

Article

Toward Digital Twin-Enabled Smart Buildings: An Evolutionary Neural Network Approach for Energy Prediction

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Abstract

The increasing pace of urbanization and climate change necessitate a holistic assessment of building energy performance during the early design phase. This study proposes an Evolutionary Field Optimization (EFO)-based multi-input multi-output artificial neural network (MIMO-ANN) model to simultaneously predict the heating load, cooling load, CO₂ emissions, and lighting energy consumption of smart buildings. The model's dataset consists of 7963 observations generated via EnergyPlus building energy simulations of standardized TOKİ residential units constructed post-earthquake in Türkiye. No operational or physically measured building energy consumption data were used in the model development process. For the validation setting, the simulation-generated dataset was split into training (60%), validation (10%), and test (30%) subsets. The EFO algorithm was employed to automatically optimize the ANN architecture by dynamically determining the optimal number of hidden layers and neurons. The optimization process demonstrated strong global search capability and fast convergence, reducing the objective function by approximately 86% within 10 iterations. Experimental results on the test subset showed exceptional predictive accuracy for simulation data, with test R² values ranging from 0.9996 to 0.9998 across all four outputs, indicating that the optimized network topology effectively avoided overfitting. While the model's performance under real-world operational uncertainties and varying occupant behaviors remains to be fully investigated, the proposed EFO-ANN framework provides a computationally efficient and highly accurate analytical core for early-stage design. It serves as a strategic decision-support tool intended for architects and engineers designing post-disaster housing, public authorities forming national energy efficiency policies, and developers building predictive engines for digital twin-enabled smart building systems.

Keywords: digital twin; smart buildings; evolutionary field optimization; artificial neural networks; post-earthquake TOKİ housing



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1. Introduction

Energy efficiency and sustainable architecture are among the top priority research areas in the construction industry globally today. The building stock's share of total energy consumption reaches 30–40% worldwide, and this rate is steadily increasing in developing countries. Increasing populations, the pace of urbanization, and the energy demand triggered by climate change necessitate a holistic assessment of building energy performance during the design phase. Policy documents such as the post-2020 European Green Deal and the Turkish National Energy Efficiency Action Plan, in particular, envision equipping next-generation buildings with smart systems that not only consume less energy but also minimize their carbon footprint [1,2].

In this context, building energy performance modeling studies have evolved into multidimensional problems where structural, climatic, and occupant-based variables are evaluated together. Because traditional statistical approaches address these multivariate relationships under linear assumptions, they fail to adequately represent complex interactions. At this point, AI-based models (especially multilayer artificial neural networks) have become powerful tools for learning and predicting energy consumption patterns. However, determining the appropriate network structure (number of layers, neuron distribution, activation functions) remains one of the most critical challenges researchers face.

Several studies in this area exist in the literature. D'Agostino and Parker present a developed framework for the cost-optimal design of Nearly Zero Energy Buildings (NZEBS) in representative climates across Europe. The methodology emphasizes the efficacy of simulation-based optimization approaches using EnergyPlus software (v9.x, U.S. DOE, Washington, DC, USA) to minimize building energy consumption. The optimization process involved 2097 simulations across 43 iterations to reach the final NZEB design configuration in Milan. The research incorporated adjustments for future climate scenarios, particularly accounting for the anticipated increase in cooling loads by 2050 (an average temperature rise of 2 °C), resulting in conservative estimates for insulation levels [3]. Ascione et al. propose Harlequin, a novel multi-stage framework for the multi-objective optimization of building energy design. This framework utilizes genetic algorithms and smart exhaustive scenario sampling to optimize energy, comfort, economic, and environmental performance indicators. For the Global Cost (GC) assessment of this non-residential building, a 20-year calculation period was employed. The optimized solutions demonstrated substantial reductions compared to the reference design, reaching a PEC reduction of 43.9 kWh_p/(m²·a) and a GC reduction of 63.9 €/m² (for a 3% discount rate) [4]. Integrated Building Information Modeling (BIM)-based optimization frameworks have demonstrated significant potential for improving building life-cycle energy performance and sustainability. Najjar et al. developed a BIM-integrated optimization framework that combines Life Cycle Assessment (LCA) with multi-objective optimization to evaluate building envelope design alternatives. Their results demonstrated improved energy efficiency and reduced environmental impacts, highlighting the effectiveness of BIM-driven decision support for sustainable building design [5]. Wang et al. propose a three-stage multi-objective optimization methodology for Passive House (PH) envelope design, factoring in energy demand, thermal comfort, and cost. The primary objectives were the minimization of the annual Energy Use Intensity (EUI) and the maximization of the Cumulative Thermal Ratio (CTR). Results indicated that the optimized solutions achieved an energy saving rate of approximately 88.2% in EUI and a thermal comfort improvement rate of approximately 63.0% in CTR compared to the base-case building. The optimal solution was associated with a short payback period of 0.48 years and a 13.1% Discomfort Rate (DCTR) [6].

A multi-objective optimization framework based on a Genetic Algorithm and EnergyPlus was proposed to minimize primary energy consumption (PEC), global cost (GC), and

discomfort hours (DH), yielding low PEC (62.0–91.9 kWh/m²a) and GC (456–665 €/m²) values while distinguishing between Nearly Zero Energy Building (NZEB) and cost-optimal solutions [7]. Waibel et al. introduced a co-simulation approach integrating building geometry and multi-energy systems, optimized via a Mixed Integer Linear Programming model, showing that near-zero carbon targets enable extensive PV integration [8]. Li and Wang proposed a multi-stage design method using an Artificial Neural Network to reduce computational cost, effectively optimizing energy systems while maintaining acceptable unmet load levels [9]. A Multi-objective Quantum Genetic Algorithm (MOQGA)-based model was developed to optimize building envelope materials by balancing energy consumption, CO₂ emissions, and investment cost, achieving improved performance over NSGA-II and reducing embodied carbon by 33.1% [10]. Du et al. proposed an LSTM-based surrogate model for district heating systems, enabling peak shaving and load shifting, with reductions of 11.5% in peak demand and 6.1% in operational cost [11]. Another study utilized a Genetic Algorithm integrated with EnergyPlus and MATLAB® R2024a (The MathWorks, Natick, MA, USA) to optimize building shape and envelope design, resulting in approximately 9% energy savings and 23% cost reduction while lowering simulation complexity [12]. Kiss and Szalay develop a modular multi-objective approach that reduces life cycle environmental impacts by 60–80% [13]. A Genetic Algorithm-based study optimizes building envelope design to minimize LCC, identifying square geometry as optimal across climates [14]. Similarly, Harkouss et al. demonstrate that optimal passive design can reduce cooling demand by 54%, heating demand by 87%, and LCC by 52% [15].

We introduced an AI-assisted decision-making framework to assess the electrical energy efficiency of conventional TOKİ dwelling units built in the aftermath of the 2023 Kahramanmaraş earthquakes. We simulated the annual consumption values of the housing units using climate data from 11 different provinces and analyzed these data using a machine learning model supported by the Whale Optimization Algorithm (WOA). As part of the study, the housing units were classified into low and high consumption categories based on Turkey's official tariff thresholds to assess their energy efficiency. The developed hybrid model achieved a high accuracy rate of 98.2%, demonstrating superior predictive performance compared to traditional methods. Ultimately, this resource provides a scientific roadmap for climate-sensitive and sustainable public housing design in post-disaster reconstruction processes [16]. Building upon these findings, the present study extends the proposed framework by incorporating a more advanced optimization strategy. In this context, the integration of the Evolutionary Field Optimization (EFO) algorithm with a multi-input, multi-output artificial neural network (MIMO-ANN) architecture is introduced to further enhance prediction accuracy and model generalization in complex energy performance modeling scenarios. This study proposes the integration of the Evolutionary Field Optimization (EFO) algorithm with a multi-input, multi-output artificial neural network (MIMO-ANN) architecture to address this problem. Based on evolutionary field theory, the EFO algorithm evaluates each individual within a multi-dimensional potential space and dynamically balances exploration and exploitation in the solution space. In this way, the optimal structure is achieved by establishing an evolutionary balance between accuracy and generalization within the complex hyperparameter space of the ANN architecture.

The housing typologies constructed by the Housing Development Administration (TOKİ) after the 6 February 2023 earthquakes were selected as the application area of the study. These typologies are buildings located in different climatic zones, based on typical plans, and with similar occupancy densities. Thanks to these characteristics, a homogeneous dataset for energy performance modeling, yet sensitive to different climatic inputs, was obtained. In the dataset containing 7963 observations, building components, façade orientations, climatic parameters, building spacing, wall characteristics, glazing

types, and window-to-wall ratios were used as independent variables, whereas heating load, cooling load, CO₂ emissions, and lighting energy consumption were defined as dependent variables. The model's input variables were first subjected to label encoding and normalization processes, and then divided into training, validation, and test sets.

The EFO algorithm optimized the network topology at each iteration, producing balanced results in terms of both accuracy and computational cost. The final model achieved $R^2 = 0.9992$ on the test data, and the normalized root mean square error (NMSE) value fell below 0.01%. These results demonstrate that the EFO-based architecture is an effective method not only for parameter optimization but also for automatic network structure design (architecture search). The main objective of this study is to evolutionarily optimize an artificial neural network architecture for predicting smart building energy performance, thereby developing a model with high accuracy, low computational cost, and strong generalization capability. This study offers an innovative solution to two fundamental problems frequently encountered in classical ANN configurations: the trial-and-error nature of network architecture selection and the low generalization success of models prone to overlearning.

In this context, the original contributions of this study can be summarized as follows:

- EFO is applied to building energy performance prediction for the first time in the architectural optimization of artificial neural networks. This method, unlike the stochastic nature of traditional heuristic algorithms (GA, PSO, GWO, etc.), introduces a guided and balanced search strategy within the framework of potential field theory.
- Thanks to the developed MIMO-ANN architecture, interdependent energy parameters such as heating, cooling, lighting, and CO₂ emissions are simultaneously estimated. Thus, a more holistic assessment of the energy-exergy balance of buildings was possible.
- The TOKİ housing typology dataset, consisting of 7963 samples used in the study, has a structure representative of four different climatic zones in Turkey. This allowed the developed model to test its generalization ability across different climatic conditions, and the results were verified with high consistency.
- The proposed EFO-optimized network architecture dynamically balances exploration and exploitation processes in the parameter space, achieving faster convergence and lower error rates compared to classical learning algorithms.

In these respects, the study presents an innovative contribution to the field of building energy, both methodologically and at the application level. The results demonstrate that metaheuristic algorithms can serve not only as optimization tools but also play an active role in shaping next-generation AI architectures. Unlike traditional optimization-based ANN training, the approach proposed in this study offers a scalable framework for smart building systems that can model the energy-emission balance for each building typology in an evolutionary manner. Therefore, this model can be considered a strategic decision-support tool for both national energy policies and sustainable urbanization visions.

2. Methodology

2.1. Dataset Creation and Preprocessing

In this study, a representative building model was selected to analyze the electrical energy performance of standard TOKİ housing units constructed after the 6 February 2023 earthquake centered in Kahramanmaraş. A typical TOKİ housing design implemented in the Hekimhan and Yeşilyurt districts of Malatya province was taken as a reference; this typology represents the dominant planning approach in the redevelopment process in the region. The model was a six-story block with a total of 20 apartments, consisting of a basement, ground floor, and four standard floors.

Dynamic building energy simulations based on the EnergyPlus (EP) engine were conducted using DB v7.3.1.003 software. The building envelope components (walls, roof, floor, windows) were defined using actual material properties used in TOKİ implementation projects. Heat losses and gains were modeled by considering the thermal conductivity (U-values) of the structural elements and the indoor-outdoor conditions and integrated with double-glazed window systems. Occupant behavior was determined according to the CIBSE TM59 (2017) guideline, and rooms were defined using appropriate Residential Space templates based on their functions. Clothing insulation, metabolic activity, interior load timing, and natural ventilation strategies were designed according to this standard. For indoor comfort and energy consumption assessments, the HVAC system was modeled as a four-pipe fan coil–air-cooled chiller combination, and the lighting system was modeled according to the TM59_Default_Light timeline. All system definitions were integrated with the EP engine. Annual simulations (1 January–31 December 2023) were conducted using separate EnergyPlus Weather (.epw) climate files for the 11 earthquake-affected provinces. These files contain hourly meteorological data, including dry-bulb temperature, relative humidity, wind speed, wind direction, solar radiation, and atmospheric pressure, which are required for building energy simulations. By incorporating province-specific climatic conditions into the EnergyPlus model, a comprehensive dataset was generated, including variables such as temperature, pressure, CO₂ emissions, electricity and gas consumption, and heating/cooling loads. The physical characteristics and thermal properties of the reference building are summarized in Table 1, whereas the operational assumptions and simulation settings adopted in the EnergyPlus model are presented in Table 2.

Table 1. Building characteristics and thermal properties.

Category	Parameter	Value/Description	Source/Note
General Information	Building type	TOKİ housing	Yeşilyurt, Malatya
	Average net floor area	105.16 m ²	3 + 1 apartment layout
Geometric Features	Number of floors	6 (basement + ground + 4 standard floors)	Total of 20 apartments
	Short side/Long side	17.80 m/35.10 m	-
Building Envelope	External wall-1	U = 0.641 W/m ² ·K	TOKİ reference material
	External wall-2	U = 1.009 W/m ² ·K	
	Roof	U = 0.361 W/m ² ·K	
	Ground floor slab	U = 2.045 W/m ² ·K	
	Window system	U = 1.825 W/m ² ·K, SHGC = 0.589	
			4 mm low-e glass + 16 mm air gap + 4 mm clear glass

Table 2. Operational and simulation parameters.

Category	Parameter	Value/Description	Source/Note
Indoor Conditions	Indoor/Outdoor temperature (reference)	21 °C/−18 °C	EP engine reference conditions
	Clothing insulation	1.0 clo (winter)–0.5 clo (summer)	CIBSE TM59 (2017)
HVAC System	System type	Four-pipe fan coil + air-cooled chiller	DB definition
	Heating system	Natural gas–Seasonal CoP = 0.85	
Domestic Hot Water (DHW)	Cooling system	Electricity–Seasonal CoP = 1.80	Electric, instantaneous heating
	Water temperature/inlet	65 °C/10 °C	
Lighting System	Power density	5.00 W/m ² –100 lux	TM59_Default_Light template
	Fixture type	Suspended (0.42 radiant, 0.18 visible, 0.40 convective fractions)	
Simulation Parameters	Simulation tool	DB v7.3.1.003 (EnergyPlus v9.x)	Earthquake-affected regions
	Simulation period	1 January–31 December 2023	
	Climate data	(.epw) files for 11 provinces	

In machine learning and statistical modeling processes, converting categorical variables into numerical values is a fundamental preprocessing step for the model to interact with the data. Since most algorithms cannot directly process categorical data, this

transformation process plays a decisive role in the model's accuracy, speed, and stability. Within the scope of this study, the process of converting categorical variables in the dataset consisting of building energy performance data into numerical format has been systematically addressed.

The dataset contains building energy performance simulation results and includes both continuous and categorical variables. Among the continuous variables are heating load (HeatingLoad), cooling load (CoolingLoad), carbon emissions (CO₂), and lighting energy (LightingEnergy). The categorical variables in this study are glazing type (Glazing-Type), location (Location), distance (Distance), wall type (WallType), and window-to-wall ratio (WWR). In addition, the building orientation (SiteOrient) variable is a discrete numerical variable. The dataset was generated using a full-factorial parametric simulation framework based on the combinations of the input variables listed in Table 3. For each of the 11 earthquake-affected provinces, simulations were performed using 6 glazing types, 4 façade orientations, 4 building spacing levels, 21 wall types, and 4 window-to-wall ratio (WWR) levels. This resulted in a total of 8064 simulation scenarios ($6 \times 4 \times 4 \times 21 \times 4$). All simulations were conducted using EnergyPlus-based building energy modeling. Following the simulation process, scenarios containing incomplete, invalid, or missing output values were excluded during data preprocessing. Consequently, the final dataset consisted of 7963 valid observations, which were subsequently used for model training, validation, and testing. The overall architecture and workflow of the proposed system are illustrated in Figure 1.

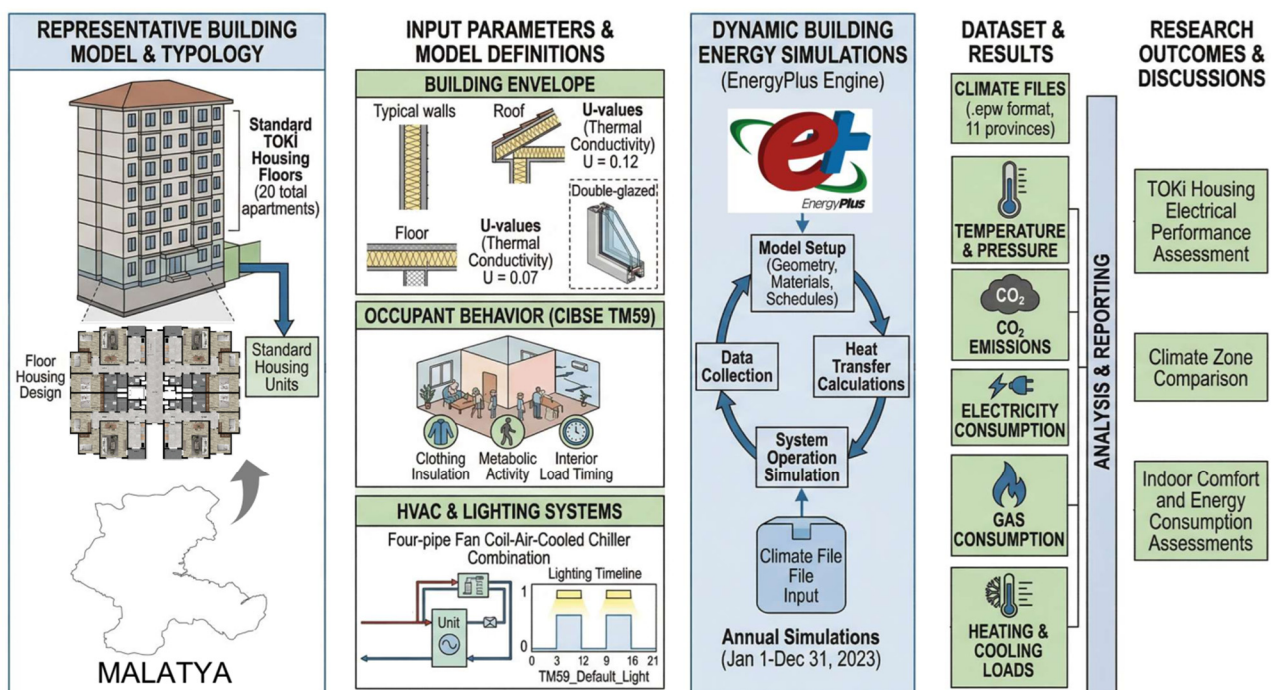


Figure 1. Block diagram of the proposed system.

The conversion of categorical variables into numerical codes has been carried out through a special algorithm developed in the MATLAB[®] R2024a programming environment. The data preprocessing process consists of transferring the dataset in Excel format to the MATLAB[®] R2024a environment, defining data types on a column basis, converting non-categorical text columns to categorical format using the categorical function, and encoding each categorical variable into consecutive integers with the help of the double

function. After the encoding process, the converted data was stored in a new Excel file, and the category-code mappings were recorded in a separate MATLAB® R2024a file.

The applied method is referred to as “label encoding.” In this method, each unique category is represented by a series of consecutive integers, starting with 1. For example, the “WallType” variable’s “Existing” value is coded as 1, “Alternative Wall Type 1” as 2, and “Alternative Wall Type 2” as 3. After this coding, the total number of observations and variables stayed the same; only five categorical columns were changed to numerical values. The numerical columns kept their original values, ensuring the data’s integrity. For example, in the first row of the original dataset, the “WallType” value was “Existing,” but after the transformation, it was coded as 21. The “WWR” value, which was “Ratio 0 (Existing Condition),” was coded as 1.

This method enables machine learning algorithms to directly process numerical data, improving computational efficiency and reducing training time. It also enhances generalization by providing a standardized representation, while allowing reversibility through mapping storage. However, label encoding may introduce artificial ordinal relationships among categorical variables, potentially misleading some algorithms, especially distance-based ones. To mitigate these issues, alternative approaches such as one-hot encoding, target encoding, binary encoding, and frequency encoding have been proposed, balancing interpretability, dimensionality, and information preservation.

In conclusion, five categorical variables in the building energy performance dataset consisting of 7963 observations were successfully converted to numerical format using the label encoding method with a MATLAB-based automatic algorithm. Data integrity has been maintained, and the possibility of reverting to categorical values has been provided through a mapping file. The dataset used in the study was obtained from building energy performance simulations and consists of 10 variables and 7963 observations. The obtained numerical dataset is directly usable in machine learning and statistical modeling studies. As presented in Table 3, the study utilizes six input variables and four output variables to characterize building energy performance.

Table 3. Definition of input and output features used in the study.

Variable Type	Parameter Name	Description/Definition	Type	Level
Input Variables (Features)	Glazing type	Type of window used (e.g., double glazing, low-e, etc.)	Categorical (encoded)	6
	Site orientation	Building façade orientation (north, south, east, west)	Discrete	4
	Location template	Climate file (EPW) used in the simulation	Categorical	11
	Building spacing (m)	Distance between buildings; determines shading effect	Categorical	4
	Wall type	External wall construction (material and thickness combination)	Categorical	21
	WWR (Window-to-Wall Ratio %)	Ratio of window area to façade surface	Categorical	4
Output Variables (Metrics)	Heating load (kWh)	Heating energy demand	Continuous	
	Cooling load (kWh)	Cooling energy demand	Continuous	
	CO ₂ emission (kg)	Annual total carbon emissions	Continuous	
	Lighting energy (kWh)	Annual electricity consumption for lighting	Continuous	

The input (independent) variables are defined as $x = [\text{GlazingType}, \text{SiteOrient}, \text{Location}, \text{Distance}, \text{WallType}, \text{WWR}]$ and the output (dependent) variables are defined as

$y = [\text{HeatingLoad}, \text{CoolingLoad}, \text{CO}_2, \text{LightingEnergy}]$. The data has been normalized using the min–max scaling method:

$$\tilde{x}_i = \frac{x_i - x_{\min}}{x_{\max} - x_{\min} + \varepsilon} \quad (1)$$

2.2. Artificial Neural Networks Model

The performance of artificial neural networks (ANNs) largely depends on the correct determination of the network architecture (topology). Hyperparameters such as the number of hidden layers and the number of neurons in each layer directly affect both training performance and generalization ability. In traditional methods, these parameters are determined through trial and error, whereas metaheuristic algorithms offer the possibility of automatic architecture search.

The model is structured as a multi-output feedforward neural network (FFNN). The network's prediction model is defined as follows:

$$\hat{y} = f_{\text{out}}(W_L f_{L-1}(W_{L-1} \dots f_1(W_1 x + b_1) \dots) + b_L) \quad (2)$$

Here, L denotes the number of hidden layers, while W_i and b_i represent the weight matrix and bias vector of the i -th layer, respectively. The function f_i denotes the activation function of the i -th layer. The input vector is given by $x \in \mathbb{R}^d$, and the predicted output vector is $y \in \mathbb{R}^m$. The activation functions are chosen as the hyperbolic tangent sigmoid (tansig) for the hidden layers and a linear function (purelin) for the output layer.

2.3. Evolutionary Field Optimization (EFO)

Evolutionary biology and evolutionary computation algorithms, based on the principle of natural evolution, are often influenced by the adaptive behaviors of individuals and species at both large and small levels, and by genetic processes observed at the molecular scale [17–19]. Evolutionary field theory was first proposed by Papadopoulos et al., who formulated a field model for uncertain systems using non-homogeneous evolutionary fields as defined by Priestley [20]. Their research has examined this concept in relation to the spectral analysis of non-stationary systems where spectral features are assumed to fluctuate over time [21,22]. The Evolutionary Field Optimization (EFO) algorithm is a population-based metaheuristic approach that maintains a balance between exploration and exploitation in the search space through field-based interactions [23]. At the implementation level, the best individual in the population is updated via a specialized metamutation process at each iteration, while the remaining individuals undergo field-adaptive crossover and mutation operations. In the EFO algorithm, each individual is represented by a vector defining the architecture of an artificial neural network:

$$C_i = [h_{i,1}, h_{i,2}, \dots, h_{i,d}], h_{i,l} \in [0, N_{\max}] \quad (3)$$

Here, $h_{i,l}$ denotes the number of neurons in the l -th hidden layer of the i -th individual. In practice, these values are discretized using the round() function when necessary, and boundary constraints are enforced. For each non-elite individual, an update rule consisting of two components is applied:

$$C'_i = C_i + c_1 p_1 + c_2 p_2 \quad (4)$$

where p_1 represents the field-adaptive crossover term and p_2 denotes the stochastic mutation component. These terms are computed as follows:

$$\begin{aligned} p_1 &= r_1 \odot (C_* - C_i) \cdot s_1, & s_1 &= \frac{|F_i - F_*|}{|F_i| + |F_*| + \varepsilon}, \\ p_2 &= (r_2 - 0.51) \cdot s_2, & s_2 &= \frac{F_i}{\text{sign}(F_i + F_*) \max(|F_i + F_*|, \varepsilon)} \end{aligned} \quad (5)$$

Here, $r_1, r_2 \sim U(0, 1)^d$ are random vectors, and c_1 and c_2 denote the crossover and mutation coefficients, respectively. The constant ε is a small positive value introduced to prevent division-by-zero errors. Boundary control is applied on a component-wise basis:

$$c'_{i,k} = \begin{cases} L_k + (U_k - L_k)u, & \text{if } c'_{i,k} \notin [L_k, U_k], u \sim U(0, 1) \\ c'_{i,k}, & \text{otherwise} \end{cases} \quad (6)$$

The best individual in the population (elite agent) is updated using a bidirectional metamutation mechanism to enhance diversity. First, the population mean and scattering value are computed:

$$\bar{C} = \frac{1}{N} \sum_{j=1}^N C_j, A_{\text{scat}} = \frac{1}{d} \sum_{k=1}^d |c_{*,k} - \bar{c}_k| \quad (7)$$

An inverse-weighted field center is defined as:

$$w = 1 - \frac{|F|}{\sum |F| + \varepsilon}, C_c = w^T C \quad (8)$$

The update of the best individual is performed probabilistically:

$$C'_* = \begin{cases} C_c + (r_3 - 0.51)P_{\text{out}}A_{\text{scat}}, & \rho < 0.5 \\ C_* + (r_3 - 0.51)P_{\text{out}}A_{\text{scat}}, & \text{otherwise} \end{cases} \quad (9)$$

where $r_3 \sim U(0, 1)^d$, $\rho \sim U(0, 1)$, and P_{out} is the mutation amplitude coefficient.

At each iteration, the old population (C, F) and the newly generated population (C', F') are merged. Their fitness values are jointly evaluated, and the best N individuals are selected:

$$(C, F) \leftarrow \underset{N}{\operatorname{argmin}} \{ (C, F) \cup (C', F') \} \quad (10)$$

This mechanism inherently preserves elitism, and the best individual C_* and its fitness F_* are updated at each iteration. The objective function defined for each architecture incorporates both error and model complexity terms:

$$J(C) = \left(1 + \alpha N(C)^2 + \beta E_{\text{train}}(C) \right) \cdot \frac{\lambda_1 E_{\text{train}}(C) + \lambda_2 E_{\text{val}}(C)}{\lambda_1 + \lambda_2} \quad (11)$$

Here, $N(C)$ denotes the total number of neurons, E_{train} and E_{val} represent the training and validation errors, respectively; α and β are complexity coefficients; and λ_1, λ_2 are error weighting parameters. The objective function is minimized during the optimization process.

$$\min_C J(C) \quad (12)$$

The EFO algorithm's performance depends on key parameters. The objective function (fobj: $\mathbb{R}^d \rightarrow \mathbb{R}$) defines the minimization target, while the dimension (dim) represents decision variables (e.g., maximum ANN hidden layers). Bounds (Lb, Ub) limit the search space, typically 0–30 neurons. Population size (N) and maximum iterations (MaxIter)

control search breadth and stopping criteria. Coefficients c_1 (crossover), c_2 (mutation), and Pout (scattering) balance exploration and exploitation. Outputs evaluate optimization quality: the best solution (Xbest) defines the optimal ANN structure, the best cost (Fbest = fobj(Xbest)) gives its performance, and BestCostHist tracks convergence across iterations. The Configuration of Hyper-Parameters is given in Table 4.

Table 4. Configuration of Hyper-Parameters.

Parameter	Symbol	Value	Description
Training Error Weight	λ_1	1	Weight assigned to the training error
Validation Error Weight	λ_2	1	Weight assigned to the validation error
Complexity Penalty Coefficient	α	0.1	Penalty for the total number of hidden neurons
Training Time Penalty Coefficient	β	0.01	Penalty applied to the number of training epochs
Crossover Coefficient	c_1	0.26	Crossover coefficient
Mutation Coefficient	c_2	1.26	Mutation coefficient
Scattering Coefficient	Pout	0.31	Metamutation amplitude
Data Split Ratio	–	60:10:30	Training:Validation:Test
Number of Evaluations	NumofEval	3	Number of repeated ANN training runs for each candidate architecture

3. Experimental Results

The convergence curve presented in Figure 2 demonstrates the effectiveness of the EFO algorithm in artificial neural network architecture optimization. The objective function value rapidly decreases from approximately 95 to 33 within the first two iterations, indicating strong global search capability. The plateau observed between iterations 2–5 reflects local search behavior, while the subsequent drop to 27 after the 5th iteration shows the algorithm’s ability to escape local optima. Following a second stagnation phase between iterations 6 and 8, the final stage exhibits a sharp decrease to 13, suggesting effective convergence of the optimization process.

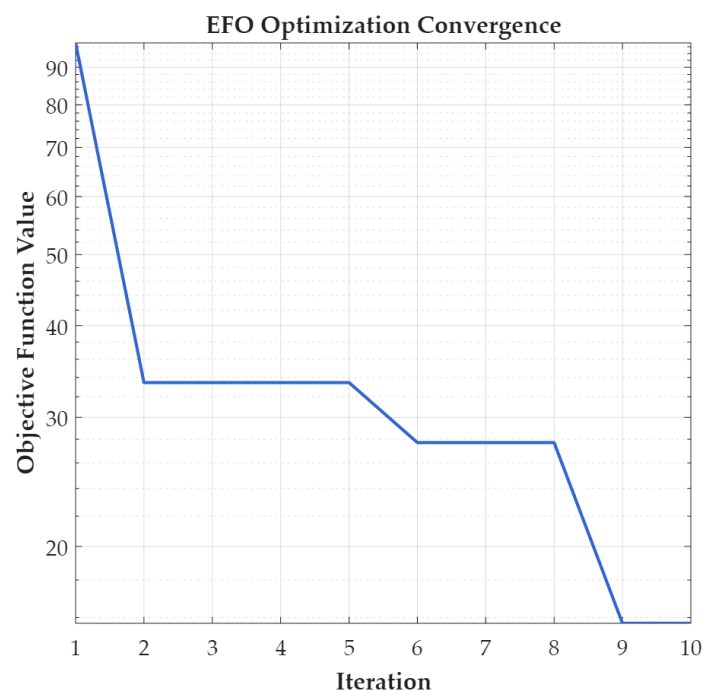


Figure 2. EFO convergence curve.

Overall, the EFO algorithm has achieved approximately an 86% improvement over the initial value over ten iterations. The three-phase decline structure in the convergence

curve (iterations 0–2, 5–6, and 8–10) indicates that the algorithm uses both global search and local convergence capabilities in a balanced manner. Successful exits from plateau regions demonstrate the effectiveness of the field interaction principle and the use of inverse weighted field centers. The obtained results demonstrate that the EFO algorithm exhibits strong predictive performance in terms of fast convergence, escape from local optima, and effective attainment of the near-optimal solution in the problem of artificial neural network architecture optimization. The EFO algorithm was configured with a population size of 30 and a maximum of 10 iterations. The initial objective function value was approximately 95, which was reduced to around 13 at the end of the optimization process, corresponding to an improvement rate of 86.30%. In terms of artificial neural network architecture, the maximum number of hidden layers was set to 5, with up to 30 neurons allowed per layer.

Figure 3 illustrates the performance of the artificial neural network model, which was optimized using the EFO algorithm, when applied to the training dataset. Scatter plots depict the correlation between actual and predicted values for Heating Load, Cooling Load, CO₂, and Lighting Energy. The attainment of $R^2 = 1.0$ across all output variables suggests that the model has effectively assimilated the training data with high precision. Furthermore, the clustering of data points along the ideal prediction line ($y = x$) and their uniform distribution within the normalized range imply that the model exhibits consistent and stable performance throughout all operational domains.

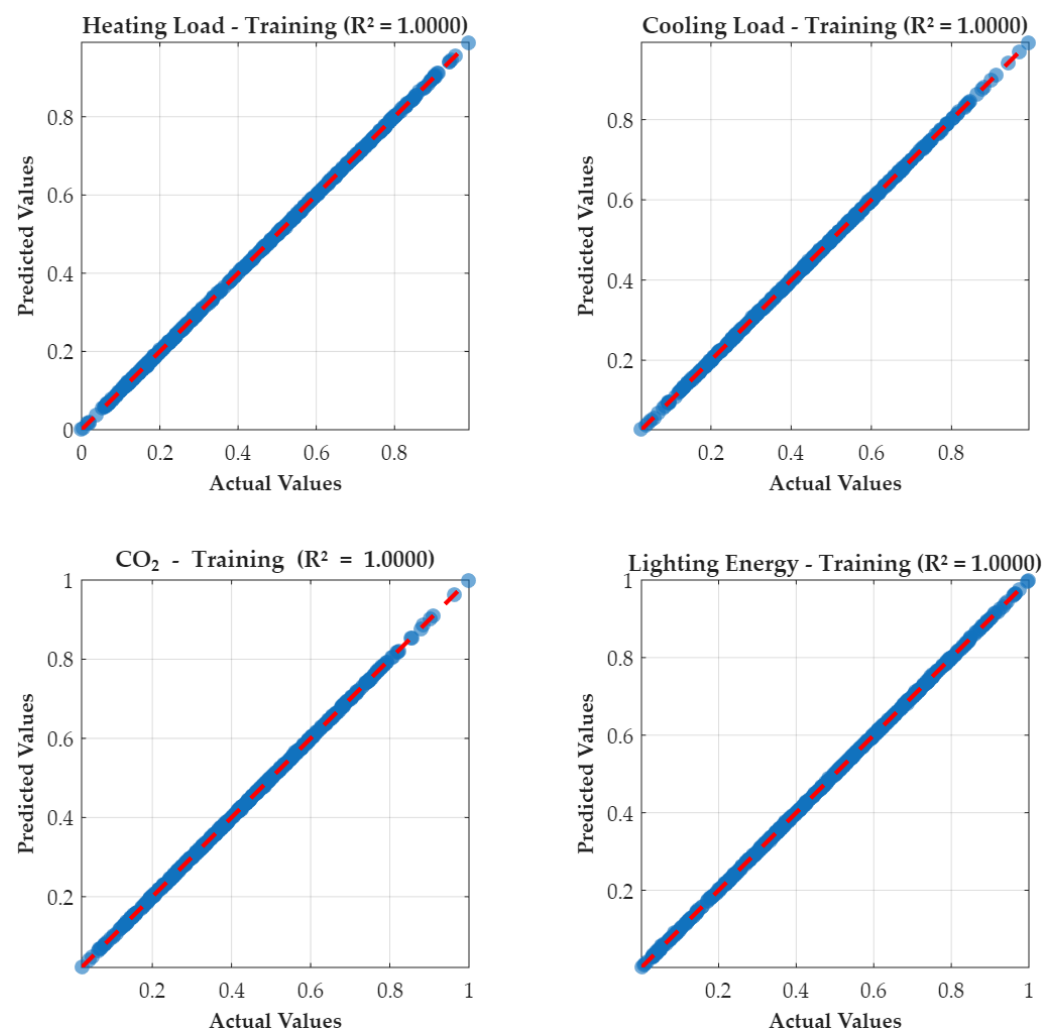


Figure 3. Actual vs. predicted values for all output variables across the training dataset.

Figure 4 shows the model's performance on the test dataset to evaluate its generalization ability. The R^2 values obtained on the data not used during the training process are 0.9998 for heating load, 0.9997 for cooling load, 0.9996 for CO_2 , and 0.9998 for lighting energy. These findings indicate that the model has a high generalization capability. The close similarity between training and test performances indicates that overfitting is not an issue and that the EFO algorithm plays an effective role in architectural optimization. Additionally, the concentration of data points around the ideal line indicates that the prediction errors are at a negligible level.

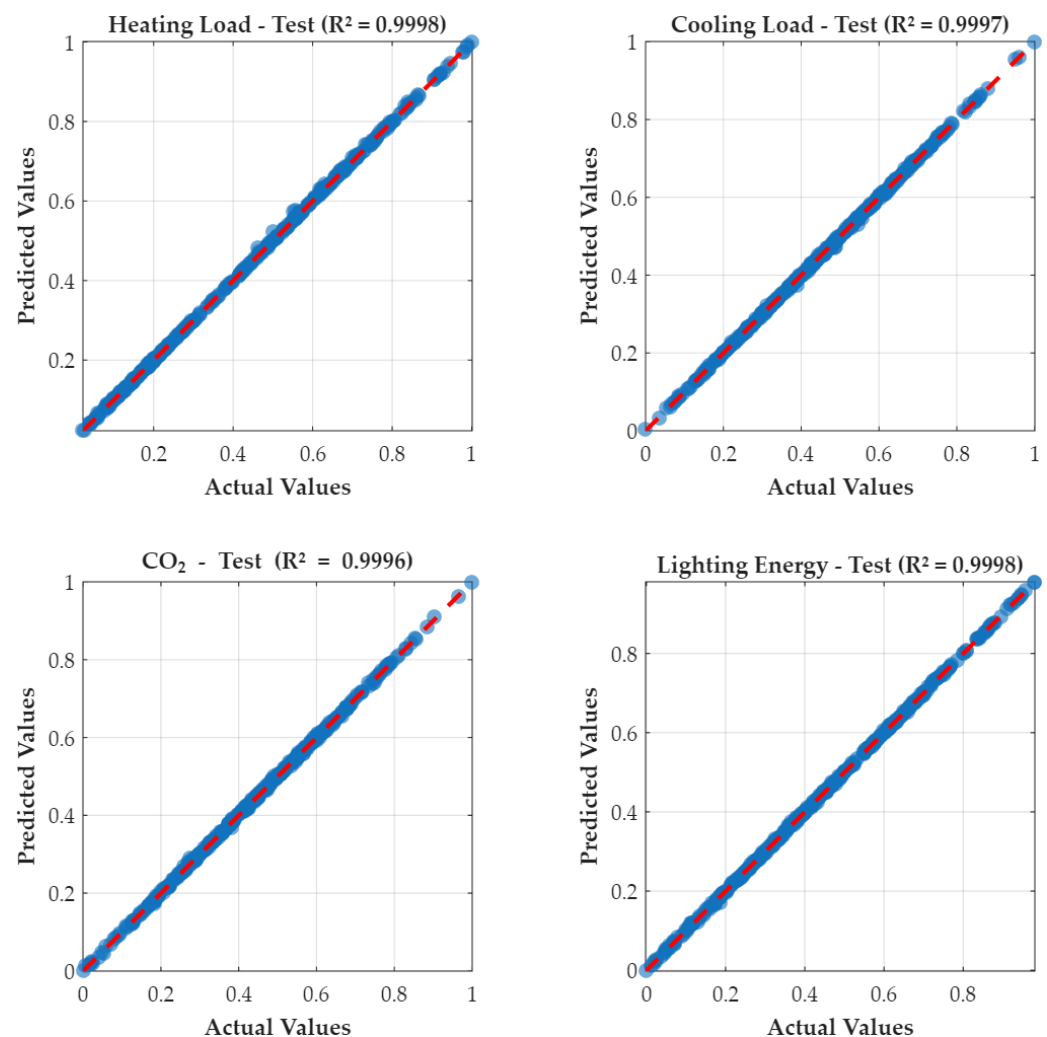


Figure 4. Actual vs. predicted values for all output variables across the test dataset.

Figure 5 shows the overall performance of the model on the entire dataset (training, validation, and test). The R^2 values, which span from 0.9998 to 0.9999 for all output variables, suggest a high degree of model accuracy. Furthermore, the uniform and symmetric distribution of data points around the ideal line throughout the entire value spectrum implies the absence of systematic errors, thereby ensuring the reliability of the model's predictions. The minimal disparity between the training and testing outcomes, with a maximum of 0.0004, corroborates the model's balanced learning structure and its robust capacity for generalization. These results indicate that the EFO-based artificial neural network model offers high accuracy and stability in multi-output regression problems.

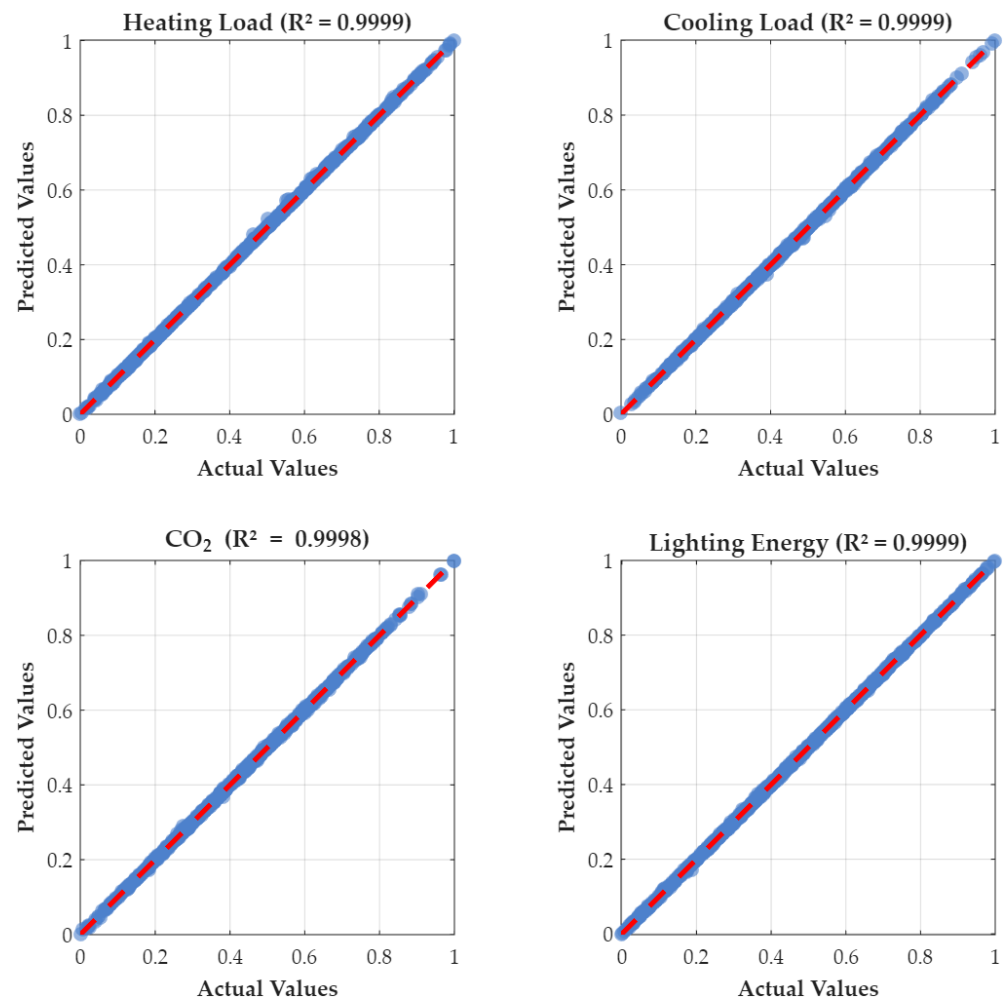


Figure 5. Actual vs. predicted values for all output variables across the complete dataset.

The performance comparison shown in Figure 6 clearly demonstrates that the EFO-optimized ANN model operates at very low error levels for its four output variables. It should be noted that the EFO process was performed using only the training and validation datasets, whereas the independent test dataset remained completely unseen during optimization and was used solely for the final performance evaluation. The MSE values on the order of 10^{-6} observed for the training dataset indicate that the model learned the underlying relationships with high accuracy, while the MSE values remaining at the 10^{-5} level on the independent test dataset demonstrate strong generalization capability. While the second output produced the lowest error during the training phase, the fourth output exhibited the lowest error during the independent test phase, indicating balanced predictive performance across different outputs. Furthermore, the R^2 values exceeding 0.999 for all output variables suggest that the optimized model achieved high prediction accuracy while maintaining good generalization performance, with no clear evidence of overfitting.

The numerical values of the training and testing performance metrics are presented in Tables 5 and 6, and the low MAE and RMSE values support the model's ability to make predictions with high accuracy. In these tables, the particularly small MAE and RMSE values during the training phase demonstrate that the model minimized error during the learning process. Although a limited increase in error values was observed during the testing phase, the fact that this increase remained at low levels demonstrates the model's strong generalization ability.

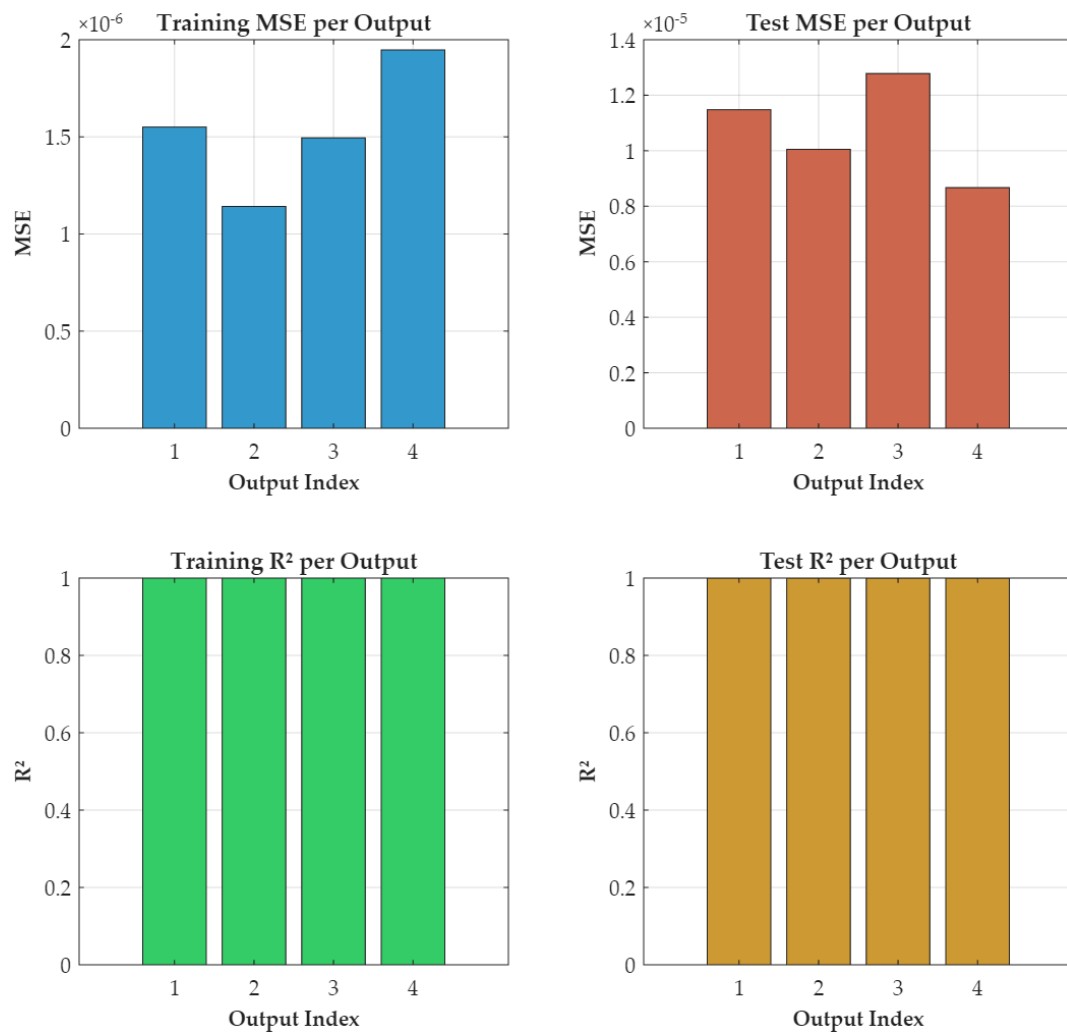


Figure 6. Output-based performance variation in training and test datasets.

Table 5. Training performance metrics.

Output Variable	MSE ($\times 10^{-6}$)	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	R ²
Heating Load	1.53	1.0	1.24	1
Cooling Load	1.13	0.8	1.06	1
CO ₂ Emissions	1.48	1.0	1.22	1
Lighting Energy	1.93	1.1	1.39	1
Average	1.52	0.98	1.23	1

Table 6. Test performance metrics.

Output Variable	MSE ($\times 10^{-5}$)	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	R ²
Heating Load	1.15	2.2	3.39	1
Cooling Load	1.01	2.3	3.18	1
CO ₂ Emissions	1.29	2.7	3.59	1
Lighting Energy	0.87	2.2	2.95	1
Average	1.08	2.35	3.28	1

The combined performance analyses presented in Figure 7 and Table 7 reveal that error values are concentrated within a narrow range across the entire dataset and that the model has learned all outputs in a balanced manner. The fact that the error differences among the four output variables are quite limited indicates that the model does not overfit

any single output and has achieved a general optimization success. The fact that RMSE values remain at approximately 0.22–0.25 and R^2 values are above 0.999 indicates that the model can explain nearly all of the variance and that prediction accuracy is quite high.

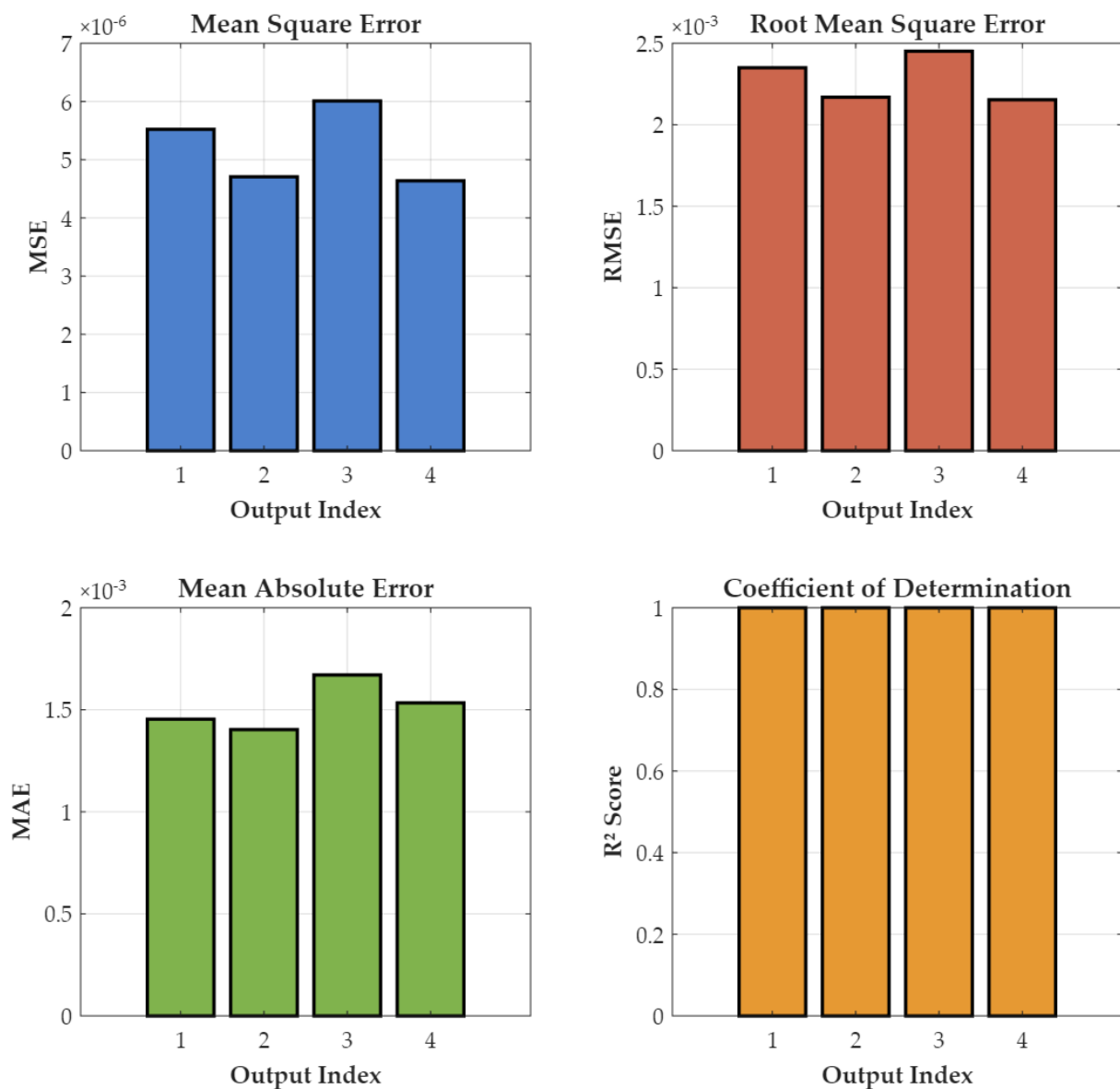


Figure 7. Variation in combined performance metrics across all outputs.

Table 7. All dataset performance metrics.

Output Variable	MSE ($\times 10^{-6}$)	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	R^2
Heating Load	5.53	1.5	2.35	1
Cooling Load	4.73	1.4	2.17	1
CO ₂ Emissions	6.01	1.7	2.45	1
Lighting Energy	4.68	1.5	2.16	1
Average	5.24	1.53	2.28	1

RMSE values range between 2.15×10^{-3} and 2.45×10^{-3} , indicating that the average error remains approximately at the level of 0.22–0.25% within the normalized scale. MAE values vary between 1.37×10^{-3} and 1.66×10^{-3} , showing a distribution consistent with the other performance metrics. The fact that R^2 values exceed 0.999 for all outputs demonstrates

that the model explains more than 99.9% of the variance. The second output consistently exhibits the best performance across all metrics, while the third output shows relatively higher error values; however, these differences are negligible in absolute terms. The overall low and closely distributed error metrics indicate that the model has been optimized in a balanced and stable manner. In general, the EFO-optimized artificial neural network model demonstrates high accuracy, strong generalization capability, and robustness against overfitting in the multi-output regression problem.

Upon examining the error characteristics, Figure 8 shows that the error distributions for all outputs exhibit a symmetric and random structure around the zero axis. This indicates that the model contains no systematic error (bias) and that the predictions are unbiased. The fact that the MAE values for heating and lighting outputs are approximately at the 0.15% level, that this value is even lower for the cooling output, and that while the CO₂ output is relatively slightly higher, it remains within acceptable limits, demonstrates that the model exhibits consistent performance for all outputs.

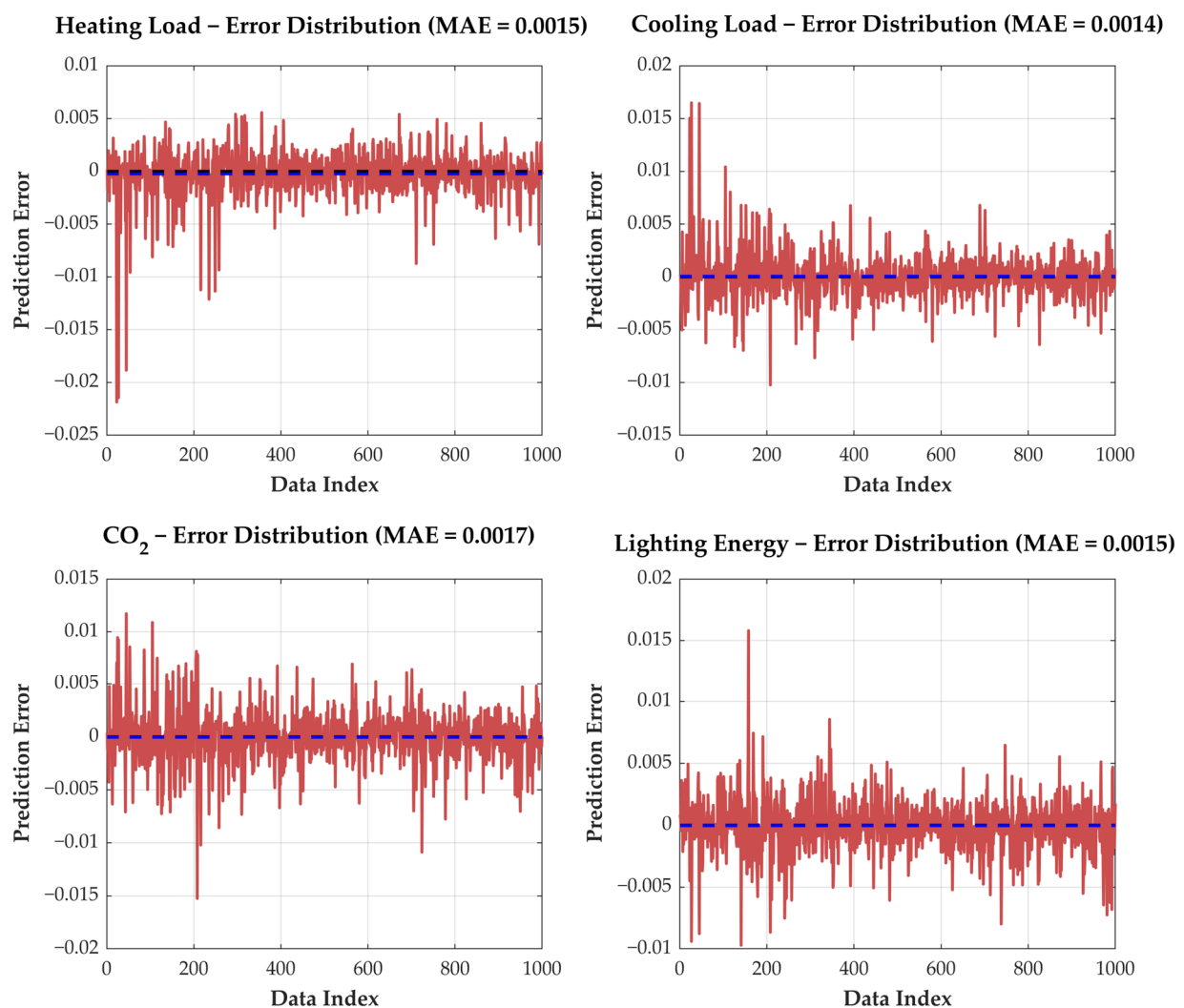


Figure 8. Variation in prediction errors.

The test results, one of the most critical indicators of generalization performance, are presented visually in Figure 9. The close alignment between actual and predicted values proves that the model operates with high accuracy on unseen data. The model's consistent performance across different operational regions (low, medium, and high value ranges) demonstrates that the system is sensitive to dynamic changes and can successfully

model sudden transitions. Achieving $R^2 > 0.9996$ for all outputs numerically supports this high performance.

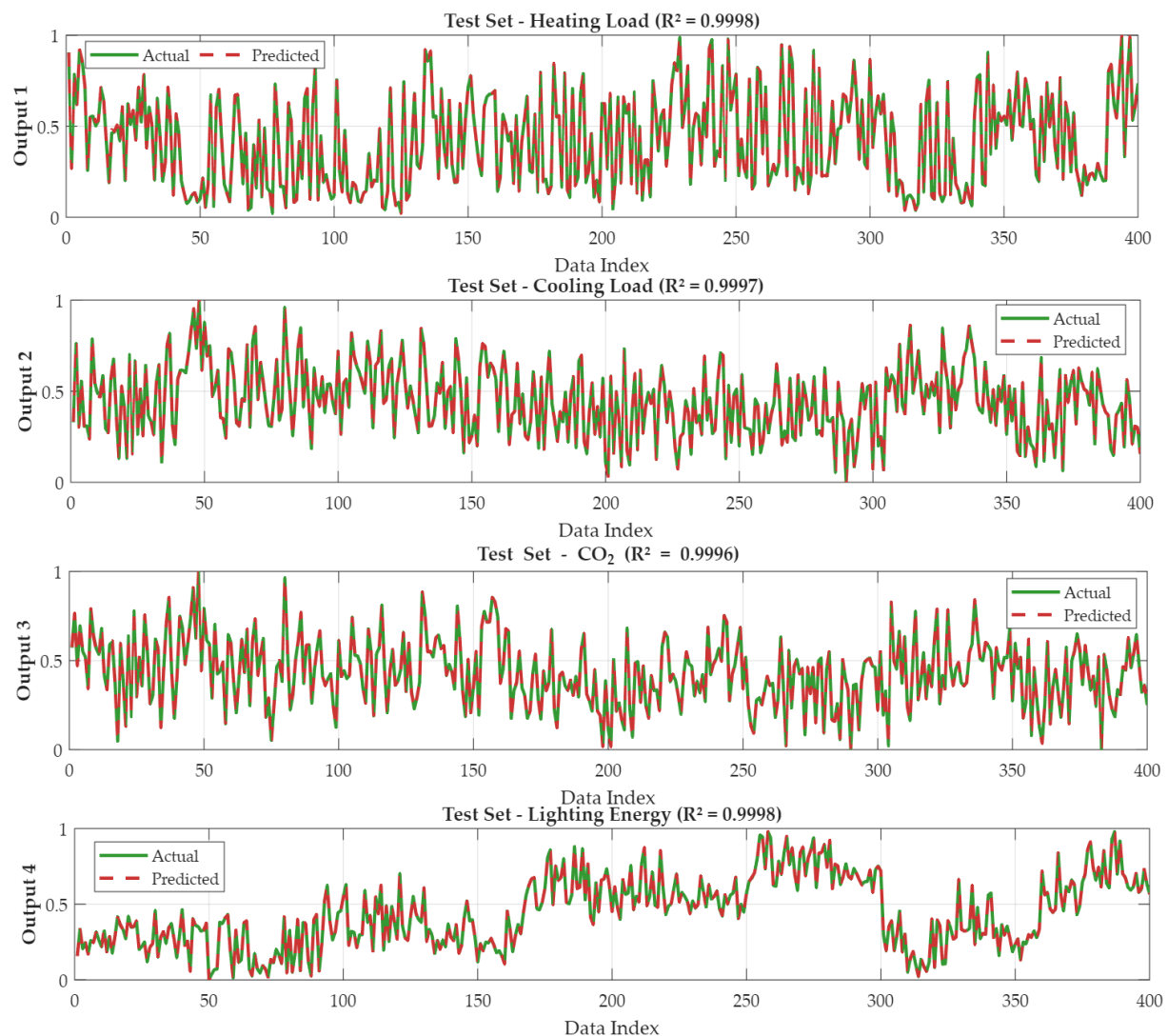


Figure 9. Actual vs. Predicted comparison on the test dataset.

Error histograms for the test dataset (Figure 10) reveal that the vast majority of errors are concentrated in the low-value range, while high-error instances are quite limited in number. The right-skewed distribution of errors and the low frequency of high-error samples indicate that there is no systematic issue that would negatively impact the model's overall accuracy. The relatively wide error distribution observed in the CO₂ output can be attributed to this variable having a more complex and multi-parameter structure; nevertheless, the error levels achieved are quite successful for practical applications.

As shown in Figure 11, the predicted values show nearly perfect agreement with the corresponding actual values for all four output parameters: heating load, cooling load, CO₂ emissions, and lighting energy consumption. This close alignment demonstrates that the proposed model has successfully learned the complex nonlinear relationships between design variables and building performance metrics. The high level of consistency observed across the entire training dataset further highlights the robustness of the learning process and the model's ability to accurately represent the underlying data patterns.

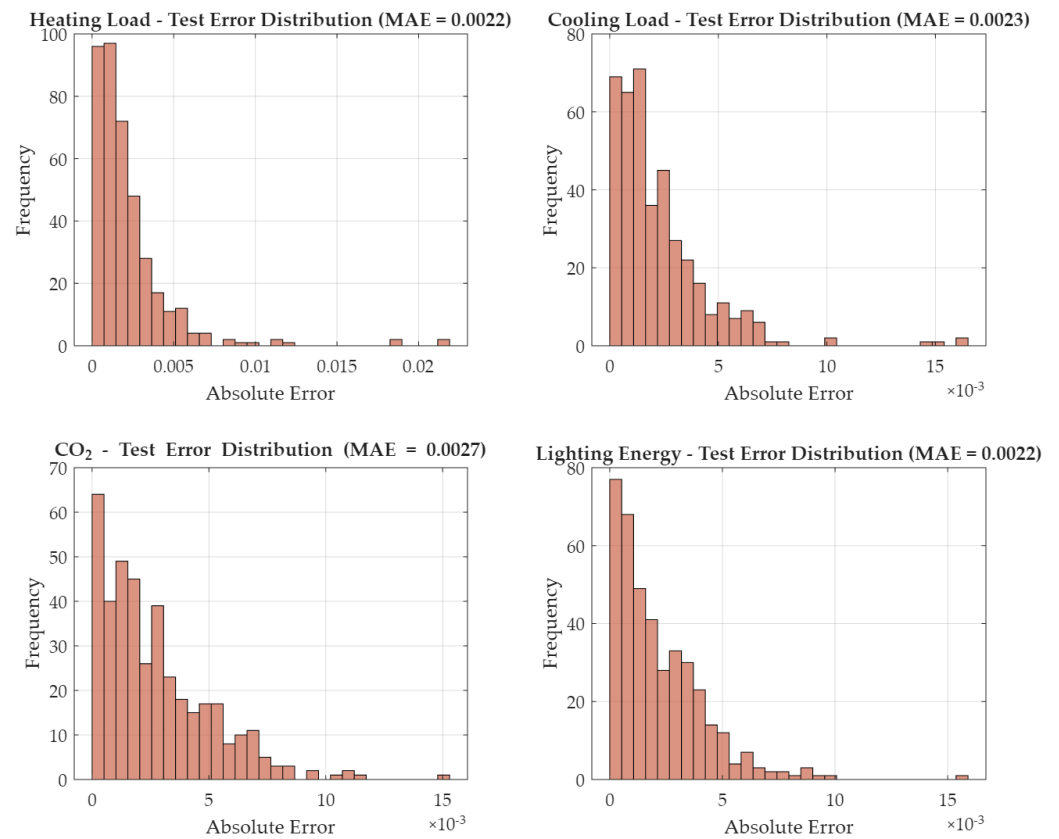


Figure 10. Statistical analysis of error distributions on the test dataset.

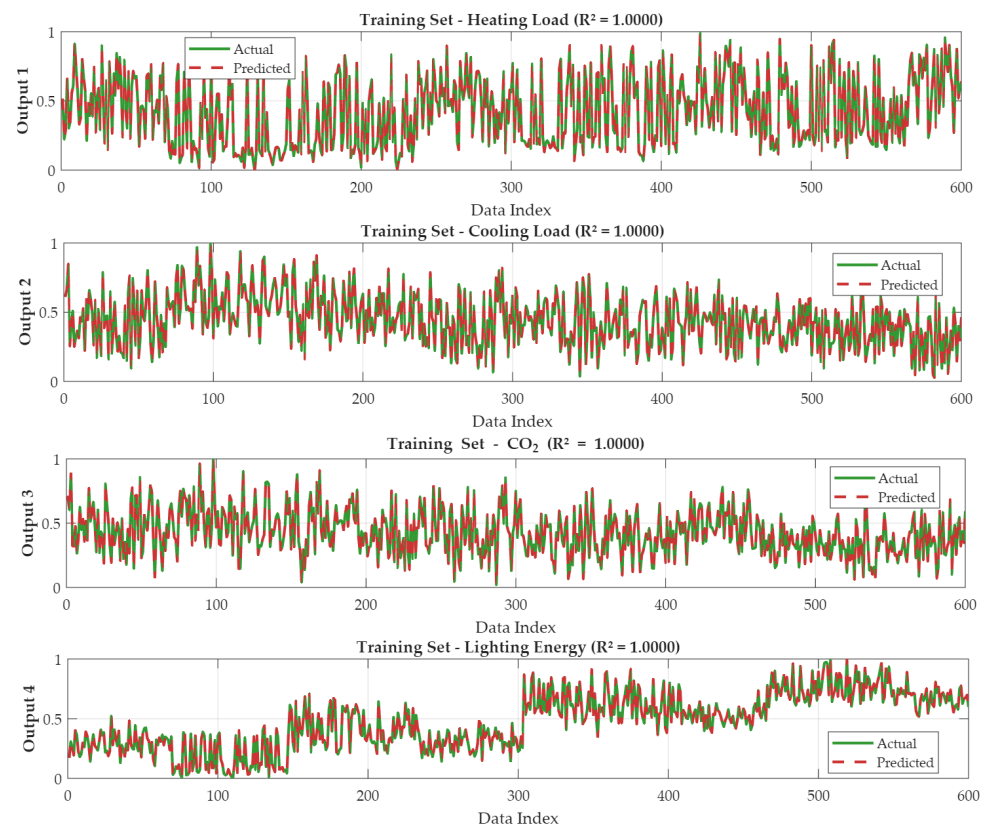


Figure 11. Actual vs. predicted comparison on the training dataset.

Additionally, Figure 12 presents the distribution of absolute prediction errors obtained during the training phase. It can be observed that the error values are concentrated near

zero, with only a small number of examples exhibiting relatively larger deviations. The obtained MAE values remain below 0.0012 for all output variables, confirming the high prediction accuracy achieved by the model. The right-skewed error distributions, combined with low average error levels, indicate that large prediction deviations occur infrequently within the analyzed dataset. Overall, the results presented in Figures 11 and 12 suggest that the proposed model captures the underlying relationships in the training data and maintains consistent predictive performance. Furthermore, the similarly high predictive accuracy observed on the test dataset indicates that the model generalizes well to unseen samples within the simulation-based dataset, with no evidence of substantial overfitting.

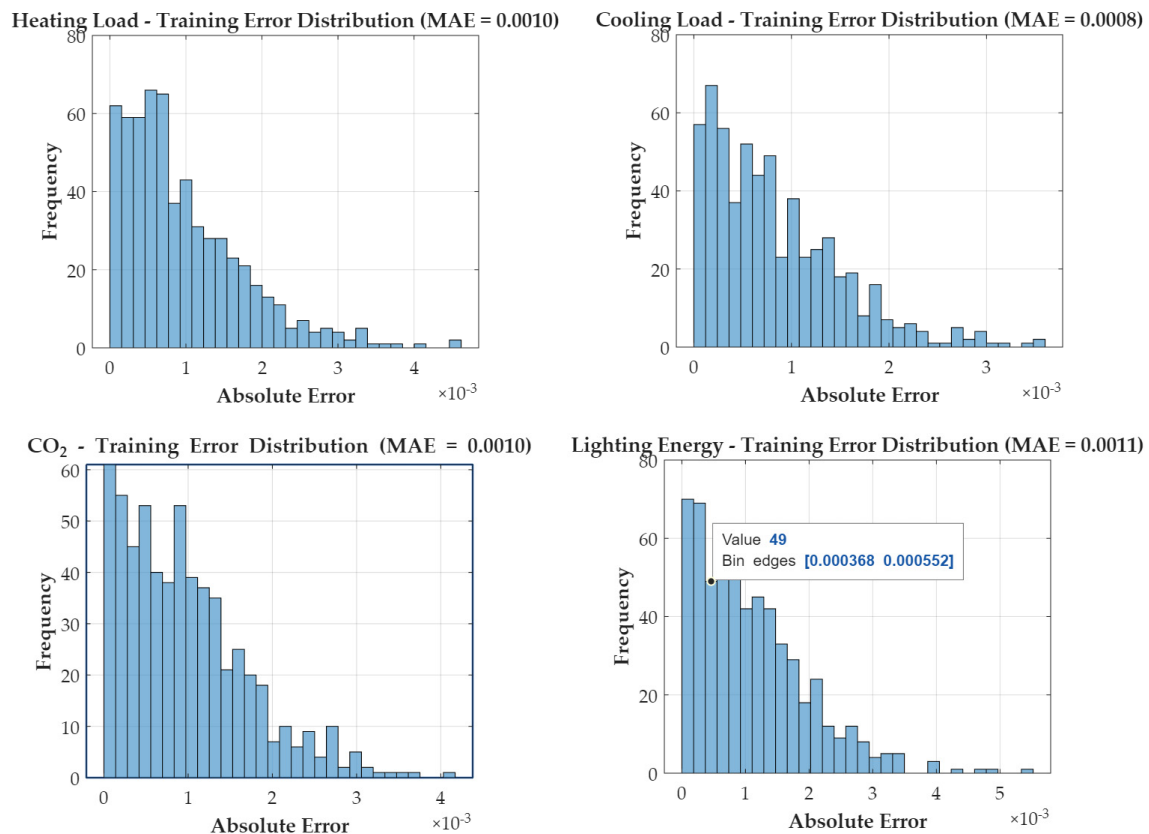


Figure 12. Statistical analysis of error distributions on the training dataset.

The comprehensive performance evaluation across the entire dataset is presented in Figure 13, where $R^2 \geq 0.9998$ and $RMSE \leq 0.0025$ confirm the model's high accuracy and stability. The high agreement between observed and predicted values across all samples demonstrates that the model can generate successful predictions even across wide data ranges. The comparative analyses presented in Table 8 reveal that performance differences between outputs are quite low and that the EFO algorithm optimizes the network architecture in a balanced manner.

Table 8. Comparative performance across outputs.

Metric	Best Output	Lowest Performance	Variation (%)
Test R^2	Heating/Lighting (0.9998)	CO ₂ (0.9996)	0.02
Test MAE	Heating/Lighting (0.0022)	CO ₂ (0.0027)	22.7
Test RMSE	Lighting (0.00295)	CO ₂ (0.00359)	21.7
Training MAE	Cooling (0.0008)	Lighting (0.0011)	37.5

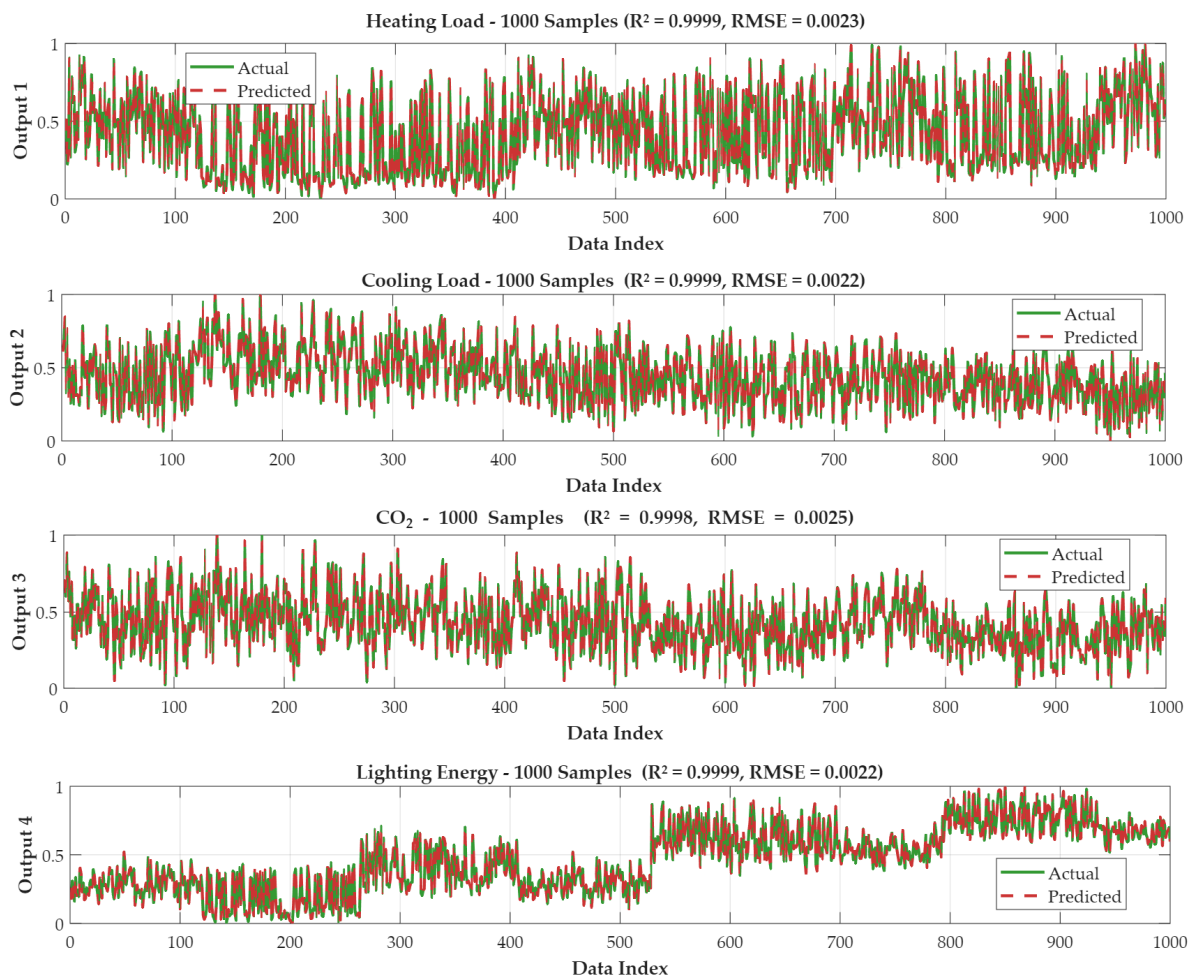


Figure 13. Actual vs. predicted comparison on the full dataset (Plot for 1000 Samples).

The fact that the performance of the full dataset is consistent with the training and testing results demonstrates that the model is robust and exhibits similar performance across different subsets of the data. R^2 values of 0.9998 and above indicate that the model can explain more than 99.98% of the variance, representing performance far exceeding that of standard methods in the literature. In conclusion, the full dataset analysis demonstrates that the developed EFO-ANN hybrid system possesses sufficient accuracy, reliability, and generalization capacity for industrial applications in multi-output regression problems.

3.1. Olden-Based Sensitivity Analysis

To improve the interpretability of the proposed EFO-ANN model, a sensitivity analysis was performed using the Olden method. The Olden method is a connection-weight approach that quantifies the relative importance of input variables by utilizing the product of connection weights between neurons across successive network layers. Unlike Garson's algorithm, which relies solely on absolute weight magnitudes, the Olden method preserves the sign of the connection weights and therefore provides information regarding both the strength and direction of the influence of each input variable on the network outputs. This characteristic enables a more comprehensive interpretation of the relationships learned by the neural network.

In this study, the relative importance values were calculated from the trained ANN connection weights and subsequently normalized to facilitate comparison among the input variables. The resulting importance scores were used to identify the most influential design parameters affecting heating load, cooling load, CO₂ emissions, and lighting energy

consumption. The Olden method has been widely applied in neural network interpretation studies because it provides a robust measure of variable importance while maintaining computational simplicity and compatibility with complex network architectures [24,25].

The sensitivity analysis reveals that the dominant input variables vary across the predicted outputs. Building spacing (30.44%) and location template (29.07%) exert the greatest influence on heating load, whereas glazing type is the most influential parameter for cooling load (50.33%) and CO₂ emissions (77.46%). For lighting energy, building spacing (29.52%), glazing type (24.09%), and location template (22.80%) are the primary contributing factors. In contrast, site orientation and WWR generally exhibit relatively low influence across most outputs. Figure 14 presents the relative importance of the input variables obtained using the Olden sensitivity analysis method, while Table 9 summarizes the corresponding relative importance values and net effects of each input variable on the predicted outputs. The results indicate that the influence of the design parameters varies considerably across the predicted outputs.

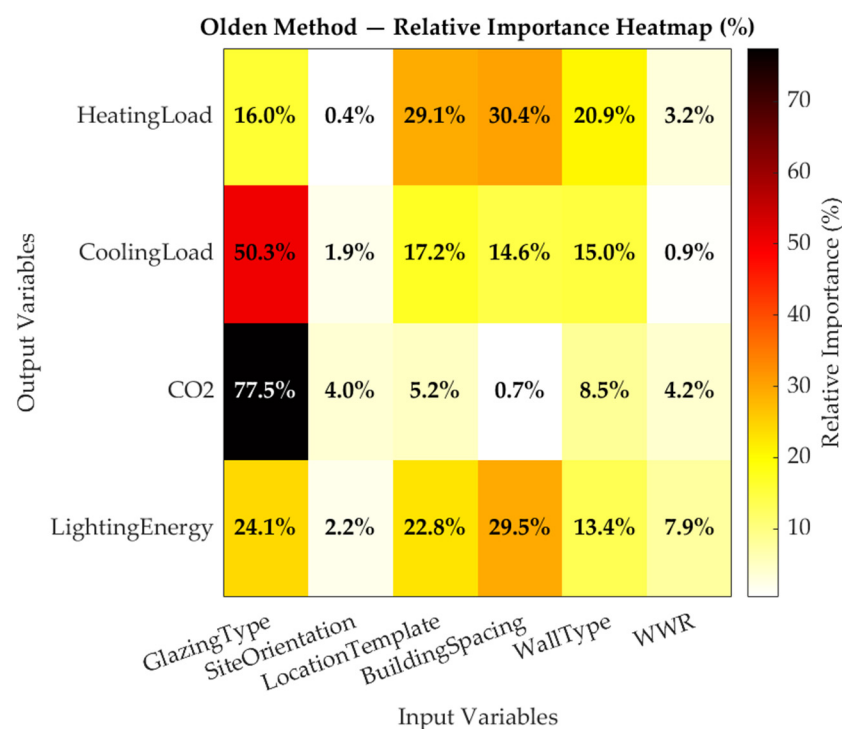


Figure 14. Heatmap of relative input variable importance derived from the Olden sensitivity analysis method.

Table 9. Sensitivity analysis results showing the relative importance and net effect of input variables on the predicted outputs.

Input Variable	Heating Load	Cooling Load	CO ₂ Emissions	Lighting Energy
Glazing Type	+9.27 (16.00%)	−22.80 (50.33%)	−22.27 (77.46%)	+9.03 (24.09%)
Site Orientation	+0.25 (0.43%)	+0.88 (1.95%)	+1.14 (3.96%)	−0.84 (2.23%)
Location Template	−16.85 (29.07%)	+7.81 (17.23%)	+1.48 (5.16%)	+8.55 (22.80%)
Building Spacing	−17.65 (30.44%)	+6.60 (14.56%)	−0.19 (0.67%)	+11.07 (29.52%)
Wall Type	−12.10 (20.87%)	+6.81 (15.03%)	+2.44 (8.50%)	+5.03 (13.42%)
WWR	+1.86 (3.20%)	+0.41 (0.91%)	+1.22 (4.24%)	−2.98 (7.93%)

Positive (+) and negative (−) signs indicate the direction of the net effect, while percentages represent the relative importance of each input variable for the corresponding output.

3.2. Comparison with a Baseline ANN Model

Tables 10 and 11 present the performance of the baseline ANN model, which employs the same network architecture ([27 27 8 5 20]), training algorithm, and data partitioning strategy as the proposed EFO-ANN framework. The results indicate that the conventional ANN achieved a satisfactory fit on the training dataset, with an average R^2 value of 0.97. However, its predictive performance decreased considerably on the independent test dataset, where the average R^2 value dropped to 0.73.

Table 10. Training performance metrics.

Output Variable	MSE ($\times 10^{-6}$)	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	R^2
Heating Load	1283.70	27.33	35.82	0.98
Cooling Load	850.18	21.04	29.15	0.97
CO ₂ Emissions	1372.88	28.15	37.05	0.95
Lighting Energy	1033.75	25	32.15	0.98
Mean	1135.13	25.38	33.54	0.97

Table 11. Test performance metrics.

Output Variable	MSE ($\times 10^{-6}$)	MAE ($\times 10^{-3}$)	RMSE ($\times 10^{-3}$)	R^2
Heating Load	17,358.09	91.263	131.75	0.71
Cooling Load	7381.62	62.710	85.91	0.79
CO ₂ Emissions	13,266.30	84.14	115.17	0.61
Lighting Energy	11,092.51	75.09	105.32	0.79
Mean	12,274.63	78.30	109.54	0.73

A detailed examination of the test results shows that CO₂ Emissions exhibited the lowest prediction accuracy ($R^2 = 0.61$), followed by Heating Load ($R^2 = 0.71$). Cooling Load and Lighting Energy achieved relatively better performance, with identical R^2 values of 0.79. Furthermore, the substantial increases in MSE, RMSE, and MAE between the training and test datasets indicate that the baseline ANN suffers from limited generalization capability and is less effective in capturing the complex nonlinear relationships between building design parameters and the target energy indicators.

In contrast, the proposed EFO-ANN framework achieved R^2 values exceeding 0.999 for all output variables on the independent test dataset. This significant performance difference demonstrates the contribution of the Evolutionary Field Optimization algorithm to improving the ANN model's prediction accuracy and generalization ability. The results indicate that the performance gains observed in this study are primarily attributable to the EFO-based optimization process rather than the ANN architecture.

4. Discussion

A comprehensive analysis of the performance of the EFO-optimized artificial neural network model in a multi-output regression problem demonstrates that the system exhibits strong predictive performance on the training, test, and full datasets. The Evolutionary Field Optimization algorithm successfully identified the optimal neural network architecture by improving the objective function value by 86% in just 10 iterations. The algorithm's ability to escape local optima and its balanced exploration-exploitation strategy are clearly evident in the three-stage improvement pattern observed in the convergence curve.

The developed model simultaneously predicts four different output variables (Heating Load, Cooling Load, CO₂ Emissions, and Lighting Energy) and achieves performance at the $R^2 > 0.999$ level for all outputs. The minimal differences between training and testing performance demonstrate that the model does not suffer from overfitting and that

the complexity penalty terms ($C_1 = 0.1$, $C_2 = 0.01$) used in the EFO objective function are effective.

The fact that the error distributions exhibit a right-skewed structure across all datasets and that the vast majority of errors are concentrated at low values indicates that the model contains no systematic error and that the predictions are unbiased. The close visual alignment between actual and predicted values confirms the reliability of the numerical metrics. The model demonstrates consistent performance across a wide operational range (0–1 normalized values), at low, medium, and high load levels, during sudden transitions, and under high-frequency fluctuations.

The minimal variation in performance across outputs demonstrates that the EFO algorithm optimizes all outputs in a balanced manner and that no single output is optimized at the expense of others. The relatively better performance of cooling load and lighting energy suggests that these parameters have more regular relationships with the input variables; conversely, the relatively higher error values for CO₂ suggest that this parameter has a more complex structure resulting from the combined effects of numerous factors.

The findings suggest that the proposed EFO-ANN framework is a promising approach for simulation-based prediction of building energy consumption and environmental performance indicators.

The EFO-optimized multi-output artificial neural network model developed within the scope of this study fully met the success index criteria based on the defined performance metric, the normalized root mean square error (NRMSE), and exceeded the target range. The success index is defined as $S = 1 - \text{NRMSE}$, with a baseline threshold value set in the range of 0.93–0.99. In the implemented model, R^2 values for the four output variables (heating load, cooling load, CO₂ emissions, and lighting energy) on the test data ranged from 0.9996 to 0.9998, while RMSE values ranged from 0.0022 to 0.0025. These values correspond to an error margin of approximately 0.22–0.25% within the normalized data range. Consequently, the performance index, calculated using the formula $S = 1 - \text{NRMSE}$, fell within the range of 0.9975–0.9978. This result demonstrates that the model reduced the error rate below 0.25%, exceeding the upper limit of the target range and fully meeting the criterion. The consistency in performance across the training, validation, and test datasets proves that the model has high generalization ability and does not suffer from overfitting. Indeed, results of $R^2 = 1.0000$ on the training data and $R^2 \approx 0.9997$ on the test data demonstrate that the system exhibits stable performance in both the learning and prediction processes. The fact that the EFO algorithm improves the objective function by 86% in a very short time (approximately 10 iterations) indicates that the algorithm utilizes both global and local search capabilities in a balanced manner. The results clearly demonstrate that the EFO-ANN hybrid system not only meets the defined success criteria but also outperforms standard optimization methods in the literature in terms of model accuracy, error margin, and generalization ability. The high prediction accuracy obtained in this study suggests that the proposed framework can be effectively employed as a decision-support tool during early-stage building design. Accurate estimation of heating, cooling, lighting, and CO₂ indicators may assist designers and policymakers in evaluating alternative building configurations before construction. Furthermore, the proposed framework may support future digital twin-enabled decision-support systems by providing simulation-based energy performance predictions.

Despite the promising predictive performance and practical applicability of the proposed EFO-ANN framework, certain limitations must be taken into account. In addition, accurate prediction of heating load, cooling load, lighting energy consumption, and CO₂ emissions can support sustainable building design and operation by enabling early evaluation of energy performance and environmental impacts. Therefore, the proposed

framework can serve as a decision-support tool for improving energy efficiency, reducing carbon emissions, and supporting sustainability-oriented building management strategies.

Although the developed model provides a strong foundation for future digital twin-enabled smart building applications, the present study does not implement a complete digital twin architecture with real-time data acquisition, bidirectional communication, and continuous model updating. Instead, it focuses on developing a highly accurate predictive engine that can serve as a core analytical component within such environments. Furthermore, the model was developed and validated using a specific simulation-based dataset with normalized variables and a predefined set of building design parameters. Consequently, its performance under real-world operational uncertainties, variations in user behavior, and different climatic conditions has not yet been fully investigated. In addition, this study focused on a single optimization algorithm and a feedforward neural network architecture. Future research could evaluate the proposed framework using real building monitoring data, different climate zones, larger datasets, and alternative machine learning architectures such as deep neural networks, transformers, or hybrid ensemble models. The integration of uncertainty analysis, explainable artificial intelligence techniques, real-time sensor data streams, and dynamic model updating within digital twin environments may further enhance the robustness, interpretability, and practical applicability of the proposed approach.

5. Conclusions

This study proposed an Evolutionary Field Optimization (EFO)-based multi-input multi-output artificial neural network framework for predicting key building energy performance indicators, including heating load, cooling load, CO₂ emissions, and lighting energy consumption. The interim outputs obtained from the studies conducted in this context validate the network's learning success and the effectiveness of the optimization process through numerical and visual outputs. The first interim output consists of an R-value table indicating that network training was successfully completed, along with scatter plots generated based on this table. For the training data, R^2 was calculated as 1.0000 for all output variables; for the test data, R^2 ranged from 0.9996 to 0.9998; and for the full dataset, R^2 ranged from 0.9998 to 0.9999. The close alignment of the data points along the $y = x$ reference line in the scatter plots indicates that the model's predicted values closely match the actual values and do not contain systematic error.

The second intermediate result is a convergence curve reflecting the change in the cost function over iterations, indicating that the network parameters have been successfully optimized. This curve shows that the Evolutionary Field Optimization algorithm achieved an 86% improvement by reducing the objective function from approximately 95 to 13 over a 10-iteration process. The convergence curve exhibited a three-phase dynamic: rapid exploration in the first phase, a temporary plateau in the middle section, and final convergence driven by the metamutation effect in the final phase. This indicates that the algorithm balances both global search (exploration) and local exploitation capabilities effectively.

Other intermediate outputs include training and test error distribution histograms, prediction-error time series plots, as well as comparative evaluations of performance metrics (MSE, RMSE, MAE, R^2) for each output variable. These visuals show that the error distributions are symmetrically clustered around the zero axis, indicating that the model produces unbiased predictions. Additionally, the optimal architectural map (number of layers and neurons) and hyperparameter configuration are included among the model's structural outputs. In conclusion, the results obtained in this study indicate that the proposed EFO-ANN framework achieved the targeted performance criteria and provided accurate predictions for the simulation-based building energy dataset.

The findings of this study have broader implications for the development of smart and energy-efficient building management systems worldwide. The EFO-ANN framework's ability to accurately predict multiple building performance indicators simultaneously demonstrates its potential as a decision-support tool during both the design and operation phases of buildings. The findings of this study suggest that integrating evolutionary optimization algorithms with multi-output neural networks can provide an effective framework for improving predictive performance in building energy modeling while preserving a manageable model complexity. Similar approaches can be adapted for smart cities, digital twin platforms, energy management systems, carbon reduction strategies, and sustainable building assessment frameworks across different climate zones and building types. Therefore, the proposed methodology offers a scalable and transferable solution to support global energy efficiency and decarbonization goals.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
ANN	Artificial Neural Network
BIM	Building Information Modeling
CIBSE	Chartered Institution of Building Services Engineers
CO ₂	Carbon Dioxide
CoP	Coefficient of Performance
CTR	Cumulative Thermal Ratio
DB	DesignBuilder
DCTR	Discomfort Rate
DH	Discomfort Hours
DHW	Domestic Hot Water
EFO	Evolutionary Field Optimization
EP	EnergyPlus
EUI	Energy Use Intensity
FFNN	Feedforward Neural Network

GA	Genetic Algorithm
GC	Global Cost
GWO	Grey Wolf Optimizer
HVAC	Heating, Ventilation and Air Conditioning
LCC	Life Cycle Cost
LSTM	Long Short-Term Memory
MAE	Mean Absolute Error
MATLAB	Matrix Laboratory
MIMO-ANN	Multi-Input Multi-Output Artificial Neural Network
MOQGA	Multi-Objective Quantum Genetic Algorithm
MSE	Mean Square Error
NMSE	Normalized Mean Square Error
NRMSE	Normalized Root Mean Square Error
NSGA-II	Non-dominated Sorting Genetic Algorithm II
NZEB	Nearly Zero Energy Building
PEC	Primary Energy Consumption
PH	Passive House
PSO	Particle Swarm Optimization
PV	Photovoltaic
R ²	Coefficient of Determination
RMSE	Root Mean Square Error
SHGC	Solar Heat Gain Coefficient
TM59	Thermal Comfort Methodology 59
TOKİ	Housing Development Administration of Türkiye
U-value	Thermal Transmittance Coefficient
WOA	Whale Optimization Algorithm
WWR	Window-to-Wall Ratio

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