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Application of Genetic Algorithm-Optimized Backpropagation Network in Library Energy Consumption Prediction

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Abstract

The development of building energy consumption prediction models is crucial for achieving sustainable development in the construction industry; however, establishing rational, accurate, and efficient models to promote energy conservation and enhance energy utilization efficiency remains a challenge. This study takes libraries as a representative building type, selecting operational hours, humidity, maximum temperature, occupancy density, and solar irradiance as key influencing factors to construct a Genetic Algorithm-optimized Backpropagation (GA-BP) neural network for energy consumption prediction. Comparative experiments with a standard Backpropagation (BP) neural network, Regularized Radial Basis Function (RRBF) neural network, and Generalized Radial Basis Function (GRBF) neural network demonstrate the superior fitting performance of the GA-BP model, providing reliable scientific support for library energy management and offering a practical framework for energy-efficient building operations.

Keywords: Energy conservation and emission reduction; Sustainable development; Energy consumption prediction; GA-BP neural network

1. Introduction

The construction industry is a crucial pillar of the national economy. The way it develops directly affects the speed and quality of a nation's economic growth. With the advancement of technology, digital transformation has become a crucial trend in how the construction sector evolves. By leveraging cutting-edge technologies such as Artificial Intelligence (AI), the Internet of Things (IoT), and Building Information Modeling (BIM), the industry can get more efficient and accurate when it comes to design, construction, and management processes. At the same time, as environmental awareness intensifies, green and sustainable development has turned into an imperative choice for the construction industry. Making this sustainable depends on predicting and analyzing energy consumption accurately. Setting up reasonable, accurate, and efficient building energy consumption prediction models is essential for optimizing energy allocation, improving energy utilization efficiency, and ultimately realizing energy conservation and emission reduction goals, thereby advancing the industry's green transformation.

Among typical building types, libraries show quite strong representativeness on account of their complex functions and specific energy usage ways. Consequently, this study chooses libraries as the primary research subject for developing and validating the proposed methodology.

Current research on library energy consumption has garnered substantial attention from scholars worldwide. Li (2023) proposed a hybrid neural network method combining multi-step ahead time series with LSTMBP (Long Short-Term Memory Backpropagation) for energy consumption prediction and energy-saving diagnosis. Wang and Yu (2022) developed a similar-day LM (Levenberg-Marquardt) neural network model for predicting energy consumption in academic libraries. In subsequent work, Wang (2021) further optimized the LM neural network architecture to enhance prediction accuracy. Meanwhile, Sun and Zeng (2017) established an energy consumption monitoring framework using Radial Basis Function (RBF) Neural Networks for systematic library energy management. Yang and Lu (2024) used graph neural networks to predict building energy consumption. Le (2024) designed an improved BIGRU energy consumption model for large-scale facilities and verified the accuracy and practicality of the model.

This text aims to deal with the limitations that traditional models have when handling the nonlinear complexities of library energy consumption which is affected by multiple factors. So, this study puts forward a Genetic Algorithm-optimized Backpropagation Neural Network (GA-BP) model. Genetic algorithm has strong global search ability, and does not easily fall into the local optimal, at the same time, also has strong scalability, easy to integrate with other technologies, suitable for more different scenarios. The BP neural network provides superior nonlinear mapping and adaptive parameter optimization through self-learning mechanisms, though conventional implementations suffer from random initialization sensitivity and local convergence tendencies. By systematically optimizing the initial parameters of BP with GA, this hybrid framework makes the prediction more robust. At the same time, it keeps the complementary strengths of both algorithms when dealing with complex nonlinear relationships.

2. Fundamental Theory

2.1. Fundamentals of BP Neural Networks

The BP neural network is a multi-layer feedforward network that is trained by the backpropagation algorithm, comprising three core components: the input layer, hidden layer, and output layer. The neurons in each of these layers are connected fully to every neuron in the layer that comes right before it. And the way the signal spreads is controlled by the weighted summation and the bias terms.

During forward propagation, input signals sequentially traverse the input layer, hidden layer. Eventually, actual outputs get generated at the output layer. When the difference between the actual outputs and the expected ones goes beyond the target accuracy, the network initiates error signal backpropagation. At this time, error signals move backward from the output layer all the way to the input layer. Meanwhile, the gradient descent optimization method actively adjusts the connection weights as well as the bias terms in all layers according to the error gradients. Through repeated training cycles, this whole process gradually reduces the prediction errors until the network reaches the performance levels that are wanted (Rumelhart et al., 1986).

In summary, the training process of a BP neural network is systematically structured into three sequential phases: network initialization, forward signal propagation, and error backpropagation. The topological structure of the BP neural network is illustrated in Figure 1.

This study develops a dual-hidden-layer BP neural network model (Figure 1) tailored to practical engineering contexts and empirical datasets. The architecture operates with input data $x = (x_1, x_2, \cdots, x_m, \cdots, x_M)$ and generates output predictions$y = (y_1, y_2, \cdots, y_k, \cdots, y_K)$, where interlayer connections are governed by weight matrices r_{mi} (input-to-first hidden layer), r_{ij} (first-to-second hidden layer), and r_{jk} (second hidden-to-output layer). Bias terms α_i, α_j, and α_k are

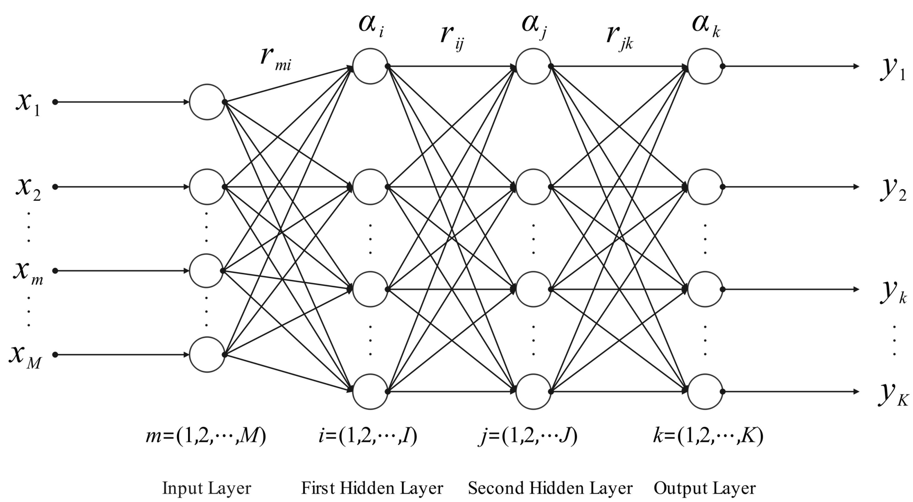

Figure 1: Topological structure of the BP neural network.

assigned to the first hidden layer, second hidden layer, and output layer, respectively, to regulate neuronal activation dynamics. This hierarchical design addresses nonlinear feature extraction through sequential layer transformations while maintaining computational tractability.

2.2. Fundamentals of GA-BP Neural Network

The BP neural network is prone to getting trapped in local optima, and this is due to its parameter initialization mechanism. The weights of the interlayer connections and the bias terms are randomly initialized in it. Then, they are refined through the gradient descent optimization. This iterative correction process often converges prematurely to suboptimal solutions while struggling to approximate the global optimum.

To address this limitation, we integrate the GA, a robust adaptive global probabilistic optimization method. GA employs crossover and mutation operators to systematically explore the solution space, enabling either the exact attainment of the global optimum or high-precision approximation. By optimizing BP's initial weights and bias terms through GA's evolutionary operations, the hybrid GA-BP framework effectively mitigates local convergence risks while enhancing prediction robustness (Fan et al., 2024).

The flowchart of the GA-BP neural network optimization process is shown in Figure 2.

As delineated in Figure 2, the GA-BP neural network optimization process initiates with the architectural initialization of the BP neural network, where connection weights (r) and bias terms (α) are encoded into chromosomal representations to form the initial population for the GA. Through iterative fitness evaluation, crossover, and mutation operations, GA evolves these parameters toward global optimality, subsequently decoding the optimized $GA - r$ and $GA - \alpha$ to replace BP's randomly initialized values. The refined BP neural network then undergoes gradient-based training via forward-backward propagation, ultimately generating prediction outcomes that synergize global search robustness with local optimization precision.

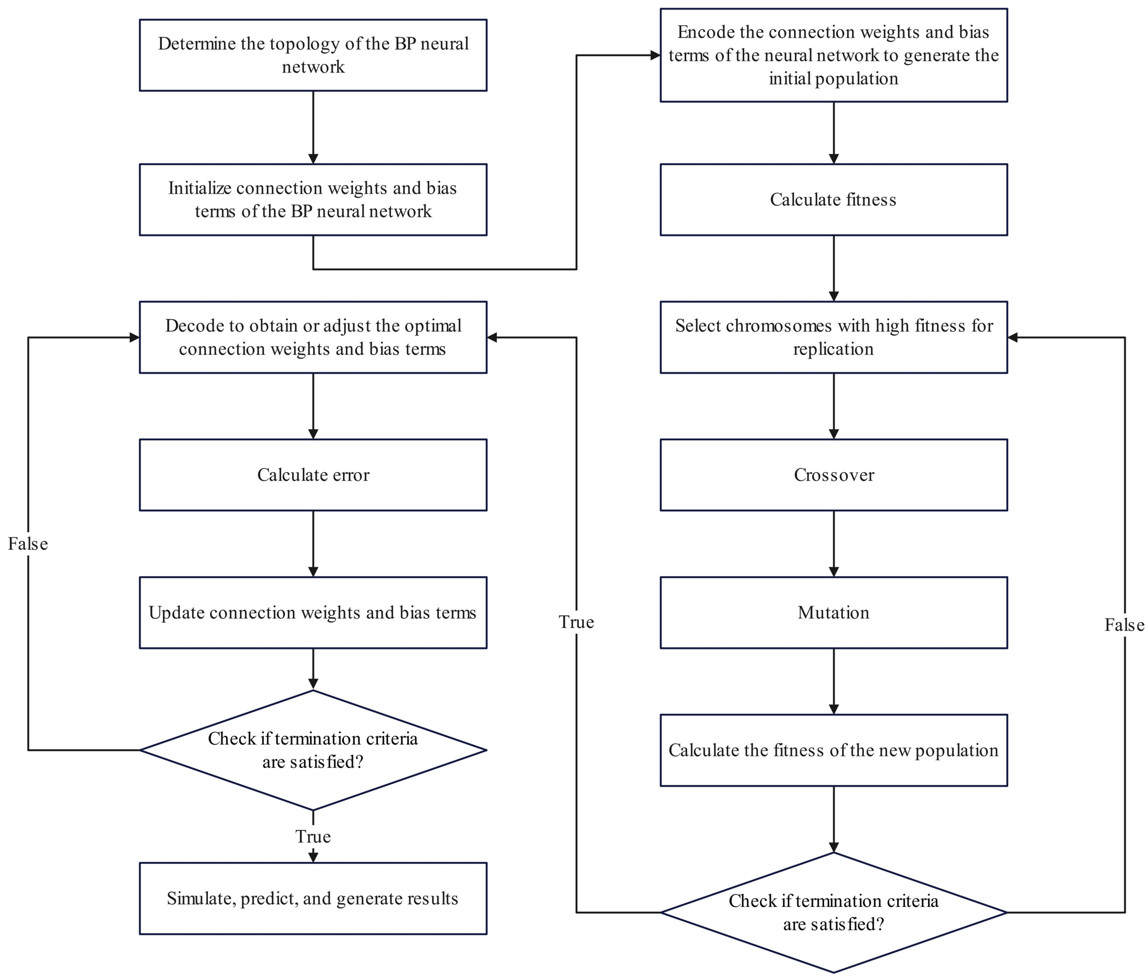

Figure 2: Flowchart of GA-BP Neural Network.

3. Simulation and Prediction of Library Energy Consumption Using GA-BP Neural Network

3.1. Selection of Influencing Factors for Library Energy Consumption Indicators

Existing studies (Tang and Li, 2005) identify four primary categories of factors influencing library energy consumption: (1) building envelope characteristics, (2) digital equipment load, (3) climatic conditions, and (4) operational patterns of HVAC systems. Building upon these findings, this study selects five critical input variables: humidity, occupancy density, solar irradiance, ambient temperature, and operational hours, with library energy consumption as the sole dependent variable.

3.2. Data Preprocessing

The experimental dataset (Sun and Zeng, 2017) comprises 30 data samples collected from a university library in Guangxi. To ensure methodological rigor, these samples are partitioned into a training set (20 samples, ~67% of total data) and an independent testing set (10 samples, ~33%)

through randomized sampling, preserving the statistical distribution characteristics of the original dataset.

The dataset undergoes normalization using the following formula to eliminate dimensional disparities among variables:

$$\widetilde{z} = \frac{2(z_i - z_{min})}{(z_{max} - z_{min})} - 1 \tag{1}$$

The normalization is performed using Equation 1: The raw input z_i is mapped to $\widetilde{z}$ through min-max normalization, where z_{min} and z_{max} represent the extremal values observed in the training data vector.

3.3. Parameter Configuration

For the BP neural network, the architectural configuration is determined based on the dataset characteristics: the input layer is set to 5 neurons, and the output layer to 1 neuron. The number of hidden layer neurons is calculated using the following empirical formula.

To meet the requirements for library energy consumption prediction, the activation functions of the BP neural network were configured as follows: a hyperbolic tangent sigmoid "tansig" function between the input and hidden layers, and a linear transfer function "purelin" between the hidden and output layers. The network was trained using the Levenberg-Marquardt "trainlm" algorithm, with the target mean squared error set to 1×10^{-3} and the maximum number of training epochs fixed at 1,000.

For the GA, the parameter configuration was implemented as follows: a population size of 58, maximum generations of 200, binary encoding with 50 bits per variable, generation gap of 0.90, crossover probability set to 0.75, and mutation probability fixed at 0.01.

3.4. Simulation Results

This study developed a GA-BP neural network-based energy consumption prediction model for libraries using MATLAB 2023a. The model was trained on a training dataset (20 samples), after which the testing dataset (10 samples) was fed into the network to generate prediction outputs. The model's performance was evaluated by comparing the actual outputs with expected outputs, calculating three error metrics: testing sample prediction error (E_{train}), training sample prediction error (E_{test}), and relative error (e_r).

To validate the model's superior performance, comparative analyses were conducted against three benchmark models: Regularized Radial Basis Function (RRBF) Neural Network, Generalized Radial Basis Function (GRBF) Neural Network, and Standard Backpropagation (BP) Neural Network.

All models were implemented on the same dataset under identical computational conditions. The GA-BP model demonstrated enhanced prediction accuracy and convergence stability compared to these baseline approaches. Figure 3 presents the simulation and prediction results of the four neural network models.

The prediction errors of each network model are summarized in Table 1, which quantifies the following key metrics.

As evidenced by the simulation and prediction results of four neural network models in Figure 3, the GA-BP neural network demonstrates significantly superior prediction accuracy compared to the other three neural network models. Quantitative analysis from Table 1 reveals that the GA-BP

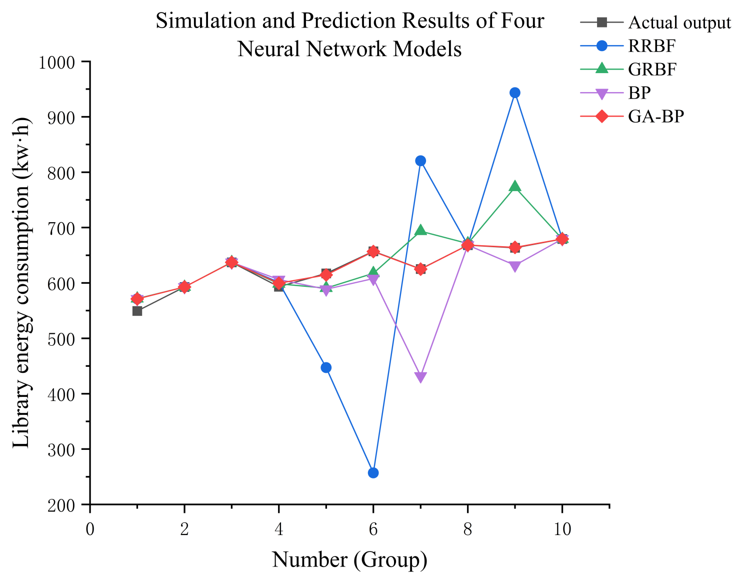

Figure 3: Simulation and Prediction Results of Four Neural Network Models.

Table 1: Prediction Errors of Neural Network Models

Model	GA-BP	BP	RRBF	GRBF
E_{test}	0.17247	1.6293	4.1696	4.1696
E_{train}	0.23723	0.23723	0.23723	0.23922
e_r	0.0046	0.0664	0.1748	0.0443

model achieves a training sample prediction error of 0.23723, a testing sample prediction error of 0.17247, and a relative error of 0.0046, consistently outperforming the benchmark models (GRBF, RRBF, BP) across all metrics. The following conclusions can be drawn regarding each model's performance:

$$GA - BP \gg BP > GRBF \gg RBF \tag{2}$$

In Equation 2, it can be observed that the GA-BP neural network demonstrates superior training capability in library energy consumption prediction tasks, accurately capturing the variation trends of energy usage. In contrast, the standard BP neural network and GRBF neural network exhibited suboptimal accuracy, while the RRBF neural network demonstrated markedly inferior performance.

4. Conclusion

This study developed a GA-BP neural network-based energy consumption prediction model for libraries and validated its superior performance against benchmark models (standard BP, GRBF, RRBF). Subsequent applications can utilize this model to forecast hourly/daily energy demands, thereby identifying temporal consumption patterns and formulating data-driven energy management strategies to support energy conservation and emission reduction initiatives in library operations.

Furthermore, the model's high accuracy (testing error: 0.17247) and robust generalization capability (relative error $< 0.5\%$) enable its extension to other building types, including academic complexes, commercial centers, and residential buildings. This methodology provides a scalable framework for digital twin-enabled building energy management, advancing the construction industry's transition toward intelligent digital transformation and green sustainable development.

References

Y. B. Fan, Y. X. Xiong, X. Li, and et al. Advances in genetic algorithm-based multi-objective optimization for building energy consumption. *Integrated Intelligent Energy*, 46(9):69–85, 2024. doi: 10.3969/j.issn.2097-0706.2024.09.009.

Z. P. Le. Research on energy consumption prediction model and information management system of large-scale buildings based on neural network, 2024.

X. Li. Energy consumption prediction model and energy-saving diagnosis of a university library in xi'an, 2023.

D. E. Rumelhart, G. E. Hinton, and R. J. Williams. Learning representations by back-propagating errors. *Nature*, 323(6088):533–536, 1986. doi: 10.1038/323533a0.

T. Sun and X. L. Zeng. Application of radial basis neural network model in library energy consumption prediction. *Intelligent Computer and Applications*, 7(2):50–52, 2017. doi: CNKI:SUN:DLXZ.0.2017-02-011.

M. Tang and Z. R. Li. Meteorological parameter processing in building energy consumption evaluation. *Wall Materials Innovation and Building Energy Efficiency*, (4):40–41, 2005. doi: CNKI:SUN:ZLJS.0.2003-02-012.

Q. Wang. Energy consumption prediction model and energy-saving strategy for a university library in northwest china, 2021.

Q. Wang and J. Q. Yu. University library energy consumption prediction based on similar-day lm neural network. *Journal of Xi'an University of Architecture & Technology (Natural Science Edition)*, 54(3):459–465, 2022. doi: 10.15986/j.1006-7930.2022.03.017.

Z. J. Yang and S. L. Lu. Prediction of building energy consumption based on graph neural network. *Journal of Tianjin Chengjian University*, 30(3):220–227, 2024. doi: 10.19479/j.2095-719x.2403220.