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# A survey on investment efficiency-oriented power grid infrastructure planning

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This paper proposes an investment efficiency-oriented strategy for power grid infrastructure planning with high penetration of renewable energy sources. First, a multi-objective investment portfolio optimization model based on data envelopment analysis is proposed to improve the cost efficiency of power grid infrastructure planning. Then, an evolutionary algorithm based on super-efficiency hyperplane projection transformation is developed to obtain the optimal Pareto frontier of the multi-objective investment portfolio. Furthermore, a super-efficiency envelope model with non-radial relaxation variables is formulated to identify an optimal investment efficiency-oriented solution from the Pareto frontier set. Comparative case studies have been implemented to demonstrate the superior performance of the proposed strategy for investment efficiency enhancement of power grid infrastructure planning.

KEYWORDS

**cost efficiency, investment portfolio, power grid planning, renewable energy, multi-objective optimization**

## 1 Introduction

Modern power grids are gradually being dominated by various renewable energy sources due to global low-carbon and environmental concerns (Yi et al., 2023). The integration of renewable energy into the grid will bring about an increase in the cost of various infrastructure investment categories because of its intermittent, volatile, and regional characteristics (Guo et al., 2023; Saxena and Shankar, 2024; Fu et al., 2022; Sha et al., 2023). Faced with mounting operational expenses and constrained investment capacities, power grids must devise portfolio optimization strategies to minimize costs while maximizing investment returns (Lu et al., 2022). The investment portfolio in power grid infrastructure is a dynamic, sequentially coupled, multi-objective discrete combinatorial optimization problem (Liu et al., 2023). Traditional infrastructure investment portfolio decisions that focus on maximizing a single benefit objective are inadequate for meeting the demands of high-quality development in power grids (Yan et al., 2022; Garifi et al., 2022; Ma et al., 2020; Guelpa et al., 2019). Therefore, this study provides practical models and algorithms for grid infrastructure investment planning oriented to maximize investment efficiency.

The main contributions of this work can be twofold, as follows: (1) a multi-objective cost efficiency-oriented investment portfolio optimization model based on

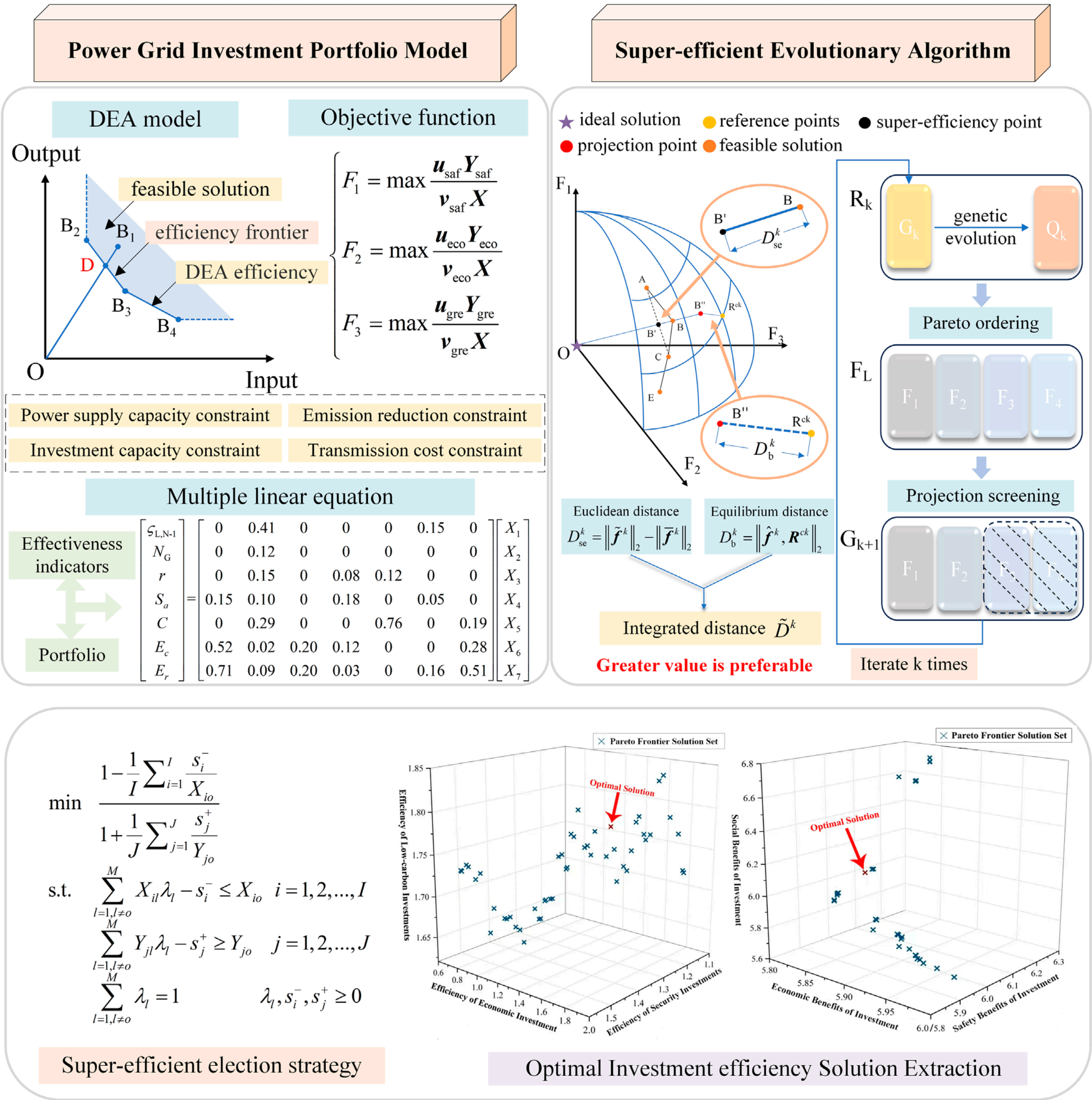


FIGURE 1
Multi-objective cost efficiency-oriented investment portfolio optimization model.

data envelopment analysis is proposed for power grid infrastructure planning, and a transformation matrix based on the LASSO regression model is established with the goal of reducing the complexity of the portfolio optimization, representing the relationship between the amount of investment and benefits. (2) An evolutionary algorithm based on super-efficiency hyperplane projection transformation is developed to obtain the optimal Pareto frontier of the multi-objective investment portfolio, and a super-efficiency envelope model with non-radial relaxation variables is formulated to identify the optimal investment efficiency-oriented solution from the Pareto frontier set.

## 2 Multi-objective cost efficiency-oriented investment portfolio optimization model

With the increase in investment demand and the concurrent decrease in investment capacity, it has become crucial for grid operators to prioritize investment efficiency when developing annual investment plans (Wu et al., 2022). Thus, it is necessary to establish a multi-objective cost efficiency-oriented investment portfolio optimization model that considers constraints such as investment capacity, power supply reliability (Cao et al., 2024a), energy conservation, and emission reduction. An investment

TABLE 1 Parameter settings of the investment portfolio optimization model.

| Parameter | Value | Parameter description |
|---|---|---|
| $X_{\max}$ | 27.6 billion yuan | Maximum investment capacity |
| $M$ | 100 | Population size |
| $\tau_c$ | 0.9 | Population crossover probability |
| $\tau_v$ | 0.1 | Population mutation probability |
| $N$ | 200 | Iteration times |
| $\varsigma_{\mathrm{L,N-1}}^{\min}$ | 98.80% | Lower limit value of N-1 line passing rate |
| $N_{\mathrm{GZ}}^{\min}$ | 1.2% | Lower limit value of the heavy overload equipment reduction rate |
| $r^{\min}$ | 2.10 MVA/MW | Lower limit value of the capacity–load ratio |
| $r^{\max}$ | 2.45 MVA/MW | Upper limit value of the capacity–load ratio |
| $S_a^{\min}$ | 2.9 MVA per household | Lower limit value of the average household power distribution capacity |
| $S_a^{\max}$ | 3.1 MVA per household | Upper limit value of the average household power distribution capacity |
| $C^{\min}$ | 184.2 yuan/kWh | Lower limit value of transmission and distribution cost per unit of electricity |
| $E_c^{\min}$ | 65,000 tons | Lower limit value of standard coal saved |
| $E_r^{\min}$ | 165,000 tons | Lower limit value of pollutant emission reduction |

efficiency-oriented model is formulated based on data envelopment analysis (DEA) by mapping power grid investment portfolios to efficiency indicators (Lee and Chen, 2024; Xu et al., 2024). Then, three investment efficiency objective functions are formulated through this approach: safety investment efficiency, economic investment efficiency, and green investment efficiency of power grid infrastructure investment, as outlined in Equation 1:

$$\begin{cases} F_1 = \max \dfrac{\boldsymbol{u}_{\mathrm{saf}}\boldsymbol{Y}_{\mathrm{saf}}}{\boldsymbol{v}_{\mathrm{saf}}\boldsymbol{X}} \\ F_2 = \max \dfrac{\boldsymbol{u}_{\mathrm{eco}}\boldsymbol{Y}_{\mathrm{eco}}}{\boldsymbol{v}_{\mathrm{eco}}\boldsymbol{X}} \\ F_3 = \max \dfrac{\boldsymbol{u}_{\mathrm{gre}}\boldsymbol{Y}_{\mathrm{gre}}}{\boldsymbol{v}_{\mathrm{gre}}\boldsymbol{X}} \end{cases}, \qquad (1)$$

$$\text{s.t.} \quad \frac{\sum_{j=1}^{J} u_j Y_j}{\sum_{i=1}^{I} v_i X_i} \le 1$$

$$u_j \ge 0, v_i \ge 0, X_i \ge 0$$

where $\boldsymbol{u}_{\mathrm{saf}}$, $\boldsymbol{u}_{\mathrm{eco}}$, and $\boldsymbol{u}_{\mathrm{gre}}$, respectively, represent the output weight vector of infrastructure investment safety, economic, and green effectiveness indicators, which can be calculated by the combination of the analytic hierarchy process (Deng and Wang, 2020; Wang et al., 2017) and the entropy weighting method (Li et al., 2024; Qin et al., 2024); $\boldsymbol{v}_{\mathrm{saf}}$, $\boldsymbol{v}_{\mathrm{eco}}$, and $\boldsymbol{v}_{gre}$ represent the input weight vector of the investment scale of infrastructure portfolio categories; $\boldsymbol{X}$ represents the vector of the investment scale of infrastructure portfolio categories, and $\mathbf{X} = [X_1, X_2, \cdots, X_i, \cdots, X_7]^T$; $\boldsymbol{Y}_{\mathrm{saf}}$, $\boldsymbol{Y}_{\mathrm{eco}}$, and $\boldsymbol{Y}_{\mathrm{gre}}$, respectively, represent the vector of the values of infrastructure investment safety, economic, and green effectiveness indicators, which can be calculated by the LASSO regression model (Tibshirani, 2011). The multi-objective cost efficiency-oriented investment portfolio optimization model is shown in Figure 1.

Several constraints have been introduced into the model to ensure that investments in grid infrastructure are rationalized (Yang et al., 2024). Constraint (2) stipulates that the total investment across all infrastructure drivers should not exceed the maximum investment capacity of the grid. The N-1 line passing rate $\varsigma_{\mathrm{L,N-1}}$ and heavy overload equipment reduction rate $N_{\mathrm{G}}$ are used to reflect the degree of improvement in power reliability. In addition, the capacity–load ratio $r$ and average household power distribution capacity $S_a$ are used to reflect the limitation to power supply capacity. Transmission and distribution cost per unit of electricity $C$ is selected to limit the profitability of the company. The amount of saved standard coal $E_c$ and pollutant emission reduction $E_r$ are chosen to reflect the effect of energy saving and emission reduction. Constraints are shown in Equations 2–4:

$$\sum_{i=1}^{I} X_i \le X_{\max}, \qquad (2)$$

$$\begin{bmatrix} \varsigma_{\mathrm{L,N-1}}^{\min} \\ N_{\mathrm{GZ}}^{\min} \\ r^{\min} \\ S_a^{\min} \\ C^{\min} \\ E_c^{\min} \\ E_r^{\min} \end{bmatrix} \le \begin{bmatrix} \varsigma_{\mathrm{L,N-1}} \\ N_{\mathrm{G}} \\ r \\ S_a \\ C \\ E_c \\ E_r \end{bmatrix} = \begin{bmatrix} 0 & 0.41 & 0 & 0 & 0 & 0.15 & 0 \\ 0 & 0.12 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0.15 & 0 & 0.08 & 0.12 & 0 & 0 \\ 0.15 & 0.10 & 0 & 0.18 & 0 & 0.05 & 0 \\ 0 & 0.29 & 0 & 0 & 0.76 & 0 & 0.19 \\ 0.52 & 0.02 & 0.20 & 0.12 & 0 & 0 & 0.28 \\ 0.71 & 0.09 & 0.20 & 0.03 & 0 & 0.16 & 0.51 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \end{bmatrix}, \qquad (3)$$

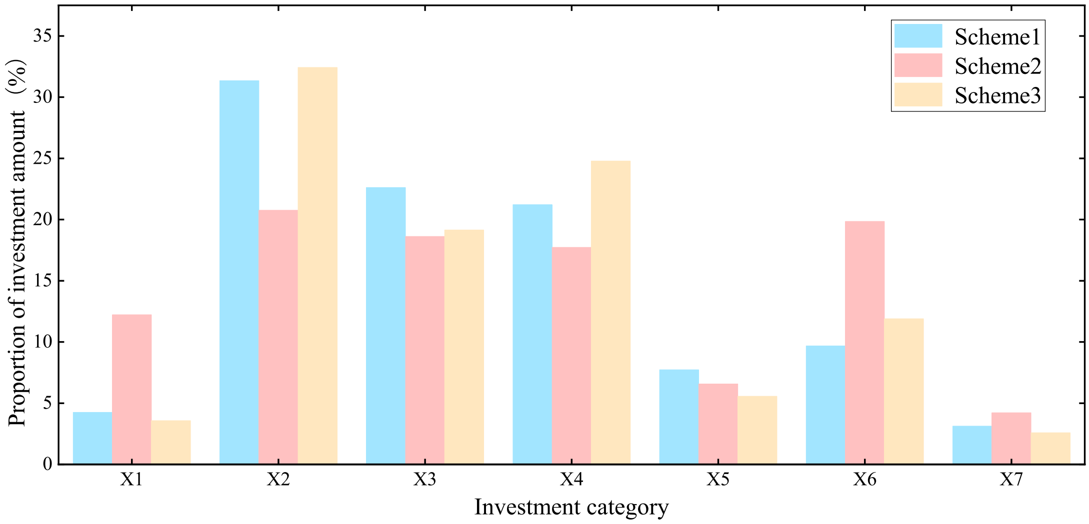


FIGURE 2
Power grid investment portfolios under different schemes.

$$\begin{bmatrix} r^{\max} \\ S_a^{\max} \end{bmatrix} \geq \begin{bmatrix} r \\ S_a \end{bmatrix} = \begin{bmatrix} 0 & 0.15 & 0.08 & 0.12 & 0 \\ 0.15 & 0.10 & 0.18 & 0 & 0.05 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_4 \\ X_5 \\ X_6 \end{bmatrix}, \tag{4}$$

where $X_{\max}$ represents the maximum scale of annual infrastructure investment of the company; $\varsigma_{\mathrm{L,N-1}}^{\min}$ represents the lower limit value of the line N-1 passing rate; $N_{\mathrm{GZ}}^{\min}$ represents the lower limit value of the decline rate of heavy overload equipment solved; $r^{\max}$ and $r^{\min}$, respectively, represent the upper and lower values of the capacity–load ratio; $S_a^{\max}$ and $S_a^{\min}$, respectively, represent the upper and lower values of the average household power distribution capacity; $C^{\min}$ represents the lower limit value of the cost of transmission and distribution of electricity per unit of electricity; $E_{\mathrm{c}}^{\min}$ represents the lower limit value of the saved standard coal; $E_r^{\min}$ represents the lower limit value of pollutant emission reduction. $X_1$ represents the investment in improving power access capacity; $X_2$ represents the investment in enhancing the transmission capacity; $X_3$ represents the investment in enhancing the flexibility capability; $X_4$ represents the investment to meet the growing load; $X_5$ represents the investment in improving the level of digitization; $X_6$ represents the investment in optimizing the grid structure; $X_7$ represents the investment in new models and new formats.

## 3 Evolutionary algorithm for power grid investment efficiency maximization

An evolutionary algorithm based on super-efficient hyperplane projection transformation (EASEHPT) is proposed to optimize multiple objectives within the model. The proposed algorithm is based on the principle of the NSGA-III algorithm (Deb and Jain, 2014), which selects sub-generation grid portfolio populations by calculating the integrated distance of non-dominated portfolio populations. Then, the grid portfolio populations are sorted according to the integrated distance, and populations that perform better in the same class will be retained. The optimal solution is selected from the Pareto efficiency frontier set of the multi-objective infrastructure portfolio through the super-efficiency selection strategy. The multi-objective evolutionary algorithm is shown in Figure 1.

This study compares all portfolio individuals in a new population with a size of 2M after the genetic evolution operation, according to three optimization objectives, $F_1$, $F_2$, and $F_3$, to achieve a Pareto non-dominated hierarchical sorting. Moreover, the single-objective optimal solution set is chosen to construct the spatial hyper-efficiency plane. Then, the Pareto non-dominated solution of the grid infrastructure investment portfolio is projected to the hyper-efficiency plane (Chen et al., 2021). The general expression for the super-efficiency plane of the three objectives is shown in Equation 5:

$$\boldsymbol{a}_1 \cdot \boldsymbol{f}_1 + \boldsymbol{a}_2 \cdot \boldsymbol{f}_2 + \boldsymbol{a}_3 \cdot \boldsymbol{f}_3 = 1, \tag{5}$$

where $(\boldsymbol{a}_1, \boldsymbol{a}_2, \boldsymbol{a}_3)$ denote the unit normal vector of the super-efficiency plane; $(\boldsymbol{f}_1, \boldsymbol{f}_2, \boldsymbol{f}_3)$ denote the extreme point vector. The ideal individuals $\left(f_{1,\min}, f_{2,\min}, f_{3,\min}\right)$ are extracted and converted to zero vectors (Chen et al., 2020), and the target individuals are normalized and projected onto the super-efficient plane is shown in Equations 6, 7:

$$\bar{f}_i^k = \frac{f_i^k - f_{i,\min}^k}{f_{i,\max}^k - f_{i,\min}^k}, \tag{6}$$

$$\hat{f}_i^k = \frac{\bar{f}_i^k}{\sum_{i=1}^{3} \bar{f}_i^k}, \tag{7}$$

TABLE 2 Investment efficiency and convergence effect of the solution set under different schemes.

| Scheme | Safety investment efficiency | Economic investment efficiency | Green investment efficiency | Comprehensive investment efficiency | Inverse generational distance | Spacing |
|---|---|---|---|---|---|---|
| Scheme 1 | 1.18 | 1.21 | 1.77 | 1.43 | 0.5374 | 0.1493 |
| Scheme 2 | 1.50 | 0.76 | 1.62 | 1.33 | — | — |
| Scheme 3 | 1.09 | 1.13 | 1.48 | 1.26 | 0.7226 | 0.2041 |

where $\bar{f}_i^k$ denotes the $i$th normalized target value under the $k$th grid infrastructure investment portfolio solution; $\hat{f}_i^k$ denotes the intercept of the $i$th target in the super-efficiency plane under the $k$th grid infrastructure investment portfolio solution; $f_{i,max}^k$ and $f_{i,min}^k$, respectively, denote the maximum and minimum values of the $i$th target under the $k$th grid infrastructure investment portfolio solution.

In this paper, the integrated distance is introduced to evaluate the super-efficiency and equilibrium performance of solutions. Assuming that the coordinates $\bar{\boldsymbol{f}}^k$ of the $k$th portfolio solution and its projection point $\hat{\boldsymbol{f}}^k$ in the super-efficiency plane are $\left(\bar{f}_1^k, \bar{f}_2^k, \bar{f}_3^k\right)$ and $\left(\hat{f}_1^k, \hat{f}_2^k, \hat{f}_3^k\right)$, and the coordinates of the intersection point with the new production frontier plane $\tilde{\boldsymbol{f}}^k$ in the super-efficiency plane are $\left(\tilde{f}_1^k, \tilde{f}_2^k, \tilde{f}_3^k\right)$, and the coordinates of the reference point $\boldsymbol{R}^{\mathrm{ck}}$ in the super-efficiency plane are $\left(r_1^{\mathrm{ck}}, r_2^{\mathrm{ck}}, r_3^{\mathrm{ck}}\right)$; then, the calculation method of the equilibrium distance $D_{\mathrm{b}}^k$, the super-efficiency distance $D_{\mathrm{se}}^k$, and the integrated distance $\tilde{D}^k$ is shown in Equations 8–10:

$$D_{\mathrm{b}}^k = \left\|\hat{\boldsymbol{f}}^k, \boldsymbol{R}^{ck}\right\|_2, \tag{8}$$

$$D_{\mathrm{se}}^k = \left\|\tilde{\boldsymbol{f}}^k\right\|_2 - \left\|\bar{\boldsymbol{f}}^k\right\|_2, \tag{9}$$

$$\tilde{D}^k = w_{\mathrm{b}}^k \cdot \frac{D_{\mathrm{b}}^{\max} - D_{\mathrm{b}}^k}{D_{\mathrm{b}}^{\max} - D_{\mathrm{b}}^{\min}} + w_{\mathrm{se}}^k \cdot \frac{D_{\mathrm{se}}^k - D_{\mathrm{se}}^{\min}}{D_{\mathrm{se}}^{\max} - D_{\mathrm{se}}^{\min}}, \tag{10}$$

where $D_{\mathrm{b}}^k$ denotes the Euclidean distance (Cao et al., 2024b) between the projection point of the $k$th grid infrastructure portfolio solution on the super-efficiency plane and the nearest super-efficiency plane reference point. The smaller the value of $D_{\mathrm{b}}^k$, the higher is the balance of the investment portfolio solution regarding the three target efficiency values. $D_{\mathrm{se}}^k$ is the Euclidean distance between the $k$th investment portfolio solution and the new production frontier. The bigger the value of $D_{\mathrm{se}}^k$, the higher the efficiency; $w_{\mathrm{b}}^k$ and $w_{\mathrm{se}}^k$, respectively, indicate the weighting coefficients of balanced performance and super-efficiency performance of the $k$th infrastructure investment portfolio solution; $D_{\mathrm{b}}^{\max}$, $D_{\mathrm{b}}^{\min}$, $D_{\mathrm{se}}^{\max}$, and $D_{\mathrm{se}}^{\min}$, respectively, represent the maximum and minimum of all equilibrium and super-efficiency distance values calculated in the solution set of the grid infrastructure investment portfolio frontiers. The integrated distance $\tilde{D}^k$ serves as an indicator of the quality of the investment solution, with larger values reflecting superior performance.

In this paper, a super-efficient envelope model with non-radial relaxation variables is introduced to select the optimal solution from the Pareto efficient frontier set of the multi-objective infrastructure investment portfolio. In this model, the relaxation variable is used to measure the deviation between the solution and the hyper-efficiency plane. Specifically, $s_i^-$ denotes the relaxation variable of the scale of the $i$th type of infrastructure investment portfolio, and $s_j^+$ denotes the relaxation variable of the value of the $j$th type of investment benefits. When $s_i^- > 0$, it means that there is a lot of waste in the investment portfolio. When $s_i^+ > 0$, it means that the output of the investment portfolio can be further improved. When the relaxation variable is zero, it means that the investment portfolio is optimal. Therefore, the optimal investment efficiency-oriented solution can be identified from the resulting Pareto frontier set. It can be found that a smaller value of $s_i^- + s_j^+$ in the solution indicates higher overall efficiency.

$$\begin{aligned} \min \quad & \frac{1 - \frac{1}{I}\sum_{i=1}^{I} \frac{s_i^-}{X_{io}}}{1 + \frac{1}{J}\sum_{j=1}^{J} \frac{s_j^+}{Y_{jo}}} \\ \text{s.t.} \quad & \sum_{l=1, l\neq o}^{M} X_{il}\lambda_l - s_i^- \le X_{io} \quad i = 1, 2, \ldots, I \\ & \sum_{l=1, l\neq o}^{M} Y_{jl}\lambda_l - s_j^+ \ge Y_{jo} \quad j = 1, 2, \ldots, J \\ & \sum_{l=1, l\neq o}^{M} \lambda_l = 1 \quad \lambda_l, s_i^-, s_j^+ \ge 0 \end{aligned}, \tag{11}$$

where $I$ denotes the total number of infrastructure portfolio categories in the population individuals; $J$ denotes the total number of investment effectiveness indicators in the population individuals; $X_{io}$ denotes the investment scale of the $i$th infrastructure portfolio category of the $o$th population individual; $Y_{jo}$ denotes the $j$th construction effectiveness value of the $o$th population individual; $X_{il}$ denotes the investment scale of the $i$th infrastructure portfolio category of the $l$th population individual; $Y_{jl}$ denotes the $j$th construction effectiveness value of the $l$th population individual; $\lambda_l$ denotes the impact factor of the $l$th population individual. Because of the existence of bilinear variable division terms in Equation 11, it cannot be solved directly, so this paper adopts the simplex method and pairwise planning to linearize the model by introducing the transformed variables $d$, $S_i^-$, $S_j^+$, and $\Lambda_l$. Let $d = 1/\left(1+\Sigma_{j=1}^{J}\left(s_j^+/Y_{jo}\right)/J\right)$; then, Equation 11 can be expressed as follows:

$$\min \quad d - \frac{1}{I}\sum_{i=1}^{I}\frac{s_i^- d}{X_{io}}$$
$$\text{s.t.}\begin{cases} 1 = d + \frac{1}{J}\sum_{j=1}^{J}\frac{s_j^+ d}{Y_{jo}} \\ \sum\limits_{l=1,l\neq o}^{M} X_{il}\lambda_l - s_i^- \leq X_{io} \quad i=1,2,\ldots,I \\ \sum\limits_{l=1,l\neq o}^{M} Y_{jl}\lambda_l - s_j^+ \geq Y_{jo} \quad j=1,2,\ldots,J \\ \sum\limits_{l=1,l\neq o}^{M} \lambda_l = 1 \quad \lambda_l, s_i^-, s_j^+ \geq 0 \end{cases}. \tag{12}$$

Let $S_i^- = s_i^- d$, $S_j^+ = s_j^+ d$, and $\Lambda_l = \lambda_l d$; then, Equation 12 can be transformed into Equation 13:

$$\min \quad d - \frac{1}{I}\sum_{i=1}^{I}\frac{S_i^-}{X_{io}}$$
$$\text{s.t.}\begin{cases} 1 = d + \frac{1}{J}\sum_{j=1}^{J}\frac{S_j^+}{Y_{jo}} \\ S_i^- = s_i^- d, S_j^+ = s_j^+ d, \Lambda_l = \lambda_l d \\ \sum\limits_{l=1,l\neq o}^{M} X_{il}\Lambda_l - S_i^- \leq X_{io} d \quad i=1,2,\ldots,I \\ \sum\limits_{l=1,l\neq o}^{M} Y_{jl}\Lambda_l - S_j^+ \geq Y_{jo} d \quad j=1,2,\ldots,J \end{cases}. \tag{13}$$

Through the above processing, the fractional planning problem is transformed into a general linear planning problem so as to obtain the optimal solution of the Pareto frontier solution.

## 4 Case studies

To validate the proposed model, taking a provincial power grid in central China as an example, three comparison schemes are established: scheme 1 uses the method proposed in this paper to select the optimal investment portfolio. Based on scheme 1, scheme 2 changes the super-efficiency selection strategy into a fuzzy multi-attribute decision-making method to obtain the optimal investment portfolio. Scheme 3 uses the NSGA-III algorithm for multi-objective optimization and combines the fuzzy multi-attribute decision-making method to select the optimal investment portfolio (Yu et al., 2019; Wang et al., 2024; Hussain et al., 2024). The parameter settings of the multi-objective cost efficiency-oriented investment portfolio optimization model are shown in Table 1. Power grid investment portfolios under different schemes are shown in Figure 2. The comparative results under different schemes are shown in Table 2.

The proposed scheme prioritizes power infrastructure investments on the transmission capacity and flexibility capability enhancements. It can be seen from Figure 2 that the investment portfolio obtained from scheme 2 prioritizes optimizing the grid structure, and the investment portfolio obtained from scheme 3 prioritizes enhancing the transmission capacity and meeting the growing load. It can be found from the analytical results that scheme 1 demonstrates superior performance on the comprehensive investment efficiency while maintaining the balanced performance in all efficiency indicators. Compared to scheme 3, the lower inverse generational distance and spacing in scheme 1 indicate that the solution set is close to the ideal Pareto front and has a better distribution of solutions. This is because the proposed algorithm employs a super-efficiency DEA model to rank these population individuals through equilibrium distances so that the better individuals can be selected from the non-dominated population individuals. Additionally, the algorithm utilizes a super-efficiency envelopment model to extract optimal solutions from the Pareto frontier set. As a result, the power grid investment portfolio achieves higher comprehensive efficiency while maintaining the balanced performance in all efficiency indicators.

The power grid investment portfolio obtained from scheme 2 demonstrates a stronger emphasis on safety investment efficiency while exhibiting notably lower economic investment efficiency and inferior comprehensive investment efficiency compared to those of scheme 1. These results stem from the decision making of scheme 2 to improve safety benefits for the goal of protecting people's livelihood and policies, and it easily leads to the lack of investment in enhancing economic benefits, resulting in the reduction in the comprehensive investment efficiency of power grids. Although scheme 3 shows relatively balanced performance in all indicators, all its investment efficiency indicators are lower than those of scheme 1. Moreover, the inverse generational distance and spacing of scheme 3 are significantly higher than those of scheme 1, indicating that its solution set is far away from the ideal Pareto frontier set.

## 5 Conclusion

In this paper, an investment efficiency-oriented strategy is proposed to improve the overall investment efficiency for power grid infrastructure planning with high penetration of renewable energy sources. The following are the key findings of this study: 1) the proposed investment portfolio model prioritizes enhancing the transmission capacity and flexibility capability of power grids with proportions of 31.35% and 22.62%, respectively, and thus, the system investment efficiency can be enhanced with renewable energy accommodation enhancement. 2) The proposed EASEHPT algorithm can improve the overall investment efficiency by 11.9% compared to traditional methods, and the obtained Pareto front solution set of the multi-objective investment portfolio exhibits both diversity and optimality.

## 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

QW: writing–original draft and writing–review and editing. MZ: conceptualization, data curation, and writing–review and editing.

JY: writing–original draft and writing–review and editing. ZS: visualization and writing–review and editing. SW: formal analysis and writing–review and editing.

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## Conflict of interest

Authors QW and MZ were employed by State Grid Hubei Electric Power Company Limited. Authors JY, ZS, and SW were employed by State Grid Hubei Electric Power Company Limited Economic and Technical Research Institute.

## Generative AI statement

The author(s) declare that no generative AI was used in the creation of this manuscript.

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