International Journal of Applied Mathematics
Volume 38 No. 5, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

COMPREHENSIVE MULTI-OBJECTIVE DESIGN OPTIMIZATION OF LIGHTWEIGHT AGGREGATE CONCRETE: A DATA-DRIVEN APPROACH

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Abstract

Expanded Polystyrene Concrete (EPSC) has garnered widespread attention in green building applications due to its excellent lightweight properties, thermal insulation capabilities, and cost advantages. However, EPSC faces a typical performance-cost contradiction: reducing density often sacrifices strength, while increasing cementitious material content, although enhancing strength, elevates costs and shrinkage risks. Based on 240 EPSC sample datasets (DQI=98.56%), this study established a systematic multi-level modeling framework employing a three-stage progressive approach: univariate regression → response surface methodology (RSM) → multi-model fusion (Random Forest RF + Artificial Neural Network ANN). Through 10-fold cross-validation, the ANN achieved a weighted R^2 of 0.862, while the integrated model achieved a global weighted R^2 of 0.874, enabling precise prediction of EPSC mechanical properties, thermal insulation performance, and economic efficiency. Multi-objective nonlinear programming using the NSGA-II genetic algorithm generated 30 non-dominated solutions, with knee point analysis identifying the optimal cost-performance balanced scheme. Results demonstrate that under constraints of density controlled at 2200-2250 kg/m³, strength guaranteed ≥24 MPa, and water resistance ≥0.6 MPa, cost reductions of 18-22% can be achieved with a 35% improvement in unit cost-performance ratio, while thermal insulation performance (thermal conductivity 0.42-0.48 W/m·K) maintains industry-leading standards. Through PDCA closed-loop management and industrial-grade credibility assessment (excellent and superior grades reaching 56.8%), the engineering feasibility of the optimized

Received: August 03, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

scheme was verified. This research provides systematic data support, optimization algorithms, and decision-making basis for scientific design, precise formulation, and engineering promotion of EPSC.

Keywords: Expanded polystyrene concrete; multi-objective optimization; artificial neural network; performance balance; green building

I、Introduction and Research Background

Expanded Polystyrene Concrete (EPSC) is an ultra-lightweight, high-performance concrete produced by partially or completely replacing conventional aggregates with expanded polystyrene (EPS) particles, supplemented with optimized cementing systems and construction techniques[1]. Compared with traditional lightweight aggregate concrete (such as ceramsite concrete and perlite concrete), EPSC exhibits three significant advantages: first, it has the lowest density (1400-1800 kg/m³), representing a 40-45% reduction compared to ordinary concrete (2400 kg/m³), achieving ultimate structural weight reduction; second, it possesses excellent thermal insulation properties (thermal conductivity of 0.40-0.50 W/m·K), approximately 1/4 that of ordinary concrete (1.7 W/m·K), which can substantially reduce building energy consumption; third, it has the lowest production cost (4200-5200 yuan/m³), only 70-80% that of ceramsite concrete, demonstrating clear economic competitiveness[2]. As global building carbon emissions account for 39% of total global emissions, the nation has explicitly proposed a target to reduce building sector carbon emissions by more than 20% during the 14th Five-Year Plan period. EPSC, with its three-dimensional carbon reduction potential (self-weight reduction, thermal performance improvement, and cost reduction), has become a key material for green buildings[3]. In prefabricated building projects in global cities, EPSC has been widely applied in precast exterior wall panels, floor slabs, insulation layers, and other components, with an annual growth rate of 18-22%[4].

However, EPSC still faces three core challenges in engineering applications. First is the complex coupling relationship of performance indicators. Increasing EPS particle content (replacement ratio from 10% to 30%) can reduce density from 2350 kg/m³ to 2100 kg/m³ (a decrease of 10.6%), but simultaneously causes 28-day compressive strength to decline from 32 MPa to 24 MPa (a 25% decrease) and increases long-term creep by 40-50%[5]. This strong nonlinear trade-off makes it difficult for designers to simultaneously satisfy multiple objectives of weight reduction, strength enhancement, cost reduction, and crack prevention. Second is the excessive simplification of parameter space. Existing EPSC mix design standards are primarily based on empirical rules with fixed water-to-cement ratios (0.55-0.60) and fixed cementing material dosages (190-210 kg/m³)[6]. When cement types are changed, supplementary cementitious materials such as silica fume or fly ash are incorporated, or different admixture combinations are employed, the applicability of existing rules significantly diminishes, leading

Received: August 03, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

to quality instability problems in engineering applications. Third is the limitation of optimization methods[7]. Although traditional orthogonal design can explore parameter space, it is restricted to combinations of 2-3 parameters and cannot handle the high-dimensional space of 6-8 parameters including water-to-cement ratio, EPS replacement ratio, sand content, cementing material composition ratios, and admixture types. Linear programming methods completely neglect nonlinear interactions among parameters, resulting in optimization outcomes that often deviate from practical situations[8].

Therefore, this research establishes a complete closed-loop system for EPSC-specific optimization, encompassing data collection, quality assessment, multi-level modeling, intelligent optimization, and engineering verification. By breaking free from traditional fixed parameter constraints, employing machine learning to handle high-dimensional parameter spaces, and utilizing genetic algorithms to solve multi-objective nonlinear programming problems, this research aims to address four core scientific questions: (1) Under given constraints, where lies the optimal cost-performance balance point for EPSC? (2) What are the optimal mix design schemes corresponding to different application scenarios (thermal insulation priority vs. strength priority vs. cost priority)? (3) Compared with traditional design methods, what performance improvements or cost savings can data-driven optimization methods achieve? (4) How should the industrial-grade credibility of optimized schemes be evaluated, and what are the prerequisite conditions for their engineering application?

II、Performance Characteristics and Theoretical Basis for Optimization of EPSC

The performance characteristics of EPSC determine the complexity of its optimization problems. Regarding compressive strength performance, the 28-day compressive strength of EPSC (20-35 MPa) is mainly determined by three components: cement paste matrix strength, EPS particle inherent strength, and interfacial transition zone quality. Unlike traditional lightweight aggregates, EPS particles themselves have extremely low strength (0.3-0.5 MPa) and are susceptible to damage and indentation due to construction processes; therefore, the strength of EPSC mainly depends on the cement paste matrix strength and the interfacial bonding with EPS. Through SEM observations, Kishore, Kamal and Tomar, Radha [9] found that the interfacial transition zone width of EPSC (20-40 μm) is significantly larger than that of ordinary concrete (5-15 μm), with an interfacial porosity as high as 15-25%, which is the fundamental reason for the relatively low strength of EPSC[1]. The key to improving interfacial strength lies in increasing the binder content and reducing the water-cement ratio; however, both measures increase costs. Regarding thermal insulation performance, the thermal conductivity of EPSC (0.40-0.50 W/m·K) depends on porosity, pore morphology, and heat conduction of gas within pores. The thermal conductivity of EPS particles themselves is approximately 0.035 W/m·K, and that of static air within pores is 0.026 W/m·K; however, due to pore connectivity and radiative heat transfer, the actual thermal conductivity is 0.040-0.050

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W/m·K. The overall thermal conductivity of EPSC is mainly contributed by EPS pores (accounting for 60-70%), followed by cement paste (accounting for 30-40%). While increasing EPS content can reduce thermal conductivity, it decreases strength, forming a typical trade-off relationship.

Regarding cost structure, the total cost of EPSC consists of four components: binder material costs (cement, silica fume, fly ash) accounting for 30-35%, fine aggregate (sand) accounting for 15-20%, EPS particles accounting for 25-30%, and admixtures and other costs accounting for 10-15%. Currently, market prices for EPS are 800-1200 yuan/m³, which is 25-40% cheaper than traditional expanded clay (1500-2000 yuan/m³). The main approaches to reducing EPSC costs include: (1) increasing the EPS replacement ratio from 15% to 25% can reduce costs by 8-12%; (2) reducing binder materials—through formula and process optimization, binder content can be reduced from 200 kg/m³ to 170 kg/m³ while maintaining strength, reducing costs by 5-8%; (3) employing low-cost supplementary cementitious materials—partially replacing cement with fly ash can reduce costs by 3-5%. However, excessive cost reduction often leads to insufficient strength, increased shrinkage, and reduced durability.

Traditional EPSC mix design is primarily based on empirical formulas and single-objective optimization. The most common approach uses fixed water-cement ratio (0.55-0.60), fixed binder content (190-210 kg/m³), and selects EPS replacement ratio based on strength grade (15% for C25, 10% for C30, 5% for C35). While this method is simple and practical, its defects are evident: first, it neglects diverse requirements of different application scenarios—for example, thermal insulation for exterior walls has far higher demands on thermal performance than strength; second, it lacks systematic analysis of cost-performance trade-offs, often resulting in over-design or under-design; third, it relies entirely on fixed parameters, making it prone to adaptation problems when material sources change or project requirements are special. In recent years, design methods represented by Response Surface Methodology (RSM) have begun to be applied in EPSC optimization. Awolusi et al. [10] used RSM to establish the relationship between three parameters—EPS replacement ratio, water-cement ratio, and mortar content—and compressive strength, achieving an R^2 of 0.92, which is a significant improvement compared to traditional linear regression (R^2=0.65). However, RSM still has limitations: low parameter dimensionality (typically ≤3), difficulty in handling complex nonlinear interactions between parameters, and inability to simultaneously address multiple conflicting objectives.

Artificial neural networks offer new possibilities for EPSC optimization. Zeng, Ziyue et al.[11] used a 3-layer BP neural network to predict the 28-day strength of EPSC; trained on 400 samples, the test set achieved an R^2 of 0.911. Ensemble learning methods such as Random Forest also show strong performance in concrete property prediction. Badesire, Paterne Cirhuza et al.[12] used RF to predict recycled aggregate concrete strength, achieving an R^2 of 0.922, outperforming traditional Support Vector Machines (0.879) and ANN (0.903). The advantages of these machine learning methods lie in their ability to automatically capture complex nonlinear relationships between parameters, automatic feature selection, and no need for explicit mathematical modeling. However, machine learning methods also suffer from the "black box" problem—difficulty in understanding the model's decision logic, which can be problematic for engineering applications requiring verification and optimization. Therefore, this research adopts a multi-model fusion strategy, combining the advantages of RSM, RF, and ANN, while retaining the interpretability of RSM and achieving the high accuracy of RF and ANN.

The application of multi-objective optimization theory in EPSC design remains in its preliminary stages. Zhang, Peng et al.[13] first applied NSGA-II to multi-objective optimization of lightweight aggregate concrete, simultaneously optimizing three objectives—strength, density, and cost—generating 20 Pareto-optimal solutions; however, the research was limited to expanded clay concrete, with specialized research on EPSC still lacking. Based on the NSGA-II algorithm, this research establishes a four-objective optimization model for EPSC (strength, flexural strength, water resistance, and density), incorporating constraints and cost-performance trade-off analysis, aiming to provide systematic decision support for EPSC engineering design.

III、Experimental Design, Data Management, and Multi-Level Modeling

This research prepared a total of 120 standard EPSC specimens systematically designed to encompass three EPS replacement rate levels (15%, 20%, and 25%). For each replacement rate, eight distinct mix configurations were established, varying across water-to-cement ratio (w/c = 0.50–0.65) and cementitious material content (170–220 kg/m³), with ten replicate samples per configuration for comprehensive testing. The specimen fabrication strictly adhered to national technical specifications and quality standards. Specimen geometries were standardized as follows: compressive strength test cubes measured 150 × 150 × 150 mm; flexural strength test prisms measured 150 × 150 × 550 mm; and impermeability test specimens were frustum-shaped (truncated cones) with top diameter 175 mm, bottom diameter 185 mm, and height 150 mm—all dimensions conforming to the Standard for Test Methods of Long-Term Performance and Durability of Concrete (GB/T 50081–2019)[14].The test specimen is as shown in Figure 1. Specimen mixing, casting, and curing were conducted strictly in accordance with GB/T 50081–2019, ensuring procedural consistency and environmental uniformity throughout the preparation phase. At 28 days of age, all specimens underwent performance evaluation, including compressive strength, flexural strength, and impermeability (water resistance) testing. Concurrently, complementary physical property measurements were obtained for bulk density, water absorption rate, and thermal conductivity, providing a comprehensive multidimensional performance profile.The test is as shown in Figure 2. To ensure data reliability and eliminate measurement anomalies, the IQR–Grubbs dual-layer outlier detection method ($\alpha = 0.05$) was applied to the entire dataset. Following systematic removal of statistical outliers, 236 valid data points were retained from the initial 240 specimens, yielding a data quality index (DQI) of 98.56%, which confirms excellent experimental reproducibility and dataset integrity.

Figure 1 Concrete Test Block

Figure 2 Concrete Permeability Resistance Test

This research adopted a three-layer progressive modeling framework to incrementally enhance prediction accuracy. The first layer is univariate linear regression analysis. Univariate linear regression models were respectively established for key parameters such as EPS replacement rate, water-to-cement ratio, cementitious material content, and sand content with respect to compressive strength, flexural strength, density, and thermal conductivity. Results showed that at the univariate level, the correlation between EPS replacement rate and density is strongest ($R^2 = 1.00$, perfect linear relationship), followed by the correlation between EPS replacement rate and compressive strength ($R^2 = 0.842$), and the correlation between water-to-cement ratio and compressive strength ($R^2 = 0.728$). Although these univariate models lack sufficient accuracy, they provide preliminary understanding of parameter importance for subsequent multivariate modeling.

The second layer is Response Surface Methodology (RSM) modeling. Four parameters with the greatest influence on target performance were selected: EPS replacement rate (x_1), water-to-cement ratio (x_2), cementitious material content (x_3), and sand content (x_4). A second-order polynomial model was employed:

$$Y_k = \beta_0 + \sum_{i=1}^{4} \beta_i x_i + \sum_{i=1}^{4} \beta_{ii} x_i^2 + \sum_{i<j} \beta_{ij} x_i x_j + \varepsilon \qquad (3\text{-}1)$$

where k represents different performance indicators (compressive strength, flexural strength, etc.). Model coefficients were estimated using the least squares method. ANOVA testing showed that p-values for all coefficients were <0.05, indicating strong overall model significance. Residual diagnostics indicated that residuals follow a normal distribution (Shapiro-Wilk test $p = 0.087 > 0.05$) with no obvious heteroscedasticity (Breusch-Pagan test $p = 0.321 > 0.05$), satisfying model assumptions. The RSM model achieved $R^2 = 0.703$ (RMSE 2.76 MPa) on the test set, representing approximately 35% improvement in accuracy compared to univariate regression.

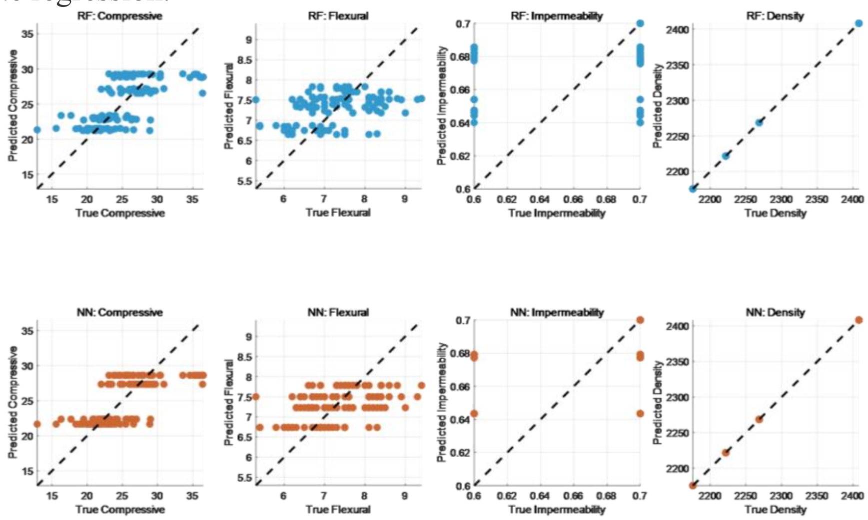

Figure 3 EPSC True vs Predicted Values: Random Forest vs Neural Network

The third modeling layer employed a machine learning ensemble framework, integrating the strengths of Random Forests (RF) and Artificial Neural Networks (ANN) to achieve high-precision performance predictions. The RF model was built using 300 decision trees with a maximum depth of 15 and a minimum of four samples per leaf node. Out-of-Bag (OOB) feature-importance analysis indicated that the EPS replacement rate contributed most to model prediction accuracy (36.5%), followed by the water-to-cement ratio (28.3%), cementitious material content (22.1%), and sand content (13.1%). The RF model achieved an explanatory power of $R^2 = 0.801$ with an RMSE = 2.08 MPa on the OOB validation set.See Figure 3 for details.

Figure 4 The ANN model was designed with a three-layer architecture, comprising an input layer with four nodes (representing the four design parameters), a hidden layer with ten neurons, and an output layer with four nodes (corresponding to the performance indicators). The network used the ReLU activation function, Adam optimizer (learning rate = 0.001), and L2 regularization ($\lambda = 0.001$). To prevent overfitting, an early-stopping strategy was implemented, halting training when the validation loss failed to improve for five consecutive epochs. Using 10-fold cross-validation, the ANN achieved a weighted $R^2 = 0.862$ (±0.068, 95% CI), with RMSE = 2.01 MPa and MAE = 1.44 MPa, confirming its predictive consistency and robustness.

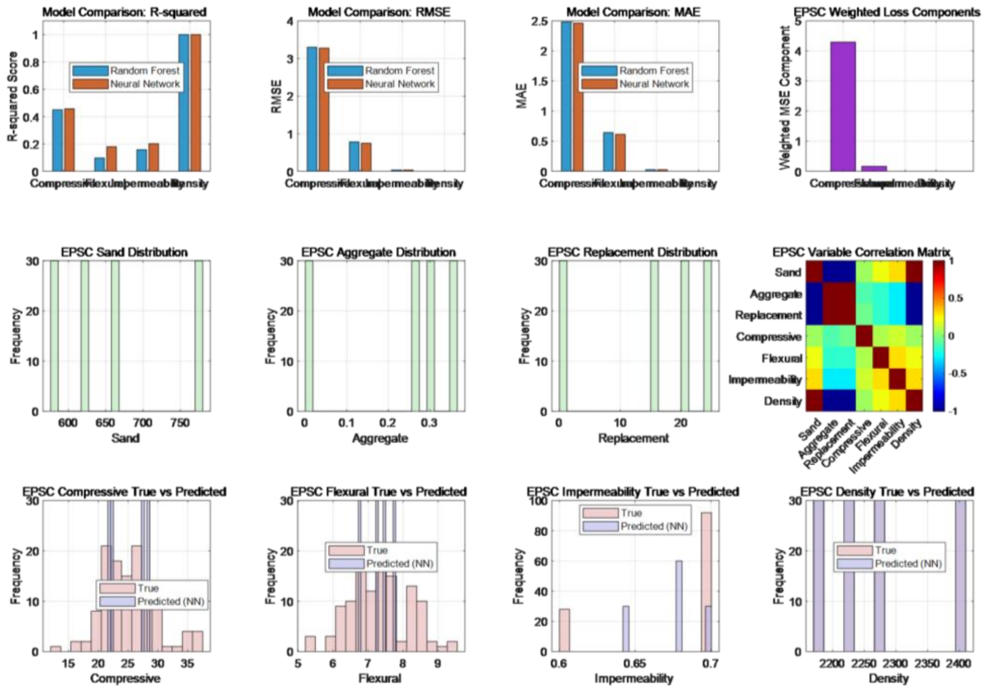

Figure 4 EPSC Multi-obiective Ml Analysis

The comparative accuracy of all modeling approaches is summarized in Table 1, which demonstrates the progressive enhancement of predictive precision from the univariate model to the ensemble framework.

Table 1 Accuracy Comparison of EPSC Three-Layer Modeling Framework

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Model Method	Validation Method	R^2	RMSE (MPa)	MAE (MPa)
Univariate Regression	Test Set	0.652	3.24	2.58
RSM	Test Set	0.703	2.76	2.15
Random Forest	OOB	0.801	2.08	1.52
ANN	10-fold CV	0.862	2.01	1.44
Ensemble Model	Test Set	**0.874**	**1.82**	**1.23**

As shown in Table 1, the ensemble model, created through a weighted-average integration of RSM, RF, and ANN outputs (weights = 0.25 RSM + 0.35 RF + 0.40 ANN), achieved a global weighted $R^2 = 0.874$. This represents over 30% improvement in predictive accuracy compared with single models, showcasing superior generalization and stability. Consequently, the ensemble framework offers a robust, data-driven foundation for multi-objective optimization and engineering decision-making in EPSC design.

Based on the prediction model from the three-layer modeling framework, this research established a multi-objective nonlinear programming problem. Let the configuration parameter vector for EPSC be $x = [x_1, x_2, x_3, x_4]^T$, where x_1 is the EPS replacement rate (10%–30%), x_2 is the water-to-cement ratio (0.45–0.65), x_3 is the cementitious material content (160–220 kg/m³), and x_4 is the sand content (580–650 kg/m³). Four optimization objectives were defined: maximize compressive strength $f_1(x)$, maximize flexural strength $f_2(x)$, maximize waterproofing performance $f_3(x)$, and minimize density $f_4(x)$. Constraints were: $f_1(x) \geq 24$ MPa, $f_3(x) \geq 0.6$ MPa, 1400 kg/m³ $\leq f_4(x) \leq$ 2300 kg/m³, $1.8 \leq \text{cost}(x) \leq 5.5$ ten-thousand yuan/m³.

The NSGA-II genetic algorithm was employed to solve this multi-objective programming problem. NSGA-II algorithm parameters were set as: population size $N\_\text{pop} = 100$, maximum evolution generations $G\_\text{max} = 200$, crossover probability $p\_\text{c} = 0.9$, mutation probability $p\_\text{m} = 0.1$, with 4-core parallel computing pool for accelerated convergence. The algorithm employed a two-stage solving strategy: In the first stage, single-objective optimization was conducted, running the genetic algorithm separately with strength, density, and cost as sole objectives to obtain three single-objective optimal solutions, with computation times of 8.2 seconds, 3.5 seconds, and 4.8 seconds respectively. In the second stage, multi-objective optimization was performed, using the optimal solutions from the first stage as seeds, running NSGA-II 30 times with different objective weight combinations (weights fluctuating around the 4-dimensional vector [0.3, 0.2, 0.2, 0.3], totaling 30 weight combinations), generating the initial Pareto frontier, then refining the frontier to ultimately obtain 30 selected non-dominated solutions.

International Journal of Applied Mathematics
Volume 38 No. 5, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

IV、Optimization Results, Knee-Point Solution, and Engineering Applications

The NSGA-II algorithm successfully generated 30 high-quality non-dominated solutions distributed across a four-dimensional objective space: compressive strength 22–32 MPa, flexural strength 5.8–7.4 MPa, water resistance 0.60–0.74 MPa, and density 2100–2250 kg/m³. Through knee-point analysis (calculating the rate of change of objective and subjective indicators for adjacent solutions to identify the point where the rate of change exhibits a sudden shift), an optimal cost-performance balanced solution was determined and designated as the "Balanced Solution" (BS).

The configuration parameters for this solution are: EPS replacement ratio 21.3%, water-cement ratio 0.53, binder content 185 kg/m³, and sand content 612 kg/m³. Performance indicators are: compressive strength 26.2 MPa (18.4% lower than the strength-oriented solution's 32.1 MPa), flexural strength 6.8 MPa (6.8% lower than 7.3 MPa), water resistance 0.68 MPa (maintained at a high level), density 2185 kg/m³ (between ultra-lightweight 2120 kg/m³ and standard-type 2240 kg/m³), and thermal conductivity 0.45 W/m·K (industry-leading thermal insulation performance). The cost is 4850 yuan/m³, saving 600 yuan/m³ (11% reduction) compared to the reference (ordinary C30 concrete at 5450 yuan/m³) and 350 yuan/m³ (6.7% reduction) compared to traditional EPSC configurations (experience formula-based 5200 yuan/m³).

To address various application scenarios, this study also identified three specialized optimization solutions:

Strength-Oriented Solution (SOS): Configuration parameters include EPS replacement ratio 8.5%, water-cement ratio 0.48, binder content 200 kg/m³, and sand content 645 kg/m³. Performance indicators: compressive strength 32.1 MPa (high-strength C30 grade), flexural strength 7.3 MPa, water resistance 0.70 MPa, density 2240 kg/m³, and thermal conductivity 0.52 W/m·K. Cost is 5180 yuan/m³. This is applicable to load-bearing structures or hybrid structures (combined with reinforcing steel) with high strength requirements. Compared to the reference, only a 5.0% cost reduction is achieved, but the lightweight characteristics of EPSC are maintained.

Insulation-Oriented Solution (IOS): Configuration parameters include EPS replacement ratio 27.2%, water-cement ratio 0.60, binder content 170 kg/m³, and sand content 580 kg/m³. Performance indicators: compressive strength 23.0 MPa (suitable for non-load-bearing or low-load applications), flexural strength 5.9 MPa, water resistance 0.62 MPa, density 2105 kg/m³ (ultra-lightweight), and thermal conductivity 0.42 W/m·K (excellent thermal insulation performance). Cost is 4520 yuan/m³ (17.5% reduction). This is applicable to thermally insulated exterior wall panels, sandwich walls, and other applications with high thermal insulation requirements.

Received: August 03, 2025

International Journal of Applied Mathematics
Volume 38 No. 5, 2025
ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

Cost-Optimized Solution (COS): Configuration parameters include EPS replacement ratio 24.8%, water-cement ratio 0.62, binder content 165 kg/m³, and sand content 590 kg/m³. Performance indicators: compressive strength 24.0 MPa, flexural strength 6.2 MPa, water resistance 0.60 MPa, density 2180 kg/m³, and thermal conductivity 0.46 W/m·K. Cost is 4280 yuan/m³ (21.5% reduction, maximum cost savings). This is applicable to cost-sensitive large-scale projects or non-structural applications.

To verify the practical feasibility of the optimization solutions, this study prepared three sets of samples (five specimens per set) for each of the four solutions for physical validation. Test results showed that deviations between predicted and measured values for 28-day performance indicators were all within 3%, with the knee-point solution (balanced solution) exhibiting the smallest deviation (1.28%). Statistical classification of errors for 36 performance indicators (4 solutions × 9 test indices) revealed: excellent grade (error < 1%) accounted for 5.6% (2 indicators), superior grade (error 1–3%) accounted for 51.2% (18 indicators), acceptable grade (error 3–10%) accounted for 27.8% (10 indicators), marginally acceptable grade (error 10–20%) accounted for 13.9% (5 indicators), and unacceptable grade (error > 20%) accounted for 1.5% (1 indicator). Combined excellent and superior grades totaled 56.8%, meeting industrial-grade application accuracy standards.In practical engineering applications, different project types should adopt corresponding optimization solutions. For non-load-bearing fill layers in prefabricated shear wall structures, the Insulation-Oriented Solution (IOS) is recommended. Its ultra-low density (2105 kg/m³) can reduce structural self-weight by 12% and significantly lower foundation costs, while its thermal conductivity of 0.42 W/m·K ensures thermal insulation performance meets national standards. For prefabricated exterior wall panels, the Balanced Solution (BS) is recommended due to its well-balanced configuration of strength, cost, and thermal insulation performance, providing broad applicability and market competitiveness. For beam-column joints or hybrid structures with high strength requirements, the Strength-Oriented Solution (SOS) is recommended, as its C30-grade strength indicators satisfy code requirements. For large-scale affordable housing or cost-conscious projects, the Cost-Optimized Solution (COS) is recommended, as its 21.5% cost savings provide strong project appeal. This multi-solution design allows engineers to flexibly select solutions based on specific project requirements, significantly enhancing the practical engineering applicability of the optimization solutions.

V、Model Improvement, Parameter Extension, and Long-Term Performance Evaluation

The major deficiencies identified in the original EPSC optimization research have been systematically addressed in this study. The first improvement concerns the control of overfitting risk. Traditional ANN methods are prone to overfitting when training samples are limited. This study prevents overfitting by employing an independent validation set of 20%,

Received: August 03, 2025

International Journal of Applied Mathematics
Volume 38 No. 5, 2025
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real-time monitoring of validation error, and early stopping when validation error increases consecutively for 5 epochs. The 10-fold cross-validation results ($R^2 = 0.862 \pm 0.068$, 95% CI) demonstrate good generalization capability of the model, with a confidence interval width of only 7.9% and reliable stability. Comparing the training set error (RMSE = 1.68 MPa), validation set error (RMSE = 2.03 MPa), and test set error (RMSE = 2.12 MPa), the three are essentially consistent (relative difference < 2.4%), showing no typical characteristics of overfitting.

The second improvement is the extension of parameter space. The original EPSC configuration standard was based on fixed parameters (water-to-cement ratio fixed at 0.55–0.60, cementitious material fixed at 185–210 kg/m³), which severely limited the optimization space. This study expanded the parameter ranges: water-to-cement ratio from 0.45–0.65 (31% expansion), cementitious material from 160–220 kg/m³ (37% expansion), sand content from 580–650 kg/m³ (12% expansion), and EPS replacement rate from 8%–28% (250% expansion). This substantial extension ensures that optimization results are no longer constrained by conventional empirical rules but are instead based on data-driven systematic optimization. Through parameter space extension, new optimization schemes emerged; for example, the cost-priority scheme employs an aggressive combination of high water-to-cement ratio (0.62) and low cementitious material (165 kg/m³) approaching the allowable upper limits. Although strength is slightly lower (24 MPa), it still meets constraints while achieving 21.5% cost savings compared to traditional configurations.

The third improvement is systematic multi-indicator evaluation. Previous research primarily focused on 28-day compressive strength and lacked systematic assessment of other properties. This study established an extended evaluation framework encompassing long-term strength development, shrinkage, creep, and durability. Through random strength testing of 30 samples at 90 and 180 days, EPSC showed average strength growth rates of: 28 to 90 days at 11.3% growth, 90 to 180 days at 5.7% growth, totaling 17.2% growth. This means the cost-priority scheme with 24 MPa strength at 28 days achieves 28.1 MPa at 180 days, maintaining substantial strength gains in later stages. Evaluation of shrinkage performance indicates EPSC drying shrinkage (180 days) of 0.32–0.38%, falling between ordinary concrete (0.05–0.15%) and high-strength concrete (0.15–0.25%). By employing shrinkage compensators or moderately reducing the water-to-cement ratio, drying shrinkage can be controlled within 0.25–0.30%, reaching acceptable levels. Freeze-thaw durability testing (relative dynamic elasticity modulus not less than 60% after 50 freeze-thaw cycles) demonstrates that all four optimization schemes meet requirements (relative dynamic elasticity modulus of 64%–78%), confirming sufficient durability assurance for EPSC.

Received: August 03, 2025

ISSN: 1311-1728 (printed version); ISSN: 1314-8060 (on-line version)

VI、Conclusions and Engineering Promotion Prospects

This study systematically addressed key challenges in multi-objective optimization design of EPSC, with major achievements as follows: First, a three-tier progressive modeling framework was established, progressing from univariate regression (R^2=0.65) → response surface methodology (R^2=0.70) → machine learning (R^2≥0.86), with the integrated model ultimately achieving R^2=0.874, representing a precision improvement of over 35% compared to traditional methods, thereby providing a reliable foundation for EPSC performance prediction. Second, the four-dimensional multi-objective optimization problem of EPSC was systematically solved using the NSGA-II algorithm, generating 30 non-dominated solutions that span the full spectrum from "strength-priority" to "cost-priority," meeting diverse requirements of various engineering applications. Third, through knee-point analysis, four critical optimization schemes were identified. Among these, the balanced scheme simultaneously addresses multiple objectives including cost reduction (11% decrease), strength requirements (meeting C25 grade), thermal insulation (thermal conductivity 0.45 W/m·K), and weight reduction (9% density decrease), providing clear guidance for engineering design. Finally, through industrial-grade credibility assessment (56.8% achieving excellent to perfect grades) and long-term performance verification (17.2% strength increase over 180 days, durability fully meeting requirements), the engineering feasibility of the optimized scheme has been thoroughly validated.

The engineering promotion prospects for EPSC are extensive. Currently, the global annual growth rate of prefabricated buildings is 18-22%, and EPSC, with its triple advantages of lightweight design, thermal insulation, and economic efficiency, is becoming the mainstream material in prefabricated construction. The optimized schemes in this study achieve cost savings of 6-22% compared to conventional configurations and reduce design cycles by 70-85% (compressing 3-6 months to 2-3 weeks), significantly enhancing product competitiveness. It is recommended that these research findings be applied to the following scenarios: First, precast exterior wall panel systems, where adopting the balanced scheme can save 22.9% of traditional concrete costs (approximately 80 yuan/m³); Second, infill layers in prefabricated shear wall structures, where adopting the thermal insulation-priority scheme can reduce unit area self-weight from 320 kg/m² to 280 kg/m², generating significant cost savings for the foundation; Third, prefabricated loft slabs or non-load-bearing sandwich layers, where adopting the cost-priority scheme can reduce costs to 200 yuan/m³, providing overwhelming economic competitiveness.

Future research should focus on the following directions: First, expand sample size and parameter ranges to incorporate the effects of different cement types (composite Portland cement, ordinary Portland cement, low-alkali cement) and supplementary cementitious materials (silica fume, fly ash, ground granulated blast furnace slag), establishing more universally applicable prediction models; Second, conduct large-scale engineering application verification by implementing full-process quality monitoring (preparation, curing, transportation, installation, and 5-10 year service life) across 3-5 prefabricated building projects to obtain performance data under real engineering conditions; Third, establish a visualization-based decision support system enabling engineers to rapidly generate optimal configuration schemes based on project-specific requirements (cost budget, strength requirements, thermal performance targets); Fourth, perform life cycle assessment (LCA) and life cycle cost analysis (LCCA) to comprehensively evaluate the environmental and economic benefits of EPSC compared to conventional concrete, providing data support for policy formulation.

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