Hindawi
International Transactions on Electrical Energy Systems
Volume 2023, Article ID 1358099, 10 pages
https://doi.org/10.1155/2023/1358099

Research Article

A Multistep Iterative Ranking Learning Method for Optimal Project Portfolio Planning of Smart Grid

Cong Liu,[1,2] Xianghua Li [1,2] Jian Liang,[3] Kun Sheng,[3] Lingzhao Kong,[4] Xiaoyan Peng,[4] and Wenxin Zhao[5]

[1] *State Grid Hunan Electric Power Company Limited Economic & Technical Research Institute, Changsha 410000, China*
[2] *Hunan Key Laboratory of Energy Internet Supply-Demand and Operation, Changsha 410000, China*
[3] *State Grid Hunan Electric Power Company Limited, Changsha 410000, China*
[4] *College of Computer Science and Electronic Engineering, Hunan University, Changsha, China*
[5] *College of Electrical and Information Engineering, Hunan University, Changsha, China*

Correspondence should be addressed to Xianghua Li; xhli987321@163.com

Received 10 November 2022; Revised 10 December 2022; Accepted 30 March 2023; Published 22 April 2023

Academic Editor: Xueqian Fu

Optimal project portfolio planning is a typical nonconvex, multiobjective, highly constrained, multitemporal coupling, and combinatorial optimization problem. This paper proposes a novel multistep iterative ranking learning method (MIRL) to solve this complex combinatorial optimization problem from massive infrastructure projects of smart grid. The optimal project portfolio planning problem of power grid is formulated as the optimization process of massive project priority sorting with an improved knapsack model. The proposed method dynamically optimizes the best infrastructure project combination for each round to maximize the economic, social, and security benefits without exceeding the annual investment limit. A pairwise-based ranking learning algorithm is used to mine the priority sorting law from massive historical combination data of power grid to initialize candidate project portfolio. In order to approach the optimal portfolio planning solution with the constraint satisfactions of project construction duration and electric load supplies, a heuristic greedy strategy is designed to search the solution dynamically for selecting the project having highest construction benefits iteratively. The effectiveness of the proposed method is proved by experiments with real-world project data of Hunan power grid in China, and experimental results show that the proposed MIRL can outperform other methods on investment efficiency, calculation time, and rationality of project construction period schedule.

1. Introduction

The vigorous development of power grid infrastructure projects is to promote the coordinated regional development for meeting the increasing load demand in various regions and mitigating the tense power supply-demand balance. Infrastructure projects of power grid usually exhibit the characteristics of large investment, long construction period, and high resource consumption. Facing the massive amount of infrastructure investment projects, it is important for power grid decision-makers to make the comprehensive evaluation of infrastructure projects and develop a scientific investment portfolio planning so as to ensure the optimization of investment returns [1].

The optimal project portfolio planning problem of power grid is a nonconvex, multitemporal coupling, strong constrained, multiobjective complex portfolio optimization problem [2, 3]. Most existing methods applied Pareto optimization [4], fuzzy multicriteria-decision-making techniques [5], integer linear programming [6], dynamic modelling [7], or expert experience to solve the portfolio optimization problem. The project evaluation index system was also formulated to quantize the power grid infrastructure projects with different weights, and the projects are optimized based on the ranking of comprehensive scores [8, 9]. However, it is difficult to comprehensively consider investment temporal constraints of new construction, renewal, and expansion projects as well as annual investment limits. When the optimal project portfolio planning problem has multiple objectives, it is usually solved through the normalization method or multiobjective heuristic algorithm [10, 11]. The adaptation of the two-phase Pareto local search (2PPLS) to the resolution of MOMKP was proposed in [12] for the multiobjective multidimensional knapsack problem. A multiobjective optimization algorithm based on the genetic algorithm and epsilon constraint method using the fuzzy decision maker was proposed to minimize the operational cost of the distribution network [13, 14]. In addition, a hybrid ensemble forecasting scheme was proposed, which uses the multiobjective Grasshopper optimization algorithm (MOGOA) to ensemble the forecasting results of each subseries [15]. In recent years, more and more studies begin to introduce machine learning methods [16, 17]. The ranking learning (LTR) is a machine learning ranking method based on supervised learning [18–20]. It has been recognized and adopted by many fields. FastAP was proposed in 2019, which has low complexity and is suitable for stochastic gradient descent [21]. A learning-to-rank-based investment portfolio optimization framework was proposed in [22] for smart grid planning, and a machine learning-driven deduction prediction methodology in [23] was proposed for power grid planning.

(1) An improved constructive knapsack model is proposed to optimize the infrastructure project portfolio planning of power grid. The project library can be formulated as a constructive knapsack, in which each project and investment size limit are considered as an item and total capacity in the knapsack, respectively. The proposed model can optimally schedule the project construction period with enhanced investment efficiency and calculation time based on NP-hard combinatorial optimization.

(2) A multistep iterative ranking learning method (MIRL) is proposed to uncover the potential preferential ranking laws from historical data. A ranking SVM-based algorithm is presented based on binary classification to establish pairwise relationship among massive infrastructure projects. The resulting project priority can be used as initial project sorting for multistep iterative optimization. A heuristic greedy strategy is designed to search the solution dynamically for selecting the project having highest construction benefits iteratively.

2. Optimal Project Portfolio Planning Based on the Knapsack Model

2.1. Problem Statement. The optimal project portfolio planning problem of power grid is to optimize suitable projects from the project library to form the best set of optimal projects so that the power grids' infrastructure development planning is more scientific and reasonable, which obtains greater investment benefits and fewer investment risks [8]. The advantage of the proposed method is that the formed set will have fine benefits in the economy, society, and security fields and can be adjusted for different scenes.

The problem is defined as follows: there are N projects in the project library, each of which contains various project attributions, such as project type, total investment, etc. The projects are optimized one by one to form the project optimal set. The project optimal set should satisfy some constraints, including the investment size constraint, the investment structure constraint, and the load demand constraint.

2.1.1. Investment Size Constraint. It means that investment by year amount of each grid infrastructure project must meet the investment size by year. In addition, the investment size constraint by the voltage level (500 kV, 220 kV, and 110 kV) needs to be considered when considering the total investment size constraint. It must be satisfied, which are known as hard constraints.

$$\begin{aligned} S_j &\leq S_j^{\max}, \\ S_j &= \sum_{i=1}^{N} x_i \cdot f_{i,j}, \end{aligned} \tag{1}$$

where S_j is the investment size of the J^{th} year of the selected new project; $S_j^{\max}$ is the maximum investment capacity of the J^{th} year of the new project; N is the total number of grid projects in the library; x_i is the preferred decision value of the I^{th} grid project; $f_{i,j}$ is the planned investment of the I^{th} grid project in the J^{th} year.

Grid project infrastructural planning includes a variety of constraints [24], and here, three representative constraints are considered as the soft constraints of the model: the new/feasible investment ratio constraint, the new/continued investment ratio constraint, and the load demand constraint, the first two of which together constitute the investment structure constraint. The satisfaction of these soft constraints can be used to evaluate the overall infrastructure project interdependence relation.

2.1.2. Investment Composition Constraint. The investment composition of power grid infrastructure planning aims to optimally schedule the investment allocation among different projects and periods. The expenditure to be incurred in the current year by projects is referred that start investing in the current year as "new investment," the total investment amount of projects that start investing in the current year as "feasibility investment," and the expenditure incurred in the current year by projects that start investing in previous years as "continued investment." Therefore, the "new/feasible investment ratio" refers to the ratio between the investment in the optimized investment projects in the current year and the total investment in all infrastructure projects. The "new/continued investment ratio" refers to the ratio of the expenditure incurred by the optimized project and previous years' projects in the following year to the overall planned expenditure in the following year. The values of new/feasible investment ratio and new/continued investment ratio are usually determined by historical infrastructure planning data of power grids. These two constraints are related but not identical, and their values must fall within a reasonable range.

$$\gamma_{\min} \le \gamma \le \gamma_{\max},$$
$$\gamma = \frac{\sum_{i=1}^{M} x_i \cdot f_{i,j}}{\sum_{i=1}^{M} x_i \cdot k_i}, \tag{2}$$

where $\gamma_{\min}$ and $\gamma_{\max}$ denote the threshold value of new/feasible investment ratio. γ is the new/feasible investment ratio calculated for the optimized project. M is the number of new constructed projects. k_i is the total feasible investment of the I^{th} project among the new constructed projects.

$$\sigma_{\min} \le \sigma \le \sigma_{\max},$$
$$\sigma = \frac{\sum_{i=1}^{N} x_i \cdot l_{i,j+1} + W_{j-1}}{T_{j+1}}, \tag{3}$$

where $\sigma_{\min}$ and $\sigma_{\max}$ denote the threshold value of the new/continued investment ratio. $l_{i,j+1}$ is the planned investment of the new constructed project I in the $(J+1)^{\text{th}}$ year; T_{j+1} is the total investment size in the $(J+1)^{\text{th}}$ year. W_{j-1} is the planned investment of the new constructed project in the $(J+1)^{\text{th}}$ year for continued investment in the $(J-1)^{\text{th}}$ year.

2.1.3. Load Demand Constraint. It is the requirement for the optimized infrastructure project to be able to supply the electricity in the current year. This constraint is to ensure that the infrastructure project can be put into production before peak periods of electricity consumption, such as the summer phase when air conditioning and cooling are widely switched on, making it possible to meet the demand for load demand in the summer and winter. To meet this constraint, decision-makers can not only consider projects with good investment returns when making infrastructure project preferences but also need to consider the construction cycle. This constraint requires that the sum of the supply capacities of the projects that can be built in the year of the infrastructural planning does not fall below a specified reasonable value.

$$\sum_{i=1}^{O_j} x_i \cdot g_i + V_{j-1} \ge D_j, \tag{4}$$

where x_i is the set of grid projects put into operation in the J^{th} year, covering the continued grid projects and new grid projects started and can be put into operation; g_i is the new capacity of grid projects put into operation; V_{j-1} is the total installed capacity already in the $(J-1)^{\text{th}}$ year; D_j is the basic electricity demand in the J^{th} year.

2.2. Dynamic Knapsack Model for Project Portfolio Priority. The classic knapsack model can be used to solve various combinatorial optimization problems [25]. In this paper, a dynamically time-constrained knapsack model is formulated to cope with the power grid project portfolio planning problem. First, each project in the library has to be regarded as an item and the project investment planning as a knapsack, and the process of infrastructural planning is formulated as the process of filling the knapsack with items. The capacity of the knapsack represents the upper limit of the overall infrastructure projects, which is a hard constraint, and the sum of the investment amounts of all the optimized infrastructure projects must not exceed the specified value.

The classical knapsack problem is only constrained by the capacity of knapsack [26], and the goal is to maximize the total value of items placed in the knapsack. It can be solved with the greedy idea of calculating the "value/volume ratio" of each item. For infrastructure project portfolio planning of the power grid, the knapsack model is more complex due to the additional soft constraints, though the overall framework has some similarities. Therefore, a heuristic greedy strategy is designed, in which each item has a dynamic priority related to not only the project itself but also all soft constraints. Firstly, an initial priority value for all projects is assigned and all projects are ranked according to the priority value, which is obtained by the ranking SVM learning algorithm to be introduced later. In each iteration, the project with the highest priority value is added into the knapsack and the priority value of all projects in the library is adjusted as the overall constraint value changes. The priority value of those projects with a positive effect on the satisfaction of soft constraints will be increased. On the contrary, the priority value of those projects with a negative effect on the satisfaction of soft constraints will be reduced. Therefore, the remaining projects are reranked according to the new priority values, and the project with the highest priority value will be placed into the knapsack in the next iteration. This process is repeated until no more infrastructure projects satisfy the investment size constraint. Figure 1 shows the overall architecture of the method.

3. Multistep Iterative Ranking Learning Method

3.1. Ranking SVM-Based Project Portfolio Optimization. The basic idea of the ranking SVM learning algorithm is to transform the ranking problem into a pairwise classification problem, which is then learned and solved using a support vector machine (SVM) classification model [19]. In ranking learning problems, the pairwise approach usually learns the ranking information through making comparison between every two samples. It forms the pairs of items to be ranked from all samples, with the labels +1 and −1 indicating the relative order of the two items in the pair. In this way, the sorting problem is transformed into a binary classification problem, and these document pairs are used to train a support vector machine (SVM) classification hyperplane to obtain a classification model.

In the MIRL, ranking SVM is used to obtain investment composition characteristics according to history investment planning data and project portfolio feature extraction. These data are processed as a training set to train the ranking SVM model. In this way, the optimized ranking law of investment projects under different scenarios is mined. When making project portfolio optimization, the project library will be input into the trained model to obtain ranking results.

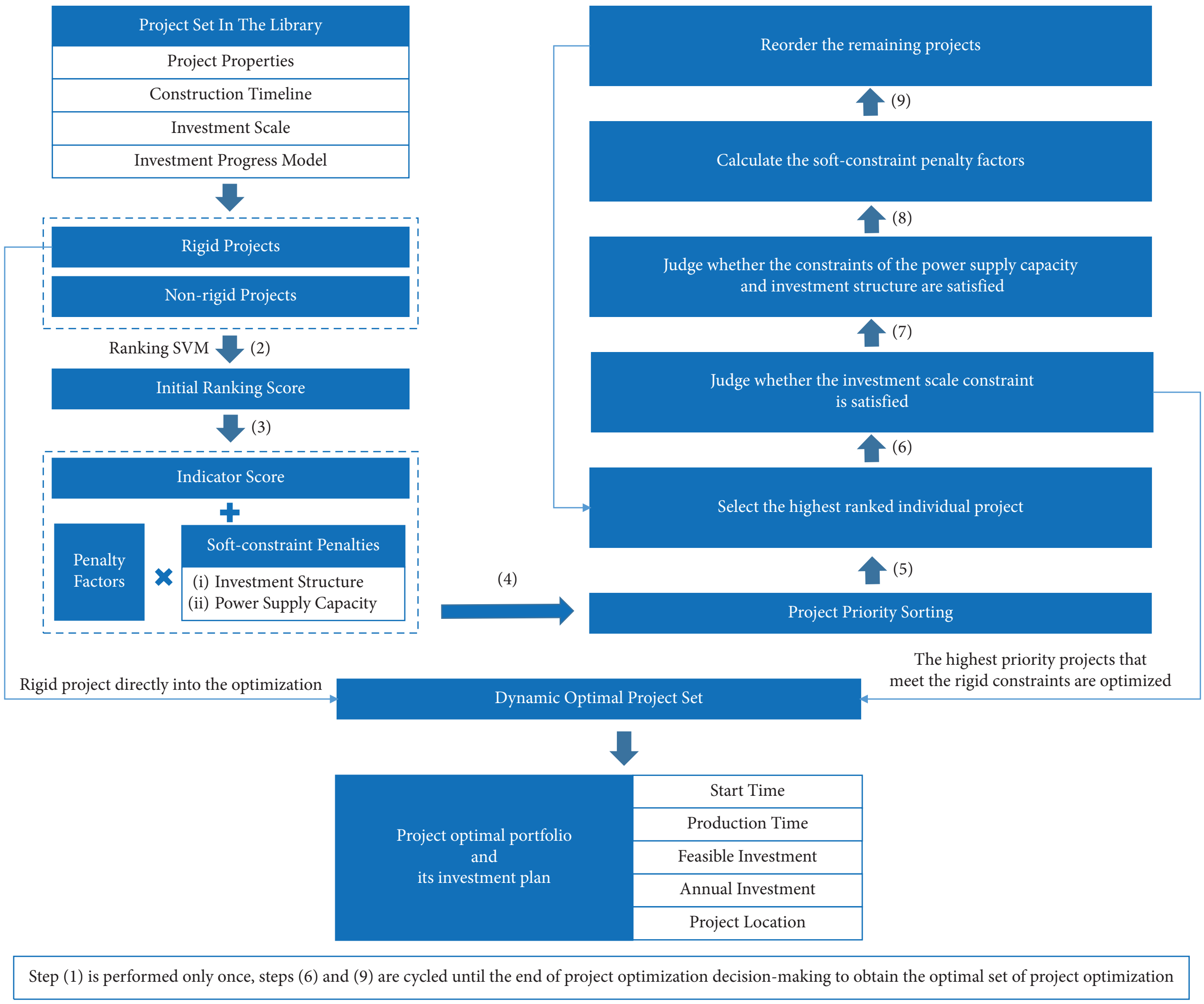

Figure 1: Overall flowchart architecture of the proposed method.

When applied specifically to the infrastructure project portfolio planning scenario of power, the input historical infrastructure project data contain multiple project features and the infrastructure projects are combined in pairs to form a sample, each sample including all features of two infrastructure projects $(x_i^{(1)}, x_i^{(2)})$ and a label y_i indicating which infrastructure project should be ranked first.

The ranking problem of the infrastructure project is transformed into a binary classification problem to solve for the classification hyperplane $(w, d_1^{(i)} - d_2^{(i)})$ and the classification decision-making model $f(d, w)$ that can correctly partition the training set and has the largest geometric interval, where w represents the normal vector of the hyperplane and d represents samples to be classified. To make better use of the existing theoretical and computational methods, this can be transformed into a quadratic convex function optimization problem, minimizing the objective function:

$$\min_{\omega,\xi} \frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{m} \xi_i. \tag{5}$$

It is subjected to the constraints:

$$s.t.\ y_i\left(\omega, x_i^{(1)} - x_i^{(2)}\right) \geq 1 - \xi_i \ (\xi_i \geq 0, i = 1, \cdots, m), \tag{6}$$

where ω is the parameter vector, C is a coefficient, and ξ_i is a relaxation variable.

The weights are updated in steps by the losses generated by misclassified samples, and the ranking relationship between any two infrastructure projects will be obtained, which is called the local ranking. The local ranking is finally transformed into an overall ranking to obtain an ordered project library based on ranking learning.

3.2. Constraint Punishment for Priority Adjustment.

As described in the previous section, the constraint penalty idea aims to adjust the constraint priority values for individual grid infrastructure projects based on their satisfaction with soft constraints, and the adjusted priority values will be used for a new round of grid infrastructure project preference ranking.

$$S_{i,j} = S_{i-1,j} + S_{y_{i,j}}, \tag{7}$$

where $S_{i,j}$ represents the priority value of the J^{th} nonrigid project in the ranking of the I^{th} round, $S_{i-1,j}$ represents the priority value of the J^{th} nonrigid project in the ranking of the $(I-1)^{\text{th}}$ round, and $S_{y_{i,j}}$ represents the I^{th} constraint score of the J^{th} nonrigid project.

For the initial ranking results output by the ranking SVM model, the initial score can be calculated from the equation as follows:

$$S_{0j} = 50 + 2 \cdot \left(N - \text{sort}_j\right), \tag{8}$$

where S_{0j} represents the priority value of the J^{th} nonrigid project in the ranking of the first round, N represents the total number of projects of all nonrigid projects, and sort_j represents the initial ranking result of the first nonrigid infrastructure project.

The constraint score represents the priority value change of the J^{th} project before the I^{th} round of grid infrastructure project portfolio planning, which is mainly determined by the penalty factors of the three constraints, while three weights are introduced to balance the influence of the constraints. It can be calculated from the equation as follows:

$$S_{y_{i,j}} = P_{T1_{i,j}} \cdot w_1 + P_{T2_{i,j}} \cdot w_2 + P_{V_{i,j}} \cdot w_3, \tag{9}$$

where w_1 represents the new/feasible investment weight of power grid infrastructure projects in the ranking of the I^{th} round and $P_{T1_{i,j}}$ represents the new/feasible investment penalty factor of the J^{th} infrastructure projects in the ranking of the I^{th} round. w_2 represents the new/continued investment weight of infrastructure projects in the ranking of the I^{th} round and $P_{T2_{i,j}}$ represents the new/continued investment penalty factor of the J^{th} infrastructure projects in the ranking of the I^{th} round. w_3 represents the new load demand capacity weight of infrastructure projects in the ranking of the I^{th} round and $P_{V_{i,j}}$ represents the new load demand penalty factor of infrastructure projects. The weight parameters w_1, w_2, and w_3 are usually set between 0 and 10 according to the importance of three constraints. In our experiment, these three parameters are set as 5.

3.3. Execution Steps of the Proposed Method. The multistep iterative ranking learning method (MIRL) proceeds as follows:

Step 1. The rigid infrastructure projects are directly optimized into the dynamic knapsack project set from the power grid projects in the library;

Step 2. All nonrigid projects are input in the trained ranking SVM model to get the initial ranking score;

Step 3. The total score S of each nonrigid project is calculated according to the initial ranking score and constraint score criteria;

Step 4. Projects are ranked according to the priority of all infrastructure projects;

Step 5. The highest ranked individual project in the library is optimized in this round of iterative optimization;

Step 6. Whether the project with the highest ranking satisfies the investment size constraint is judged. If it is satisfied, then the project is optimized into the dynamic backpack project collection. If it is not satisfied, the project is removed and it no longer participates in the optimization process;

Step 7. The load demand capacity V and investment structure constraint T is calculated after the optimization of this project;

Step 8. Whether the accounting results satisfy the constraints of investment size and investment structure is judged. If it is satisfied, the constraint penalty factor P_V becomes 0, as well as P_{T1} and P_{T2} are not adjusted. If it is not satisfied, the adjustment of the penalty factor P_V is increased, as well as P_{T1} and P_{T2} are adjusted from negative correlation direction; that is, the two constraint penalty P_{T1} and P_{T2} factors are adjusted according to the actual situation;

Step 9. The remaining projects in the library are reordered;

Step 10. We repeat steps six through nine until the optimal set of projects is obtained.

The algorithm input includes the project library, constraint parameters, investment schedule model, and historical data. Each project can be labelled with engineering properties including the investment scale, line length, power capacity, voltage rating, and construction time sequence. The algorithm output can obtain infrastructural project combination with optimal investment schedule.

4. Comparative Results and Discussion

4.1. Experimental Data and Settings. In this section, a multistep iterative ranking learning method for project portfolio optimization of power grids in a certain province is proposed. Taking 2021 as an example, the optimized list of new constructed power grid infrastructure projects is taken as the set of power grid infrastructure projects in the library. The four voltage levels (500 kV, 220 kV, 110 kV, and 35 kV) contain a total of 456 projects, with a total feasible investment of 238.60 million yuan. As shown in Table 1, the total feasible investment, total number of projects, and number of rigid projects of the four voltage levels are introduced, respectively.

According to Table 2, we can know the total investment size and constraints of the four voltage levels. In the current year, the total investment size of 500 kV, 220 kV, 110 kV, and 35 kV is 27.32, 63.82, 51.15, and 11.80, respectively. The ratio of new/feasible investment is 0.17–0.39, 0.17–0.33, 0.39–0.50, and 0.66–0.83, respectively. In the next year, the total investment size of 500 kV, 220 kV, 110 kV, and 35 kV is 46.2, 50.6, 42.9, and 15.4, respectively, and the ratio of new/continued investment is 0.22–0.39, 0.28–0.50, 0.44–0.61, and 0.66–0.83, respectively.

Table 1: Total feasible investment and the number of projects of 500 kV/220 kV/110 kV/35 kV.

	500 kV	220 kV	110 kV	35 kV	Total
The total number of projects	13	57	246	184	501
Total feasible investment/100 million yuan	58.11	77.39	86.45	16.65	238.60
The number of rigid projects	2	6	9	26	43

Table 2: Total investment size and constraints of 500 kV/220 kV/110 kV/35 kV.

Year	Index	500 kV	220 kV	110 kV	35 kV	Total
Current year	Total investment size (100 million yuan)	27.32	63.82	51.15	11.80	154.10
	Investment size of newly constructed projects (100 million yuan)	5.02	8.83	18.98	8.8	41.62
	Load demand capacity (MVA)	2090	8107	6500.5	822.4	—
	The ratio of new/feasible investment	0.17–0.39	0.17–0.33	0.39–0.50	0.66–0.83	0.33–0.66
Next year	Total investment size (100 million yuan)	46.2	50.6	42.9	15.4	155.1
	The ratio of new/continued investment	0.22–0.39	0.28–0.50	0.44–0.61	0.66–0.83	0.50–0.61

4.2. Results Analysis Based on Comparing with the Existing Method. In order to reflect the superiority of the multistep iterative ranking learning method for project portfolio optimization of power grids proposed in this paper, it is compared with the existing power grid project investment optimization decision-making methods. The existing method of the first type is the manual project optimization decision-making method used by most power grid companies. This method mainly relies on expert experiences, and the decision-making process is time-consuming. The second method is the integer linear programming algorithm, and the third method is the multiobjective NSGA-III algorithm. The fourth method introduces a greedy strategy and constructs the optimization decision-making process into a knapsack model, which dynamically selects investment projects iteratively. The fifth method is the multistep iterative dynamic decision-making model for project portfolio optimization of power grids proposed in this paper, which is built based on the fourth method by adding the ranking SVM learning algorithm.

For the proposed ranking SVM learning algorithm, the training set is input to train the model at first. The performance of the ranking SVM learning algorithm is related to the sample numbers of the training set. The learning curve of the ranking SVM is shown in Figure 2. As shown in Figure 2, the classification accuracy of the ranking SVM converges when the sample numbers approach 20000.

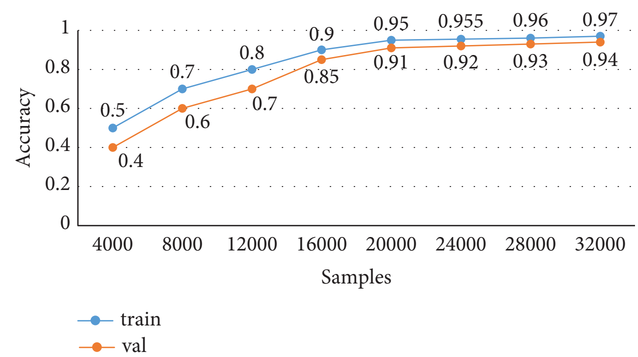

Figure 2: Classification accuracy of ranking SVM with different sample numbers.

Four models are, respectively, used to evaluate the optimization decision-making results of power grid investment projects in a province in the current year, and the comparative analysis of the satisfaction of five methods about the investment structure constraint is shown in Figure 3. The ratio of new/feasible investment in the current year and the ratio of new/continued investment in the next year of the proposed method are the highest, which are 39% and 56%, respectively. The proposed method without the ranking SVM is the second highest, which are 37% and 54%, respectively. According to the total investment size, we can find that the proposed method has the smallest. The manual optimization algorithm has the largest total investment size, which is 147.42 million yuan. Therefore, we can know that the efficiency of investment of the proposed method is the highest. However, according to Table 3, the optimization time of the proposed method without ranking SVM is the shortest, which is 0.2 seconds. The optimization time of the proposed method is a little longer, which is 10 seconds. Furthermore, the proposed method also includes 4 hours of the model training time. The optimization time of the other three models only includes the calculation time. The manual optimization algorithm takes the longest time of 15 days, so it is time-consuming. In summary, the multistep iterative ranking learning method proposed in this paper can prioritize projects more objectively by adjusting the priority of projects in optimization decision-making, to better satisfy each constraint and arrange projects more rationally. The proposed MIRL can outperform other methods on investment efficiency, calculation time, and rationality of project construction period schedule.

Considering that the ranking SVM learning algorithm integrates the machine learning mechanism, it can mine and extract investment characteristics and rules in different scenarios from historical planning data. Figures 4–7 show the portfolio planning results of four types of six investment performance indicators, respectively. The four types are comprehensive balance type, economic benefit oriented, social benefit oriented, and security benefit oriented, respectively. Four voltage levels of 500 kV, 220 kV, 110 kV, and

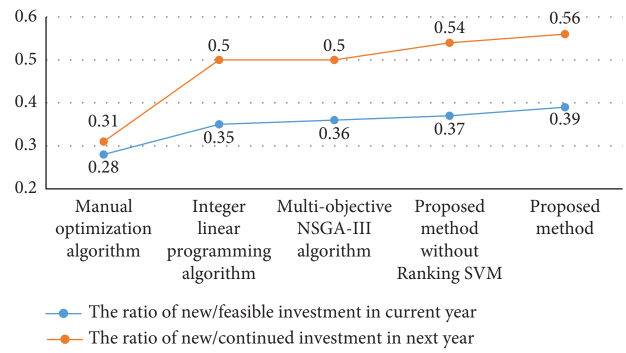

FIGURE 3: The satisfaction of five models about the investment structure constraint.

TABLE 3: The comparative analysis of five methods.

	Manual optimization algorithm	Integer linear programming algorithm	Multiobjective NSGA-III algorithm	Proposed method without ranking SVM	Proposed method
The number of optimized projects	288	350	325	278	266
Total investment size (100 million yuan)	147.42	117.30	116.70	111.74	**107.40**
The ratio of new/feasible investment in the current year	28%	35%	36%	37%	**39%**
The ratio of new/continued investment in the next year	31%	50%	50%	54%	**56%**
The time of optimization	15 days	3.5 s	40 minutes	0.2 s	4 hours + 10 s

Bold values represent that the proposed method has the best result on our evaluation criteria.

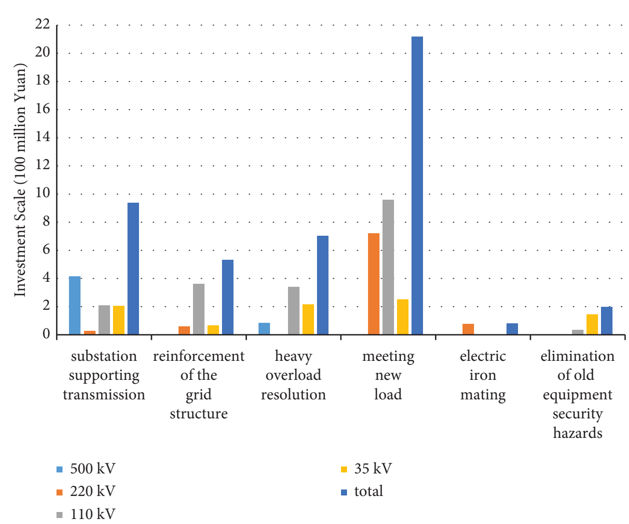

FIGURE 4: Optimal solution with a comprehensive balance objective at 500 kV/220 kV/110 kV/35 kV voltage levels.

35 kV are considered for each type. Each type contains three kinds of investment benefits, and the proportion of each benefit is different. For the comprehensive balance type, the proportion of the three benefits of economic, social, and security is 0.33, 0.33, and 0.34, respectively. For the other three types, the proportion of investment benefits corresponding to the oriented type is 0.5 and the proportion of the other two investment benefits is 0.25. For example, for the economic benefit-oriented type, the proportion of the three benefits of economic, social, and security is 0.50, 0.25, and 0.25. The economic indicator is meeting new load, the social indicators are the reinforcement of the grid structure, and the security indicator is heavy overload resolution and elimination of old equipment security hazards. As can be seen from Figure 4–7, the comprehensive balance type has good results in all three indicators and the other three

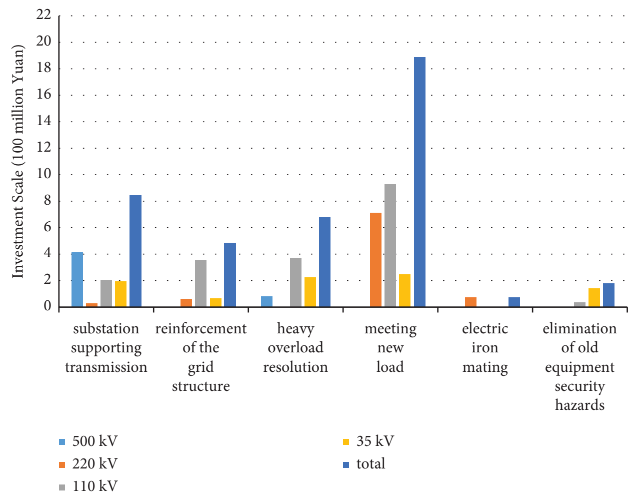

Figure 5: Optimal solution with an economic benefit objective at 500 kV/220 kV/110 kV/35 kV voltage levels.

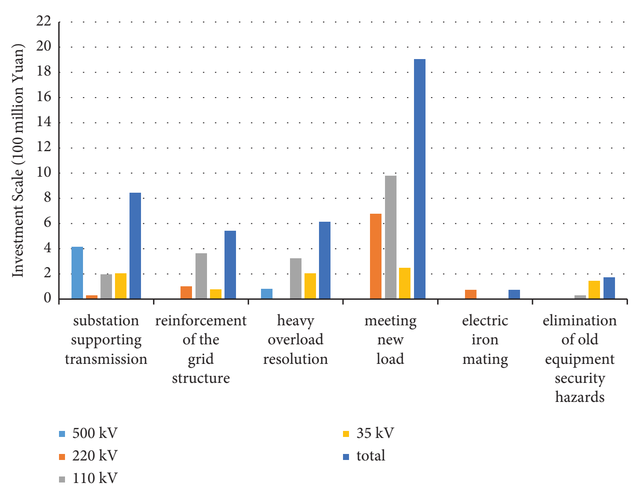

Figure 6: Optimal solution with a social benefit objective at 500 kV/220 kV/110 kV/35 kV voltage levels.

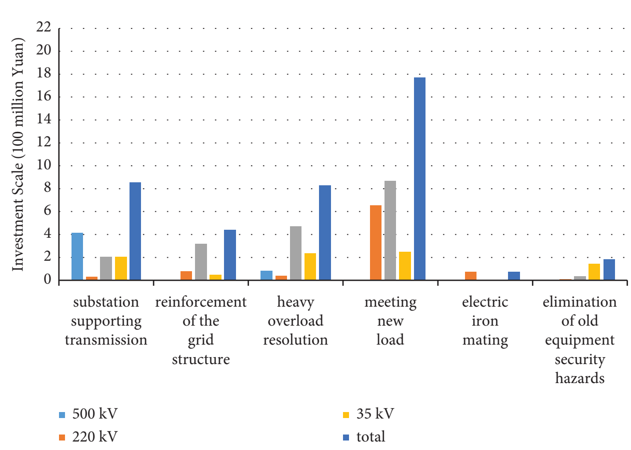

Figure 7: Optimal solution with a security benefit objective at 500 kV/220 kV/110 kV/35 kV voltage levels.

benefit-oriented types have good investment results, respectively, for this type of indicator. To sum up, the method proposed in this paper has good investment results for different investment scenarios, so this method can provide a more scientific and reasonable project optimization ranking under typical investment patterns.

5. Conclusions

In this paper, a novel multistep iterative ranking learning method (MIRL) is proposed to solve the complex combinatorial optimization problem from massive infrastructure projects of smart grid. Firstly, a dynamic knapsack model is proposed for the project portfolio priority. Then, the ranking SVM algorithm integrates the machine learning mechanism, which can mine and extract investment characteristics and rules under different investment orientations from historical investment plan data, and provides more scientific and reasonable project ranking under typical investment modes. The proposed method dynamically optimizes the best infrastructure project in each round to form an optimization set, so as to maximize the economic, social, and security benefits without exceeding the annual investment limit.

The annual investment planning data of the current year are input to the model to obtain the output results. We conduct a detailed analysis of seven indicators, such as the number of optimized projects, total research investment, the ratio of new/feasible investment in current year, and the ratio of new/continued investment in the next year. We can get the following results: the ranking SVM algorithm has the highest new/feasible investment ratio and new/continued investment ratio, 39% and 56%, respectively. However, the training time of this method is long, which leads to the fact that the whole process of infrastructure project optimization decision-making is not the shortest. In summary, the ranking SVM algorithm by learning the characteristics of historical investment, based on project attributes and construction necessity and other indicators to determine the order of the project, the priority selected projects with a higher overall efficiency and according to the constraints to meet the appropriate adjustment project priority so that each constraint could meet the situation better. As a result, the proposed MIRL can outperform other methods on investment efficiency, calculation time, and rationality of project construction period schedule.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

This work was supported by the State Grid Science and Technology Project (no. 5100-202123009A).

References

[1] Z. Du, H. Weng, D. Liu, T. Tang, and J. Zhao, "Evaluation index system and comprehensive evaluation methods of the power grid infrastructure projects," in *Proceedings of the 2016 International Conference on Advances in Energy, Environment and Chemical Science*, pp. 9–1, Atlantis Press, Amsterdam, Netherlands, May 2016.

[2] A. H. Ali and A. Najafi, "Optimization and performance improvement of grid-connected PV plant based on ANN-PSO and P&O algorithms," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 1278492, 15 pages, 2022.

[3] A. Rastgou and S. Hosseini-Hemati, "Simultaneous planning of the medium and low voltage distribution networks under uncertainty: a Bi-level optimization approach," *International Transactions on Electrical Energy Systems*, vol. 2022, Article ID 2267926, 19 pages, 2022.

[4] Y. Wu, T. Zhang, R. Gao, and C. Wu, "Portfolio planning of renewable energy with energy storage technologies for different applications from electricity grid," *Applied Energy*, vol. 287, Article ID 116562, 2021.

[5] A. Chaidez and Y. Sang, "Optimal energy portfolio planning for power system considering the impact of winter storms," in *Proceedings of the 2021 North American Power Symposium (NAPS)*, pp. 1–5, College Station, TX, USA, November 2021.

[6] Y. F. Li, G. H. Huang, Y. P. Li, Y. Xu, and W. Chen, "Regional-scale electric power system planning under uncertainty—a multistage interval-stochastic integer linear programming approach," *Energy Policy*, vol. 38, no. 1, pp. 475–490, 2010.

[7] Y. Cao, B. Zhou, C. Y. Chung, Z. Shuai, Z. Hua, and Y. Sun, "Dynamic modelling and mutual coordination of electricity and watershed networks for spatio-temporal operational flexibility enhancement under rainy climates," *IEEE Transactions on Smart Grid*, pp. 1–13, 2022.

[8] Y. Sha, W. Li, J. Yan, W. Li, and X. Huang, "Research on investment scale calculation and accurate management of power grid projects based on three-level strategy," *IEEE Access*, vol. 9, Article ID 67176, 67185 pages, 2021.

[9] X. Fu and Y. Z. Zhou, "Collaborative optimization of sustainable energy systems and PV-Greenhouses in rural areas," *IEEE Transactions on Sustainable Energy*, vol. 14, no. 1, pp. 642–656, 2022.

[10] B. Xu, Y. Zhang, D. Gong, Y. Guo, and M. Rong, "Environment sensitivity-based cooperative co-evolutionary algorithms for dynamic multi-objective optimization," *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, vol. 15, no. 6, pp. 1877–1890, 2018.

[11] X. Fu and H. S. Niu, "Key Technologies and Applications of Agricultural Energy Internet for Agricultural Planting and Fisheries Industry," *Information Processing In Agriculture*, pp. 1–40, 2022.

[12] T. Lust and J. Teghem, "The multi-objective multidimensional knapsack problem: a survey and a new approach," *International Transactions in Operational Research*, vol. 19, no. 4, pp. 495–520, February 2012.

[13] Z. Huang, B. Fang, and J. Deng, "Multi-objective optimization strategy for distribution network considering V2G-enabled electric vehicles in building integrated energy system," *Protection and Control of Modern Power Systems*, vol. 5, no. 1, pp. 7–55, 2020.

[14] R. Ashrafi, M. Amirahmadi, M. Tolou-Askari, and V. Ghods, "Multi-objective resilience enhancement program in smart grids during extreme weather conditions," *International Journal of Electrical Power & Energy Systems*, vol. 129, Article ID 106824, 2021.

[15] J. Wang, L. Zhang, Z. Liu, and X. Niu, "A novel decomposition-ensemble forecasting system for dynamic dispatching of smart grid with sub-model selection and intelligent optimization," *Expert Systems with Applications*, vol. 201, Article ID 117201, 2022.

[16] X. Fu, "Statistical machine learning model for capacitor planning considering uncertainties in photovoltaic power," *Protection and Control of Modern Power Systems*, vol. 7, no. 1, p. 5, 2022.

[17] X. Fu, Q. Guo, and H. Sun, "Statistical machine learning model for stochastic optimal planning of distribution networks considering a dynamic correlation and dimension reduction," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 2904–2917, 2020.

[18] T. Y. Liu, "Learning to rank for information retrieval," *Foundations and Trends® in Information Retrieval*, vol. 3, no. 3, pp. 225–331, 2007.

[19] Z. Cao, T. Qin, and T. Y. Liu, "Learning to rank: from pairwise approach to listwise approach," in *Proceedings of the 24th international conference on Machine learning*, pp. 129–136, Corvalis, OR, USA, June 2007.

[20] H. Li, "A short introduction to learning to rank," *IEICE - Transactions on Info and Systems*, vol. 94, no. 10, pp. 1854–1862, 2011.

[21] F. Cakir, K. He, and X. Xia, "Deep metric learning to rank," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1861–1870, June 2019.

[22] W. Zhao, X. Liu, Y. Wu, T. Zhang, and L. Zhang, "A learning-to-rank-based investment portfolio optimization framework for smart grid planning," *Frontiers in Energy Research*, vol. 10, Article ID 852520, 2022.

[23] Y. Wu, X. Li, L. Zhang, C. Liu, W. Zhao, and T. Zhang, "Machine learning–driven deduction prediction methodology for power grid infrastructure investment and planning," *Frontiers in Energy Research*, vol. 10, Article ID 893492, 2022.

[24] S. Bruch, S. Han, and M. Bendersky, "A stochastic treatment of learning to rank scoring functions," in *Proceedings of the 13th International Conference on Web Search and Data Mining*, pp. 61–69, Houston, TX, USA, January 2020.

[25] M. Assi and R. A. Haraty, "A survey of the knapsack problem," in *Proceedings of the 2018 International Arab Conference on Information Technology (ACIT)*, pp. 1–6, Werdanye, Lebanon, November 2018.

[26] C. Changdar, G. S. Mahapatra, and R. K. Pal, "An improved genetic algorithm based approach to solve constrained knapsack problem in fuzzy environment," *Expert Systems with Applications*, vol. 42, no. 4, pp. 2276–2286, 2015.