INTEGRATING GENETIC ALGORITHMS AND RBF NEURAL NETWORKS IN THE EARLY DESIGN STAGE OF GYMNASIUM FOR MULTI-OBJECTIVE OPTIMIZATION FRAMEWORK

ZHAOXIANG FAN[1], SHUONING TANG[2]and MENGXUAN LIU[3]
[1,2,3]Tongji University.
[1]18346101349@163.com, 0000-0002-2271-8393
[2]zong20210427@163.com, 0000-0002-9445-9714
[3]liumengxuan93@163.com, 0000-0003-4576-7689

Abstract. The early design phase of the gymnasium's enclosing interfaces directly affects the indoor daylighting and thermal environmental performance. The optimization framework proposed in this study aims to simultaneously balance and optimize conflicting objectives, including the maximum daylight factor (DF), minimum daylight glare index (DGP), and minimum solar radiation (RS) for gymnasium. This approach aims to maximize daylighting performance in hot summer regions while avoiding glare, reducing energy consumption, and ultimately enhancing both daylight comfort and energy efficiency during the sports facility design process. Using the SPEA-2 genetic algorithm, the study explored the Pareto front solutions for three different skylight patterns and established a predictive model for design results based on a Radial Basis Function (RBF) neural network. Compared to traditional Multi-Objective Optimization (MOO) frameworks, this optimization method improves computational efficiency and provides more intelligent decision support for the early-stage design of gymnasiums.

Keywords. Multi-Objective Optimization (MOO), Building Performance Simulation (BPS), Parametric Design (PD), Predictive Model.

1. Introduction

Balancing indoor daylighting, thermal comfort, and energy performance is one of the most critical objectives in the design of sports facilities (Yang, et al., 2018). Existing research has shown that indoor daylighting and thermal environmental performance can directly impact sports experiences (Bale and Vertinsky, 2004), comfort levels (Fantozzi and Lamberti, 2019), and safety and health (Fan, et al., 2023), with continuous effects on the energy consumption of environmental regulation in sports arena interiors (Fan, et al., 2023). However, the impact of different morphological parameters of sports arenas on environmental objectives is often contradictory, and the current challenge lies in ensuring a balance among various targets after complex

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performance goal calculations during the optimization process. Although multi-objective optimization based on building performance simulation has been widely applied, as demonstrated by Wang Pan et al., who established an MOO framework for large sports arena roof structure morphology and spatial layout, evaluating the comprehensive performance of three different roof structures in two cases (Wang, et al., 2019). Nathan Brown from MIT proposed a new approach involving parameterized design space formulation, interactive optimization, and design based on structural morphological diversity (Nathan, 2019). However, existing optimization frameworks often require crossing multiple software platforms and entail significant computational time. This study aims to establish a multi-objective optimization framework to achieve automatic morphological optimization based on performance analysis in the early design stages of gymnasiums. In this process, the SPEA-2 genetic algorithm and Radial Basis Function (RBF) neural network will be introduced for optimization calculations and analysis prediction of result datasets. The framework will predict sports hall morphologies in the early design stages based on performance data, replacing the subjective decision-making process of architects with empirical experience (Figure 1).

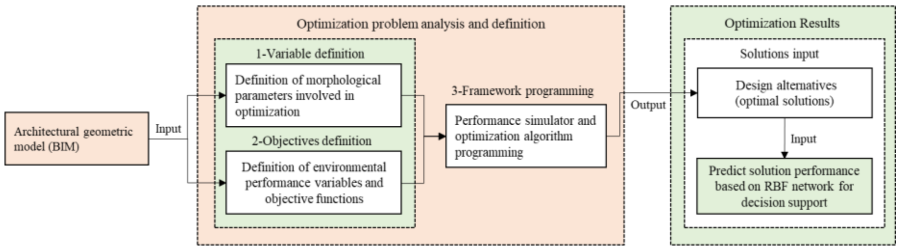

Figure 1. Overall research framework

2. Methodology

2.1. MULTI-OBJECTIVE OPTIMIZATION

In general, the definition of decision variables (inputs) and objective variables (outputs) is a prerequisite and a crucial step in addressing MOO problems. In single-objective optimization, feasible solutions can be ranked based on the value of the objective function, meaning that for any n decision variables $x_1, x_2, x_3, ..., x_n \in X_k$, there exists $f_m(x_n) \geqslant f_m(x_{n-1})$ or $f_m(x_n) \leqslant f_m(x_{n-1})$ to determine their superiority or inferiority. However, in MOO problems, the determination of the final optimization results is based on the relative concepts generated by balancing the contradictions among various optimization objectives. For MOO, with n decision variables, m objective functions, and k constraint conditions, the mathematical function is represented as Eq. (1):

$$\mathrm{Min/MaxF}(x_k) = \begin{vmatrix} f_1(x_1) & f_1(x_2) & \dots & f_1(x_n) \\ f_2(x_1) & f_2(x_2) & \dots & f_2(x_n) \\ \vdots & \vdots & & \vdots \\ f_m(x_1) & f_m(x_2) & \dots & f_m(x_n) \end{vmatrix}, x \in X \quad (1)$$

Where, $F(x_k)$ represents the set of objective functions in the objective function space, while X is the set of decision variables that includes the space containing the optimal solution. Here, $f_m(x_n)$ denotes the individual optimization objective functions, and x is a subset of decision variables. The results of Multi-Objective Optimization (MOO) are categorized into two types: non-dominated solutions and dominated solutions. The non-dominated solutions of the final population are also known as Pareto front solutions, representing the alternative solution set under the combination of decision variable parameters obtained through the algorithm's multi-objective optimization.

2.2. RBF NETWORK

The RBF network is an artificial neural network that uses radial basis functions as activation functions. The output of an RBF network is a linear combination of the radial basis functions of the input and the parameters of the neurons (Chen, Cowan, and Grant, 1991). It can approximate any continuous function with arbitrary precision and is particularly well-suited for solving classification problems. The functional representation of the RBF network is given by Eq. (2):

$$\mathrm{RBF}(x) = \sum_{i=1}^{h} w_{ij} \exp\left(-\frac{1}{2\sigma^2}||x - c_i||^2\right) \quad j = 1,2,3,\ldots,n \quad (2)$$

Where, $\mathrm{RBF}(x)$ represents the output of the radial basis function, where x is the input data vector, c_i represents the center vector of the radial basis function, i denotes the number of input signal source nodes, j represents the number of neurons in each hidden layer, and σ represents the width parameter of the radial basis function, controlling the extent of the function's expansion. RBF is a feedforward neural network with a structure divided into three layers: 1) Input layer, consisting of signal source nodes; 2) Hidden layer, where the transformation function is RBF, and the number of units is determined by the requirements of the problem; 3) Output layer, responding to the input patterns. The transformation from the input space to the hidden layer space is nonlinear, while the transformation from the hidden layer space to the output layer space is linear (Figure 2).

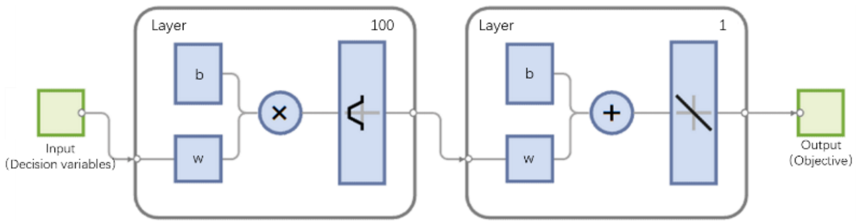

Figure 2. The structure of RBF neural network.

3. Optimization process

The research focuses on the main decision variables of the gymnasium interface morphology parameters, conducting MOO studies with daylighting factor (DF), average daylight glare probability (DGP), and average cumulative solar radiation (RS) as objective variables. This is carried out concerning key interface morphology parameters, including skylight, sidelight, and shading parameters. The aim is to explore different combinations of interface opening and closing degree parameters under the consideration of various daylight and thermal environmental performance goals, along with their performance distribution characteristics. The basic framework of this part is illustrated in Figure 3.

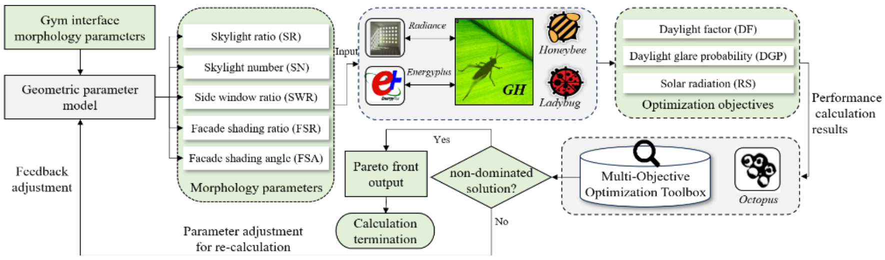

Figure 3. MOO framework for gymnasium interface morphology parameters

In this segment of the study, the gymnasium interface morphology parameters, namely skylight ratio (SR), skylight column number (SN), side window ratio (SWR), facade shading ratio (FSR), and facade shading angle (FSA), will serve as the input genes for genetic algorithms to form the decision space. The optimization will explore the results of the combination of morphology parameters based on DF, DGP, and RS. Furthermore, a comparative analysis of the changing trends between different generations of optimized solution sets will be conducted. This aims to explore and compare the distribution characteristics and variation patterns of different morphology parameters and environmental objectives within the optimization solution set.

3.1. DECISION VARIABLES

In this study, the input decision variables for the interface morphology parameters are as follows: x_1—SR, x_2—SN, x_3—SWR, x_4—FSR, x_5—FSA. The output variables are the DF of the sports hall's activity field, the average DGP from unfavourable viewpoints, and the average cumulative RS in the sports hall.

The study is divided into an optimization process for flat skylights, strip skylights, and point skylights. The decision variables X correspond to the numerical models of gymnasium under different opening and closing forms, where the model supports the continuous combination of values for X within different ranges of morphological variables. Thus, it forms the search space for different decision variables. Different parameter combinations correspond to a relatively extensive set of design configurations (Table 1).

Type	Acronym	Variable Names	Unit	Range
	SR	Skylight ratio	--	0.1-1.0
Decision	SN	Skylight number	--	1-10
Variables	SWR	Side window ratio	--	0.1-1.0
(Inputs)	FSR	Façade shading ratio	--	0.1-1.0
	FSA	Façade shading angle	°	0-90
Objective	$DF_{sports\ hall}$	Daylight factor	%	--
Variables	$DGP_{ave\text{-}court}$	Average daylight glare probability	--	--
(Outputs)	$RS_{ave\text{-}court}$	Average cumulative solar radiation	kWh/㎡	--

Table 1. Decision variables (inputs) and objective variables (outputs)

3.2. OPTIMIZATION OBJECTIVES

In this optimization process, three objectives are set as the DF, the average DGP, and the average cumulative RS within the sports hall. Three conflicting objective functions are used to define the trade-off between maximizing the DF while minimizing both the DGP and the cumulative RS intensity. Therefore, in the optimization objective setting, the objective function $F_1(y)$ corresponds to the negative maximum value of the daylighting factor, $F_2(y)$ corresponds to the minimum value of the daylight glare probability, and $F_3(y)$ corresponds to the minimum value of the cumulative radiation in the sports hall, as shown in Eq. (3)-(5):

$$F_1(y) = -DF_{max}(x) \quad (3)$$

$$F_2(y) = DGP_{min}(x) \quad (4)$$

$$F_3(y) = RS_{min}(x) \quad (5)$$

4. Results

4.1. DECISION VARIABLES DISTRIBUTION

In this section, a MOO exploration was conducted for the combination pattern set of sports arena interface parameters (side facade, roof interface). The optimization process was carried out separately for three typical skylight forms in the gymnasium: strip skylight, point skylight, and flat skylight. Using the intelligent driving of the SPEA-2 genetic algorithm toolbox, the study independently performed performance calculations and iterative comparisons for multiple scenarios using Ladybug tools. During the calculation process, the non-dominated solution ratios for strip, point, and flat skylight patterns all exceeded 80% by the 20th generation. The optimization solutions from the 20th generation were selected as the final alternative solution set.

From the overall distribution of optimization solutions, the three skylight forms exhibit similar performance in terms of DF, DGP, and cumulative RS, with no significant differences in performance distribution. Figures 4 depicts the distribution of Pareto front solutions' objective values for point skylight, one typical pattern under different interface opening and closing parameter combinations. Partial geometric models of typical optimized solutions under different skylight ratios are also presented, ranging from left to right, corresponding to different optimal solutions and combination differences of other morphological parameters as skylight ratio increases. The lower part shows the parallel set plot of the correlation between optimized solution morphological parameters and target variables, as well as a typical set of optimized solutions classification according to skylight ratio.

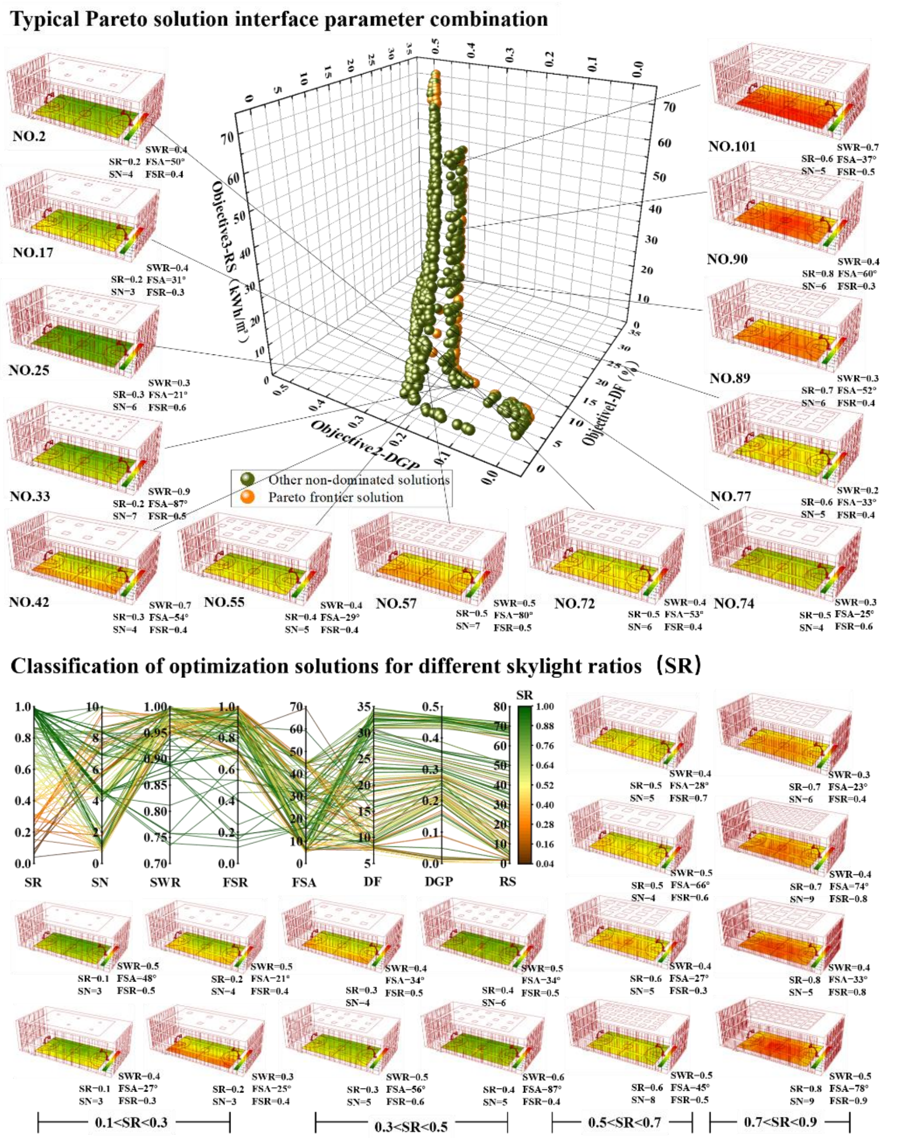

Figure 4. Parameter distribution and classification of optimal solutions under point skylight pattern

4.2. OBJECTIVE VARIABLES DISTRIBUTION

Figure 5 illustrates the distribution and changing trends of objective values of Pareto front solutions in key generations during the optimization process for different skylight patterns. For the strip skylight pattern, with the increase in the number of iterations, different objectives show different changing trends. Considering the range of optimized solutions at the 20th generation, the 10th, 15th, and 20th generations are selected as key generations for comparison. Taking the daylighting factor as an

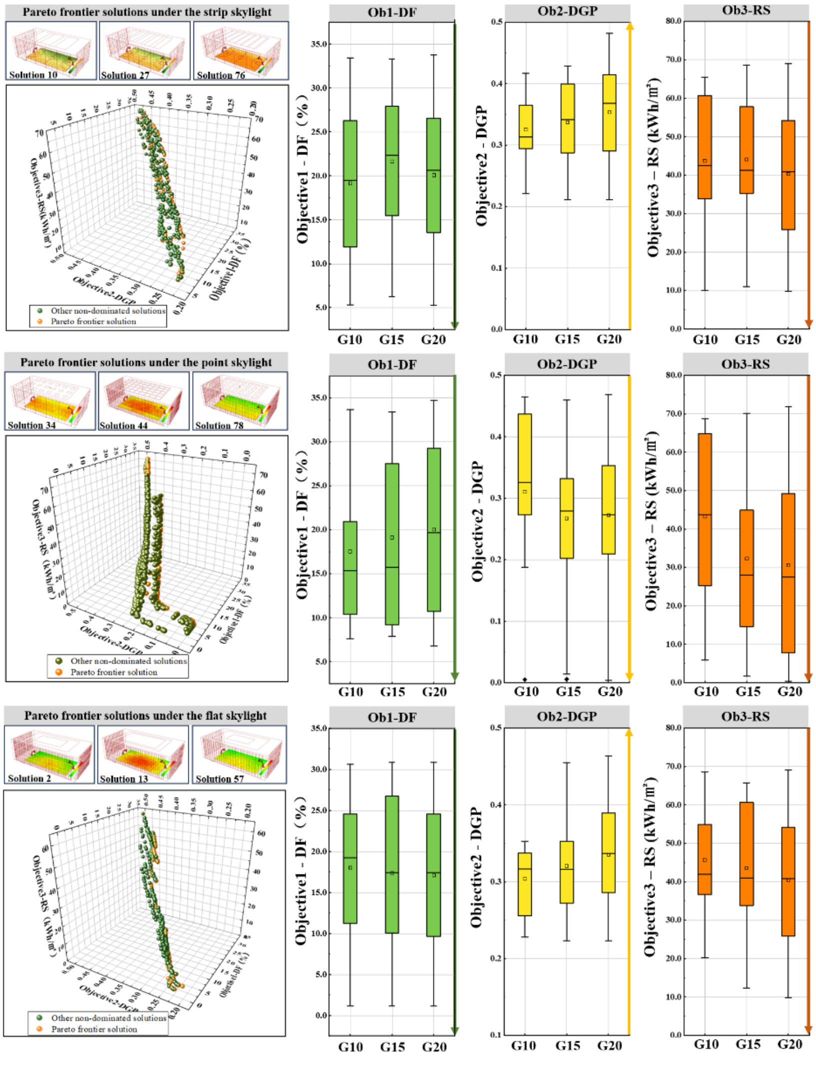

Figure 5. Distribution of objectives in different generations of optimization solutions

example, the range of the Pareto front solutions is primarily between 12% and 26% at the 10th generation, expanding to 15.5%-27.5% at the 15th generation, and finally ranging between 13.5% and 26% in the final generation (20th). The average daylighting factor of the optimized solutions increased from 18% to 20%, representing an improvement of approximately 11%.

In addition, clustering analysis was conducted on the morphological parameters of different schemes. A morphological parameter map was then generated based on the Euclidean distances between parameters (as shown in Figure 6). This facilitates designers in making better choices for further development.

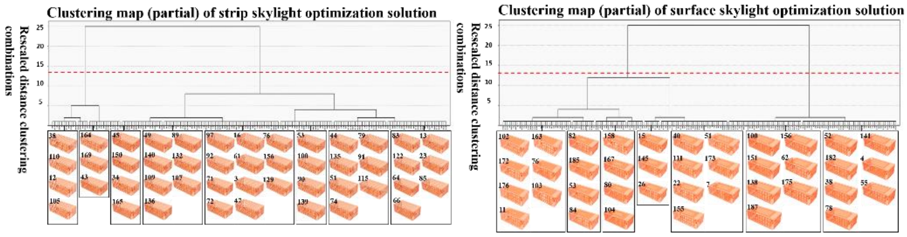

Figure 6. Optimized solution morphological parameter clustering map

4.3. PREDICTION MODEL

In the RBF optimization model, the set of shape parameters outputted by the MOO serves as the independent variables (inputs), while the environmental target dataset serves as the dependent variables (outputs). The hidden layer had 129 neurons; the radial basis expansion rate was set at 500. Learning was conducted separately for different skylight patterns. In this process, 70% of the data samples were used as training samples, and 30% were used for testing. Figure 7 illustrates the prediction results for

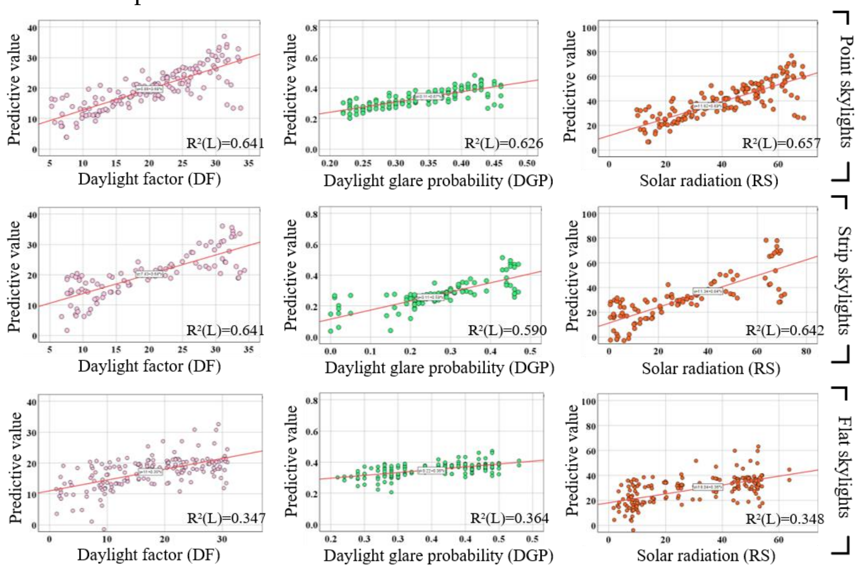

Figure 7. The comparison between the actual values and predicted values of the prediction model

different performance objectives. The prediction model for the point skylight pattern showed the highest fitting degree, achieving an explanatory level (R^2) of 65.7% for solar radiation. In contrast, the prediction model for the flat skylight pattern had a relatively lower fitting degree, approximately 35%. This may be related to overfitting caused by a high expansion rate. Figure 8 shows the predicted RMSE of strip skylights for different objectives, among which the prediction error of daylight comfort is the lowest, with RMSE% of about 17%. In further research, different expansion rates will be adjusted for different morphological parameter sets to improve the explanatory level of the prediction model.

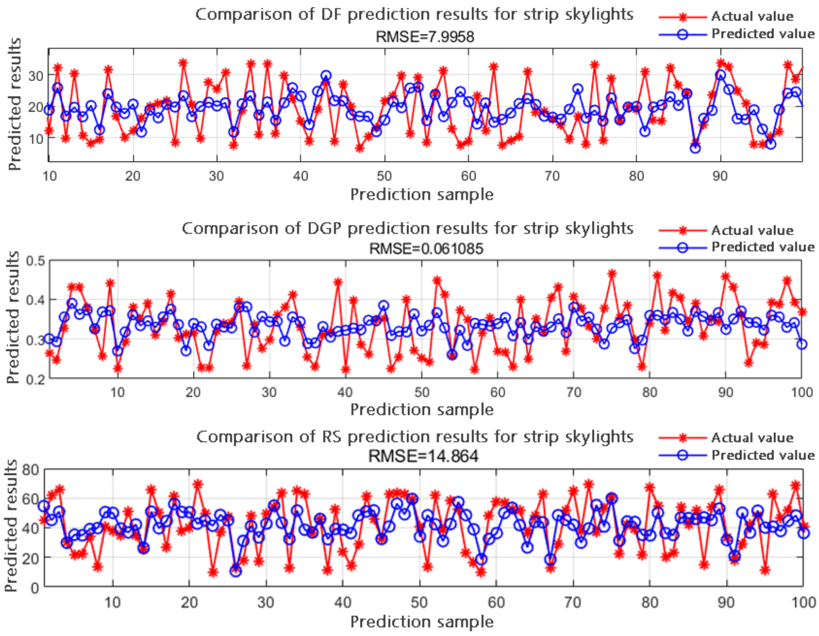

Figure 8. RMSE comparison of strip skylight prediction models

5. Discussion

The study tested the effectiveness of BPS-based MOO in enhancing the daylighting and thermal performance of facades and skylights in the early stages of stadium design. Compared to manual testing methods, this approach is more continuous, explores more comprehensive solution parameters, and can form predictions for new designs based on existing optimization solution sets. However, the study still has some limitations, mainly reflected in:

1) The prototype of the study only optimized the facade and skylights of a square sports hall, lacking discussions on other irregular-shaped gymnasiums. In future research, the scope of parametric prototypes will be expanded to adapt to a wider range of gymnasium optimizations. Additionally, more shading and skylight opening styles should be refined for discussion and comparison to expand the search range of decision variables.

2) The study tested the gymnasium facade and skylights as an integrated system, using a standard CIE sky model. It ignored the impact of different orientations on sunlight and radiation, which typically varies based on the geographic location and climate zone of the case. This difference can be addressed by further comparing simulation results for different directions (east, west, south, north) to provide more refined optimization results.

3) The prediction model in this study was mainly achieved through data modelling. In future research, exploring the correlation mechanism between optimization result maps and morphological variable images using GNN tools can lead to more intuitive and efficient predictions of gymnasium design performance. This can reduce the time cost of long-term simulation and provide a more visual design assistance for the green design and sustainable optimization of sports buildings.

6. Conclusion

This study proposes a multi-objective optimization and prediction method based on genetic algorithms and RBF neural networks through the optimization of morphological parameters of community sports stadium interfaces (facade and skylights). The aim is to collaboratively enhance the early-stage design of stadiums for daylighting, daylight comfort, and energy load optimization. This approach seeks to improve the passive environmental regulation capability of design outcomes. The decision variables in this study include the stadium skylight ratio (SR), skylight numbers (SN), side window ratio (SWR), facade shading ratio (FSR), and facade shading angle (FSA). The optimization objectives are daylight glare probability (DGP), daylight factor (DF), and daylight radiation load (RS). The study compares the multi-objective optimization results of environmental performance in three different skylight modes of sports hall. Additionally, it establishes a design prediction model based on RBF neural networks for the Pareto front solution set. This method provides a technical framework and decision support for intelligent prediction and automatic optimization of environmental performance in the early-stage design of gymnasiums.

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