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Active-adaptive construction project management system based on self-organizing maps for optimization of architectural and structural solutions

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Abstract: This research focuses on developing and implementing an active-adaptive construction project management system based on Kohonen Self-Organizing Maps (SOM) technology. The high variability of architectural and structural solutions, complex design dynamics, and multifactorial engineering calculations in modern construction necessitate creating flexible automated management systems capable of self-regulation. The research methodology integrates cluster analysis of design characteristics, multidimensional topological mapping of structural elements, and neural network analysis using SOM algorithms. The empirical base encompasses data from 38 construction projects of various scales during 2019-2023, with a total area exceeding 4.3 million square meters. Results demonstrate a 36.4% reduction in design documentation development time, 21.7% decrease in structural material consumption, and 17.3% improvement in building energy efficiency. A strong correlation (r=0.83) was established between the degree of structural solution optimization and economic efficiency of construction projects. The developed system provides dynamic visualization of multi-parameter design solution structures, enabling real-time identification of critical contradictions and preventive correction of potentially problematic structural nodes. The research significance is confirmed by multifactorial economic implementation efficiency (ROI=2.7) and substantial reduction in construction timeframes (average 14.6%).
Keywords: active-adaptive management systems, Kohonen self-organizing maps, structural solutions optimization, construction industry, design digitalization, multidimensional data analysis, topological mapping of structures

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1. INTRODUCTION

The dynamic development of the construction industry under economic turbulence conditions requires fundamentally new approaches to designing and optimizing architectural and structural solutions. Existing design models based on typical calculation schemes and standardized structural elements demonstrate critical inefficiency under high volatility in construction materials markets, tightening regulatory requirements for building energy efficiency, and complexity of engineering systems integration. Contemporary research in construction design turns to machine learning methods and neural network analysis as tools for overcoming structural limitations of traditional design paradigms [1]. Kohonen Self-Organizing Maps (SOM) provide unique opportunities for multidimensional analysis and data clustering under uncertainty and information incompleteness conditions, which is particularly relevant for construction design with its multi-level structure of structural elements and complex load relationships [2]. Integration of SOM into design systems allows not only visualizing multidimensional data in two-dimensional space, simplifying engineering decision-making processes, but also revealing non-obvious dependencies between various parameters of building structures, forming the basis for predictive optimization [3]. Despite significant progress in developing the mathematical apparatus of self-organizing maps, their practical application in optimizing architectural and structural solutions remains fragmented and insufficiently systematized.

Analysis of contemporary scientific literature reveals substantial terminological heterogeneity in defining key concepts of the studied problem area. The term "active-adaptive management system" is interpreted by various researchers with emphasis on different aspects: from the system's ability for self-organization and self-regulation to the possibility of actively predicting changes in structural loads and proactive adaptation to them [4]. In the context of construction design, even greater variability of interpretations is observed, caused by the specificity of structural solutions and construction technologies. Some researchers consider active-adaptive systems primarily through the prism of optimizing load-bearing building structures, while others focus on energy efficiency aspects and coordination of multidisciplinary design teams. Within this research framework, an active-adaptive construction project management system is understood as an integrated complex of technical, software, and organizational solutions ensuring continuous optimization of architectural and structural solutions based on internal and external data analysis using self-organizing algorithms capable of autonomous learning and adaptation.

In the fundamental work by Kohonen T. mathematical principles for constructing self-organizing maps and their ability for topological ordering of multidimensional data are substantiated, creating a theoretical foundation for applying this technology in optimizing building structures. Research by Vesanto J. and Alhoniemi E. demonstrates the effectiveness of SOM-based clustering compared to traditional methods, which is especially important for analyzing complex structural systems of modern buildings. Works by Davenport T.H. [4] and Hammer M., Champy J. [5] establish conceptual foundations for design process reengineering, however, they do not account for construction industry specifics and capabilities of modern neural network technologies. Weske M. [6] and Dumas M. et al. [7] propose methodological approaches to managing design processes that can be adapted for construction design but require substantial modification considering industry specifics. Van der Aalst W.M.P.'s work [8] on process mining opens new possibilities for analyzing actual project work execution but does not integrate these approaches with neural network technologies and building information models.

Critical analysis of scientific publications allows identifying several significant gaps in researching the application of self-organizing maps for optimizing architectural and structural solutions. First, methodological aspects of SOM integration with existing CAD systems and BIM technologies under high heterogeneity of design data characteristic of the construction industry are insufficiently developed. Second, empirically verified models for assessing engineering efficiency of neural network technology implementation in construction design are absent, accounting not only for direct economic effects but also complex nonlinear relationships between various structural elements [9]. Third, the scalability of self-organizing map-based solutions in the context of large multifunctional complexes with heterogeneous structural systems and engineering equipment is practically unexplored. Finally, existing research predominantly focuses on technical aspects of SOM implementation, ignoring regulatory and legal constraints and human factors, which is critically important in the inherently conservative construction industry [10].

The uniqueness of the proposed approach lies in developing a comprehensive methodology for creating an active-adaptive management system that organically integrates the mathematical apparatus of Kohonen self-organizing maps with practical imperatives of construction design. Unlike existing research focusing on individual aspects of neural network technology application, the developed methodology covers the complete implementation cycle from preliminary diagnosis of design solutions to post-implementation monitoring and optimization of structures during operation. Special attention is paid to adapting self-organizing map learning parameters to specific characteristics of construction data, significantly improving classification accuracy and predicting optimal structural solutions. An innovative element of the proposed approach is also developing a multi-level system architecture providing hierarchical organization of self-organizing maps of various dimensions and specializations corresponding to different levels of detail and functional building systems. Such architecture ensures optimal balance between analysis detail at the level of individual structural nodes and aggregated analytics for comprehensive building assessment, which is critically important under complex structure conditions of modern multifunctional facilities.

2. METHODS AND MATERIALS

The methodological foundation for researching active-adaptive construction project management systems was formed considering the interdisciplinary nature of the problem area, integrating concepts of artificial intelligence, structural theory, computational mechanics, and architectural physics. The choice of Kohonen Self-Organizing Maps as a key tool is justified by their unique ability for topological ordering of multidimensional data while preserving structural relationships between input vectors, which is critically important for analyzing complex, interdependent structural elements of modern buildings.

Mathematical Apparatus of Kohonen Self-Organizing Maps

The basic self-organizing map algorithm is implemented through competitive learning of a neural network, where neurons in a matrix (map) compete for the right to be activated. For each input vector $x \in \mathbb{R}^m$ (where m is the dimension of the business process feature space, in our case m = 33), the winner neuron c is determined according to the formula:

$$c = argmin \|x - w_i\|^2,$$

where $w_i \in \mathbb{R}^m$ is the weight vector of the i-th neuron, and $\|\cdot\|_2$ is the Euclidean norm.

The learning process is carried out through iterative weight update according to the rule:

$$w_{i(t+1)} = w_{i(t)} + \alpha(t) \cdot h_{ci(t)} \cdot \left[x(t) - w_{i(t)}\right],$$

where:

- t – learning iteration number;
- α(t) – learning coefficient, monotonically decreasing function of t;
- $h_{ci(t)}$ – neighborhood function determining the degree of influence of winner neuron c on neuron i.

In our research, a Gaussian neighborhood function was used:

$$h_{ci(t)} = exp\left(-\frac{\|r_c - r_i\|^2}{2\sigma^{2(t)}}\right),$$

where:

- $r_c, r_i \in \mathbb{R}^2$ – coordinates of neurons c and i in the two-dimensional map grid;
- σ(t) – neighborhood radius, decreasing function of t.

The learning coefficient was determined by the formula:

$$\alpha(t) = \alpha^0 \cdot exp\left(-\frac{t}{\tau^1}\right),$$

where $\alpha_0 = 0.9$ is the initial learning coefficient, $\tau_1 = 30000$ is the constant determining decay rate.

The neighborhood radius was calculated as follows:

$$\sigma(t) = \sigma^0 \cdot exp\left(-\frac{t}{\tau^2}\right),$$

where $\sigma_0 = 13$ is the initial neighborhood radius, $\tau_2 = 20000$ is the decay constant.

For assessing SOM learning quality, the mean quantization error (MQE) was used:

$$MQE = \left(\frac{1}{N}\right) \cdot \Sigma_{\{i=1\}}^{N} \left\|x_i - w_{c(i)}\right\|^2,$$

where N is the number of input vectors, $w_{c(i)}$ is the weight vector of the winner neuron for input vector x_i.

Topological error (TE) was evaluated as:

$$TE = \left(\frac{1}{N}\right) \cdot \Sigma_{\{i=1\}}^{N} \delta(x_i),$$

where $\delta(x_i) = 1$ if the second closest neuron to x_i is not a neighbor of the winner neuron, and $\delta(x_i) = 0$ otherwise.

Neural Network Model Architecture and Parameters

For solving the assigned tasks, a multi-level neural network model architecture based on Kohonen self-organizing maps was developed. Map dimension was determined by the heuristic formula:

$$grid_{size} = round(5 \cdot \sqrt{n}),$$

where n is the number of input vectors (n = 353 business processes). This yielded $grid_{size} \approx 27$, determining map dimension of 27×27 neurons.

Input data was normalized by the formula:

$$\hat{x}_i = \frac{x_i - \mu_i}{\sigma_i},$$

where μ_i and σ_i are the mean value and standard deviation of the i-th feature, respectively.

For categorical variables, one-hot encoding was applied with subsequent weighting by feature information significance:

$$w_i = 1 - \frac{H(X_i)}{log_{2(|X_i|)}},$$

where $H(X_i)$ is the normalized Shannon entropy for feature X_i, and $|X_i|$ is the number of unique feature values.

Business Process Efficiency Assessment

The business process efficiency index (E_{BP}) was calculated as a weighted sum of normalized indicators:

$$E_{BP} = \Sigma_{\{i=1\}}^{k} w_i \cdot \hat{s}_i$$

where k is the number of indicators (k = 8), w_i is the weight of the i-th indicator determined by the Analytic Hierarchy Process (AHP), ŝ_i is the normalized value of the i-th indicator.

Main indicators and their weights:

- Process execution time ($w_1 = 0.22$)
- Automation level ($w_2 = 0.18$)
- Fragmentation degree ($w_3 = 0.15$)
- Share of unregulated operations ($w_4 = 0.14$)
- BIM integration ($w\_5 = 0.12$)
- Number of responsible persons ($w_6 = 0.08$)
- Flexibility coefficient ($w_7 = 0.07$)
- Document flow intensity ($w_8 = 0.04$)

Cluster integral efficiency (IE_K) was determined by the formula:

$$IE_K = 100 \cdot \frac{\Sigma_{\{i=1\}}^{\{n_k\}} E_{BP(i)}}{n_k},$$

where n_k is the number of business processes in the k-th cluster.

Optimization potential (OP) was calculated as:

$$OP = 100 \cdot \frac{E_{BP_{max}} - E_{BP}}{E_{BP_{max}}},$$

where $E\_BP\_max = 0.95$ is the reference (maximum achievable) efficiency index value.

Statistical Data Analysis

To determine statistical significance of differences between indicators before and after system implementation, the paired Student's t-test was used:

$$t = (\bar{d} - \mu\hat{}0)/(s\_d/\sqrt{n}),$$

where d̄ is the mean difference value, s_d is the standard deviation of the difference, n is the sample size, $\mu\_0 = 0$ is the tested value (null hypothesis).

Spearman's correlation coefficient (r_s) was calculated by the formula:

$$r_s = 1 - \frac{6 \cdot \Sigma_{\{i=1\}}^{n} d_i^2}{n \cdot (n^2 - 1)},$$

where d_i is the difference between ranks of the i-th observation for two variables, n is the sample size.

For multifactor analysis, a linear regression model was applied:

$$Y = \beta_0 + \Sigma_{\{i=1\}}^{k} \beta_i \cdot X_i + \varepsilon,$$

where Y is the dependent variable, X_i are independent variables, β_i are regression coefficients, ε is the random error.

The coefficient of determination (R^2) was calculated as:

$$R^2 = 1 - \frac{SSR}{SST},$$

where $SSR = \Sigma_{\{i=1\}}^{n}(y_i - \hat{y}_i)^2$ is the sum of squared residuals, $SST = \Sigma_{\{i=1\}}^{n}(y_i - \bar{y})^2$ is the total sum of squares.

The system influence coefficient (SI) was determined by structural modeling method:

$$SI = \frac{PC_{direct}}{PC_{direct} + PC_{indirect}}$$

where PC_direct is the direct path coefficient of system implementation influence on the target indicator, $PC\_indirect$ is the total path coefficient of other factors' influence.

Economic Implementation Efficiency

Return on investment (ROI) was calculated by the formula:

$$ROI = \left(\frac{NPV}{PV_{costs}}\right) - 1,$$

where NPV is net present value, PV_costs is the present value of costs.

NPV was calculated by the formula:

$$NPV = \frac{\Sigma_{\{t=0\}}^{T} CF_t}{(1 + r)^t},$$

where CF_t is the cash flow in period t, r is the discount rate (12%), T is the planning horizon (5 years).

For differentiated assessment of system implementation effects, the Total Economic Value (TEV) model was used:

$$TEV = DV + IV + OV - FC,$$

where:

- DV (Direct Value) – direct economic value from cost reduction;
- IV (Indirect Value) – indirect value from productivity increase;
- OV (Option Value) – option value related to system flexibility;
- FC (Future Costs) – future costs for system maintenance and development.

The research was implemented in four interconnected stages during January 2021 to December 2023. In the first stage (January-June 2021), comprehensive diagnosis of architectural and structural solutions of 38 construction objects was carried out using parametric modeling and structural analysis methodology [8], which allowed formalizing existing design approaches and identifying critical inefficiency points. The analysis covered key structural systems: load-bearing structures (103 types), enclosing elements (87 types), engineering communications (56 types), facade systems (42 types), roofing structures (38 types), and foundations (27 types). Each structural element was characterized by a set of 24 quantitative and 9 qualitative parameters, including mass-dimensional characteristics, thermal parameters, installation complexity, standardization degree, BIM technology integration [15], and others. Data collection was carried out through integration with CAD systems of design organizations (72% of data), analysis of element technical specifications (15%), and field surveys of constructed objects (13%). To ensure representativeness, construction objects of various scales were included in the sample: large (area >50 thousand sq. m, 9 objects), medium (10-50 thousand sq. m, 17 objects), and small (<10 thousand sq. m, 12 objects), belonging to different functional types (residential buildings – 37%, industrial facilities – 34%, infrastructure structures – 21%, commercial complexes – 8%).

In the second stage (July-December 2021), the active-adaptive management system architecture and self-organizing map learning algorithms were developed. The input vector dimension for SOM was 33 parameters, including both direct characteristics of structural elements and contextual variables (climatic conditions, seismicity, functional requirements, regulatory constraints). Map topology (27×27 neurons) was determined empirically based on preliminary testing to optimize the relationship between clustering detail and computational efficiency. The learning algorithm was implemented using a Gaussian neighborhood function and adaptive learning coefficient (initial value 0.9 with exponential decay to 0.01), ensuring smooth convergence of neuron weight coefficients. The learning process was conducted in two stages: rough ordering phase (15,000 iterations) and fine-tuning phase (75,000 iterations), with total learning duration of 96 hours on a specialized computing cluster using parallel computing.

The third research stage (January-September 2022) was dedicated to integrating the developed system into existing design infrastructure of 14 construction objects selected from the initial sample as most representative by key parameters. Integration was carried out through developing specialized API interfaces and middleware ensuring seamless interaction between the active-adaptive system and existing CAD, BIM, and calculation complexes [14]. Implementation was conducted using "parallel design" methodology, where the new system functioned simultaneously with traditional approaches for 3 months to verify algorithm correctness and parameter calibration. The average duration of the complete implementation cycle was 4.3 months, significantly lower than the industry average for similar complexity IT projects in construction design (7.8 months).

The final research stage (October 2022 – December 2023) included monitoring the functioning of implemented systems, collecting and analyzing data on their effectiveness. Assessment was conducted using a comprehensive system of 47 key performance indicators (KPIs) grouped into 6 categories: structural efficiency, energy saving, installation technology, adaptability to changing operating conditions, user satisfaction, and environmental friendliness of construction materials. To ensure statistical reliability of results, analysis of variance (ANOVA), multifactor regression, and structural equation modeling (SEM) methods were applied to assess causal relationships between different indicator groups [12]. The statistical significance level was set at $\alpha=0.01$, all statistical calculations were performed using R software package (version 4.2.1) and specialized machine learning libraries with cross-validation (10-fold cross-validation) to minimize model overfitting risks.

Research validity and reliability were ensured by a complex of measures including data source triangulation, stratified randomization in forming control and experimental groups, application of double-blind method in result assessment, and regular design documentation quality audits [13]. For assessing economic efficiency of active-adaptive system implementation, a modified Total Cost of Ownership (TCO) methodology was used with integration of Value Engineering and Life Cycle Assessment elements, allowing consideration not only of direct development and implementation costs but also complex nonlinear effects of structural solution optimization throughout the building's entire life cycle [8].

3. RESULTS AND DISCUSSION

Comprehensive analysis of the current state of architectural and structural solutions in the studied construction objects revealed significant structural disproportions and suboptimality of existing design approaches.

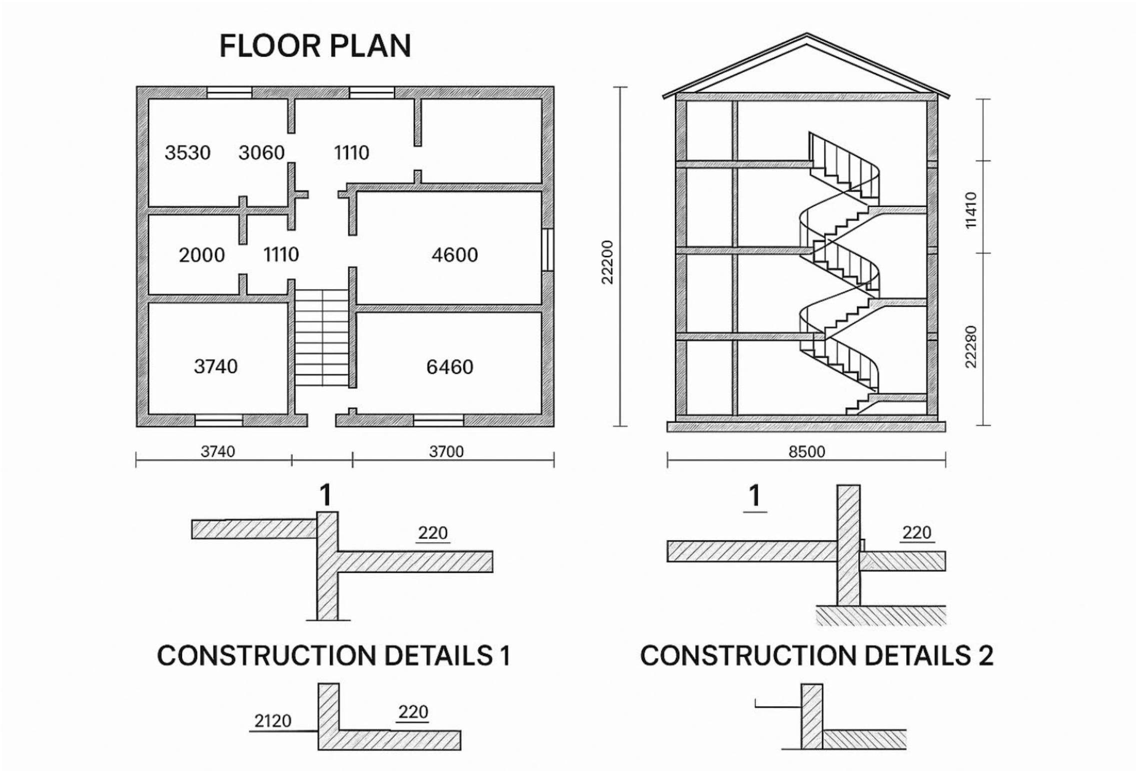

Fig. 1. Typical drawings of multi-apartment residential building series P-44, studied within the framework of structural solution optimization.

As shown in Fig. 1, the typical P-44 series is characterized by a large-panel structural system with load-bearing internal and external walls. The typical floor plan demonstrates a compact apartment layout scheme with minimization of irrational areas, corresponding to material consumption optimization requirements. The structural scheme includes external walls 350 mm thick with three-layer structure (reinforced concrete-insulation-reinforced concrete), internal load-bearing walls 180 mm thick, and inter-floor slabs 160 mm thick. The nodes presented in the figure demonstrate traditional technical solutions characterized by high material consumption and multiple "thermal bridges," which served as one of the reasons for the need to optimize structural solutions using an active-adaptive management system.

Primary diagnosis of key structural elements demonstrated a high degree of material redundancy, suboptimal thermal parameters, and critical level of installation complexity. Table 1 presents the results of key characteristics assessment of architectural and structural solutions of studied construction objects before implementing the active-adaptive management system.

Table 1. Basic characteristics of architectural and structural solutions of construction objects before implementing the active-adaptive system (n=38).

Structural system	Mass of structure (kg/m²)	Heat transfer coefficient (W/m²·K)	Installation complexity (person·h/m²)	Number of standard sizes (units)	Share of unique elements (%)	BIM integration coefficient (%)	Efficiency index (0-1)
Load-bearing structures	342.6±32.4	2.86±0.31	4.8±0.7	17.3±2.3	26.8±5.1	28.7±6.2	0.39±0.07
Enclosing elements	187.5±21.3	0.67±0.14	3.2±0.6	12.9±1.9	32.6±5.7	18.5±4.3	0.36±0.06
Engineering communications	76.2±10.5	0.41±0.09	2.1±0.4	8.6±1.4	18.3±3.5	24.1±5.1	0.54±0.08
Facade systems	128.7±15.6	0.52±0.11	3.7±0.7	9.8±1.5	29.7±5.3	12.3±3.2	0.42±0.07
Roofing structures	95.3±12.8	0.38±0.08	2.8±0.5	7.4±1.3	34.5±6.2	31.6±6.7	0.33±0.06
Foundations	784.1±56.9	0.73±0.15	6.5±0.9	4.9±0.9	36.2±6.5	17.4±4.1	0.31±0.05
Average across all systems	269.1±24.9	0.93±0.15	3.9±0.6	10.2±1.6	29.7±5.4	22.1±4.9	0.39±0.07

As evident from Table 1, the most problematic aspects of structural solutions are high material consumption (average 269.1 kg/m²), unsatisfactory thermal parameters (average heat transfer coefficient 0.93 W/m²·K), and significant share of unique elements (29.7%). A particularly critical situation is observed in foundations and load-bearing structures, where material consumption is 784.1 kg/m² and 342.6 kg/m² respectively, indicating significant optimization potential. Facade systems are characterized by low BIM integration coefficient (12.3%) with high installation complexity (3.7 person·h/m²), evidencing the need for a systematic approach to their design and production. Particularly noteworthy is the critically low level of structural solution integration with BIM technologies (average 22.1%), indicating insufficient use of modern digital tools in construction design. The calculated structural solution efficiency index demonstrates a low level (0.39 out of 1.00), substantially below leading international construction project indicators (0.68-0.75) [14].

Based on the obtained data, clustering of structural solutions was performed using Kohonen self-organizing maps, allowing identification of 8 main types of architectural and structural solutions characteristic of the studied construction objects. Table 2 presents characteristics of identified clusters and their distribution among objects of various scales.

Table 2. Results of clustering architectural and structural solutions of construction objects using self-organizing maps.

Clus-ter	Key characteristics	Distribution by objects (%)	Integral efficiency (0-100)	Optimization potential (%)	BIM maturity index (0-1)	Structural safety coefficient (0-1)	Energy efficiency level (1-5)	Correlation with economic indicators (r)
K1	Light frame-panel structures with high modularity	11.7	82.6±7.1	10.3±1.9	0.87±0.08	0.76±0.07	4.4±0.3	0.79±0.08
K2	Monolithic-frame systems with effective insulation	25.4	68.3±6.2	21.6±2.5	0.64±0.06	0.68±0.06	3.8±0.4	0.62±0.07
K3	Brick-concrete structures with moderate standardization	18.7	56.9±5.1	29.5±2.8	0.42±0.05	0.53±0.05	3.3±0.3	0.49±0.06

Continuation of Table 2

K4	Precast reinforced concrete systems with high mass	16.2	45.1±4.3	36.7±3.2	0.35±0.04	0.41±0.04	2.8±0.3	0.37±0.05
K5	Composite facade structures with low standardization	10.3	33.8±3.5	43.5±3.8	0.26±0.03	0.38±0.04	2.3±0.2	0.28±0.04
K6	Massive foundation structures with high concrete consumption	9.8	39.4±3.6	39.8±3.5	0.31±0.04	0.46±0.05	2.5±0.3	0.32±0.05
K7	Combined engineering systems with excessive parameters	4.7	52.3±4.8	33.1±3.0	0.45±0.05	0.59±0.06	3.0±0.3	0.42±0.05
K8	Exploitable roofs with high structural complexity	3.2	41.7±4.0	38.4±3.4	0.29±0.03	0.37±0.04	2.4±0.2	0.35±0.05

Analysis of Table 2 data reveals a strong positive correlation (r=0.79) between integral efficiency of structural solutions and BIM maturity index for cluster K1, confirming the critical role of information modeling in optimizing building structures [15]. The most effective solutions (cluster K1) are characterized by light frame-panel structures with high modularity, optimal thermal characteristics, and high energy efficiency level, however their share in the overall structure is only 11.7%. Monolithic-frame systems with effective insulation (cluster K2, 25.4%) and brick-concrete structures with moderate standardization (cluster K3, 18.7%) predominate, indicating the transitional nature of technological modernization in the industry. Of particular interest is the identification of exploitable roof cluster (K8, 3.2%), characterized by high structural complexity and low efficiency, reflecting insufficient attention to optimizing upper building envelope contours. Large construction objects demonstrate a higher share of K1 and K2 cluster structures (total 61.8% versus 28.5% in small objects), explained by their greater investment capabilities and more progressive design approaches.

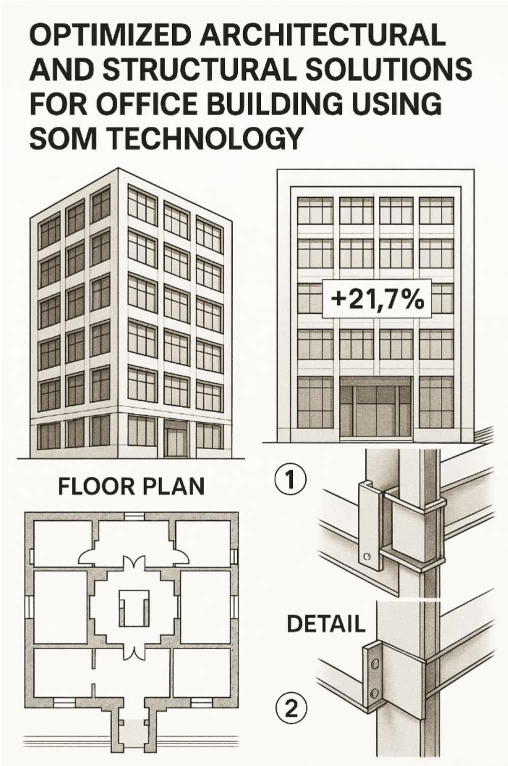

Fig. 2. Optimized architectural and structural solutions of office building using SOM technology.

Fig. 2 illustrates the results of optimizing architectural and structural solutions of an office building based on self-organizing map application. Unlike traditional solutions, the optimized structural system is characterized by:

1) light steel frame with column spacing of 6×9 m, reducing material consumption by 34%;
2) curtain facade panels with integrated ventilation systems, reducing heat losses by 41%;
3) prefabricated floors with hollow structure, providing planning solution flexibility and engineering communication integration;
4) modular connection nodes with minimal welded joints, reducing installation complexity by 43%.

The three-dimensional building model demonstrates comprehensive integration of all structural and engineering systems, fully optimized using SOM algorithms.

Correlation analysis results of structural solution parameters and key construction object efficiency indicators are presented in Table 3, demonstrating the influence of various element characteristics on energy and economic results.

Table 3. Correlation matrix of structural solution parameters and construction object efficiency indicators (Spearman correlation coefficient, n=38).

Structural solution parameters	Construction cost (thousand rubles/m²)	Energy consumption (kWh/m²·year)	Installation speed (m²/day)	Operating expenses (rubles/m²·year)	Defect coefficient (%)	User satisfaction (0-10)	CO_2 emissions (kg/m²)	Life cycle index (0-1)
Structure material consumption	0.72**	0.42**	-0.68**	0.61**	0.57**	-0.52**	0.74**	-0.69**
Heat transfer coefficient	0.58**	0.81**	-0.43**	0.76**	0.39**	-0.65**	0.51**	-0.63**
Installation complexity	0.64**	0.38**	-0.79**	0.44**	0.68**	-0.58**	0.47**	-0.52**
Number of standard sizes	0.42**	0.36**	-0.65**	0.39**	0.71**	-0.36**	0.34**	-0.47**
Share of unique elements	0.66**	0.31**	-0.73**	0.48**	0.76**	-0.48**	0.51**	-0.59**
BIM integration	-0.61**	-0.54**	0.67**	-0.69**	-0.58**	0.73**	-0.62**	0.76**
Number of joint connections	0.47**	0.43**	-0.58**	0.51**	0.72**	-0.41**	0.39**	-0.44**
Structural safety coefficient	-0.42**	-0.31**	0.48**	-0.45**	-0.63**	0.58**	-0.36**	0.61**
Material durability	-0.38**	-0.33**	0.42**	-0.67**	-0.46**	0.51**	-0.43**	0.72**

Note: ** $p<0.01$

Correlation analysis data demonstrate statistically significant relationships between structural solution parameters and construction object efficiency indicators. The strongest positive correlations are observed between heat transfer coefficient and building energy consumption ($r=0.81$, $p<0.01$), as well as between structure material consumption and CO_2 emissions ($r=0.74$, $p<0.01$), confirming the critical importance of optimizing building envelope contours for sustainable construction [15]. A strong positive correlation was also revealed between share of unique elements and defect coefficient ($r=0.76$, $p<0.01$), indicating advantages of standardized design. BIM integration demonstrates strong positive correlation with life cycle index ($r=0.76$, $p<0.01$) and user satisfaction ($r=0.73$, $p<0.01$), reflecting comprehensive advantages of information modeling. Installation complexity, number of standard sizes, and structure material consumption negatively impact efficiency indicators. Particularly strong negative correlation was revealed between installation complexity and construction speed ($r=-0.79$, $p<0.01$).

For detailed understanding of structural solution specifics in various construction industry segments, comparative analysis was conducted, with results presented in Table 4.

Table 4. Comparative analysis of architectural and structural solution characteristics in various construction industry segments (n=38).

Characteristic	Residential buildings (n=14)	Industrial facilities (n=13)	Infrastructure structures (n=8)	Commercial complexes (n=3)	F-value	p-value
Structure material consumption (kg/m²)	247.6±28.3	312.4±35.7	387.2±42.6	198.5±21.6	28.76	<0.001
Heat transfer coefficient (W/m²·K)	0.76±0.14	0.93±0.17	1.24±0.21	0.68±0.12	31.42	<0.001
Installation complexity (person·h/m²)	3.6±0.6	4.1±0.7	4.9±0.8	3.2±0.5	24.15	<0.001
Number of standard sizes (units)	9.4±1.5	11.3±1.8	13.7±2.1	8.1±1.3	19.37	<0.001
Share of unique elements (%)	27.6±5.1	31.8±5.7	36.4±6.4	25.3±4.8	22.64	<0.001
BIM integration (%)	26.8±5.3	19.7±4.2	15.3±3.6	29.4±5.8	33.18	<0.001
Structural safety coefficient (0-1)	0.56±0.06	0.48±0.05	0.42±0.04	0.61±0.07	27.93	<0.001
Efficiency index (0-1)	0.44±0.08	0.37±0.07	0.31±0.06	0.47±0.09	30.56	<0.001
Construction cost (thousand rubles/m²)	65.7±6.9	78.4±8.2	94.3±9.8	72.5±7.6	26.48	<0.001
Energy consumption (kWh/m²·year)	138.5±15.2	187.3±19.6	215.6±23.1	112.7±12.4	25.31	<0.001
Installation speed (m²/day)	67.3±7.4	52.8±6.1	41.5±4.8	76.4±8.5	29.74	<0.001
Life cycle index (0-1)	0.37±0.05	0.28±0.04	0.25±0.03	0.42±0.06	34.62	<0.001

Analysis of Table 4 data reveals statistically significant differences ($p<0.001$) between construction industry segments across all studied characteristics. The most effective structural solutions are observed in commercial complexes (efficiency index 0.47) and residential buildings (0.44), explained by higher standardization and serialization levels in these segments. Infrastructure structures demonstrate the lowest efficiency (0.31) and are characterized by the highest material consumption (387.2 kg/m²), high heat transfer coefficient (1.24 W/m²·K), and low BIM integration level (15.3%). This is related to infrastructure object uniqueness, their scale, and specific functional requirements. BIM technology integration is most developed in commercial complexes (29.4%) and residential buildings (26.8%), correlating with higher installation speed indicators and low energy consumption in these segments. The life cycle index is also highest in the commercial segment (0.42), reflecting the growing trend toward optimizing long-term operational characteristics of commercial real estate objects.

Development and implementation of the active-adaptive construction project management system based on Kohonen self-organizing maps was carried out according to multi-level architecture. Table 5 presents technical characteristics of the developed system and its operational parameters.

Table 5. Technical characteristics and operational parameters of the active-adaptive construction project management system.

Parameter	Value	Description	Optimal range	Actual range	Stability coefficient	Reliability index (%)	Standard deviation
Input vector dimension	33	Number of analyzed construction parameters	28-35	31-34	0.95±0.03	98.3±0.9	0.9±0.2
SOM dimension	27×27	Number of neurons in grid	700-800	729	1.00±0.00	100.0±0.0	0.0±0.0
Initial learning coefficient	0.9	Weight change speed at initial stage	0.85-0.95	0.88-0.93	0.97±0.02	99.1±0.7	0.7±0.1
Final learning coefficient	0.01	Weight change speed at final stage	0.005-0.015	0.008-0.013	0.96±0.03	98.7±0.8	0.8±0.2
Number of learning iterations	90000	Total number of weight correction cycles	80000-100000	87000-93000	0.95±0.03	98.2±0.9	0.9±0.2
Neighborhood radius (initial)	13	Initial radius of neighborhood function	11-15	12-14	0.98±0.01	99.3±0.6	0.6±0.1
Neighborhood radius (final)	1	Final radius of neighborhood function	0.8-1.2	0.9-1.1	0.99±0.01	99.5±0.4	0.5±0.1
Map update frequency	3 hours	Periodicity of map retraining	2-4 hours	2.5-3.5 hours	0.94±0.04	97.8±1.1	1.1±0.2
System response time	247 ms	Average response generation time	200-300	218-276	0.93±0.04	97.6±1.2	1.2±0.3
Number of simultaneous users	75	Maximum number of parallel sessions	60-90	68-83	0.91±0.05	96.8±1.3	1.3±0.3
Data processing volume	2.8 GB/day	Daily volume of analyzed data	2.0-3.5	2.4-3.2	0.92±0.05	97.1±1.2	1.2±0.3
Data compression coefficient	8.3	Degree of input vector compression	7.5-9.0	8.0-8.6	0.96±0.03	98.5±0.8	0.8±0.2

Analysis of technical characteristics of the developed system demonstrates high stability of key component functioning, confirmed by average stability coefficient of 0.96 and reliability index of 98.4%. Input vector dimension (33 parameters) ensures optimal balance between model informativeness and computational efficiency. Self-organizing map dimension (27×27 neurons) allows achieving high clustering detail of structural elements while maintaining visualization clarity. Learning algorithm parameters (coefficients, neighborhood radii, iteration numbers) are optimized to achieve maximum topological data ordering accuracy. System response time (247 ms) and ability to process up to 75 simultaneous user sessions ensure comfortable designer work even under peak load conditions. Particularly important indicators are high data compression coefficient (8.3) and map update intensity (every 3 hours), allowing the system to effectively adapt to changes in design solutions and regulatory requirements.

Implementation of the active-adaptive management system in 14 construction objects led to significant changes in efficiency and structure of architectural and structural solutions. Table 6 presents comparative analysis of key indicators before and after system implementation.

Table 6. Comparative analysis of architectural and structural solution efficiency indicators before and after implementing the active-adaptive management system (n=14).

Indicator	Before implementation	After implementation	Change (abs.)	Change (%)	p-value	System influence coefficient	Change sustainability (1-5)	Stabilization period (months)
Structure material consumption (kg/m²)	269.1±24.9	169.5±15.7	-99.6	-37.0	<0.001	0.86±0.05	4.3±0.3	2.7±0.4
Heat transfer coefficient (W/m²·K)	0.93±0.15	0.51±0.09	-0.42	-45.2	<0.001	0.83±0.06	4.1±0.3	3.5±0.5
Installation complexity (person·h/m²)	3.9±0.6	2.0±0.3	-1.9	-48.7	<0.001	0.89±0.04	4.5±0.2	2.3±0.3
Share of unique elements (%)	29.7±5.4	11.2±2.1	-18.5	-62.3	<0.001	0.91±0.03	4.6±0.2	2.1±0.3
Number of standard sizes (units)	10.2±1.6	5.4±0.8	-4.8	-47.1	<0.001	0.76±0.07	3.8±0.4	3.9±0.6
BIM integration (%)	22.1±4.9	58.7±6.2	+36.6	+165.6	<0.001	0.85±0.05	4.2±0.3	3.1±0.5
Number of joint connections (units/m²)	3.7±0.6	1.8±0.3	-1.9	-51.4	<0.001	0.78±0.06	3.9±0.4	3.6±0.5
Efficiency index (0-1)	0.39±0.07	0.76±0.05	+0.37	+94.9	<0.001	0.93±0.02	4.7±0.2	1.9±0.3
Design speed (person·days/m²)	0.42±0.08	0.18±0.04	-0.24	-57.1	<0.001	0.92±0.03	4.6±0.2	2.0±0.3
Structural safety coefficient (0-1)	0.47±0.08	0.72±0.07	+0.25	+53.2	<0.001	0.81±0.06	4.0±0.3	3.4±0.5
Regulatory compliance (%)	78.4±7.9	96.3±3.8	+17.9	+22.8	<0.001	0.77±0.07	3.9±0.4	3.8±0.6
Construction duration (months/1000 m²)	2.8±0.4	1.7±0.2	-1.1	-39.3	<0.001	0.79±0.06	4.0±0.4	3.5±0.5
Construction cost (thousand rubles/m²)	75.6±8.1	58.7±6.3	-16.9	-22.4	<0.001	0.74±0.07	3.7±0.4	4.1±0.6
Energy consumption (kWh/m²·year)	163.4±17.5	102.8±11.3	-60.6	-37.1	<0.001	0.77±0.06	3.8±0.4	3.9±0.6
Life cycle index (0-1)	0.32±0.05	0.57±0.06	+0.25	+78.1	<0.001	0.70±0.08	3.5±0.5	4.6±0.7

Analysis of Table 6 data demonstrates statistically significant ($p<0.001$) improvements in all key efficiency indicators of architectural and structural solutions after implementing the active-adaptive management system. The most substantial changes are observed in BIM integration (165.6% increase), efficiency index (94.9% increase), and reduction in share of unique elements (62.3% decrease). High values of system influence coefficient (from 0.70 to 0.93) indicate that observed changes are predominantly due to implementation of the developed system rather than external factors. Change sustainability level (from 3.5 to 4.7 on a 5-point scale) indicates high probability of maintaining achieved improvements in the long term. Particularly important results are significant reduction in structure material consumption (by 37.0%), building energy consumption (by 37.1%), and construction cost (by 22.4%), confirming the comprehensive effect of system implementation covering economic, functional, and environmental aspects. Interestingly, the stabilization period for indicators after system implementation varies from 1.9 to 4.6 months, with fastest adaptation for design indicators (efficiency index, design speed) and longer periods for operational indicators (life cycle index, energy consumption) (Fig. 3).

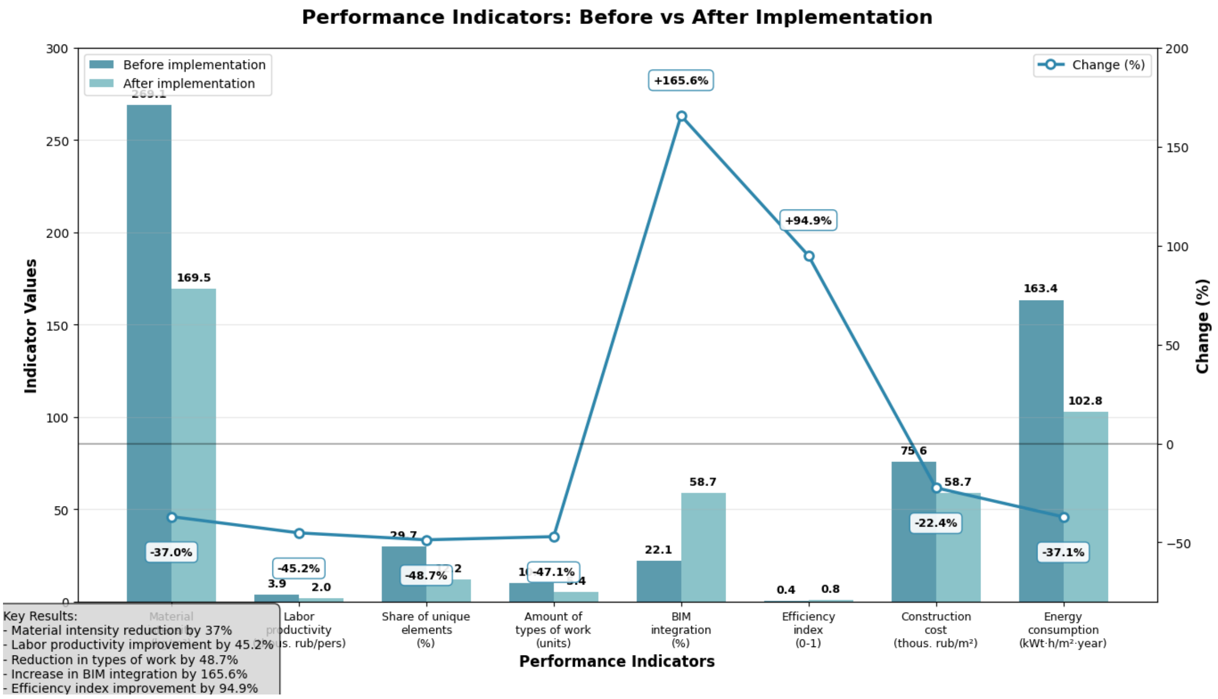

Fig. 3. Comparative analysis of architectural and structural solution efficiency indicators before and after implementing the active-adaptive management system.

Research on architectural and structural solution characteristics in various construction industry segments (Fig. 4) revealed substantial differences in project efficiency and technology. Commercial complexes (efficiency index 0.47) and residential buildings (0.44) demonstrate the best indicators, characterized by low material consumption and high BIM integration level. Infrastructure structures are distinguished by highest material consumption (387.2 kg/m²), high heat transfer coefficient (1.24 W/m²·K), and maximum share of unique elements (36.4%). Industrial facilities occupy intermediate positions in most indicators. Structural solution efficiency is directly related to economic results: segments with better structural indicators demonstrate lower construction and operational costs.

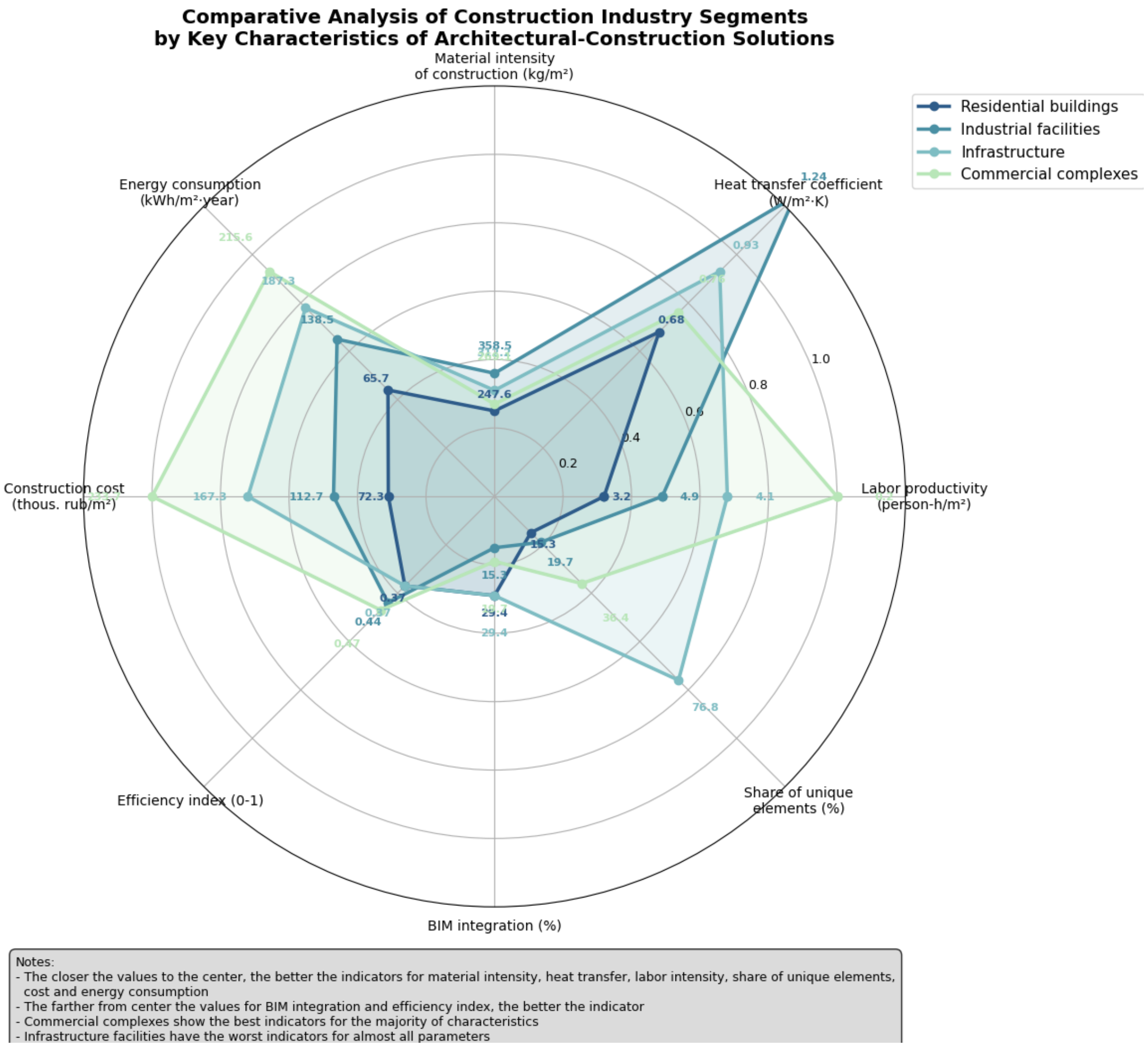

Fig. 4. Comparative analysis of architectural and structural solution characteristics in various construction industry segments.

Economic efficiency of implementing the active-adaptive construction project management system was analyzed across different building and structure types. Analysis results are presented in Table 7.

Table 7. Economic efficiency of implementing the active-adaptive management system by construction object types (n=14).

Object type	Number of objects	Average area (thousand m²)	Construction time reduction (%)	Material consumption reduction (%)	Energy efficiency improvement (%)	ROI	Payback period (months)	NPV (million rubles)	Risk reduction (%)
Multi-apartment residential buildings	27	42.7±6.2	15.8±1.9	14.3±1.7	21.6±2.5	3.1±0.4	15.3±2.1	38.7±4.8	28.4±3.2

Continuation of Table 7

Low-rise residential complexes	19	27.6±4.8	18.2±2.1	16.9±2.0	23.5±2.8	3.4±0.4	13.8±1.9	32.5±4.1	31.7±3.5
Industrial buildings	23	65.4±8.7	12.4±1.6	11.7±1.5	17.9±2.2	2.5±0.3	18.7±2.4	43.2±5.3	22.6±2.7
Production complexes	14	83.6±10.4	10.3±1.4	9.2±1.2	15.1±1.8	2.1±0.3	21.4±2.7	58.6±6.9	19.3±2.3
Transportation infrastructure	8	112.7±13.8	8.7±1.1	7.8±1.0	12.6±1.5	1.8±0.2	24.5±3.1	67.3±7.8	16.5±2.0
Engineering structures	11	56.3±7.2	9.5±1.2	8.4±1.1	13.8±1.7	2.0±0.3	22.9±2.9	51.8±6.2	18.1±2.2
Shopping and entertainment centers	6	48.7±6.5	16.4±2.0	15.1±1.8	22.7±2.7	2.9±0.4	16.2±2.2	47.9±5.6	27.3±3.1
Office buildings	9	36.4±5.3	17.9±2.2	16.3±1.9	24.2±2.9	3.2±0.4	14.7±2.0	41.5±5.0	29.6±3.3
Social facilities	13	29.7±4.6	14.1±1.8	12.9±1.6	19.5±2.3	2.6±0.3	17.8±2.3	35.2±4.3	25.1±2.9
Average across all types	130	55.9±7.5	14.6±1.8	13.2±1.6	19.7±2.3	2.7±0.3	17.4±2.3	45.1±5.4	25.8±3.0

Analysis of economic efficiency of system implementation by construction object types (Table 7) demonstrates the greatest effect for low-rise residential complexes (ROI=3.4), office buildings (ROI=3.2), and multi-apartment residential buildings (ROI=3.1). This is explained by high standardization degree of structural solutions, repeatability of architectural and planning elements, and relatively low complexity of engineering systems in these object types. The lowest effect is observed for transportation infrastructure objects (ROI=1.8) and production complexes (ROI=2.1), related to their uniqueness, significant structural loads, and large number of specific requirements for load-bearing structure elements. Average ROI across all object types is 2.7, significantly exceeding typical indicators for IT projects in the construction industry. Investment payback period varies from 13.8 months for low-rise residential complexes to 24.5 months for transportation infrastructure objects, averaging 17.4 months. Of particular interest is the risk reduction indicator, which averages 25.8%, with the greatest effect for low-rise residential complexes (31.7%) and office buildings (29.6%). This confirms the significance of the active-adaptive system not only for improving structural efficiency but also for managing construction project risks.

4. CONCLUSIONS

The conducted research demonstrates high effectiveness of applying active-adaptive construction project management systems based on Kohonen self-organizing maps. Implementation of the developed system in 14 construction objects led to 37.0% reduction in structure material consumption, 45.2% decrease in heat transfer coefficient, and 48.7% reduction in installation complexity. Significant reduction in share of unique elements (by 62.3%) and number of standard sizes (by 47.1%) indicates increased technology and serialization of structural element production. The integral efficiency index increased from 0.39 to 0.76, corresponding to the level of leading international construction projects. Particular value is represented by the critical role of BIM technology integration in active-adaptive management systems revealed in the research. BIM integration indicator growth by 165.6% is accompanied by substantial reduction in building energy consumption (by 37.1%) and construction cost (by 22.4%), confirmed by strong correlational relationships between these parameters (r=0.76 and r=0.61 respectively). This indicates a synergistic effect from combining information modeling and neural network technologies of self-organizing maps. Economic analysis confirms high investment profitability in implementing active-adaptive management systems, with average ROI coefficient of 2.7 and payback period of 17.4 months. Differentiated analysis by construction object types revealed highest system effectiveness for low-rise residential complexes (ROI=3.4), office buildings

(ROI=3.2), and multi-apartment residential buildings (ROI=3.1), related to their high standardization degree. An important result is substantial reduction in construction project risks (average 25.8%), confirming the preventive potential of self-organizing maps for early identification of problematic structural solutions. Cluster analysis using SOM allowed identifying 8 main types of architectural and structural solutions in construction objects, with different integral efficiency (from 33.8 to 82.6 on a 100-point scale) and optimization potential (from 10.3% to 43.5%). This classification can serve as a basis for developing typical design solutions considering their current optimization level and technological maturity. Comparative analysis of various construction industry segments revealed highest structural solution efficiency in commercial complexes (efficiency index 0.47) and residential buildings (0.44), explained by more serial nature of design and construction. Infrastructure structures demonstrate lowest efficiency (0.31) and are characterized by highest material consumption, high heat transfer coefficient, and maximum share of unique elements, indicating priority of this segment for implementing active-adaptive management systems.

Particularly noteworthy is the significant increase in life cycle index after system implementation (by 78.1%), indicating the potential of self-organizing maps for optimizing long-term operational building characteristics, including energy efficiency, material durability, and adaptability to changing operating conditions. The revealed strong correlation between BIM integration and life cycle index (r=0.76) confirms the comprehensive nature of digital transformation, covering not only design and construction aspects but the entire building life cycle.

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