Proceedings of the 2nd International Conference on Software Engineering and Machine Learning
DOI: 10.54254/2755-2721/67/20240485

Application research of genetic algorithm in construction resource optimization and progress impact prediction

Chengyue Zhang[1,2,*], Ronggui Liu[1,3], Xiaoqian Zhang[1,4]

[1]School of Civil Engineering, Nantong Institute of Technology, Nantong 226002, China

[2]20190192@ntit.edu.cn
[3]20151041@ntit.edu.cn
[4]19850051113@163.com
*corresponding author

Abstract. With the acceleration of urbanization and the continuous advancement of infrastructure construction, the optimization of construction resources and the prediction of progress impact have become important issues in the field of engineering construction. This is one of the important contents in engineering project management, aiming to ensure the reasonable satisfaction of resource demand during construction and maximize the utilization of resources. The types and quantities of resources required are vast, making scheduling and allocation difficult, with waste being a common phenomenon. In the complex and ever-changing construction environment, it is difficult to achieve the maximization of resource utilization and precise control of progress. The accuracy of progress prediction directly affects the allocation of construction resources and cost control. Most construction enterprises still use traditional, experience-based estimation methods for progress prediction, which are easily influenced by various factors. At the same time, due to the numerous uncertainties in the construction process, progress prediction faces great difficulties. This requires the use of artificial intelligence, big data analysis, etc., to improve the accuracy of prediction. At the same time, strengthening project management and team coordination capabilities to ensure the smooth progress of construction work. This paper mainly utilizes principal component analysis and qualitative and quantitative analysis to experimentally analyze genetic algorithms, machine learning models, regression analysis, time series analysis, and construction resource allocation. The experimental results show that the prediction results of machine learning models and regression analysis are 0.54, which is 0.01 higher than the actual results.

Keywords: Genetic Algorithm, Construction Progress, Resource Optimization, Prediction Methods.

1. Introduction

In the modernization of construction, the control and planning of engineering project progress play a crucial role in construction projects. Construction resources are essential components in the implementation process of construction projects. They not only include direct factors such as labor and materials but also encompass other indirect elements, such as labor subcontracting and technical support provided by equipment leasing. Construction resource optimization involves calculating the optimal

DOI: 10.54254/2755-2721/67/20240485

parameter values using limited multiple objective functions. This paper aims to conduct in-depth research on the optimization of construction resources and the prediction of progress impacts using genetic algorithms. By utilizing the fundamental principles and characteristics of genetic algorithms, combined with methods and models for optimizing construction resource allocation and predicting progress impacts, a model is constructed. This model can automatically optimize resource allocation and predict progress impacts according to the actual situation of construction projects, providing scientific and rational decision support for construction enterprises.

Genetic algorithm, as an optimization algorithm based on biological evolution principles, possesses good global search capabilities and robustness, capable of handling multi-objective and multi-constraint optimization problems. Applying genetic algorithms to the optimization of construction resource allocation and prediction of progress impacts helps to improve the rationality of resource allocation and the scientific management of progress, providing strong guarantees for the smooth implementation of engineering construction.

This paper first describes the importance of resource and progress allocation prediction in engineering projects, and elucidates the performance advantages of genetic algorithms. Secondly, it showcases the achievements of scholars studying genetic algorithms. Subsequently, this paper analyzes the principles, techniques, etc., of genetic algorithms and integrates them with construction resources. Similarly, it describes methods for construction resource allocation and progress prediction, and designs a progress-resource coordination optimization system. Finally, this paper conducts simulation experiments on engineering resource allocation and progress prediction, obtaining relevant data and conclusions.

2. Related Work

Current research mainly focuses on traditional optimization algorithms, such as linear programming, integer programming, and dynamic programming. However, these methods often face challenges such as large computational complexity, low efficiency, and difficulty in finding global optimal solutions when dealing with complex construction environments and large-scale resource allocations. Existing methods fail to meet the practical requirements of optimizing construction resource allocation and predicting progress impacts.

Tahesin Samira Delwar proposed an adaptive genetic algorithm for optimizing the performance of 5G power amplifiers. This algorithm can automatically adjust the parameters of the genetic algorithm according to the actual requirements of the power amplifier, thereby improving the optimization effect [1]. Alfredo Lima proposed a mathematical heuristic method that combines biased random key genetic algorithms to solve the minimum broadcast time problem [2]. Debaditya Barman optimized query recommendations through cooperative evolution strategy and proposed a cooperative coevolutionary genetic algorithm, which improved the accuracy of recommendations [3]. Ensar Arif Sagbas studied a real-time pressure detection method based on genetic algorithm-optimized feature subset and k-nearest neighbor algorithm, effectively detecting real-time pressure from smartphone sensor data [4]. Nhat-To Huynh proposed a ceramic tile defect classification method based on two-dimensional genetic convolutional neural networks [5]. Ahmet Kara studied deep learning methods with attention mechanisms for soil moisture prediction, improving soil moisture prediction results through genetic algorithms [6]. Zulqurnain Sabir used efficient computational methods to solve a nonlinear dysentery model in biology, solving nonlinear equation systems using genetic algorithms to improve computational efficiency [7]. Mohamad Reza Davoudi proposed a feature selection method based on genetic algorithms to improve the efficiency of phishing website identification [8]. Apurva Jha combined recursive feature elimination and genetic algorithms to optimize team selection in fantasy cricket matches [9]. Pelayo Quirós studied a population pyramid projection method based on Monte Carlo simulation and genetic algorithms [10]. Therefore, researching methods and strategies for optimizing construction resource allocation and predicting progress impacts is of significant practical significance.

DOI: 10.54254/2755-2721/67/20240485

3. Application of Genetic Algorithm in Construction Resource Allocation and Progress Prediction

3.1. Genetic Algorithm

Genetic algorithms effectively search solution spaces and find optimal solutions by simulating natural selection and genetic mechanisms in biological evolution [11-12]. In this algorithm, any possible solution is referred to as a "chromosome" and encoded as binary or real chains [13-14]. During each generation of evolution, the fitness of chromosomes is evaluated through an adaptive function, and the most suitable chromosomes are selected for reproduction and crossover to produce a new generation [15-16]. These offspring undergo mutation and selection, eventually forming a new population. Its advantages lie in its ability to handle multi-objective, constrained, and large-scale optimization problems, as well as its good overall exploration capability and robustness [17-18].

When optimizing construction resource allocation and predicting the impact on progress, genetic algorithms can simulate the dynamics and complexity of the construction process, optimize resource allocation, and schedule planning to improve construction efficiency and quality. Additionally, genetic algorithms can create prediction models to forecast and control construction progress. Genetic algorithms use selection operators to perform the survival of the fittest individuals in the population [19-20]. The expected number of survivors without replacement random selection is represented as:

$$N_i = g_i/\bar{g} = g_i/\sum g_i/m \tag{1}$$

Where, N_i is the number of survivors of each corresponding individual in the next generation population. Selection methods are based on fitness ranking, with tournament selection randomly selecting a certain number of individuals from the population until a predetermined number is reached. The design and implementation of crossover operators are closely related to the problem. The basic genetic algorithm consists of an 8-tuple:

$$GA = (B, P, C, Q, X, J, Y, Z) \tag{2}$$

Where, B, P, C, Q, X, J, Y, Z represent encoding, fitness evaluation function, initial population, population size (20, 100), selection operator, crossover operator (0.4, 0.99), mutation operator (0.0001, 0.1), and termination generation (100, 1000). The optimization problem with the maximum objective function g(a) is as follows:

$$F(a) = \begin{cases} 0 & , if \;\; g(a) + +D_{min} \leq 0 \\ g(a) + D_{min}, & if \;\; g(a) + +D_{min} > 0 \end{cases} \tag{3}$$

Where, D_{min} is a relatively small number. When solving problems using genetic algorithms, it is necessary to establish a connection between the actual representation of the target problem and the chromosome bit string structure of the genetic algorithm. The binary coding method is the most commonly used encoding method in genetic algorithms. Currently, there are three main types of fitness scale transformation methods: linear scale transformation, power scale transformation, and exponential scale transformation.

3.2. Construction Resource Allocation and Progress Prediction Methods

The phenomenon of resource waste is common in engineering projects, which not only increases project costs but may also affect project progress and quality. Methods and strategies for optimizing construction resource allocation are crucial for improving construction efficiency and reducing costs. In construction resource optimization, genetic algorithms can be applied to optimize the allocation of labor, materials, equipment, and other resources. Based on the quantity and duration requirements of the project, the optimal number of workers and entry times for different trades can be automatically calculated. Consideration of resource constraints and limitations, such as maximum equipment usage time and minimum maintenance time, is necessary to ensure smooth construction progress. In addition

DOI: 10.54254/2755-2721/67/20240485

to genetic algorithms, other common methods for optimizing construction resource allocation include mathematical methods such as linear programming, integer programming, and heuristic search methods.

Predicting progress impacts is of paramount importance in construction project management. It not only helps project managers better understand project progress and anticipate potential issues but also allows timely adjustments to resources and optimization of plans to reduce unnecessary costs and time waste. To predict progress impacts, this paper employs methods such as time series analysis, regression analysis, and machine learning models. Time series analysis predicts the trend of progress changes over a period based on historical construction progress. Regression analysis analyzes factors affecting construction progress and establishes mathematical models. Machine learning models train and learn from historical data to automatically extract data features. These methods all require sufficient data support, so the quality and completeness of data are crucial for the accuracy of prediction results.

3.3. Design and Development of Progress-Resource Coordination Optimization System

The progress-resource coordination optimization system designed in this paper mainly consists of four parts: data extraction, genetic optimization process, summary of optimized image data information, and optimization result query. In the data extraction part, the progress-resource schedule and resource constraint tables are read, and relevant parameter information is inputted to generate the initial population. It is determined whether the maximum number of iterations has been reached. If so, the process continues; otherwise, it is necessary to assess whether each chromosome meets logical relationships and resource constraint conditions. When satisfied, the chromosomes that meet the constraints form a new population. If not, the chromosomes that do not meet the constraints are directly eliminated, and then the fitness is calculated. Through selection, crossover, mutation, and generation of genetic images, an equal number of new chromosomes are produced in the new population as the eliminated chromosomes, ensuring that the population size remains the same as the initial population. This constitutes the genetic optimization process. If the maximum number of iterations is reached, it is necessary to reassess whether each chromosome meets logical relationships and resource constraint conditions. All chromosomes in the new population that meet the conditions are converted into progress plans. Then, based on the progress plan, the resource demand is calculated, and historical genetic images are integrated and summarized according to the objective function to generate the optimal progress plan and resource allocation. This constitutes the summary of optimized image data information. Querying the optimized progress plan and resource arrangement is the result query.

The core work of progress-resource cyclical optimization under genetic algorithms is the main function of the system. Cyclical optimization is completed within the limits of the number of iterations. The size of the initial population and the number of iterations depend on the complexity of the engineering project. For projects with higher complexity, larger values for the initial population and the number of iterations result in better optimization performance. The system mainly optimizes the progress plan under the condition of limited resources. During the actual construction phase of engineering projects, due to the simultaneous construction of multiple activities with high daily demand for the same type of resources, or delays in the procurement of certain resources, in order to ensure the continuity and balance of construction, a limit value is set for the daily supply of certain resources. Under this limit value, the system automatically calculates the daily resource demand for each progress plan. The interface design of the system must meet requirements for simplicity, minimal memory usage, consistency, standardization, flexibility, and aesthetics. The system's functions include reading initial resource tables and resource constraint tables, inputting parameters, single-resource and multi-resource optimization, as well as querying and processing optimization results. Effective control of project duration, quality, and cost is key to construction project management. In engineering progress optimization, many factors influence project planning, with human factors having the greatest impact in project management. Key factors include proprietary factors, identification design factors, structural management factors, natural environmental factors, and social environmental factors. The three main control objectives of construction projects are progress, cost, and quality. This paper should consider factors such as quality, progress, and cost increases to determine priority selection factors for each

DOI: 10.54254/2755-2721/67/20240485

compression object. By analyzing the relationship between construction time, cost, and quality, relevant models are established to form an integrated optimization model.

4. Engineering Resource Allocation and Progress Prediction Simulation Experiment

4.1. Selection of Experimental Objects

This study selected a local ongoing project as the subject of investigation and experimentation. The project consists of earthwork excavation, basement, and main structural engineering. The main structural engineering occupies a long time and requires significant investment. After determining the construction sequence, labor needs to be arranged. Therefore, the labor demand plan obtained from the investigation is shown in Table 1:

Table 1. Labor Demand Plan

	Foundation project	Main project	Roofing project
Mason	11	0	0
Reinforcement worker	42	42	0
Carpentry	47	47	0
Scaffolder	32	32	0
Concrete worker	17	7	5
Brick and tile worker	22	42	0
Waterproof worker	27	0	17
Miscellaneous worker	17	17	8

In addition to labor costs, there are also material and machinery inputs. The duration is determined based on labor and engineering quantities, with a focus on quality issues during the construction process.

4.2. Experimental Design

This paper first utilizes genetic algorithms to allocate resources for the project and then uses combination forecasting methods for progress impact prediction. Each week's resource allocation results are analyzed on a weekly basis. Meanwhile, in the progress impact analysis, principal component analysis is first used to analyze the weight of influencing factors, followed by comparison with other algorithms. Time series analysis and regression analysis are combined as Scheme One, a combination of machine learning models and regression analysis as Scheme Two, and a combination of time series analysis and machine learning models as Scheme Three. Additionally, short-term forecasts in this paper require time series analysis or simple regression analysis, while long-term forecasts can use machine learning models and complex regression analysis. The prediction models constructed in this paper need to fully consider influencing factors such as engineering quantities, resource inputs, climatic conditions, and policies and regulations.

DOI: 10.54254/2755-2721/67/20240485

4.3. Results Analysis

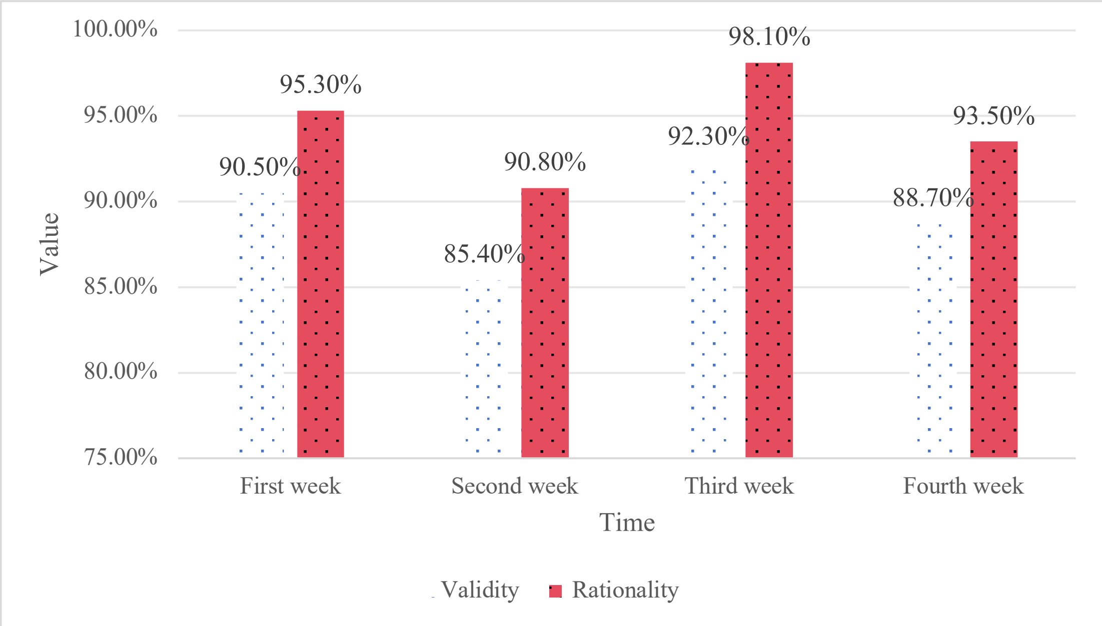

Figure 1. Construction Resource Allocation Results

As shown in Figure 1, with the assistance of genetic algorithms, the effectiveness of construction resource allocation in the first week is 90.5%, and the rationality is 95.3%. The construction resource allocation results of the third week with genetic algorithms are optimal, with effectiveness at 92.3% and rationality at 98.1%. The allocation results of the second week are slightly inferior, with effectiveness at only 85.4% and rationality of resource allocation at 90.8%. Additionally, the effectiveness of resource allocation in the fourth week is 88.7%.

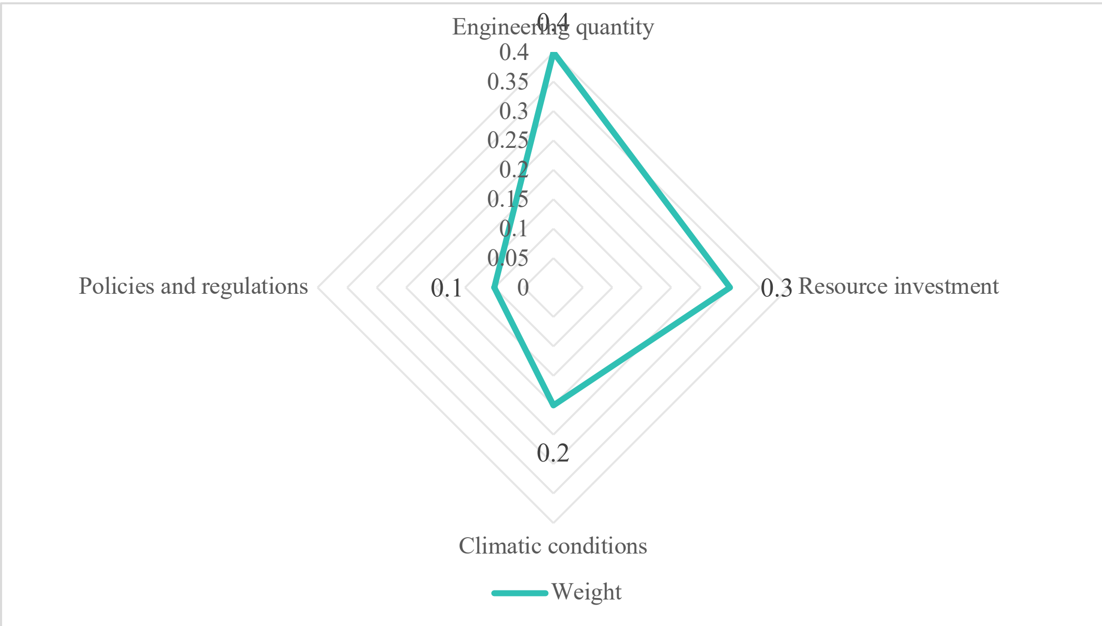

Figure 2. Comparison of Weight Values of Factors Affecting Progress

DOI: 10.54254/2755-2721/67/20240485

As shown in Figure 2, the quality of engineering is the most important factor affecting project progress, with the highest weight value (0.4), followed by resource input at 0.3. Climate factors also have a certain impact on project progress (weight 0.2), while the impact of policy rules is relatively small (weight 0.1).

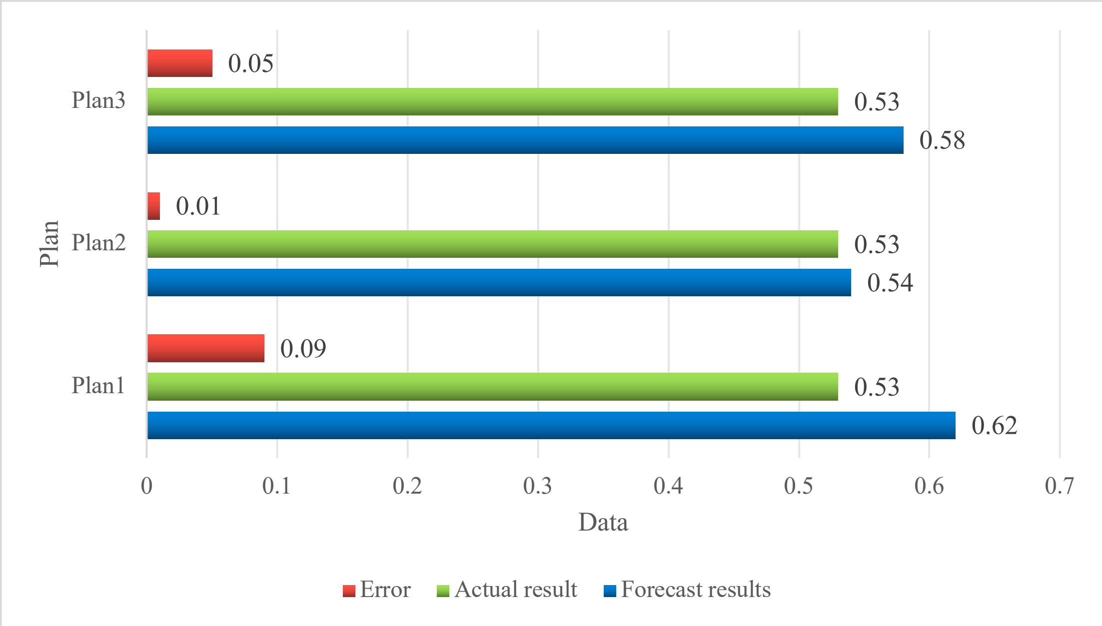

Figure 3. Analysis of Progress Impact Prediction for Different Schemes

As shown in Figure 3, the actual progress of the investigated project is 0.53. The prediction result of the combination of time series analysis and regression analysis is 0.62, with an error of 0.09 compared to the actual result. The prediction value of time series analysis and machine learning model is 0.58, with an error of 0.05. Therefore, the accuracy of machine learning model and regression analysis is the highest in this progress analysis.

The ability to predict progress impact is crucial for optimizing construction resource allocation, but this ability is still in the developmental stage and needs further improvement. Only by continuously improving the ability to predict progress impact can we better achieve optimized resource allocation and improve the efficiency and management level of engineering projects.

5. Conclusion

In order to ensure the high efficiency of the optimization process, it is necessary to reasonably allocate resources among various types of work to achieve the best results. In this paper, a mathematical model is established based on genetic algorithms and program analysis methods. Representative values are set for each work interval as the constraints that maximize the correlation between variables. The paper combines the work plan with the actual construction process, uses network diagrams to determine the relationships between each process and the workload of each stage, then conducts scheduling management. Additionally, measures are formulated according to the requirements of the engineering project to ensure that the construction quality meets contractual requirements. The paper decomposes project progress goals into subtasks and formulates work schedules and labor arrangements based on the completion status of each sub-item. Genetic algorithms enhance the effectiveness of construction resource allocation, and the introduction of machine learning and regression analysis results in progress predictions that are closest to the actual results.

Acknowledgement

Support for this program is provided by Nantong Institute of Technology Research project 2022XK(Z)15

References

[1] Tahesin Samira Delwar, Abrar Siddique, Unal Aras, Jee-Youl Ryu: A Design of Adaptive Genetic Algorithm-Based Optimized Power Amplifier for 5G Applications. Circuits Syst. Signal Process. 43(1): 2-21 (2024)
[2] Alfredo Lima, André L. L. de Aquino, Bruno C. S. Nogueira, Rian G. S. Pinheiro: A matheuristic approach for the minimum broadcast time problem using a biased random-key genetic algorithm. Int. Trans. Oper. Res. 31(1): 246-273 (2024)
[3] Debaditya Barman, Ritam Sarkar, Nirmalya Chowdhury: A cooperative co-evolutionary genetic algorithm for query recommendation. Multim. Tools Appl. 83(4): 11461-11491 (2024)
[4] Ensar Arif Sagbas, Serdar Korukoglu, Serkan Balli: Real-time stress detection from smartphone sensor data using genetic algorithm-based feature subset optimization and k-nearest neighbor algorithm. Multim. Tools Appl. 83(1): 1-32 (2024)
[5] Nhat-To Huynh: An approach for classifying ceramic tile defects based on a two-dimensional Genetic CNN algorithm. Neural Comput. Appl. 36(1): 385-397 (2024)
[6] Ahmet Kara, Engin Pekel, Erdener Ozcetin, Gazi Bilal Yildiz: Genetic algorithm optimized a deep learning method with attention mechanism for soil moisture prediction. Neural Comput. Appl. 36(4): 1761-1772 (2024)
[7] Zulqurnain Sabir, Mohamed R. Ali, Muhammad Asif Zahoor Raja, R. Sadat: An efficient computational procedure to solve the biological nonlinear Leptospirosis model using the genetic algorithms. Soft Comput. 28(1): 607-625 (2024)
[8] Mohamad Reza Davoudi, Alireza Yari: Improving the Feature Section Method Based on Genetic Algorithm to Increase the Efficiency of Detecting Phishing Websites. Autom. Control. Comput. Sci. 57(3): 213-221 (2023)
[9] Apurva Jha, Arpan Kumar Kar, Agam Gupta: Optimization of team selection in fantasy cricket: a hybrid approach using recursive feature elimination and genetic algorithm. Ann. Oper. Res. 325(1): 289-317 (2023)
[10] Pelayo Quirós, Fernando Sánchez Lasheras: Methodology for the projection of population pyramids based on Monte Carlo simulation and genetic algorithms. Appl. Intell. 53(16): 18989-19006 (2023)
[11] Mohammad K. Fallah, Mahmood Fazlali, Masoud Daneshtalab: A symbiosis between population based incremental learning and LP-relaxation based parallel genetic algorithm for solving integer linear programming models. Computing 105(5): 1121-1139 (2023)
[12] Nizheen A. Ali, Ramadhan J. Mstafa: Optimizing Region of Interest Selection for Effective Embedding in Video Steganography Based on Genetic Algorithms. Comput. Syst. Sci. Eng. 47(2): 1451-1469 (2023)
[13] M. Mythreyee, A. Nalini: Genetic Algorithm Based Smart Grid System for Distributed Renewable Energy Sources. Comput. Syst. Sci. Eng. 45(1): 819-837 (2023)
[14] Dinh Phamtoan, Tai Vovan: The fuzzy cluster analysis for interval value using genetic algorithm and its application in image recognition. Comput. Stat. 38(1): 25-51 (2023)
[15] Munish Saini, Eshan Sengupta, Madanjit Singh, Harnoor Singh, Jaswinder Singh: Sustainable Development Goal for Quality Education (SDG 4): A study on SDG 4 to extract the pattern of association among the indicators of SDG 4 employing a genetic algorithm. Educ. Inf. Technol. 28(2): 2031-2069 (2023)
[16] Ioannis G. Tsoulos, Nikolaos P. Anastasopoulos, Georgios Ntritsos, Alexandros T. Tzallas: Train RBF networks with a hybrid genetic algorithm. Evol. Intell. 16(1): 375-381 (2023)
[17] Pablo Barredo, Jorge Puente: Precise makespan optimization via hybrid genetic algorithm for scientific workflow scheduling problem. Nat. Comput. 22(4): 615-630 (2023)

DOI: 10.54254/2755-2721/67/20240485

[18] Nicholas Chancellor: Modernizing quantum annealing II: genetic algorithms with the inference primitive formalism. Nat. Comput. 22(4): 737-752 (2023)
[19] Loïc Mosser, Laurent Barbé, Lennart Rubbert, Pierre Renaud: Towards Automatic Design of Soft Pneumatic Actuators: Inner Structure Design Using CNN Model and Bézier Curve-Based Genetic Algorithm. IEEE Robotics Autom. Lett. 8(10): 6603-6610 (2023)
[20] Manash Hazarika: An improved genetic algorithm for the machine-part cell formation problem. Int. J. Syst. Assur. Eng. Manag. 14(1): 206-219 (2023)