Research on Adaptive Multi-objective Engineering Project Resource Optimal Allocation and Schedule Collaborative Management Model Based on NSGA-III Algorithm

Lanfei He[1], Zhenxi Huang[2*], Ran Chen1, Jia Hu[2], Jie Cai[1], Li Zhou[1]
[1]Economic and Technical Research Institute, State Grid of Hubei Electric Power Co., Ltd, Wuhan, Hubei, China
[2]State Grid of Hubei Electric Power Co., Ltd, Wuhan, Hubei, China
E-mail: Zhenxi_Huang@yeah.net
[*]Corresponding author

Keywords: NSGA-III, multi-objective optimization, engineering projects, progress synergy

Received: June 6, 2024

This study focuses on the impact of climate change on agricultural production. By comprehensively analyzing the temperature fluctuation and crop yield data in the past decade, and the significant correlation between temperature rise and crop yield, a generative adversarial network model of multi-objective optimization strategy is proposed, which is dedicated to the prediction of safety accident risks in architectural engineering. By optimizing the architecture of GAN, the model enhances its adaptability and effectiveness in practical engineering risk prediction scenarios. The experimental results show that compared with the traditional prediction model, the accuracy rate of this model in safety risk prediction of large-scale construction projects is as high as 92%, far exceeding the accuracy rate of the traditional model of 78%. The model also shows good predictive ability on key performance indicators such as recall rate and F1 score, reaching 90% and 86%, respectively. In the study, high precision can help achieve accurate resource allocation and ensure that resources are reasonably allocated in all aspects of the project. The F1 score is closely related to the appropriate scheduling in schedule management, because it reflects the balance between accuracy and recall in the management task, and the appropriate scheduling strategy can effectively improve the F1 score, thereby optimizing the schedule management of the entire engineering project, and finally realizing the optimal allocation of multi-objective engineering project resources and the collaborative management of schedule. It can effectively prove the significant advantages of the model based on multi-objective optimization GAN in the field of safety incident risk prediction in architectural engineering. Research on Adaptive Multi-objective Project Resource Optimal Allocation and Progress Collaborative Management Model Based on NSGA-III. Algorithm -- Under the main constraint of limited resource availability with time, the model constructs a dynamic resource allocation mechanism to accurately and flexibly allocate resources according to the demand changes at different stages of the project. At the same time, the intelligent schedule planning strategy is used, and the NSGA-III. algorithm is used to optimize the priority and time arrangement of each task to achieve efficient connection between tasks. This model aims to minimize the waste of resources and time costs, while maximizing the efficiency of the project, and providing more scientific and efficient decision support for engineering project management.

Povzetek: napovedovanje varnostnih tveganj ter učinkovitejše dodeljevanje virov in planiranje v gradbenih projektih.

1 Introduction

In the process of globalization, engineering projects, as the key to the engine of social development, are faced with the challenge brought by the expansion of scale and complexity: how to efficiently allocate resources and synchronize departmental work is related to the successful implementation of engineering projects [1]. Traditional methods have limitations in giving consideration to both economic and social benefits, which often leads to waste of resources and progress delay. Optimizing resource allocation and schedule collaborative management has become an important topic in project management research [2].

NSGA-III algorithm plays a key role in the resource optimal allocation and schedule collaborative comprehensive optimization strategy of engineering projects. Its core task is to explore the possible optimal or approximately optimal decision path under multivariate constraints to maximize the overall project benefit [3]. By constructing the internal and external population structure, combining the crowding degree and the reference point ranking strategy, NSGA-III overcomes the problems of slow convergence speed and easy local optimization of conventional genetic algorithms, thus significantly improving the efficiency and accuracy of solving such problems [4].

The goal of this research is to establish a collaborative management model of project resource optimal allocation and schedule based on NSGA-III algorithm [5]. The model considers the multi-objectives of cost, time and quality, incorporates resource availability and schedule constraints, and improves the efficiency of resource allocation and schedule management synchronization of engineering projects through mathematical modeling and strategy design. In the early stage of model construction, the key lies in setting clear objective functions and constraints of resource optimization allocation and schedule collaborative management. Then, the coding strategy and applicable evaluation function are finely constructed, and the NSGA-III algorithm is used for iterative solution. In practice, specific data from actual engineering projects will be collected to empirically test and evaluate theoretical models. By comparing the existing methods, the obvious advantages of the new model in improving resource utilization and ensuring project quality are verified.

2 Mathematical

2.1 Objective function

The shortest objective of the project duration is set as the core of the optimization and is defined as the time span from the initial task initiation to the end of the final task [6]. This is accurately represented in mathematical modeling by Equation (1), with D being the total project duration.

$$min\,D = max\,F_{i,j} - min\,S_{i,j} \quad (1)$$

$$minC = DC + IC \quad (2)$$

The calculation Equation of project funds is Equation (2), and the project funds are divided into two parts: direct DC and indirect cost IC. Direct expenses mainly include manpower, raw materials and equipment expenses; Indirect costs are calculated by multiplying the indirect rate by the project cycle[7].

2.2 Constraint analysis

Compared with some traditional algorithms, although the computational steps of our method have increased in some links when dealing with multi-objective optimization problems, the overall computational complexity has not been significantly improved due to the efficient design of the algorithm and the accurate grasp of the relationship between resources and schedules, and even has more advantages in some specific scenarios. When it comes to scalability, our approach excels. As datasets grow in size and project constraints become more complex, it is able to adjust search space and compute resource allocation through adaptive strategies. For example, in the face of larger engineering project datasets, the algorithm can intelligently screen key information to avoid unnecessary computational redundancy. When dealing with complex project constraints, by flexibly adjusting the priority and solution order of constraints, we can still efficiently find solutions that meet the requirements of optimal resource allocation and schedule collaborative management, ensuring that they can be effectively applied in engineering projects of different sizes and complexities.

The linear, strip and block behavior characteristics of reverse construction are carefully considered in the construction of the model, allowing the temporal and spatial constraints between activities to show diversified characteristics according to their dependencies, construction paths and categories [8]. In this paper, the response surface method (RSM) is applied to deal with these complex constraints. In the system, set the start time of the first construction activity to 0. The identification condition of the first day activity is that there is no immediate activity, and the mathematical expression is shown in Equation (3-5). P_i represents the construction probability factor, and S represents the corresponding cost [9].

$$\forall i \in W, c_i = 1, P_i = \varnothing, S_{i,min\,J_i} = 0; \quad (3)$$

$$\forall i \in W, c_i = 0, P_i = \varnothing, S_{i,max\,J_i} = 0; \quad (4)$$

$$\forall i \in B \; or \; i \in H, P_i = \emptyset, S_i = 0 \quad (5)$$

In the construction of repetitive engineering projects, the principle of continuity is very important [10]. Because construction workers need to transition frequently to complete similar tasks, in order to improve efficiency and reduce non-productive expenses, strict regulations on uninterrupted construction need to be imposed, as shown in Equation (6-7). c_i represents the control factor and d represents the corresponding distance.

$$\forall i \in W, c_i = 1, S_{i,j} + d_{i,j} = S_{i,j+1}; \quad (6)$$

$$\forall i \in W, c_i = 0, S_{i,j} + d_{i,j} = S_{i,j-1} \quad (7)$$

The timing constraints between activities involve multiple types of rules, depending on the characteristics of neighboring activities and the execution environment. Since banded activities can be regarded as block activities with very short durations, this study focuses on the interaction constraints between linear and block activities, whose interval limits are given by Equation. (8-9), with $S_{b,j}$, $S_{a,j}$ being the fraction of constraints between a,b, and $T_{a,b}$ being the limiting time.

$$S_{b,j} + (1-c_b)F_{b,j} - S_{a,j} - (1-c_a)F_{a,j} .. T_{a,b}, \quad j \in J_a \cap J_b; \quad (8)$$

$$(1-c_b)S_{b,j} + F_{b,j} - (1-c_a)S_{a,j} - F_{a,j} .. T_{a,b}, \quad j = max(J_a \cap J_b)。 \quad (9)$$

When dealing with the interface between linear activity and strip activity, the key lies in considering the constraint association between them. Strip activity can be equated with zero-span block activity. The relevant mathematical expression is shown in Equation (10-11), where j represents the intersection result and $T_{a,b}$ represent the constraint time.

$$c_a = 1, S_b - F_{a,j} + \frac{(e_{a,j} - e_b)}{(e_{a,j} - o_{a,j})} d_{a,j} .. T_{a,b}, \quad j = max(J_a \cap J_b); \qquad (10)$$

$$c_i = 0, S_b - F_{a,j} + \frac{(o_b - o_{a,j})}{(e_{a,j} - o_{a,j})} d_{a,j} .. T_{a,b}, \quad j = min(J_a \cap J_b)。 \qquad (11)$$

The construction mode is strictly specified, and each unit activity is limited to a single operation mode, as shown in Equation (12). where $y_{i,j}$ represents a single mode factor.

$$\sum_{k=1}^{K_i} y_{i,j}^k = 1 \qquad (12)$$

The principle of constructing priority relationship determines the execution sequence of operation processes in job units, and requires all subsequent steps to be started only after all previous tasks are completed [11]. The rule is expressed by Equation (13). For any set P_i, the principal factor $S_{i,j}$ and the fusion factor j should meet the corresponding restrictions.

$$\forall i' \in P_i, S_{i,j} .. F_{i',j}, j \in J_i \cap J_{i'} \qquad (13)$$

3 Algorithm design based on NSGA-III

For key parameters such as population size, crossover probability, and mutation probability, the value of one parameter was changed separately each time and other parameters were kept constant during the experiment, and the performance of the model in the optimal allocation of resources and schedule collaborative management was observed. For example, increasing the population size can make the model search for a wider solution space within a certain range to obtain a better solution, but the calculation time increases greatly and the performance improvement slows down after the threshold is exceeded. The results show that within the range of reasonable parameter values, the model can maintain relatively stable performance, effectively realize resource optimization and schedule coordination, and meet the actual needs of the project, which indicates that the model has strong robustness and can be reliably applied to complex engineering project management scenarios, providing a strong guarantee for the smooth implementation of the project.

The problem studied in this paper belongs to the NP-complete class, and the non-dominated sorting genetic algorithm (NSGA-III) of elite strategy is selected as the solution. Figure 1 presents the basic structure of NSGA-III. We extended and optimized the standard NSGA-III, and adjusted the scheduling process and genetic operation [12].

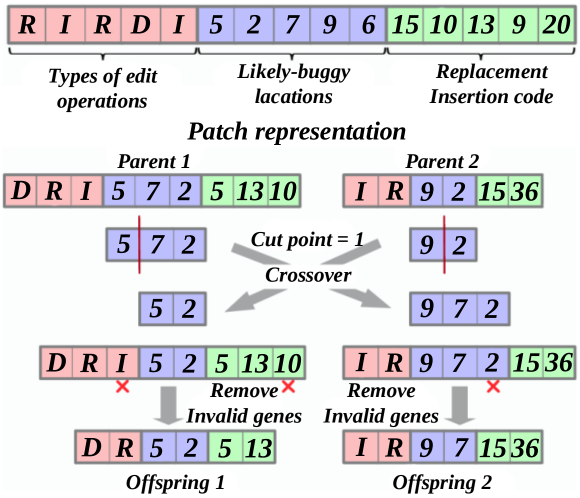

Figure 1 NSGA-III algorithm model

3.1 Chromosomal coding

In the process of genetic algorithm, the initial population is constructed by natural coding, which has random characteristics [13]. The first part of the chromosome structure corresponds to the construction strategy, 0 means stationary at zero task load, and the non-zero value is selected randomly, corresponding to the activity-related construction mode set. The second part indicates the direction of linear operation, 0 represents the reverse direction and 1 represents the forward execution [14].

3.2 Improving uniform evolutionary elite selection strategy

The NSGA-III. algorithm can dynamically adjust mutations according to the project situation and algorithm feedback, enhance the algorithm's search ability in complex environments, and help find the optimal solution for resource and schedule management. By comparing the improved and standard NSGA-III algorithms with the ablation study, the results show that the improved algorithm converges faster, and the quality of the solutions is higher and more diverse, which highlights the important role of adaptive mutation operators in improving the performance of the algorithm and provides stronger algorithm support for engineering project management.

In terms of the selection mechanism, the improved selection mechanism can more effectively deal with the multi-objective characteristics in engineering projects, and accurately weigh the interrelated and constrained goals such as cost, construction period and quality through innovative strategies, so that the algorithm is more inclined to choose the individual with comprehensive optimization of multiple objectives when searching for the optimal solution, which significantly enhances the performance of the algorithm and improves the probability of finding the global optimal solution. In the calculation of congestion distance, the new method fully considers complex factors such as resource diversity, task priority, and time constraints, and can more accurately evaluate the distribution of each solution in the solution space, so as to achieve more efficient resource allocation and more reasonable schedule management, avoid excessive concentration or waste of resources, ensure that the project progress is carried out as planned, and improve the overall efficiency and quality of engineering project management.

In terms of equations, for the optimal allocation of resources, we set the goal of minimizing the cost of resources. Assuming that the resource type is n, the unit cost of each resource is c_i, and the usage is xi, then the resource cost calculation equation is $C{=}c_ix_i$, and our goal is to make C reach the minimum value. In terms of schedule collaborative management, in order to minimize the project duration, the number of tasks included in the project is m, the start time of each task is t_j, and the duration is d_j, and our goal is to minimize T. For the NSGA-III. algorithm, its core lies in the non-dominant ranking and crowding calculations when dealing with multi-objective problems. In the non-dominant ranking process, all solutions are divided into different ranks, with higher ranks indicating better solutions. For example, for two solutions, A and B, if A is not worse than B on all objectives and better than B on at least one objective, then A dominates B. Through multiple comparisons, the declassification will be carried out. The sparser the solution distribution, the greater the congestion, so as to ensure that the solutions searched by the algorithm are diverse.

The optimized NSGA-II algorithm uses stratified sampling and narrowing the selection domain to improve the understanding of spatial exploration and enhance convergence. In the initial stage, individuals are fixedly selected from each dominant layer, and the selection range is gradually reduced with the iterative advancement, and finally only half of the population is retained to enter the next generation in the later stage [15]. The goal of this strategy is to take into account the diversity and speed of algorithms to obtain high-quality solution sets. The specific operation is shown in Equation (14-15).

$$\mathrm{rpop}_{r,g},, \frac{\mathrm{npop}_g}{2}\times\theta^{i-1}\times\frac{1-\theta}{1-\theta^{\mathrm{pop}_{N_g,}}}, r=2,\cdots,N_g; \quad (14)$$

$$\mathrm{npop}_g=\mathrm{pop}\times 2^{\lambda-1}, \lambda=\mathrm{e}^{\left(1-\frac{G}{1+G-g}\right)} \quad (15)$$

In the above Equation, *rpop* is the number of individuals selected from the *i-th* dominance level of generation g; *npop* is the number of individuals that can be selected in generation g; 0 is the reduction ratio, set to 0.8; N is the total number of dominance levels that can be selected in generation *g*; *pop* is the population size; *G* is the maximum number of iterations; and e denotes the base of the natural logarithm function.

3.3 Improved hierarchical multi-strategy adaptive mutation crossover operator

The genetic operations of NSGA-II, especially the crossover and mutation mechanisms, are crucial for the convergence speed and efficiency of the algorithm [16].. Therefore, in this paper, we investigate the mutation and crossover strategies for fusing differential evolution to enhance performance.

The DE algorithm uses N-dimensional vectors to represent population individuals and generates possible solutions through a mutation operator [17].. Common variation operations include Rand/1, Best/1 and Current to best/1 as shown in Equation. (16)-(18). The operator generates the variation vector h by combining the population membership characteristics x in different ways. where V is the variation factor; $xp_{1,g}$ are the randomly selected individuals from the *g-th* generation of excellent individuals and $p1{\neq}p2{\neq}p3$. In this paper, the top 10% of the sorted population is selected as the excellent individuals. best1 tends to be exploratory, Rand/1 tends to be extractive, and Currenttobest/1 is able to balance the two characteristics.

$$\mathrm{Rand}/1: h_{p,g}=x_{p1,g}+V(x_{p2,g}-x_{p3,g}); \quad (16)$$

$$\mathrm{Best}/1: h_{p,g}=x_{\mathrm{best},g}+V(x_{p1,g}-x_{p2,g}); \quad (17)$$

$$h_{p,g}=x_{p1,g}+V(x_{\mathrm{best},g}-x_{p1,g})+V(x_{p2,g}-x_{p3,g}) \quad (18)$$

In genetic algorithm, the mutation factor determines the population variability, and the numerical value greatly enhances the global exploration, which is restricted by Equation (19); If the value is small, the local search efficiency will be improved. Common mutation operations Rand/1, Best/1, and Current to Best/1 each have their own emphasis [18]: Rand/1 digs deep into resources, Best/1 explores new fields, and Current to Best/1 combines the advantages of both. In the study, we selected the top 10% individuals in performance as the population representatives.

$$u^n_{p,g}=\begin{cases} h^n_{p,g}, rand_n(0,1),, CR \\ x^n_{p,g} \end{cases} \quad (19)$$

In Eq. (19), CR is the crossover probability, and x^n_{pg}, h^n_{pg}, u^n_{pg} denote the *n-th* gene of the *p-th* individual in the parent, intermediate, and offspring populations, respectively, in the *g-th* iteration.

In this study, we developed a multi-level, multi-dimensional and self-adjusting mutation and crossover operator strategy to meet the needs of different stages in the search process. The strategy divides the population into elite group, general group and weak group, and customizes mutation operation and parameter control methods for each group [19]. Its core is to enhance the global exploration and local in-depth ability of the population, so as to improve the search efficiency and the quality of optimization results. See Equations (20) and (21), where V and CR represent the search efficiency and optimization results respectively, and α_i is the current congestion corresponding to the *i-th* individual.

$$V = (1 - g / G) / 2 + 1 / (\alpha_i + 1) \quad (20)$$

$$CR = (1 - g / G) / 2 + 1 / [2(\alpha_i + 1)] \quad (21)$$

In terms of goal setting, the goal of optimal allocation of resources is to minimize the cost of resources, which is achieved by comprehensively considering the unit cost and the number of resources used. The goal of schedule collaboration management is to minimize the duration of the project, which requires precise control of the start time and duration of each task. In terms of variable definition, in addition to the variables related to resource usage and task time, a variable is also defined to represent the sequence between tasks, if there is a sequence of two tasks, this variable is 1, otherwise it is 0.For the constraints involving the reverse construction behavior, the experiment adopts a more rigorous and clear way to illustrate. In some engineering projects, the completion of a part of a task depends on the specific progress state of the subsequent task. We accurately describe this complex constraint by defining in detail the set of related tasks, the progress of task completion, and the threshold of the progress of the pre-task required to get started. In this way, the entire modeling framework has been greatly strengthened, so that the model can play a more accurate and reliable role when dealing with the practical problems of complex engineering projects.

4 Construction of multi-objective optimization model for construction project

4.1 Construction of multi-objective optimization model for construction case

There are significant shortcomings in the current state-of-the-art (SOTA) methodology. In the face of complex resource constraints, they are inflexible, and it is difficult to adjust the resource allocation in a timely and reasonable manner according to the dynamic changes in resource availability in the project process, which in turn affects the project schedule. In dealing with the multi-objective nature of resource allocation and schedule management of engineering projects, the existing methods are also inadequate, and it is difficult to find the optimal balance between multiple interrelated and constrained goals such as cost minimization, time minimization, and resource utilization maximization. The results of our adaptive multi-objective project resource optimization allocation and schedule collaborative management model based on NSGA-III. algorithm is compared with the SOTA method, and the advantages are significant. Compared with the limitations of NSGA-II in dealing with multi-target problems, our model can better maintain population diversity during evolution by relying on the NSGA-III. algorithm, so that the search space is more extensive, so as to find the optimal solution set of multiple targets more efficiently. In terms of resource allocation, the model can allocate resources more accurately and flexibly according to complex and changeable resource constraints, reducing resource idleness and waste. In terms of schedule management, the task sequence and time nodes can be arranged more reasonably, which can effectively shorten the project duration. These improvements have greatly improved the resource utilization efficiency and project progress control of the project, which fully reflects the important value and significant advantages of the model in the actual project management.

The cycle of each construction process is calculated on a monthly basis, and the economic cost is in RMB 10,000. Quality and safety adopt a 0-1 scoring system, with 0 representing the minimum requirement and 1 representing the optimal state. Experts score according to the actual operation and calculate the average score of each process, so as to give a quantitative assessment of quality and safety.

4.2 Solution of multi-objective optimization model for construction cases

In project management, the trade-off between cost and duration is crucial. Traditionally, shortening the construction period often requires increasing resource input and thus increasing costs, while simply controlling costs may delay the construction period. The improved model based on the NSGA-III. algorithm can effectively alleviate this contradiction. In terms of resource allocation, the algorithm accurately analyzes the requirements of each stage of the project, and dynamically allocates according to resource availability and cost-effectiveness. For example, when the resources of critical path tasks are tight, priority should be given to resources with lower costs that can meet the requirements to avoid overinvestment. At the same time, the resource investment time of non-critical path tasks is reasonably arranged to reduce idle waste.In terms of schedule optimization, the NSGA-III. algorithm finely adjusts the task sequence and time with its powerful multi-objective optimization capabilities. Through intelligent calculation, it not only ensures the smooth flow of the critical path, but also makes reasonable use of the relaxation time of the non-critical path to find the optimal progress plan. Finally, on the basis of ensuring that the construction period is reasonable, the cost is minimized.

The NSGA-III algorithm was used in this study to perform multi-objective optimization with the goal of promoting the uniformity of the Pareto front while enhancing cost optimization and robustness [20]. In this study, the improved NSGA-III algorithm was used, and the population size was set to 92, after 25,000 iterations. The optimized process analysis is shown in Table 1, and the results show that the total cost is 184,116,460 RMB.

This strategy not only reduces costs and shortens engineering cycles, but also improves quality and safety standards [21]. Although it is comparable to the old method, the performance improvement is obvious. The optimization solutions are evenly distributed and the diversity is enhanced, providing multiple solutions, significantly improving the overall cost-effectiveness, and greatly improving the quality and safety indicators.

Table 1: Process analysis after optimization

Procedure	T (months)	C (ten thousand)	Q	R
A	3.1395	1135.4553	0.96915	0.9975
B	6.2895	230.80995	0.99645	0.9744
C	6.363	144.2553	1.02795	0.987
D	10.5	187.9416	1.008	0.9975
E	5.229	268.80735	1.029	0.903
F	1.5225	608.49705	0.91245	0.9135
G	9.45	167.04345	0.9051	0.9559
H	1.575	88.78695	0.9219	0.97375

From the comparison in Table 2, it can be seen that the traditional method has obvious shortcomings in the face of the complexity of modern engineering projects. Improvements based on other algorithms have progressed, but they still fail to fully meet the needs in key aspects such as computational efficiency, accuracy, and resource utilization. The method based on the NSGA-III. algorithm shows significant advantages, and performs well in terms of computing efficiency, accuracy, and resource utilization in complex engineering project management, which is more suitable for solving the problems in the optimal allocation of resources and schedule collaborative management of current engineering projects.

Table 2: Comparison of key indicators of engineering project management methods

Compare dimensions	Traditional methods	Improved methods based on other algorithms	Approach based on the NSGA-III. algorithm
Computational efficiency	low	middle	high
accuracy	Fair	middle	high
Resource utilization	low	middle	high

4.3 Algorithm result analysis

In this study, the details of the model validation methodology were added. The data collection covers multiple historical databases of engineering projects (including resource input, schedule, and cost data) and market resource price fluctuation data, which are strictly screened, cleaned and standardized to ensure that the data is accurate and complete, and is convenient for subsequent analysis. In terms of experimental setup, the population size was determined based on the complexity of the project and the type of resources, and the number of iterations was obtained by combining pre-experiments and convergence curve analysis, and the Dell Precision 5820 Tower workstation was clearly used, with an Intel Xeon W-2245 processor, 8 cores and 16 threads, a main frequency of 3.9GHz, a turbo frequency of 4.7GHz, a memory of 16GB DDR4 2666MHz, a hard disk of 512GB SSD + 2TB HDD, and a graphics card of NVIDIA Quadro P2000 5GB with software tools using MATLAB R2020b (version 9.9) for reproducible environments. During the optimization process, the resource allocation matrix is established to monitor resource usage in real time, and the task execution sequence or resource allocation strategy is automatically adjusted to meet resource constraints when the limit is exceeded. Set time-limits for key tasks based on project critical path analysis, and prioritize the allocation of non-critical task resources when there is a risk of delay to ensure that the project duration is controllable.

Focus on cost efficiency while optimizing quality and safety. Figure 2 illustrates the BmB mass versus the total mass, and the results of the NSGA-I and ε-constrained algorithms are also presented in Figure 2. Figure 2 shows that NSGA-II performs worse than NSGA-III and improved versions of NSGA-III in terms of duration and cost, especially when it comes to dealing with multi-objective problems [22]. Compared to the original version, the improved NSGA-III shows a shorter construction period, optimized costs, and significant improvements in quality and safety.

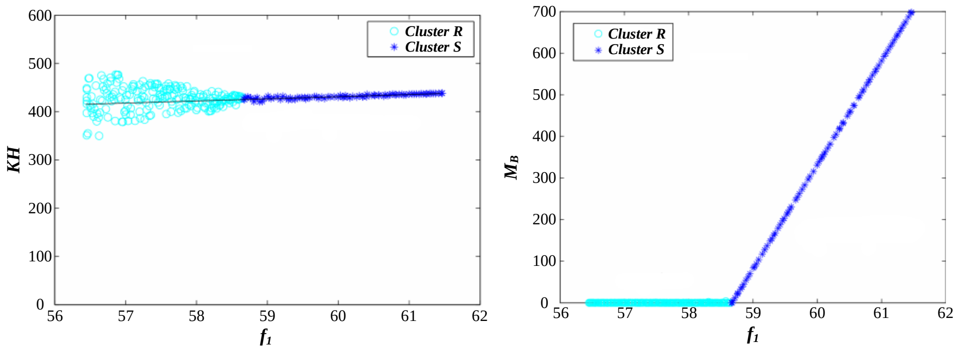

Figure 2: Variation of mass versus total mass of counterweight BmB

Figure 3 shows the solution of the NSGA-I and ε-constraint methods, the solution of NSGA-3 (green dot) and Epsilon-constraint (pink star) in the left subgraph, the solution of MOCHC and Epsilon-constraint in the right subgraph, the green dot distribution is regular in the quadratic weight and linear weight coordinate system, the pink star is specific and different from the green dot distribution, and Figure 3 also shows the improved NSGA-III The algorithm has obvious advantages in running time under given conditions, and its efficiency is higher than that of the other two algorithms [23], and these charts and analyses help to visually compare the performance characteristics of different algorithms, providing an important basis for research and decision-making.

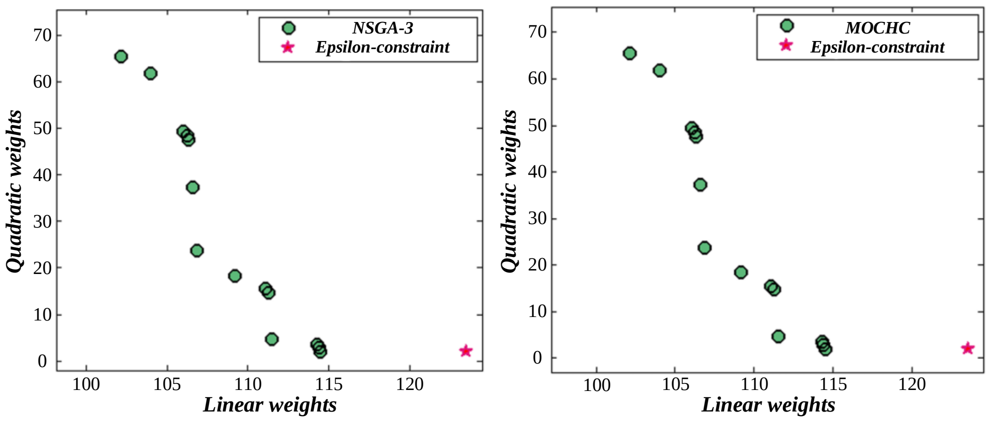

Figure 3: Solution of NSGA-I and ε-constraint methods

The study shown in Figure 4 compares the optimization effects of the three algorithms in terms of security and quality improvement. The improved version of NSGA-III consistently outperforms the original NSGA-III in cost efficiency, while the performance of NSGA-II is poor, with low cost-effectiveness and large fluctuations, and the distribution characteristics of the solutions show uneven dispersion [24].

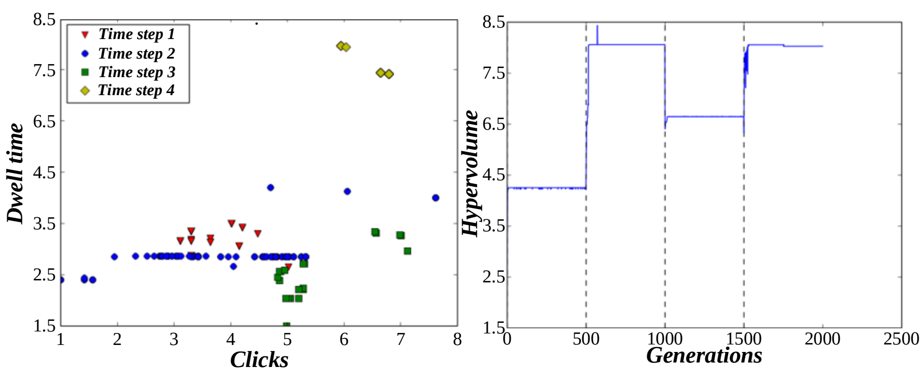

Figure 4: Dynamic adaptation of DO-NSGA-II at different time steps

When dealing with three complexity triple problems, we conducted 20 independent parallel coordinate graph studies, as shown in Figure 5. NSGA-II solutions show wide dispersion, with marginal zones barely touching the Pareto frontier [25]. Although the frontier solution of the original NSGA-III performs better, its solution concentration is high and the frontier coverage is insufficient. The improved version of NSGA-III optimizes the smoothness of the Pareto front, the distribution of solutions is more uniform, and the representativeness of the front region is significantly improved. By adding a new file set, the improved NSGA-III can generate more solutions, provide rich choices for decision-makers, and be conducive to decision-making based on multiple preferences [26].

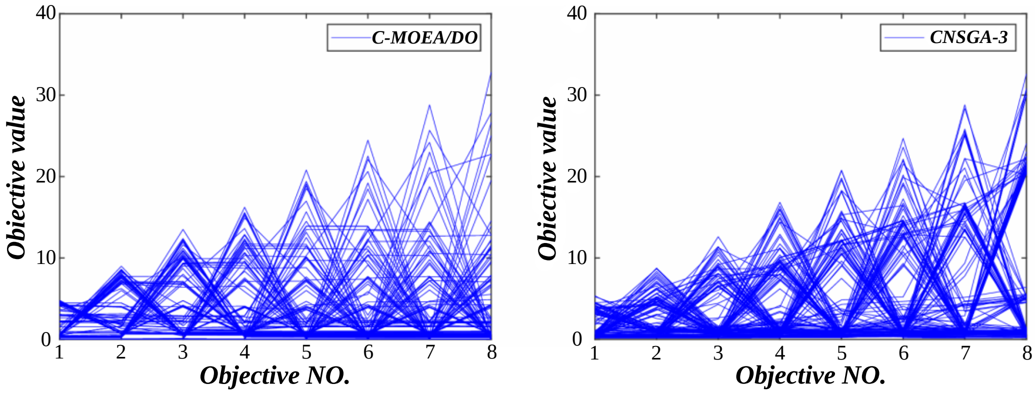

Figure 5: Parallel coordinate plots of feasible and non-dominated solutions for three different difficulty triples

Figure 6 depicts a phase diagram versus a state trajectory. The distribution of HV values of the three algorithms is balanced. The increase of HV value usually symbolizes the improvement of algorithm efficiency [27]. Quantitative analysis shows that the average HV value of modified NSGA-III is the highest, reflecting its superior performance in solution set optimization. The box plot shows that the improved algorithm has the longest box plot, which indicates that its evaluation index distribution is more uniform, its stability is stronger and its performance is more robust.

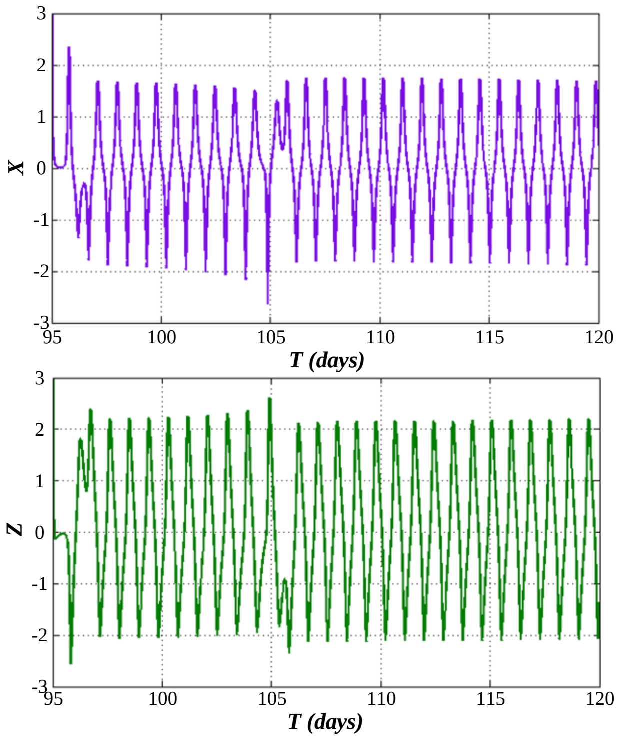

Figure 6: Proportionality of phase diagram and state trajectory

5 Scheduling model and solution

5.1 Scheduling model establishment

In project implementation, scheduling management in assembly stage is very important. Including prefabricated component hoisting, cast-in-place structure construction and component integration, the assembly scheduling algorithm model is shown in Figure 7. The assembly cycle directly determines the schedule of subsequent production and transportation, and the first task is to Equationte and implement efficient scheduling strategies to shorten the assembly period [28].

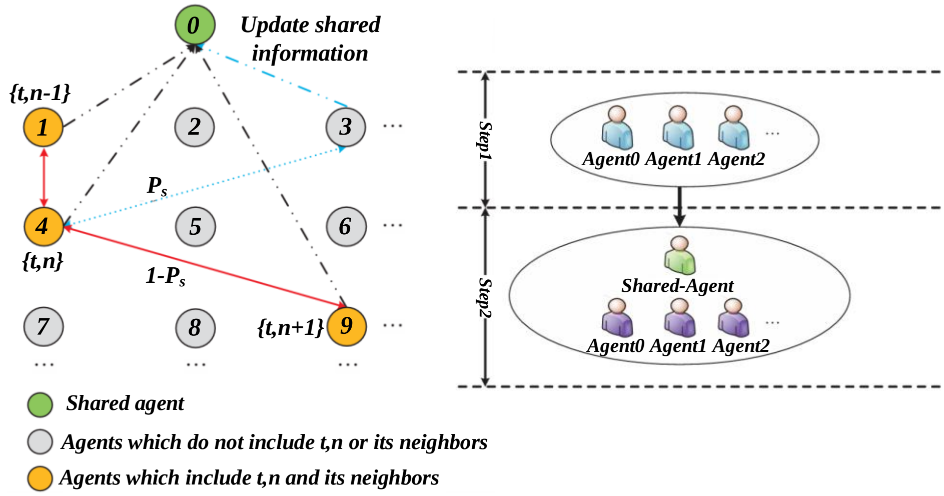

Figure 7: Scheduling algorithm model

5.2 Solution of model based on genetic algorithm

In modeling, natural number coding is used to number the construction and assembly steps of standard layer sequentially, from 1 to m, and m represents the total number of steps. The length of the chromosome is equal to the number of steps, each containing m genes, whose values range from 1 to m, and the number corresponds to the process number [29].

The configuration procedure shall be performed in the order of 2-1-7-4-3-6-5. When resources are limited, if processes 1 and 7 require R1 together, if conditions permit, they should be executed synchronously to meet R1, and can be operated in parallel; Otherwise, the execution order of 1 before 7 must be followed.

The roulette strategy includes the following steps [30]: First, calculate the fitness value of each individual; Second, design a selection mechanism positively correlated with fitness, and make roulette choice; Third, through random number decision, the adapter is selected based on the selection mechanism.

5.3 Case analysis

The construction process mainly includes: 1) measurement, positioning and setting-out; 2) Prefabrication and on-site installation of steel skeleton; 3) Hoisting operation of external wall components; 4) Gap filling and grouting treatment; 5) Construction of formwork support; 6) Hoisting technology of laminated beam and slab; 7) Fine binding of steel bars on the slab surface; 8) Assembly of accessories related to climbing frame; 9) Hoisting of balcony and stair structure; 10) Concrete pouring and subsequent maintenance management.

The affordable housing project is divided into two independent units, and each floor serves as a separate construction assembly line to realize the interspersed operation mode between the two units. Each process in the experiment includes: positioning measurement, cast-in-place steel bar binding, external wall bracket installation, formwork support construction, laminated beam and slab hoisting, balcony and stair hoisting, concrete pouring and maintenance, etc., which have different time-consuming and resource requirements, and have strict process dependence between them. The core task of the assembly stage is to seek the best optimization of the construction schedule under the premise of resources such as tower crane, measuring equipment and formwork, and the goal is to minimize the total assembly cycle T of the project under the constraint of resource constraints. This is essentially a resource-limited project scheduling problem, which needs to be solved urgently.

Figure 8 shows the characteristics of the Pareto optimal frontier. In this study, the advanced tools of MATLAB 2017a are used to optimize the model by integrating genetic algorithms. The specific setting parameters are as follows: the population size is set to NP = 80, the maximum number of iterations maxgen = 200, the selection crossover probability Pc = 0.8, the mutation probability Pm = 0.2, and the probability of inter-generational genetic operation Pe = 0.9. After 130 rounds of iterative calculation, we were able to obtain a minimum duration of 8 days.

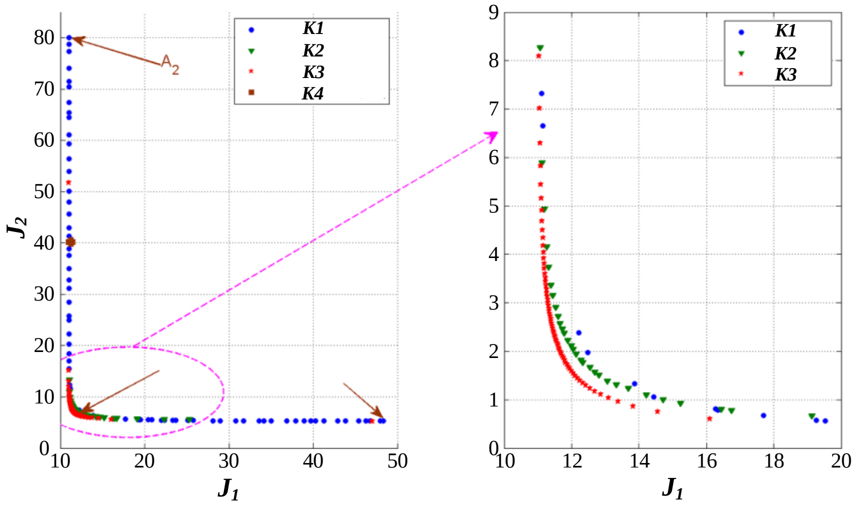

Figure 8: Pareto optimal frontier

Within the specified standard construction period of 8 days, according to resource limitations, the operation process is carefully planned day by day. The first day of work covers the measurement positioning and steel bar binding of Unit 1, the installation of external wall components, the setting of laminated beam and slab formwork supports, and the measurement preparation of Unit 2, ensuring the successful completion of the first-floor structure construction within 8 days, thus advancing to the completion of all pre-assembled floors.

On the second and third days of project execution, the demand for template configuration and hoisting operations peaked. Any negligence in the management of resource R3 in these critical time periods could pose a potential threat to the smooth conduct of subsequent tasks, which could lead to engineering delays. Therefore, managers should pay special attention to and strictly monitor the resource allocation and scheduling of these two days to prevent the delay of schedule caused by supply shortages.

6 Scheduling model and solution of production stage

6.1 Establishment of scheduling model in production stage

The duration TA of the assembly stage directly determines the duration of the manufacturing stage TB. In the specified process, TA must be less than or equal to TB from the time Order 1 + i M is placed to the completion of assembly. The goal is to find an optimal scheduling strategy that minimizes resource consumption and production cycle within a strict time limit δ. The specific task is to determine the duration vector P satisfying T ≤ δ for n activities to minimize the total project cost c (P). The project is divided into 2 + n task units, numbered {2, 3,..., n+1}. Activity 1 represents the project start and n+2 symbolizes the project end (regarded as a virtual step). Each entity operation unit j (1 < j < = n) has Mj execution options. The start time of activity mj is labeled Sj, lasts pjm days, and has a direct cost of cjm. The cost of prefabricated components consists of the product of direct cost cjm multiplied by xim corresponding to the selection mode, plus indirect costs r and d. For a given project deadline δ, find the best scheduling strategy in the production stage, with a view to minimizing the duration and minimizing the total cost at the same time.

6.2 Solution of model based on multi-objective genetic algorithm

In this paper, a two-layer coding framework (AL, ML) is adopted, where AL represents the task sequence and ML corresponds to the operation mode set. Each task j proceeds in AL with strict pre-dependencies. For task j in AL, its execution mode m (j) is unique. By setting the mode list, the working hours and resource requirements are determined accordingly, so that the multi-mode problem is transformed into a single-mode problem for in-depth research.

In the dual coding system of workflow and mode, the initial implementation of job coding (AL) is that each production step is standardized as a continuous integer number, from 1 to n, where n represents the total number of processes. These steps are labeled sequentially according to the process rules, such as 1, 2, 3,..., n. The chromosome structure of the job code is constant and the length is n, where each number 1 to n corresponds to a gene value, which respectively indicates the arrangement order of the processes.

In the secondary coding structure, natural number tokens, such as 1, 2, 3,..., m, are used to represent m modes of operation. For example, shows that when there are three execution modes, the secondary chromosome is fixed in length m, and each number from 1 to m represents a gene value, uniquely indicating the corresponding task execution mode.

6.3 Case analysis

The manufacturing process of prefabricated components is divided into stages according to molds and categories: preconditioning molds, component assembly, reinforcement placement and concrete pouring. The operating modes are M1 (Frugal), M2 (Regular) and M3 (Full Load). The study uses the product analysis of chaotic Henan diagram and Roche diagram, as shown in Figure 9. The labor demand is R1, the labor cost is 150 yuan/day, and the daily indirect cost is 80 yuan. The equipment assembly takes 8 days (TA = 8), the production cycle is the same as 8 days, and the accumulated storage cost reaches 200 yuan.

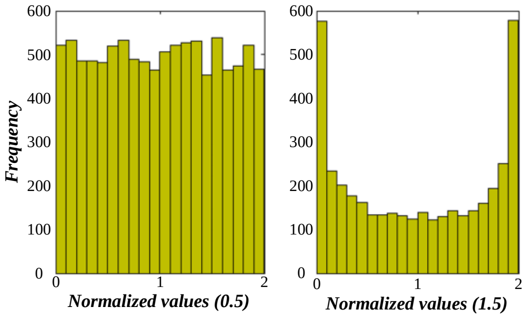

Figure 9: Multiplication of chaotic Henan River diagram and Loch diagram

The production process of prefabricated components is divided into three operation modes: M1 (saving type), M2 (standard type) and M3 (full load type), which have obvious differences in resource and time utilization. The maintenance stage adopts a unified mode, but the maintenance requirements vary from component to component. The logical sequence between the processes is strict, and the time limit (TA) of the assembly stage directly affects the time frame (TB) of the manufacturing stage. The assembly stage needs to complete the production of Mi+1 orders from the beginning to the end period.

In the production process, the primary goal is to find the comprehensive optimal scheduling with the shortest time and the lowest cost under the constraint of meeting the predetermined deadline δ. The goal is to find an n-activity time series P satisfying $T \leq \delta$ to achieve the lowest total cost c (P) of the project. As shown in Figure 10, there are significant differences between traditional single-objective genetic programming and multi-objective genetic programming-decomposition co-evolution algorithms in this context. Due to the unique execution characteristics of each activity, the problem is a multi-modal trade-off between deadline and cost.

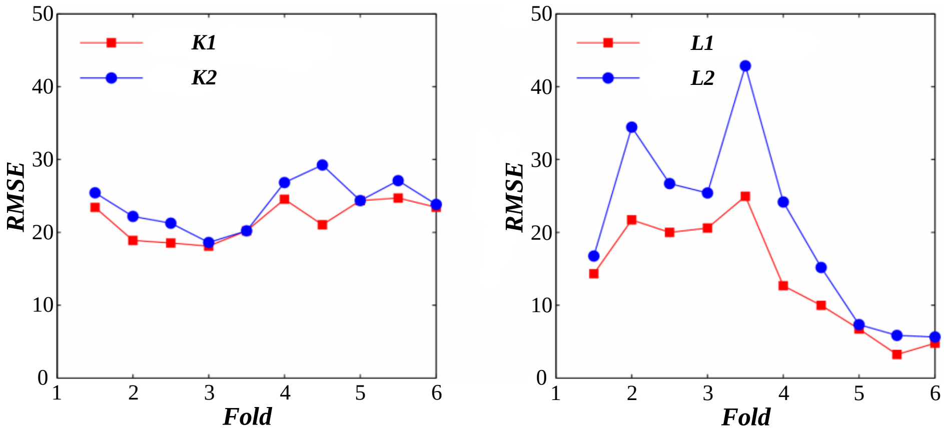

Figure 10: Traditional single-target GP and GP-MOEA/D

In MATLAB 2017a, we used the advanced version of nsGA-II to solve the model. The experimental configuration is as follows: the population size NP is set to 50, the maximum number of iterations maxgen is 200, the crossover probability Pc is 0.8, and the mutation probability Pm is 0.2. After 200 iterations, the Pareto optimal solution distribution of duration and cost is obtained. It can be seen from Figure 11 that the optimal solution distribution shows a nonlinear decreasing trend: with the shortening of the construction period, the cost shows an upward trend, which reveals an obvious inverse relationship between the two.

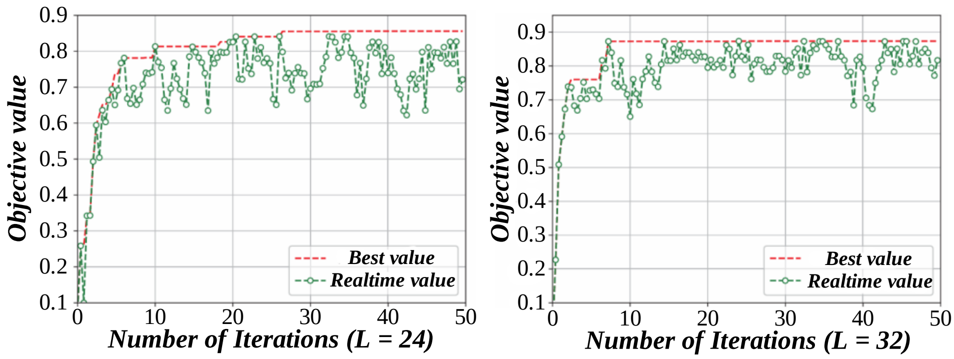

Figure 11: Optimal solution trend analysis

When optimizing the production cycle of prefabricated components and reducing resource consumption, we often encounter a delicate balance between time and cost. Efficient production may lead to higher costs, while resource frugality may extend construction schedules. Pareto efficiency analysis can reveal this optimal combination. Solution 1 has the lowest construction period (d1 = 5.5 days), but the highest resource cost (c1 = 73,690 yuan); In contrast, solution 14 is more economical in resource cost (c14 = 61,766 yuan), but has the longest construction period (d14 = 7.7 days). There is an obvious gap between the construction period and resource cost between the optimal solutions, so decision makers should choose the most suitable scheme according to their own priorities.

7 Conclusion

In building structure research, it is crucial for deep learning-driven risk assessment models to use artificial intelligence, especially in improving employee safety and engineering quality. In recent years, the multi-objective optimization generative adversarial network model has outstanding accuracy and adaptability in accident risk prediction. In this study, a cutting-edge multi-objective optimization strategy is used to improve the effect of GAN in building accident risk prediction. Through the construction and detailed analysis of large-scale accident database, the prediction accuracy of the new model has been significantly improved. In large-scale project tests, the accuracy, recall rate and F1 scores have reached 92%, 90% and 86%, highlighting its powerful prediction performance. In engineering practice, building safety accident risk prediction models with generative adversarial network-driven multi-objective optimization will achieve significant enhancements. In future research, a more intelligent risk management platform will be built by combining with advanced technologies such as the Internet of Things and big data, which will strongly support security protection in the field of architectural engineering.

References

[1] Zhou, W., Sun, G., Miwa, S., Yang, Z., Li, Z., Zhang, D., & Wang, J. (2023). An intelligent optimization method for the HCSB blanket based on an improved multi-objective NSGA-III algorithm and an adaptive BP neural network. Nuclear Engineering and Technology, 55(9), 3150-3163. doi:10.1016/j.net.2023.05.024 https://doi.org/10.1016/j.net.2023.05.024

[2] Zhao, J., Feng, Y., Wu, J., & Gao, Z. (2023). FHR-NSGA-III: A hybrid many-objective optimizer for intercity multimodal timetable optimization considering travel mode choice. Information Sciences, 649. doi:10.1016/j.ins.2023.119654

[3] Xue, F., & Wu, D. (2020). NSGA-III algorithm with maximum ranking strategy for many-objective optimisation. International Journal of Bio-Inspired Computation, 15(1), 14-23. Retrieved from <Go to ISI>://WOS:000521121800002

[4] Yannibelli, V., Pacini, E., Monge, D., Mateos, C., & Rodriguez, G. (2020). A Comparative Analysis of NSGA-II and NSGA-III for Autoscaling Parameter Sweep Experiments in the Cloud. Scientific Programming, 2020. doi:10.1155/2020/4653204

[5] Yang, H., Xu, Z., Shi, Y., Tang, W., Liu, C., Yunusa-Kaltungo, A., & Cui, H. (2023). Multi-objective optimization designs of phase change material-enhanced building using the integration of the Stacking model and NSGA-III algorithm. Journal of Energy Storage, 68. doi:10.1016/j.est.2023.107807

[6] Xue, B., Hao, X., Liu, X., Han, Z., & Zhou, H. (2020). Simulation of an NSGA-III Based Fireball Inner-Temperature-Field Reconstructive Method. Ieee Access, 8, 43908-43919. doi:10.1109/access.2020.2977853

[7] Ma, W., Zhang, J., Han, Y., Zheng, H., Ma, D., & Chen, M. (2022). A chaos-coupled multi-objective scheduling decision method for liner shipping based on the NSGA-III algorithm. Computers & Industrial Engineering, 174. doi:10.1016/j.cie.2022.108732

[8] Wu, P., & Chen, Y. (2022). Establishing a Novel Algorithm for Highly Responsive Storage Space Allocation Based on NAR and Improved NSGA-III. Complexity, 2022. doi:10.1155/2022/4247290

[9] Xu, J., Sun, C., & Rui, G. (2024). NSGA-III-XGBoost-Based Stochastic Reliability Analysis of Deep Soft Rock Tunnel. Applied Sciences-Basel, 14(5). doi:10.3390/app14052127

[10] Tang, H., Xiao, Y., Zhang, W., Lei, D., Wang, J., & Xu, T. (2024). A DQL-NSGA-III algorithm for solving the flexible job shop dynamic scheduling problem. Expert Systems with Applications, 237. doi:10.1016/j.eswa.2023.121723

[11] Yang, Y., Zhang, J., Sun, W., & Pu, Y. (2021). Research on NSGA-III in Location-routing-inventory problem of pharmaceutical logistics intermodal network. Journal of Intelligent & Fuzzy Systems, 41(1), 699-713. doi:10.3233/jifs-202508

[12] Yi, J.-H., Xing, L.-N., Wang, G.-G., Dong, J., Vasilakos, A. V., Alavi, A. H., & Wang, L. (2020). Behavior of crossover operators in NSGA-III for large-scale optimization problems. Information Sciences, 509, 470-487. doi:10.1016/j.ins.2018.10.005

[13] Zeng, L., Shi, J., Li, Y., Wang, S., & Li, W. (2024). A Strengthened Dominance Relation NSGA-III Algorithm Based on Differential Evolution to Solve Job Shop Scheduling Problem. Cmc-Computers Materials & Continua, 78(1), 375-392. doi:10.32604/cmc.2023.045803

[14] Kumar, A., & Kumar, T. V. V. (2022). Multi-Objective Big Data View Materialization Using NSGA-III. International Journal of Decision Support System Technology, 14(1). doi:10.4018/ijdsst.311066

[15] Razmi, A., Rahbar, M., & Bemanian, M. (2022). PCA-ANN integrated NSGA-III framework for dormitory building design optimization: Energy

efficiency, daylight, and thermal comfort. Applied Energy, 305. doi:10.1016/j.apenergy.2021.117828

[16] Awad, M., Abouhawwash, M., & Agiza, H. N. (2022). On NSGA-II and NSGA-III in Portfolio Management. Intelligent Automation and Soft Computing, 32(3), 1893-1904. doi:10.32604/iasc.2022.023510

[17] Ji, K., Chen, W., Wu, X., Pang, H., Hu, J., Liu, S., . . . Tang, G. (2023). High Frequency Stability Constraints Based MMC Controller Design Using NSGA-III Algorithm. Csee Journal of Power and Energy Systems, 9(2), 623-633. doi:10.17775/cseejpes.2020.03810

[18] Li, H., & Wu, X. (2021). A survival duration-guided NSGA-III for sustainable flexible job shop scheduling problem considering dual resources. Iet Collaborative Intelligent Manufacturing, 3(2), 119-130. doi:10.1049/cim2.12003

[19] Han, K., Xu, B., Guo, S., Gong, W., Chatzinotas, S., Maity, I., . . . Ren, Q. (2024). Non-Grid-Mesh Topology Design for MegaLEO Constellations: An Algorithm Based on NSGA-III. Ieee Transactions on Communications, 72(5), 2881-2896. doi:10.1109/tcomm.2024.3354782

[20] Pal, P., Sharma, R. P., Tripathi, S., Kumar, C., & Ramesh, D. (2023). NSGA-III Based Heterogeneous Transmission Range Selection for Node Deployment in IEEE 802.15.4 Infrastructure for Sugarcane and Rice Crop Monitoring in a Humid Sub-Tropical Region. Ieee Transactions on Wireless Communications, 22(6), 3643-3656. doi:10.1109/twc.2022.3220146

[21] Khettabi, I., Benyoucef, L., & Boutiche, M. A. (2022). Sustainable multi-objective process planning in reconfigurable manufacturing environment: adapted new dynamic NSGA-II vs New NSGA-III. International Journal of Production Research, 60(20), 6329-6349. doi:10.1080/00207543.2022.2044537

[22] Maleki, J., Masoumi, Z., Hakimpour, F., & Coello Coello, C. A. (2022). Many-objective land use planning using a hypercube-based NSGA-III algorithm. Transactions in Gis, 26(2), 609-644. doi:10.1111/tgis.12876

[23] Guo, Y., Zhu, X., Deng, J., Li, S., & Li, H. (2022). Multi-objective planning for voltage sag compensation of sparse distribution networks with unified power quality conditioner using improved NSGA-III optimization. Energy Reports, 8, 8-17. doi:10.1016/j.egyr.2022.08.120

[24] Adekoya, O., & Aneiba, A. (2022). An Adapted Nondominated Sorting Genetic Algorithm III (NSGA-III) With Repair-Based Operator for Solving Controller Placement Problem in Software-Defined Wide Area Networks. Ieee Open Journal of the Communications Society, 3, 888-901. doi:10.1109/ojcoms.2022.3172551

[25] Amorim, E. A., & Rocha, C. (2020). Optimization of Wind-Thermal Economic-Emission Dispatch Problem using NSGA-III. Ieee Latin America Transactions, 18(09), 1555-1562. doi:10.1109/tla.2020.9381797

[26] Zhang, S., Xie, J., & Wang, H. (2022). Fuzzy Adaptive NSGA-III for Large-Scale Optimization Problems. International Journal of Fuzzy Systems, 24(3), 1619-1633. doi:10.1007/s40815-021-01220-9

[27] Martinez-Comesana, M., Eguia-Oller, P., Martinez-Torres, J., Febrero-Garrido, L., & Granada-alvarez, E. (2022). Optimisation of thermal comfort and indoor air quality estimations applied to in-use buildings combining NSGA-III and XGBoost. Sustainable Cities and Society, 80. doi:10.1016/j.scs.2022.103723

[28] Gopu, A., Thirugnanasambandam, K., Rajakumar, R., Alghamdi, A. S., Alshamrani, S. S., Maharajan, K., & Rashid, M. (2023). Energy-efficient virtual machine placement in distributed cloud using NSGA-III algorithm. Journal of Cloud Computing-Advances Systems and Applications, 12(1). doi:10.1186/s13677-023-00501-y

[29] Liu, Y., You, K., Jiang, Y., Wu, Z., Liu, Z., Peng, G., & Zhou, C. (2022). Multi-objective optimal scheduling of automated construction equipment using non-dominated sorting genetic algorithm (NSGA-III). Automation in Construction, 143. doi:10.1016/j.autcon.2022.104587

[30] Gupta, R., & Nanda, S. J. (2022). Solving time varying many-objective TSP with dynamic ?-NSGA-III algorithm. Applied Soft Computing, 118. doi:10.1016/j.asoc.2022.108493