Environmental and Economic Benefit Analysis of Urban Construction Projects Based on Data Envelopment Analysis and Simulated Annealing Algorithm

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***Abstract*—With the continuous advancement of urbanization and the sustained growth of urban population, city building projects are facing severe challenges. How to analyze their environmental and economic benefits has become an urgent problem to be solved. Therefore, based on the proposed method for calculating the environmental and economic benefits of city building projects, this study uses a cross efficiency data envelopment analysis model for evaluation and solution. Then, an improved simulated annealing algorithm is used to achieve environmental and economic benefit optimization. The results showed that the improved simulated annealing algorithm tended to stabilize after 480 iterations, with maximum and minimum values of 0.86 and 0.21, respectively. The maximum F1 value was 0.988, indicating better performance. In the selected three urban construction projects, the cross efficiency data envelopment analysis model achieved high environmental and economic benefits, demonstrating the effectiveness of the model. After optimizing using the improved simulation degradation algorithm, the maximum economic benefit was increased by 850000 yuan, proving the effectiveness of the proposed method in analyzing the environmental and economic benefits of urban construction projects. It can provide more scientific decision support for construction project planning.**

***Keywords*—DEA; simulated annealing algorithm; city building; environment; economics; benefit**

I. INTRODUCTION

With the continuous improvement of urbanization level, China's construction industry has undergone technological innovation, and urban construction has developed rapidly [1]. During this process, many problems have arisen in the construction industry, especially sustainable development, which has had a huge impact on energy and the environment [2-3]. The reason is that urban buildings have a relatively long lifecycle, and their impact on the environment and energy consumption is also long-term, which makes it difficult for further expansion plans or existing renovations of the city to meet various requirements. Specifically, the construction unit needs to balance the impact on the surrounding environment while meeting the requirements for quantity and quality. Therefore, the analysis of environmental and economic benefits of urban construction projects has become a key research direction for many professionals. The existing analysis methods include cost-benefit analysis, life cycle assessment, regression analysis, etc. However, cost-benefit analysis is difficult to accurately quantify environmental impacts, and the evaluation of non-market factors is subjective. Although life cycle assessment methods can comprehensively consider environmental impacts, the implementation process is complex, data requirements are high, and it is difficult to provide decision support in a short period of time. Regression analysis relies on linear assumptions and is not suitable for handling nonlinear relationships. At the same time, it has high requirements for data and is easily affected by outliers. In recent years, Data Envelopment Analysis (DEA) models, Simulated Annealing (SA) algorithms, and multi-objective optimization provide theoretical and technical references for this direction [4-6]. In response to the prominent contradiction between the increase of water resources and the decrease of water supply, Wang Z et al. successfully constructed a multi-objective optimization configuration model using multi-objective programming theory. The results showed that the model had strong scientific practicality, which was of great significance for solving practical multi-objective optimization problems [7]. To solve the production demand fluctuations in unstable markets, Zhang Z et al. designed an optimized SERU model through a novel SERU production system that combined genetic algorithm and SA to achieve maximum profit increase. The results indicated that this model could effectively handle the SERU loading problem and had good robustness in solving the SERU loading model [8]. Gabi D et al. proposed a SA optimization scheme based on fruit flies to address the premature convergence of metaheuristic techniques and the imbalance between global and local searches. The scheme balanced local and global searches and was statistically analyzed using a 95% confidence interval. The results showed that the scheme could improve resource utilization by returning the minimum completion time and execution cost [9]. In response to the insufficient effectiveness and accuracy of grasshopper behavior research algorithms, Yu C et al. combined SA mechanism with original grasshopper optimization algorithm, and evaluated the relative ranking of this algorithm in CEC2017 through Friedman. The results showed that the proposed grasshopper optimization algorithm could effectively solve complex optimization problems and achieve results that meet or even exceed expectations [10]. In response to the shortcomings of previous design methods in geothermal energy development, Liu J et al. proposed an innovative design framework that combined numerical simulation and SA, equipped with an energy lining system that generated thermal energy through circulating heat carrying fluids. The results indicated that the method still demonstrated strong processing ability under multiple factor crossover, which could guide practical applications [11]. In response to the slow convergence of existing slime mold algorithms in local search spaces, Ch L K et al. discovered the optimal solution of the objective function by mixing slime mold algorithms and SA algorithms to better change parameters. The non-convex, nonlinear, and typical engineering design difficulties were analyzed. The results showed that the mixed slime mold SA algorithm was more reasonable than other optimization techniques [12]. Camanho A S et al. conducted a literature review on the DEA of economic efficiency, including the optimization of costs, revenues, and profits. The application of different modeling methods was analyzed, providing new development directions for efficiency evaluation [13]. In response to the problem that traditional DEA cannot fully explore valuable information in big data, Zhu J focused on the development of nonlinear networks to propose corresponding DEA models. The results demonstrated the effectiveness of DEA in big data modeling [14].

By analyzing the research on DEA model and SA algorithm, both DEA model and SA algorithm have their own advantages, which are widely used in the fields of resource utilization efficiency and complex system optimization. Among them, the DEA model can effectively evaluate the relative efficiency of multiple decision-making units and is suitable for comprehensive evaluation of environmental and economic benefits. The SA algorithm can effectively search for global or approximate optimal solutions in the search space by simulating the physical annealing process. Its randomness and flexibility enable it to avoid getting stuck in local optima in complex multi-objective optimization problems. However, there is relatively little research on the combination of the two methods. Meanwhile, the economic input and output of urban construction projects have their own particularities, and the environmental impact also includes many complex factors. Therefore, starting from this point, the study combines DEA model and SA algorithm, proposes a method for calculating the environmental and economic benefits of urban construction projects, uses the cross efficiency DEA model for evaluation and solving, and combines the improved SA algorithm to optimize the environmental and economic benefits. Among them, the cross efficiency DEA model can better handle the relative efficiency evaluation between samples and reduce stability issues. The improved SA algorithm improves computational efficiency through optimization strategies and can quickly find approximate optimal solutions. The combination of these two methods can simultaneously consider economic and environmental benefits, providing a more comprehensive solution that is more suitable for the needs of complex urban construction projects.

The research content mainly includes four parts. The first part reviews the relevant research on DEA model and simulated annealing algorithm. The second part introduces the research methods. The first section analyzes the main factors in the environmental and economic benefits of urban construction projects and proposes calculation methods. The second section proposes a cross efficiency DEA model to solve multi-objective optimization problems of economic and environmental benefits. The third section proposes a combination of improved SA algorithm for optimizing economic and environmental benefits. The third part validated the performance of the improved SA algorithm and conducted empirical analysis on the environmental and economic benefits of urban construction projects. The fourth part summarizes and discusses the research results, and proposes future prospects.

II. Methods and Materials

In this chapter, the study first analyzes the main factors in the environmental and economic benefits of urban construction projects, and proposes calculation methods. Then, a combination of cross efficiency DEA model combined with improved SA algorithm is designed to optimize economic and environmental benefits.

A. Calculation of Environmental and Economic Benefits of Urban Construction Projects

The specific economic benefit indicators of urban construction projects are mainly divided into revenue indicators and cost indicators. Among them, the revenue indicators include the company's sales revenue, sales profit, and net profit. Cost indicators include material costs, labor costs, manufacturing costs, operating costs, and other aspects [15-16]. In the early stages of a construction project, costs mainly include market research, feasibility analysis, and technology development. Among them, urban buildings often face technical difficulties in the construction process. Technology research and development expenses are mainly investment related expenses for this research object. The construction cost can be divided into two parts: direct and indirect expenses. The labor, machinery, and material costs incurred during the construction project are considered direct expenses. The management fees, maintenance fees, and recycling fees of enterprises are classified as indirect expenses. Management fees refer to the property management fees incurred during the use of urban buildings, while maintenance fees are the maintenance costs incurred during the use process. The recycling cost includes the cost of dismantling components, cleaning the site, and processing fees for recycling, that is, the economic cost of dismantling, recycling, and utilization stages. In addition, the economic benefits of urban buildings include energy and resource conservation benefits, and energy conservation includes water and energy conservation. By calculating the unit electricity consumption throughout the life cycle of the building, the savings per square meter of urban buildings can be obtained, expressed as N_1. By consulting and referring to the local electricity standard P_1, the specific energy-saving benefits can be obtained, as shown in Eq. (1).

$$E_1 = N_1 * P_1 * A + S \tag{1}$$

In Eq. (1), A is the urban building area. S represents other energy saving costs. Combined with the local fixed price, the water-saving amount of urban buildings can be converted into water-saving benefits, as shown in Eq. (2).

$$E_2 = N_2 * P_2 \tag{2}$$

In Eq. (2), N_2 represents the water saving of urban construction projects. The benefits of resource conservation are mainly reflected in two aspects, namely the material saving benefits and time-saving benefits of urban construction. After comparing the differences in time efficiency between traditional and urban buildings for each floor, the time-saving benefits can be measured, as shown in Eq. (3).

$$E_3 = C * \left(\frac{D_c - D_z}{D_c} \right) \tag{3}$$

In Eq. (3), D_c and D_z represent the construction days of traditional and urban building projects, respectively. C represents the total cost of urban construction. Material saving benefits refer to the economic and environmental benefits obtained by optimizing resource utilization, improving material utilization efficiency, reducing raw material consumption and waste, and thereby reducing production costs and environmental burdens [17]. The specific calculation method is shown in Eq. (4).

$$E_4 = \sum N_i * P_i \tag{4}$$

A corresponding evaluation index system is created based on environmental benefits and costs to comprehensively assess the environmental impact and economic benefits of the model. Energy consumption includes water and electricity consumption, with water energy consumption referring to the amount of water resources used in the operation and model application of the power system. The energy consumption involves the amount of electricity consumed during model training and practical applications, including the computing resources required during model operation and the electricity consumed by equipment. Resource consumption includes the amount of wood, steel, and other resources consumed. Wood consumption involves the used wood resources in model development and system construction processes. Steel consumption includes the steel resources used in equipment manufacturing, infrastructure construction, and other aspects. The specific indicator system is shown in Fig. 1.

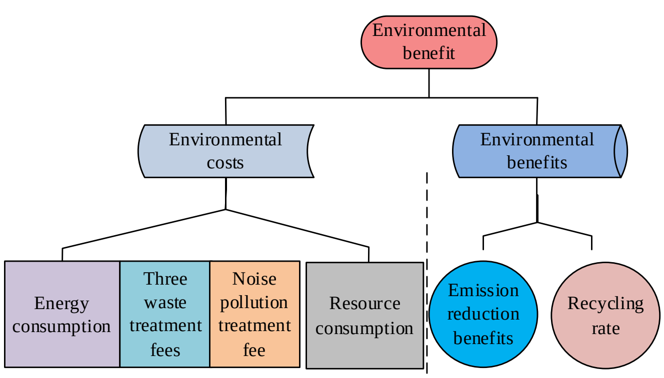


Fig. 1. Evaluation index system based on environmental benefits and environmental costs.

In order to fully evaluate the environmental impact of the project, the cost of waste treatment cannot be ignored. The cost of three wastes treatment refers to the cost of treating the wastewater, exhaust gas, noise, and solid waste generated during urban construction projects. The wastewater treatment fee covers the cost of wastewater treatment and discharge generated during construction and production processes, including the cost of wastewater collection, treatment, purification, and standard discharge. The cost of exhaust gas treatment mainly targets the exhaust gas generated during the construction process and vehicle exhaust. Usually, the exhaust emissions during the construction process do not exceed national standards, so there is less demand for treatment. The cost of solid waste disposal involves the disposal of solid waste generated during construction and production processes, such as construction waste, material residues, etc. The cost of noise pollution control includes the expenses required for implementing noise reduction measures, such as noise isolation and equipment maintenance. In the noise detection of urban buildings, the evaluation is mainly based on the relevant regulations of the urban area, as shown in Table I. The noise control can be assessed by measuring the residents' perception of noise in some areas.

TABLE I. URBAN REGIONAL NOISE ASSESSMENT STANDARDS

Adjacent	Distance/m
A type of standard applicable area	40~50
Applicable areas of Class II standards	23~35
Applicable areas of Class II standards	15~25

To reduce particulate matter emissions, the study adopts a five point sampling method, using a TH-150AH sampler to collect air samples and measure the particulate matter content in these samples. Then, the measured particulate matter content is compared with the relevant comprehensive standards. According to estimates, each square meter of dust reduction can bring 6.1 yuan in ecological benefits. Measures to reduce particulate matter not only help reduce environmental pollution, but also generate certain economic value. The specific income expression is shown in Eq. (5).

$$F = f * A * B \tag{5}$$

In equation (5), f represents the reduction of air particulate matter. B represents the ecological benefits of dust reduction in prefabricated buildings.

B. Cross Efficiency DEA Model

The study analyzed the main factors in the environmental and economic benefits of urban construction projects and proposed corresponding calculation methods. Next, it is necessary to solve the multi-objective optimization problem of economic and environmental benefits. As a non-parametric evaluation method, DEA is easy to calculate and can effectively process multi output and multi input data [18]. By creating an optimized model, it is possible to define an effective Pareto front and evaluate the efficiency of its object. In addition, the best weight combination among each decision unit can also be obtained. Therefore, when dealing with the subjective problems caused by decision-makers' likes and dislikes in multi-objective programming, combining with multi-objective optimization solutions can be relatively easy to solve. Although traditional DEA models can effectively obtain decision units, they can only work on one decision unit, and the ranking of each decision unit depends on self-evaluation, resulting in significant errors. In response to the above two points, a method of cross evaluating its efficiency value is applied. According to the analysis, although the traditional DEA model inevitably lacks extremism, it is more suitable for dealing with practical situations [19]. In addition, traditional DEA models output decision units with many efficiency values of 1, which makes it difficult to distinguish whether they are of high quality. Cross efficiency DEA can further and hierarchically divide the decision units constructed by all efficiency values, and then obtain the rankings of all decision units. The cross efficiency DEA used in the study first calculates the negative ideal solution corresponding to the target value, including two maximization and minimization objectives. The negative ideal solutions for maximizing and minimizing the objectives are shown in Eq. (6).

$$\begin{cases} a_{ij}^{\min} = \min\left\{a_{i1}, a_{i2}, ..., a_{ij}\right\}, i = 1,2 \\ b_{ij}^{\max} = \max\left\{a_{i1}, a_{i2}, ..., a_{ij}\right\}, i = 3,4 \end{cases} \tag{6}$$

In Eq. (6), a_{ij} represents the maximization objective. b_{ij} represents minimization objective. Subsequently, the target values of each scheme are subtracted from the corresponding negative ideal solutions in all schemes to obtain the indicator values. The indicator value of the j-th scheme is Y_j. The conversions of a_{ij} and b_{ij} are shown in Eq. (7).

$$\begin{cases} y_{ij} = a_{ij} - a_{ij}^{\min}, i = 1,....o \\ y_{ij} = b_{ij}^{\max} - b_{ij}, i = 3,4, j = 1....o \end{cases} \tag{7}$$

After conversion, a set of homogeneous indicators can be obtained, which are then passed into the cross efficiency DEA to identify objective and effective solutions. After evaluating and analyzing the cross efficiency DEA, the efficiency ranking is then carried out. The top ranked solution is the optimal solution. For each evaluated multi-objective optimization scheme, since the objective transformation no longer involves input-output relationships, the input is usually considered as 1. Under the condition of unchanged scale benefits, applying the Charnes-Cooper transformation can obtain a linear programming model, as shown in Eq. (8).

$$\max E_{dd} = \sum_{i=1}^{4} \mu_{id} y_{id} - \delta \tag{8}$$

In Eq. (8), d is the evaluation scheme. E_{dd} is its self-evaluation relative efficiency. By solving the model, the optimal solution for scheme d is obtained. Through the evaluation and analysis of this optimal solution, the cross efficiency value of the scheme is obtained, as shown in Eq. (9).

$$E_{dj}^{*} = \frac{\sum_{i=1}^{4} \mu_{id}^{*} y_{ij}}{1-\delta^{2}} (d, j = 1,....,r) \tag{9}$$

After calculating the cross efficiency matrix, the arithmetic mean method is used to obtain the cross efficiency value, as shown in Eq. (10).

$$E_{j}^{*} = \frac{1}{n} \sum_{d=1}^{n} E_{dj}^{*} (n = r, j = 1,....,r) \tag{10}$$

Among them, the higher the efficiency value, the more reasonable and excellent the solution is. By sorting efficiency values according to demand, the most effective solution can be identified, presenting decision-makers with an optimal solution that is not influenced by subjective factors. The application process of the cross efficiency DEA method is shown in Fig. 2.

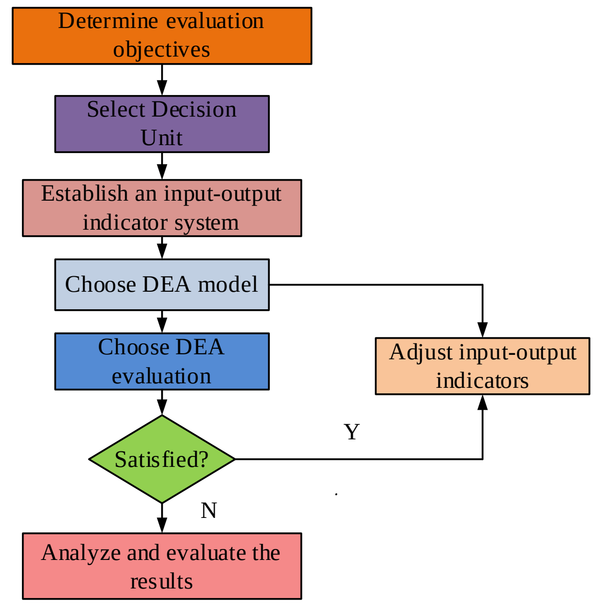


Fig. 2. Application process of cross efficiency DEA method.

C. *Benefit Optimization Combined with Improved SA Algorithm*

After using the cross efficiency DEA model for evaluation and solution, the study further adopts an improved simulated annealing algorithm to optimize environmental and economic benefits. SA algorithm is based on the basic principle of solid annealing and belongs to a probability-based algorithm [20-21]. Specifically, in the solid annealing, the solid is first heated to a certain degree and then slowly cooled. Due to heating, the particles inside the solid appear disordered, and the corresponding internal energy gradually increases. However, slow cooling gradually makes the particles more ordered, and equilibrium states are achieved at all temperature levels. Finally, when reaching room temperature, it becomes the ground state, and the internal energy decreases to the minimum [22]. The heating process, isothermal process, and cooling process together constitute the solid annealing process, which can actually simulate combinatorial optimization problems. That is, the solution space of the problem corresponds to the internal state of the object, the optimal solution corresponds to the lowest energy state, the objective function corresponds to the energy, and the initial temperature setting corresponds to the melting process. The Metropolis criterion optimizes the isothermal process, and the parameter controls the temperature drop corresponding to the cooling process. The corresponding relationship is shown in Fig. 3.

The SA algorithm can escape from local optima until the global optimum is found. The calculation process is simple, making it highly applicable to combinatorial optimization problems. However, this algorithm is limited by the parameter of cooling rate, often resulting in significant time waste or the optimal solution being skipped, and has a long convergence time. Therefore, the study first introduces genetic algorithm to avoid getting stuck in local optima. A mixed mutation operator is proposed to divide the mutation process into insertion mutation, reversal mutation, and swapping mutation, reducing the randomness in the mutation process. Secondly, the Metropolis criterion is inserted to determine the entry of paternal chromosomes into the offspring population. The higher the fitness value, the greater the probability of passing. Based on these two operations, an improved SA algorithm is proposed, which can ensure the overall optimal solution results and accelerate the solving process. The improved SA algorithm first performs chromosome encoding using real number encoding. Then, real numbers in s rows and t columns that match the actual meaning are randomly obtained. Among them, t is the number of genes on the chromosome, and s is the initial population size. This generates the initial population. Afterwards, the selection operation is performed. To ensure the completeness of the optimal individual, the optimal preservation strategy, namely the elite preservation strategy, is adopted, combined with the roulette wheel method for joint screening. The elite retention strategy can enable the best individual to enter their offspring and conduct selective selection among secondary individuals, which can further place them on the offspring chromosome. Based on the roulette wheel selection method, individuals with lower fitness have a significantly increased probability of entering offspring. The individual's selection probability is shown in Eq. (11).

$$P_{selected} = \frac{fitness(a_i)}{\sum_{i=1}^{n} fitness(a_i)} \tag{11}$$

In Eq. (11), a_i represents an individual. $P_{selected}$ is the probability of being selected. $\sum_{i=1}^{n} fitness(a_i)$ is the sum of fitness values. After screening excellent paternal chromosomes, crossover operations can be carried out. In this process, it is necessary to exchange the two selected paternal chromosomes, so that offspring can inherit the excellent characteristics of the paternal chromosomes. To ensure the efficiency of the calculation, the single point crossing method is used in the study. A point on the crossing point of the parental chromosome is randomly selected, and two parental chromosomes are subjected to cleavage treatment to obtain the offspring chromosome after replacement. The effect before and after single point crossing is shown in Fig. 4.

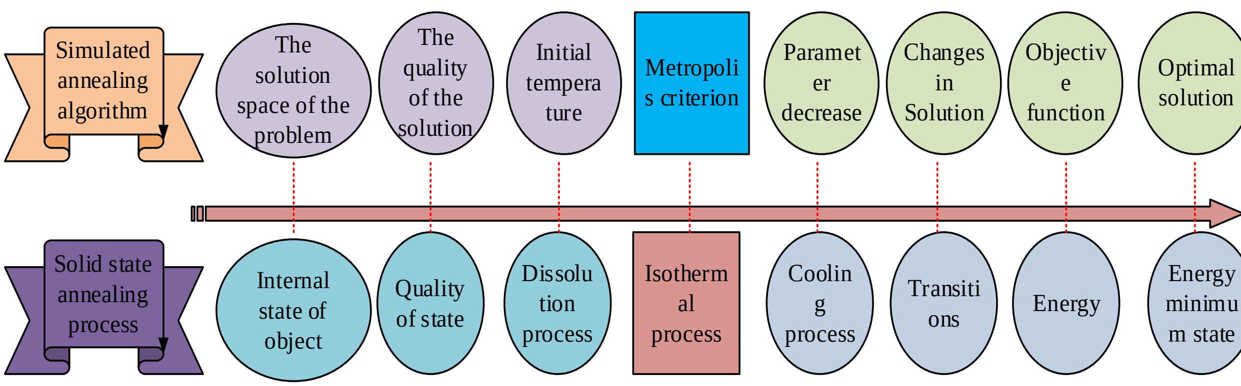


Fig. 3. The correspondence between simulated annealing algorithm and annealing process.

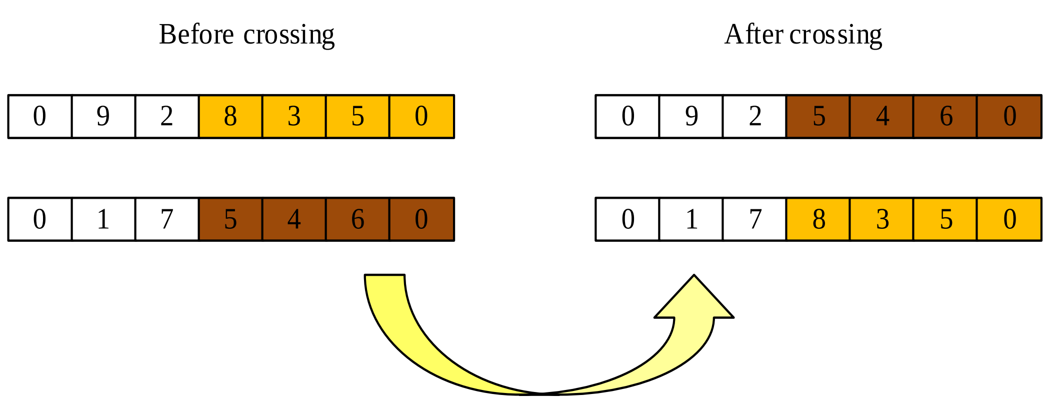


Fig. 4. Single point crossing effect before and after.

After applying crossover operations to genetic algorithms, the study improves the two-point variability theory by dividing variability into three stages: swapping, inversion, and insertion, forming a new mutation operator that avoids the local minima. After inserting the mutation, the Metropolis criterion is further introduced to determine whether the superior and inferior solutions are accepted. Firstly, the model function is solved to obtain an optimized solution, which serves as the initial value for the SA algorithm. Then, the SA algorithm is used to complete the local search in the surrounding space of the initial solution, and the local optimal solution is obtained from it. Finally, the Metropolis criterion is used to determine whether the new solution is accepted or not. When the difference between the model function of the local optimal solution and the original model function is less than 0, it can be determined as an acceptable new solution. Otherwise, it needs to be determined through Eq. (12).

$$p = \exp\left(-\frac{C_{new} - C_{old}}{T}\right) \tag{12}$$

In Eq. (12), T represents the current temperature. p represents the probability of the new solution being accepted. C_{new} represents the model function of the local optimal solution. C_{old} represents the original model function. In the probability of accepting a solution, a random number within the range of 0 to 1 is generated for comparison. When the random number is greater than p, the acceptable new solution can be retained and used as the solution of the model function. Otherwise, the new solution needs to be accepted, and the above steps need to be repeated continuously to update the annealing temperature. When the improved SA algorithm reaches the maximum number of iterations or continuously inputs the same result, the entire operation ends. Otherwise, it needs to be repeated continuously until the best result is obtained. Therefore, the operational flow of the improved SA algorithm can be presented in Fig. 5.

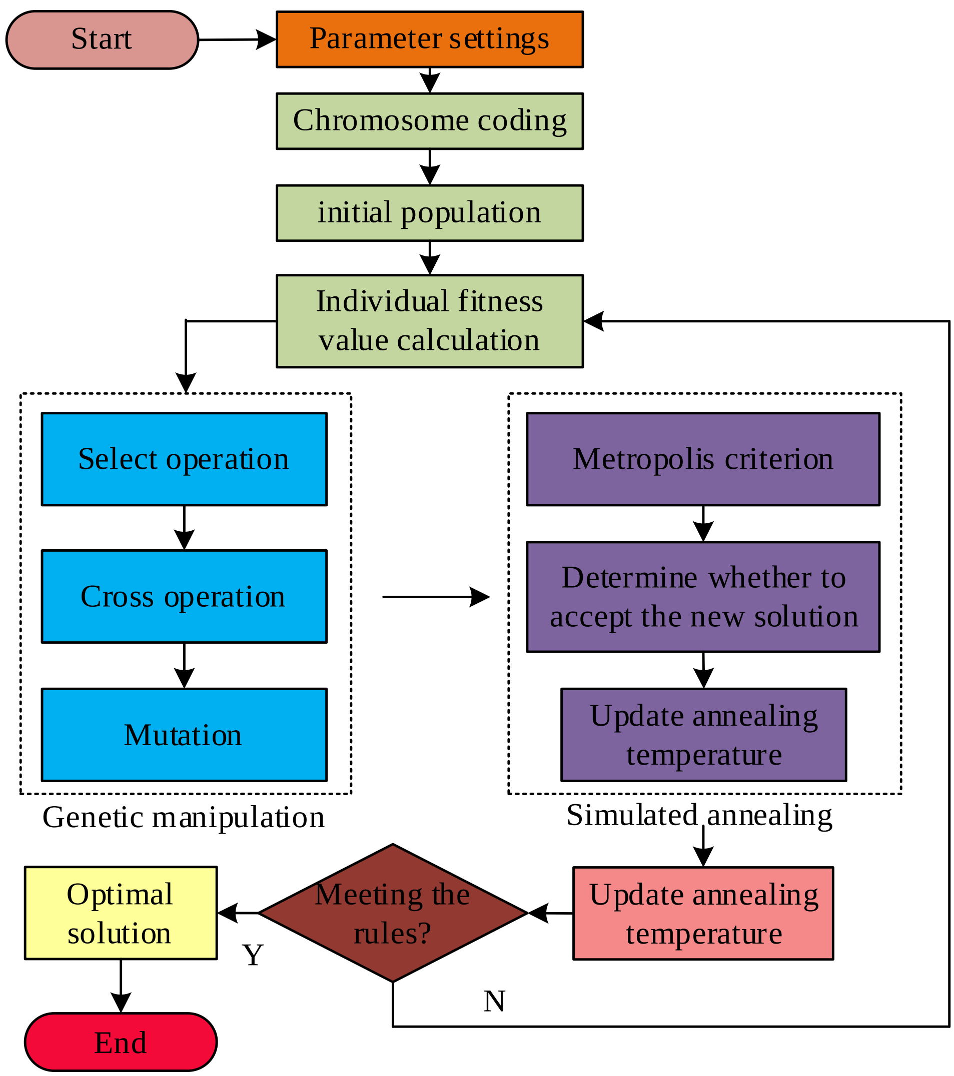


Fig. 5. The calculation process of the improved simulated annealing algorithm.

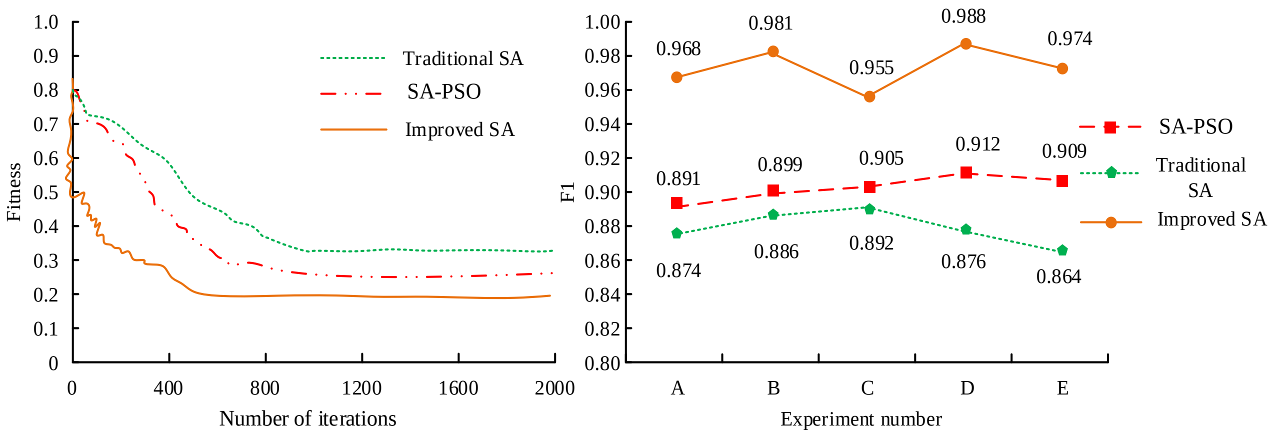
III. Results

To verify the effectiveness of the proposed method for analyzing the environmental and economic benefits of urban construction projects, the study first validates the performance of the improved SA algorithm. Then, environmental and economic benefit analysis is conducted by combining cross efficiency DEA.

A. *Performance Testing of Improved Simulated Annealing Algorithm*

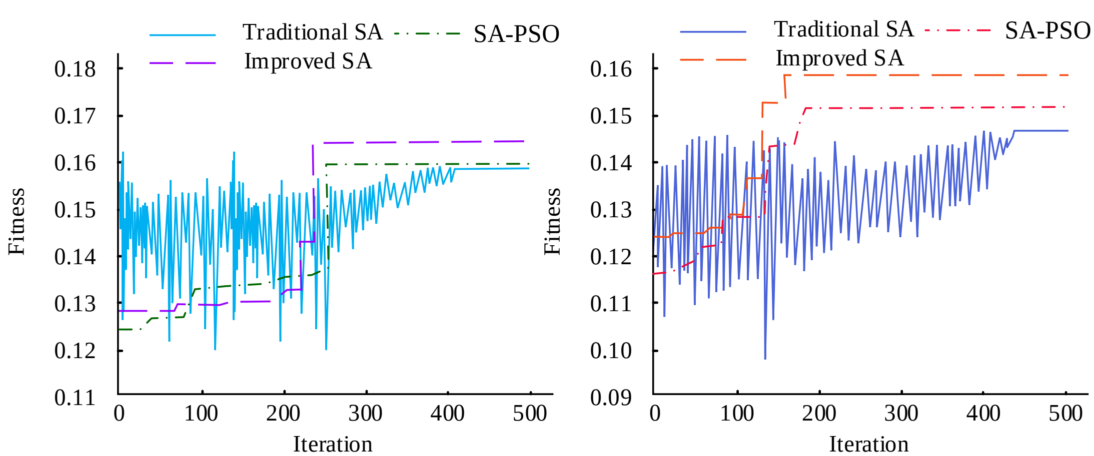
The performance testing of the improved SA algorithm mainly relies on Matlab 2020a simulation software, with Windows 11 operating system, 128GB of memory, and Intel Core i5-9300H central processor. During the testing process, traditional SA algorithm and SA-PSO algorithm are selected for comparison. The selected comparison indicators include fitness and F1 value, with an iteration of 2000 times. The dataset is CEC2022, which is a standard test function used to evaluate and compare the performance of optimization algorithms. This dataset can fully examine the search ability and robustness of optimization algorithms. The fitness and F1 value changes of the three methods are shown in Fig. 6.

From Fig. 6(a), during the variation of fitness values, the maximum fitness value of the improved SA was 0.86 and the minimum value was 0.21. It tended to stabilize after 480 iterations. The minimum fitness values of SA-PSO and traditional SA algorithms were 0.28 and 0.37, respectively, and both tended to stabilize after 1000 iterations, with a significantly slower convergence speed. According to Fig. 6(b), in the 5 experiments numbered A, B, C, D, and E, the maximum F1 value of the improved SA algorithm was 0.988 and the minimum value was 0.955. The average values of SA-PSO and traditional SA algorithms were 0.903 and 0.878, respectively. This proves that the improved SA algorithm has better overall performance. To further validate the performance of the improved SA algorithm, tests were conducted on two different datasets, including the Wine and Iris datasets in the UCI machine learning library. The Iris dataset is relatively small and simple, while the Wine dataset is relatively complex, and the relationships between features may be more complex, which can affect the convergence speed and stability of the algorithm. The proposed improved SA algorithm is more suitable for datasets with complex feature relationships or higher dimensions, as it can better explore and utilize the characteristics of the search space. The changes in fitness obtained are shown in Fig. 7.



(a) Fitness (b) F1

Fig. 6. The fitness and F1 value changes of three methods.



(a) Data set Wine (b) Data set Iris

Fig. 7. Comparison of fitness values in different datasets.

From Fig. 7(a), the convergence curve of the traditional SA algorithm started with significant fluctuations and instability, and then decreased as the number of iterations increased. The algorithm eventually stabilized at 410 iterations, the fitness value was approximately 0.158. The convergence curve of the improved SA algorithm was smoother, rising in a ladder shape, and tended to stabilize at around 0.166 after 256 iterations. From Fig. 7(b), the convergence curve of the SA-PSO algorithm was relatively stable, but the improved SA algorithm still showed a ladder shape increase with a fitness value of about 0.157, indicating relatively better performance. The study continues to test the running time of the three algorithms. The results are shown in Fig. 8.

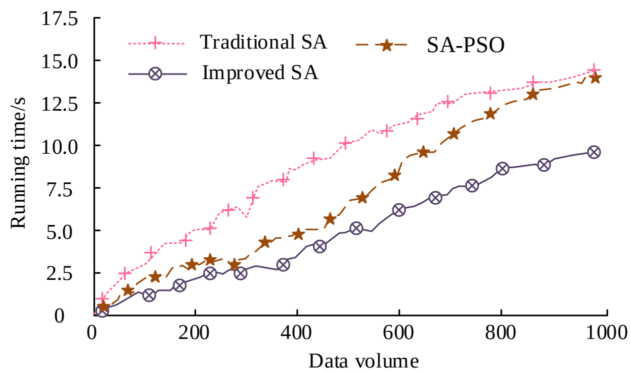


Fig. 8. The running time test results of three algorithms.

From Fig. 8, in terms of running time, with the increase of data volume, both the traditional SA algorithm and SA-PSO algorithm had a relatively fast increase in running time, with the highest being 14.2s and 14.6s, respectively. The running time curve of the improved SA algorithm always lowered than the other two algorithms, and the highest was only 9.7s, indicating significantly better running efficiency. Finally, the initial value dependency of the improved SA algorithm is validated, as shown in Table II.

From Table II, as for the improved SA algorithm, the standard deviation of the optimal value after 100 iterations was 0.00734, and the standard deviations of the optimization time and optimization iteration were 12.22352 and 3.55342, respectively. The standard deviations are relatively small, especially for the optimal value. This indicates that the stability of the optimization time and results is good, further proving the high robustness of the algorithm.

B. *Empirical Analysis of Environmental and Economic Benefits of Urban Construction Projects*

In order to analyze the effectiveness of the proposed method in analyzing the environmental and economic benefits of urban construction projects, three construction projects are selected from three provincial capitals in China, namely Project A, Project B, and Project C, with corresponding total construction areas of 21511m^2, 238500m^2, and 341000m^2, respectively. Firstly, the cross efficiency DEA model is used to solve the problem. The results are shown in Table III.

From Table III, the cross efficiency DEA model was effective for all three selected projects, achieving technical and scale efficiency in terms of cost and benefit, and having a high ecological efficiency. Both environmental and economic benefits were high. Based on this solution result, the improved SA algorithm is used to optimize the environment and economic benefits. The results are shown in Fig. 9.

From Fig. 9(a), in terms of environmental benefits, all three projects were improved to varying degrees, with the highest reaching 120000 yuan. From Fig. 9(b), after optimization, the economic benefits were significantly improved, with three projects increasing by 600000 yuan, 800000 yuan, and 850000 yuan respectively. From this, the proposed method can effectively improve the environmental and economic benefits of urban construction projects, and provide guidance for the implementation and later development of urban construction projects.

TABLE II. INITIAL VALUE DEPENDENCY VERIFICATION RESULTS

Solution results	Solution results	Optimization time	Optimal iterations
1	0.027416	82.78755	15
2	0.023774	75.24132	21
3	0.017184	88.46139	18
4	0.024701	93.57563	20
...	...	...	...
100	0.038525	81.86583	20
Standard deviation	0.00734	12.22352	3.55342

TABLE III. THE SOLUTION RESULTS OF THE CROSS EFFICIENCY DEA MODEL FOR THREE PROJECTS

Project	Insufficient output		Allocate redundancy		Ecological efficiency
	Economic benefits	*Environmental benefit*	*Indirect costs*	*Technical cost*	
Project A	0	0	0	0	1
Project B	0	0	0	2147.34	1
Project C	0	2.47	6.84	0	0.9987

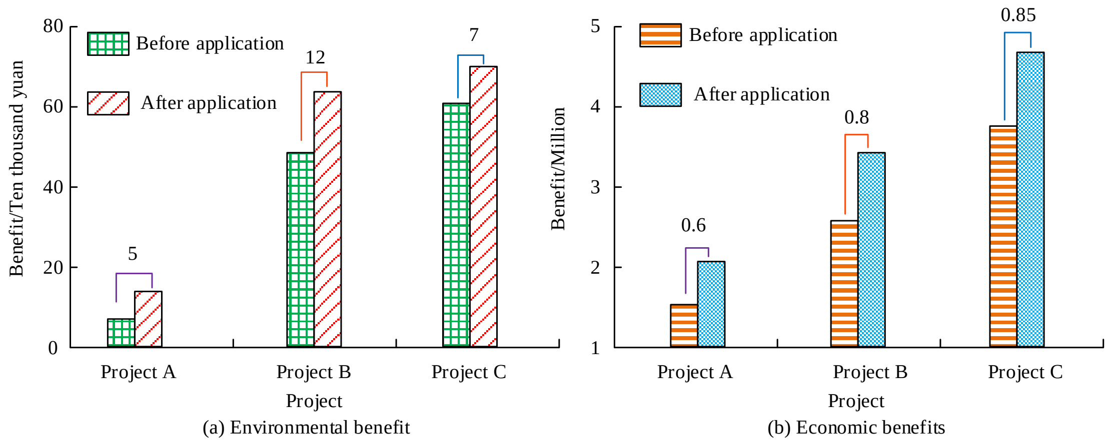


Fig. 9. Comparison of environmental and economic benefits before and after optimization.

IV. Discussion

To accurately analyze the economic and environmental benefits of urban construction projects, a cross efficiency DEA model was studied and designed, and a hybrid mutation operator and genetic algorithm were proposed to improve the SA algorithm. Finally, performance testing and practical verification were conducted. The results show that in the CEC2022 dataset, the maximum F1 value of the improved SA algorithm is 0.988 and the minimum value is 0.955, indicating better overall performance. The test results on different Wine and Iris datasets show that the convergence curve of the improved SA algorithm is smoother, and the fitness value ultimately stabilizes at 0.166. At the same time, the fitness curve of the improved SA algorithm shows a stepwise increase, resulting in better performance. In terms of running time, with the increase of data volume, the maximum running time of the improved SA algorithm is only 9.7 seconds, and the running efficiency is significantly better than the other two methods. Liu et al. introduced the SA algorithm into the adaptive particle swarm optimization algorithm to address the multi-objective allocation problem of maximizing weapon attack effectiveness, and proposed an adaptive SA optimization algorithm. The results show that the improved SA algorithm exhibits good performance in terms of convergence speed and global optimization ability, significantly better than a single SA algorithm, and can ensure maximum attack effectiveness [23]. The improved SA algorithm outperforms the basic SA algorithm in terms of performance. The difference is that in this study, a hybrid mutation operator and genetic algorithm were used to optimize the SA algorithm. The design of the hybrid mutation operator makes it easy to adjust the type and parameters of the mutation operator according to the characteristics of different construction projects, thereby optimizing the performance of the algorithm in specific scenarios. The population mechanism of genetic algorithm enables multiple solutions to be evaluated simultaneously, thereby improving the global optimization ability of the algorithm. However, Liu S et al. used adaptive particle swarm optimization algorithm for optimization, which lacks targeted optimization ability in specific scenarios. In addition, the applicability of the cross efficiency DEA model has been demonstrated in solving urban construction projects. After optimizing using the proposed method, the economic and environmental benefits of the three projects were significantly improved, with a maximum increase of 850000 yuan and 120000 yuan respectively, once again verifying the comprehensiveness of the proposed method in considering environmental and economic benefits and providing more comprehensive information. SoltanifarM et al. used a cross efficiency DEA model to rank decision units. The results show that this method can effectively consider the mutual influence between decision units when evaluating efficiency, thereby providing a more accurate and fair efficiency ranking [24]. By calculating cross efficiency, different decision-making units can not only compare their own inputs and outputs, but also use the efficiency of other decision-making units as a benchmark. This relative evaluation method makes the results more reliable. This once again confirms the effectiveness of the cross efficiency DEA model. The research provides powerful tools for decision support in actual urban construction projects, with broad application potential, and can promote sustainable urban construction in the future.

The improved SA algorithm and cross efficiency DEA model proposed in the study have achieved good performance in the economic and environmental benefit assessment of urban construction projects, but there are still some limitations. Firstly, the parameter selection and adjustment of the model depend on specific datasets, and the lack of automated parameter tuning mechanisms may affect its universality. Secondly, the model did not consider the impact of dynamic environmental changes on the efficiency of decision-making units, which may limit its applicability in practical applications. Future research can focus on enhancing the adaptive capability of models, introducing more complex multi-objective optimization frameworks, and exploring the application of new technologies such as deep learning in the optimization process to improve the robustness and real-time decision-making ability of algorithms.

V. Conclusion

A cross efficiency DEA model was studied and designed for the economic and environmental benefit analysis of urban construction projects, and an improved SA algorithm was proposed. The results showed that in the five experiments numbered A, B, C, D, and E, the maximum F1 value of the improved SA algorithm was 0.988 and the minimum value was 0.955. The average values of SA-PSO and traditional SA algorithms are 0.903 and 0.878, respectively. This proves that the improved SA algorithm has better overall performance. In terms of running time, with the increase of data volume, the running time of both traditional SA algorithm and SA-PSO algorithm has grown rapidly, with the highest being 14.2s and 14.6s respectively. The running time curve of the improved SA algorithm has always been lower than the other two algorithms, and the highest is only 9.7s, indicating significantly better running efficiency. In addition, the applicability of the cross efficiency DEA model has been demonstrated in solving urban construction projects. After optimizing using the proposed method, the economic and environmental benefits of the three projects have significantly improved, with a maximum increase of 850000 yuan and 120000 yuan, respectively. The method proposed by the research institute can effectively consider the environmental and economic benefits in urban construction projects. In practical applications, by optimizing the improved SA algorithm, research can quickly identify projects with excellent performance, promote the rational allocation and use of resources, and enhance the overall sustainability of the project. Further research can explore the applicability of improved algorithms in other fields and promote their application in a wider range of decision support systems.

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