{om} is the manipulation coefficient, which is taken as 5% in Mirjalili et al. (2017).

For C_{cha} and I_{dis}, it can be calculated by.

$$C_{\mathrm{cha}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{n=1}^{N_{\mathrm{BESS}}} \sum_{t=1}^{T} \left[\rho_{\mathrm{pur}}(t) \cdot P_{\mathrm{cha},n}(t)\right]\right), \tag{5}$$

$$I_{\mathrm{dis}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{n=1}^{N_{\mathrm{BESS}}} \sum_{t=1}^{T} \left[\rho_{\mathrm{sell}}(t) \cdot P_{\mathrm{dis},n}(t)\right]\right), \tag{6}$$

where M_d refers to the number of scenes, D_m is the number of days corresponding to the mth scenario, $\rho_{\mathrm{pur}}(t)$ and $\rho_{\mathrm{sell}}(t)$ represent the power purchase and sale price of BESS in t period, respectively (Moscato, 1989),$P_{\mathrm{cha},n}(t)$ and $P_{\mathrm{dis},n}(t)$ are the charging and discharging power of the nth BESS in t period, respectively, and T is a scheduling cycle, that is, 24 h.

In addition, for I_{sub}, it gives.

$$I_{\mathrm{sub}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{n=1}^{N_{\mathrm{BESS}}} \sum_{t=1}^{T} \left[\lambda \cdot P_{\mathrm{dis},n}(t)\right]\right). \tag{7}$$

For C_{cur}, it can be calculated by.

$$C_{\mathrm{cur}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{t=1}^{T} \left[P_{\mathrm{wind}}(t) + P_{\mathrm{PV}}(t) + P_{\mathrm{cha/dis}}(t) - P_{\mathrm{load}}(t) - P_{\mathrm{Ploss}}(t)\right]\right) \cdot \gamma, \tag{8}$$

where $P_{\mathrm{Ploss}}(t)$ is the power of line loss andγ is a benefit subsidy given by the government to the BESS to absorb new energy (Neri and Cotta, 2012).

For C_{Ploss}, it needs to satisfy the following equation.

$$C_{\mathrm{Ploss}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{n=1}^{N_{\mathrm{BESS}}} \sum_{t=1}^{T} \left[\rho_{\mathrm{sell}}(t) \cdot P_{\mathrm{Ploss}}(t)\right]\right). \tag{9}$$

For C_{ENV}, it gives.

$$C_{\mathrm{ENV}} = \sum_{m=1}^{M_{\mathrm{d}}} D_m \cdot \left(\sum_{t=1}^{T} P_{\mathrm{grid}}(t) \cdot \sum_{p=1}^{P} \left(U_p \cdot u_p\right)\right), \mathrm{s.t.} P_{\mathrm{grid}}(t) > 0, \tag{10}$$

where $P_{\mathrm{grid}}(t)$ refers to the quantity of electricity purchased by the distribution network from the superior power grid in t period. (Mirjalili et al., 2017).

2.2 Constraint Conditions

The constraints of the model include system operation constraints, that is, node power balance constraints, node voltage constraints, parallel node power constraints, and wind and light rejection constraints. These constraints ensure the safety and reliability of the operation state of the whole distribution network, and promote consumption of new energy as much as possible by meeting the wind and light rejection rate (Eusuff and Lansey, 2003).

2.2.1 Node Voltage Constraints

$$V_i(t) = \sqrt{\left(V_j(t) - \left(r_{ij} \cdot P_{ij}(t) + x_{ij} \cdot Q_{ij}(t)\right)\right)^2 + \left(r_{ij} \cdot P_{ij}(t) + x_{ij} \cdot Q_{ij}(t)\right)^2}, \tag{11}$$

where $P_{ij}(t)$ and $Q_{ij}(t)$ are the reactive and active power flowing through and between nodes, respectively, and r_{ij} represent the resistance of the transmission line under the resistance (Coello et al., 2004).

2.2.2 BESS Power and Capacity Constraints

$$\begin{cases} E_{\mathrm{BESS}}^{\min} \le E_{\mathrm{BESS},n} \le E_{\mathrm{BESS}}^{\max}, \\ P_{\mathrm{BESS}}^{\min} \le PL_{\mathrm{grid}} \le P_{\mathrm{BESS}}^{\max}, \end{cases} \tag{12}$$

where $E_{\mathrm{BESS}}^{\min}$, $E_{\mathrm{BESS}}^{\max}$, $P_{\mathrm{BESS}}^{\min}$, and $P_{\mathrm{BESS}}^{\max}$ represent the upper and lower limits of the BESS configuration capacity and the upper and lower limits of the configuration power, respectively, under the conditions of installation site, grid-connected power, and total load (Faramarzi et al., 2020). It should be noted that, in order to ensure that the BESSs can meet the load demand of the distribution network as much as possible without wasting energy storage resources, this study sets the total installed BESSs within the range of 10%–90% of the total system load power to set the rated power of a single BESS. Upper and lower limits.

2.2.3 BESS Installation Position Constraints

$$\begin{cases} L_{\mathrm{BESS},n} \in N_{\mathrm{nodes}}, L_{\mathrm{BESS},n} \ne L_{\mathrm{grid}}, \\ L_{\mathrm{BESS},n} \ne L_{\mathrm{BESS},n+1}, \end{cases} \tag{13}$$

where $L_{\mathrm{BESS},n}$ is the installation node of the nth BESS. It should be noted that the BESS can be installed on any node except the contact point, but not on the same node.

2.2.4 State of Charge of BESSs

The state of charge (SOC) of BESSs at any time is an important parameter of charge–discharge operation, which is described by capacity, charge–discharge power, charge–discharge efficiency, and other variables. The BESS SOC is calculated as follows:

$$\begin{cases} SOC_i(t) = (1-\delta\cdot\Delta t)\cdot SOC_i(t-1) + \left(P_{\text{cha},i}(t)\cdot\eta_{\text{cha},i}\right)\cdot\Delta t, \\ SOC_i(t) = (1-\delta\cdot\Delta t)\cdot SOC_i(t-1) - \left(P_{\text{dis},i}(t)/\eta_{\text{dis},i}\right)\cdot\Delta t, \end{cases} \tag{14}$$

where $P_{cha,i}(t)$ and $P_{\text{dis},i}(t)$ are the charging and discharging power of the node in the period, respectively; $\eta_{cha,i}$ and $\eta_{\text{dis},i}$ are the charging and discharging efficiency of the node in the period, respectively.

3 NON-DOMINATED SORTING GENETIC ALGORITHM BASED ON PARETO

3.1 Non-Dominated Sorting Genetic Algorithm

At present, the multi-objective optimization algorithm can be divided into two types: based on the Pareto optimal solution and non-Pareto optimal solution. The principle of the non-Pareto method is a genetic algorithm based on vector evaluation, which is easy to fall into local optimal solution, so this algorithm needs to be improved. The elite strategy is added on the basis of the first-generation non-dominated genetic algorithm. It is a more practical multi-objective optimization algorithm.

3.1.1 Construction Method

Setting the population to P, n_P, and S_P, these are the parameters that the algorithm needs to calculate for each individual population, where n_P individuals dominate the number of individuals P in the population and S_P is the set of individuals in the individual population P. When traversing the entire population, the total computational complexity of these two parameters is 0 (Tian et al., 2019).

3.1.2 Methods to Maintain the Distribution and Diversity of Solution Groups

Among them, there are two sub targets f_1 and f_2, and $P[i]_{distance}$ distance is the aggregation distance, and then the distance of individual i is.

$$P[i]_{distance} = \left(f_1P[i+1] - f_1P[i-1] + f_2P[i+1]\right) - f_2P[i-1]. \tag{15}$$

In order to make the solution more uniform in the target space, the crowding degree (n_d) is the following formula.

$$n_d = \left(f_mP[i+1] - f_m P[i-1]\right)/\left(f_m^{max} - f_m^{min}\right). \tag{16}$$

3.1.3 Crowding Distance

NSGA-II maintains population diversity by calculating the crowding distance. Crowding distance describes a group (Schott, 1995; Wang et al., 2010; Long et al., 2022). First, let the individual i be represented by d, and set $d_i = 0$. In addition, let fm be the objective function, $m = 1, 2, \ldots M$. The maximum value of the function value is set to $d_1 = d_L = \infty$. In particular, the calculation method of non-boundary individual i congestion distance is as follows:

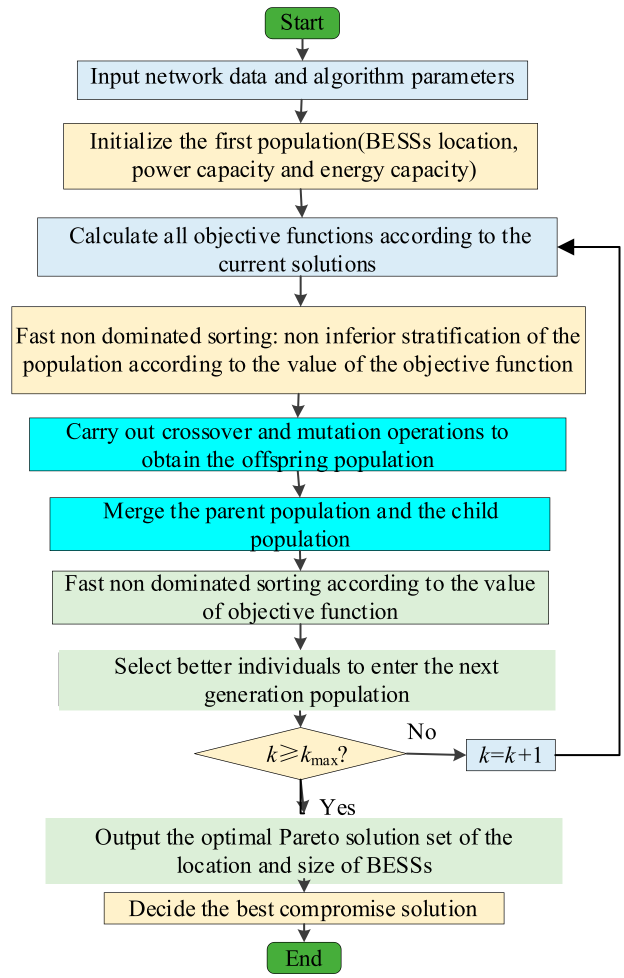

FIGURE 1 | Flowchart of NSGA-II for the optimal location and size of BESSs.

$$d_i = \sum_{m=1}^{M} \frac{\left|f_m(i-1) - f_m(i+1)\right|}{f_m^{max} - f_m^{min}}. \tag{17}$$

3.2 Pareto Solution Set Storage and Filtering

The Pareto solution set will be updated continuously during NSGA-II iteration. After obtaining a new solution set in each iteration, NSGA-II must compare it with the Pareto optimal solution set in the storage pool one by one, so as to judge whether the new solution set dominates the solution in the storage pool, and then update the storage pool. NSGA-II will eliminate some optimal solutions by the following formula.

$$\begin{cases} \left|F_m(x_i) - F_m\left(x_j\right) < D_h\right|, m = 1,\ 2,\ 3, \\ D_m = \dfrac{F_m^{\max} - F_m^{\min}}{N_r}, \end{cases} \tag{18}$$

where $F_m(x_i)$ is the mth objective function, and D_m is the Pareto leading edge distance threshold of the mth objective function value. In addition, the flowchart of NSGA-II is shown in **Figure 1**.

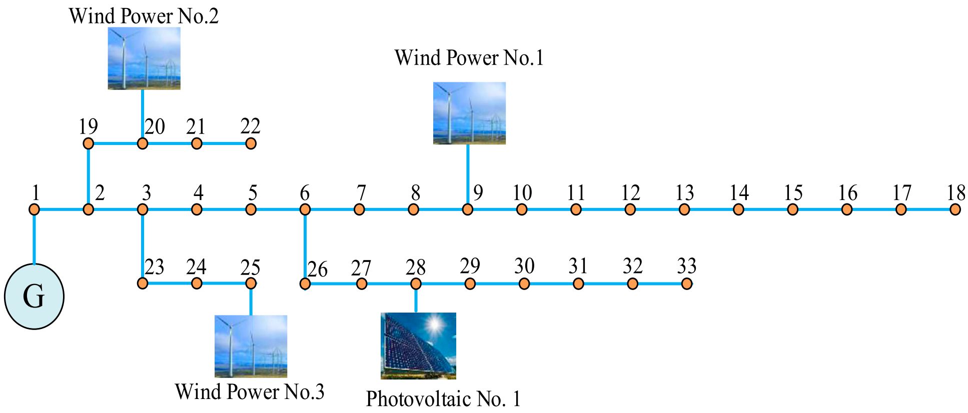

FIGURE 2 | Extended IEEE-33 node system topology.

TABLE 1 | Relevant parameters of BESSs.

Parameter	Symbol	Value
Fixed investment cost	*Cap*	1,000,000 (yuan/per BESS)
Unit power cost	*a*	1,370,000 (yuan/MW)
Power generation online subsidy	λ	0.1yuan/kW·h
Operation and maintenance cost coefficient	ρ_{om}	5%
Discount rate	*r*	6.33%
Charging efficiency	η_{cha}	95%
Discharge efficiency	η_{dis}	95%
Self-discharge rate	δ	1%

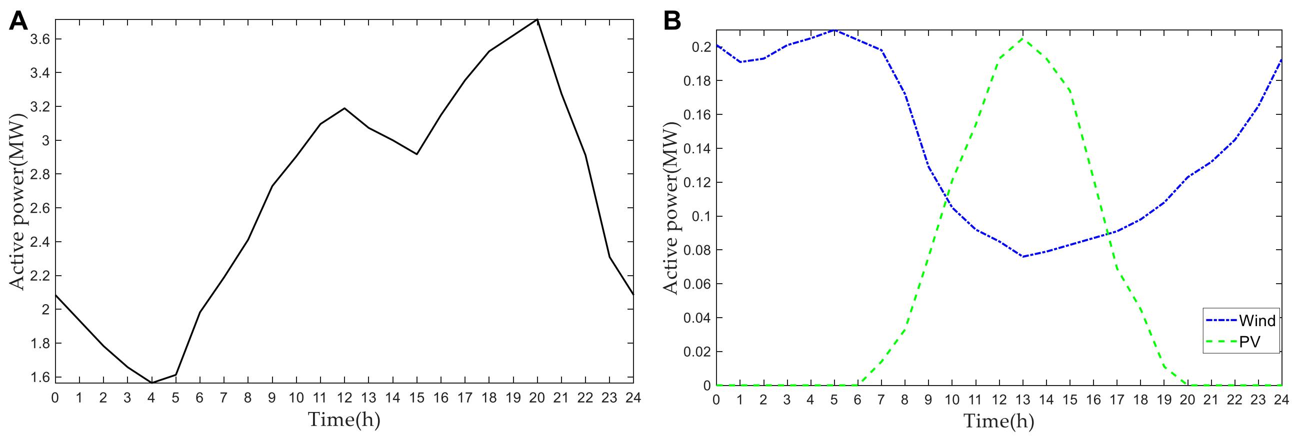

FIGURE 3 | Typical daily curves. **(A)** hourly load curve. **(B)** wind and photovoltaic power curve.

4 CASE STUDIES

In this section, in order to verify the effectiveness and superiority of the BESS optimal configuration model and its solution method proposed in this study, it is necessary to conduct simulation analysis based on the distribution network standard test system. Therefore, this study takes the power system IEEE-33 system as the basic simulation model, connects some nodes of the test system to new energy sources, and simulates the distribution network operating environment with source load uncertainty. NSGA-II is used to solve the BESS double-layer multi-objective optimal configuration model, and different optimal configuration

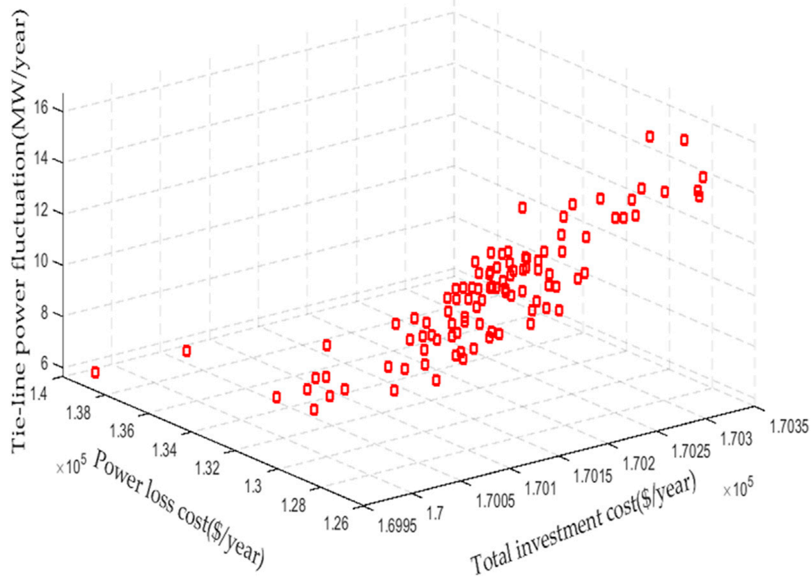

FIGURE 4 | Three-objective Pareto front results.

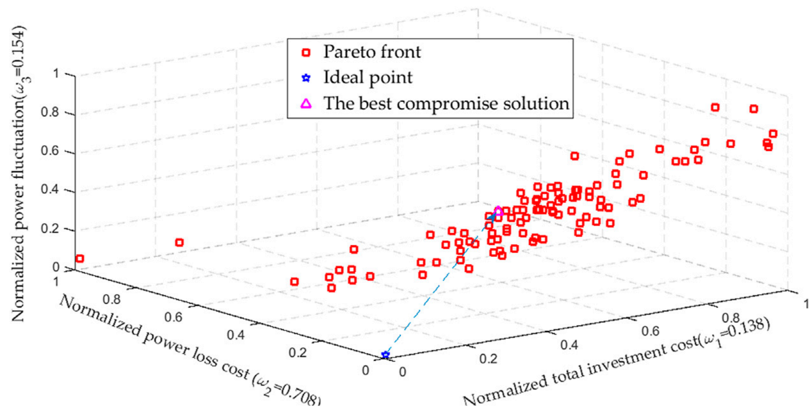

FIGURE 5 | Schematic diagram of IPDM based on NSGA-II.

schemes are compared to verify the superiority of the algorithm in this study.

The grid structure is shown in **Figure 2**, in which the public coupling point is connected with the superior power grid and node one to realize the power exchange between the superior network and the distribution network.

The example in this study assumes that two BESSs are configured in the extended IEEE-33 node distribution network, the allowable installation position of each BESS is node (Moscato, 1989; Liu et al., 2020), and the installation positions of the two BESSs are mutually exclusive. In addition, the configured rated capacity range is (Sepulveda Rangel et al., 2018; Zhou et al., 2021) MW·h; the range of rated power is [0.25,2] MW, and the range of BESS charge and discharge power is [−2,2] MW. The lithium battery with mature technology and wide application is selected as the energy storage element of BESS. The relevant parameters of lithium battery are shown in **Table 1**.

Typical daily curves of (a) hourly load curves and (b) wind and photovoltaic power curves are shown in **Figure 3**. In addition, set the population size of the NSGA-II to 100, and the maximum number of iterations to 500. In particular, the multi-objective optimization and the size of the repository are chosen to be 100.

4.1 Simulation Results

Figures 4, **5** show the three-objective Pareto front and the approximate ideal Pareto optimal front after five independent operations, respectively. In addition, the Pareto non-dominated solution set obtained by NSGA-II proposed in this study is

TABLE 2 | Results of NSGA2.

The best compromise allocation scheme of BESS			Objective function values under the best compromise allocation scheme			Weights of objective function
Bus location	Energy capacity (kWh)	Power capacity (kW)	Investment cost ($/year)	Loss cost ($/year)	Tie-line power fluctuation (MW/year)	(ω_1, ω_2, ω_3)
(13, 18)	(384, 396.7)	(69.5, 92)	1.701e + 05	1.283e + 05	11.91	(0.138,0.708,0.154)

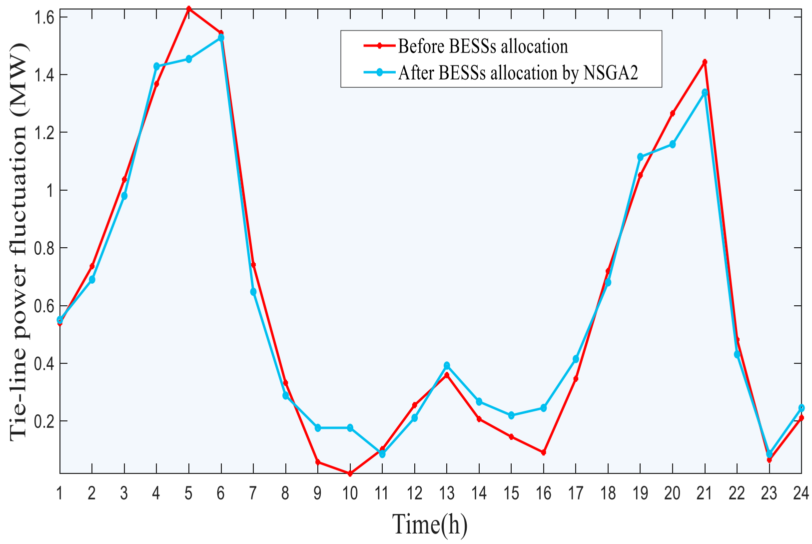

FIGURE 6 | Annual average load curve of the distribution network before and after BESS allocation.

excellent under the same number of iterations, population number, and external archive set size.

In addition, **Table 2** presents the scheme for the BESS assignment of the two algorithms, and gives the objective function value. NSGA-II in the optimal positioning of BESS and the determined multi-objective optimization model.

In addition, the peak-to-valley difference of the equivalent load of the distribution network increases significantly, and the load fluctuation intensifies. **Figure 6** shows that the load regulation demand of the distribution network increases, and the power fluctuation of the tie-line increases accordingly. In particular, after the rational configuration of BESS, the peak-to-valley of the distribution network has been reduced, and the power fluctuation has also been improved. Compared with the scenario before the BESS configuration, the total tie-line power fluctuation for the whole year decreased from 14.75 to 11.91MW, with an improvement rate of 19.25%; the daily maximum load peak-to-valley difference also decreased from 1.61 to 1.42MW, with an improvement rate of 11.8%.

Therefore, the BESS can reduce the pressure of power grid peak regulation and the investment of backup units in the distribution network and the expansion of substation equipment, and make more efficient use of electric energy. At the same time, the BESS with its fast power regulation ability stabilizes the load fluctuation to a certain extent, improves the power stability of the power grid, and improves the power supply quality.

5 CONCLUSION

Focusing on the optimal configuration of BESS in the distribution network, this study researches source-load uncertainty analysis, the establishment of an optimal configuration model, and model solving algorithm design. A multi-objective optimization configuration model and a multi-objective optimization algorithm with excellent performance are designed to solve the BESS configuration scheme that can take into account the demands of various stakeholders. The main research work and contributions are as follows:

1) This study comprehensively introduced the application scenarios of energy storage, summarized the parameter characteristics, advantages and disadvantages, and application scope of various energy storage technologies, expounded on the structure, circuit, and operation mechanism of BESS, and then analyzed the energy storage from the perspective of the distribution network;
2) NSGA-II with good optimization performance is adopted, and according to the Pareto multi-objective optimization theory and the roulette method based on crowding distance sorting,

the original GA is improved. The Pareto solution set storage and screening mechanism based on the crowding distance also enables the algorithm to more effectively approach high-quality optimal solutions and obtain uniform distribution;

3) The results show that the NSGA-II method with equilibrium indicators can provide decision-makers with a more scientific and effective decision-making scheme, and realize the best trade-off and ideal decision-making among the system.
4) The analysis of the optimization results of the distribution network also proves that the optimal configuration scheme of the BESS can be reasonably charged and discharged, while ensuring its economical operation, effectively improving the voltage quality.
5) The simulation result shows that the annual total power fluctuation and the daily maximum load peak-to-valley difference have been reduced by 19.25% and 11.8%, respectively.

In particular, the benefits of the conventional power supply side, the grid side, and the new energy side have been quantitatively analyzed and included in the total system investment and operation cost, it is not comprehensive and cannot accurately reflect the benefits that BESS brings to the entire power system. Second, the cost and benefit of BESS in the whole life cycle should be calculated, and its economic benefit evaluation index should be further improved in the follow up. In addition, the outer multi-objective optimization model mainly considers two reliability indicators of distribution network voltage fluctuation and load fluctuation. Other factors can be considered in future research to further study the influence and impact of BESS on the distribution network.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material; further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

Data simulation is performed by HQ. KL helped in writing of the manuscript. ZC provided ideas and helped in funding and writing.

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Conflict of Interest: HQ and ZC were employed by the company Guangxi Power Grid Co., Ltd. and KL was employed by the company Central Southern China Electric Power Design Institute Co., Ltd.

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