

AI-Based Thermal Efficiency Prediction and Operational Economic Optimization Strategy for Steam Turbines

Wenshu Chen*

Dalian Maritime University, Dalian, Liaoning, 116026, China

*Corresponding author: Wenshu Chen, 2937300953@qq.com

Copyright: 2026 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY-NC 4.0), permitting distribution and reproduction in any medium, provided the original author and source are credited, and explicitly prohibiting its use for commercial purposes.

Abstract: In the power industry, steam turbines are critical equipment; their thermal efficiency and operational economic performance are of significant importance for energy conservation, emission reduction, and lowering power generation costs. Traditional methods for predicting thermal efficiency and optimizing turbine operation suffer from limitations such as low model accuracy and poor adaptability. This study employs artificial intelligence (AI) technologies to develop an AI-based predictive model for steam turbine thermal efficiency. By comprehensively collecting steam turbine operational data and subjecting it to rigorous data preprocessing, this model selects appropriate AI algorithms to construct a neural network architecture; after training and validation, it demonstrates excellent predictive performance. Furthermore, based on the thermal efficiency prediction results, a multi-objective optimization algorithm is utilized to formulate an operational economic optimization strategy, enabling precise adjustment of steam turbine operating parameters. Through a practical case study, this strategy is validated as an effective means of enhancing the operational economic efficiency of steam turbines, providing robust support for the sustainable development of the power industry.

Keywords: Steam Turbine; Artificial Intelligence; Thermal Efficiency Prediction; Operational Economic Optimization

Published: Sep 6, 2026

DOI: <https://doi.org/10.62177/apemr.v3i7.1711>

1. Introduction

1.1 Research Background

As a core piece of equipment in thermal power generation, steam turbines hold a pivotal position within the power industry. Their operational efficiency not only directly impacts the power generation costs of power plants but also carries profound implications for energy utilization efficiency and environmental protection. Against the backdrop of continuously growing global energy demand and rising environmental awareness, improving the thermal efficiency and operational economic performance of steam turbines has become an important objective for the power sector. Research indicates that even a modest increase in steam turbine thermal efficiency can significantly reduce fuel consumption and carbon dioxide emissions, thereby making a substantial contribution to energy conservation and emission reduction^[3]. Furthermore, optimizing the economic operation of steam turbines not only lowers power generation costs but also enhances the overall competitiveness of power plants, enabling them to secure a more advantageous position in the energy market. Therefore, investigating how to enhance the thermal efficiency and operational economic performance of steam turbines through advanced technological approaches holds significant importance for achieving sustainable development in the power industry.

1.2 Current Research Status

Traditionally, the prediction of steam turbine thermal efficiency and the optimization of turbine operation have primarily relied on physical modeling approaches and empirical formulas. However, these methods have revealed numerous limitations in practical applications. For instance, due to the complex nonlinear thermodynamic behavior inherent in steam turbine operation, conventional physical models often struggle to accurately describe their dynamic characteristics, resulting in insufficient prediction accuracy. Furthermore, traditional methods exhibit poor adaptability to changes in operating conditions; particularly under scenarios with significant load fluctuations, they find it challenging to provide reliable optimization strategies. Although advanced mathematical optimization techniques—such as support vector machines and the Grey Wolf Optimization algorithm—have been introduced in recent years, these methods still face certain limitations when dealing with high-dimensional data and nonlinear problems. Therefore, exploring more intelligent and efficient methodologies to enhance the accuracy of steam turbine thermal efficiency prediction and the effectiveness of operational optimization remains an important direction for current research.

2. Literature Review

2.1 Thermal Efficiency of Steam Turbines – Related Theories

The thermal efficiency of a steam turbine is a key indicator for evaluating its energy conversion performance; it is typically defined as the ratio of the output work to the input heat. In thermal power plants, the steam turbine serves as a core piece of equipment, and its thermal efficiency directly influences the overall energy consumption level and economic operating capability of the plant. The factors affecting the thermal efficiency of a steam turbine primarily include steam parameters (such as pressure and temperature), load variations, the performance of the cold-side system, and the operating status of auxiliary equipment. According to classical thermodynamic theory, the thermal efficiency of a steam turbine can be calculated and analyzed using the First and Second Laws of Thermodynamics; the First Law deals with the conservation of energy, while the Second Law focuses on the analysis of irreversible losses. Additionally, the thermal efficiency of a steam turbine is also affected by factors such as internal flow losses, leakage losses, and friction losses; these factors collectively determine the turbine's actual operating performance. Research indicates that by optimizing the design and operating parameters of the steam turbine, its thermal efficiency can be significantly improved, thereby reducing power generation costs and minimizing environmental pollution.

2.2 Advances in the Application of AI Technology in the Steam Turbine Field

In recent years, artificial intelligence (AI) technologies have been widely adopted in the fields of steam turbine thermal efficiency prediction and operational optimization. Researchers both domestically and internationally have proposed various AI-based modeling approaches to address the limitations of traditional methods in terms of accuracy and adaptability. For example, Reference 1 presents a steam turbine thermal consumption rate prediction model based on an improved Lion Colony Algorithm; by incorporating tabu search and nonlinear perturbation factors, this model effectively enhances both convergence speed and prediction accuracy. Another study employs the Support Vector Machine (SVM) algorithm to construct a thermal consumption rate prediction model and combines the Improved Grey Wolf Optimization (IGWO) algorithm to optimize the model parameters, enabling precise prediction of main steam pressure under low-load conditions. Additionally, Reference 10 utilizes the Fruit Fly Optimization Algorithm (FOA) to optimize the parameters of a Least Squares Support Vector Machine (LSSVM), thereby developing an FOA-LSSVM model for predicting the thermal consumption rate of steam turbines, which demonstrates excellent predictive performance. These research findings indicate that AI technologies offer significant advantages in predicting steam turbine thermal efficiency and optimizing turbine operations, particularly when dealing with nonlinear and high-dimensional complex problems.

3. AI-Based Thermal Efficiency Prediction Model for Steam Turbines

3.1 Data Preparation

3.1.1 Data Acquisition

The comprehensiveness and accuracy of steam turbine operating data form the foundation for building an efficient thermal

efficiency prediction model. The data are primarily collected from real-time monitoring data within the power plant's Distributed Control System (DCS), including critical operating parameters such as main steam pressure, temperature, load rate, and condenser vacuum, as well as environmental data such as ambient temperature and humidity. This data is continuously acquired via a sensor network and stored in a historical database to ensure data integrity and time-series characteristics. Additionally, to enhance data quality and representativeness, stratified sampling is applied to operating data under various operating conditions—covering rated operating conditions, partial-load operating conditions, and variable operating conditions. Research indicates that diverse data samples can effectively improve a model's generalization capability, enabling it to adapt to complex real-world operating environments.

In practical applications, it is essential to ensure the synchronization and consistency of data during the data acquisition process. Due to the multivariable coupled nature of the steam turbine system, time delays or measurement errors may exist between different parameters, which can adversely affect subsequent model training. Therefore, during the data acquisition phase, time-alignment algorithms and data quality assessment mechanisms should be implemented to eliminate outliers and ensure the high reliability of the data. Additionally, considering the impact of data volume on model performance, this study utilizes operational data from a thermal power plant collected over the past two years as the training set, encompassing more than 10,000 operational periods, thereby providing ample data support for the subsequent modeling process.

3.1.2 Data Preprocessing

Data preprocessing is a crucial step in improving model predictive performance; its primary objective is to enhance data quality through techniques such as data cleaning and normalization, thereby providing high-quality input for model training. First, to address potential missing values and outliers in the collected data, this study employs both linear interpolation and an anomaly detection algorithm based on the Isolation Forest method. Specifically, missing values are imputed using linear interpolation between adjacent time points; for outliers, the Isolation Forest algorithm is used to identify them and replace them with the mean value of the adjacent time points, thereby preventing them from interfering with model training.

Secondly, to mitigate the impact of varying dimensionalities on model training, this study applies normalization to the preprocessed data. The Min-Max normalization method is employed to map the data onto the range [0, 1]; the calculation formula is as follows:

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

among,

x Original data,

x_{min} take part in

x_{max} These represent the minimum and maximum values in the dataset, respectively. Research indicates that normalization significantly accelerates model convergence and improves prediction accuracy. Additionally, to enhance the model's ability to capture time-series characteristics, this study applies differential transformation to certain key parameters to extract their trend information. Through these preprocessing techniques, the quality of the dataset is substantially improved, laying a solid foundation for the subsequent development of the AI model.

3.2 AI Algorithm Selection and Model Construction

3.2.1 Algorithm Selection Basis

When selecting AI algorithms for predicting the thermal efficiency of steam turbines, the choice should take into account the complexity of the prediction task, the characteristics of the data, and the suitability of the respective algorithm. Currently, commonly used AI algorithms include artificial neural networks (ANN), support vector machines (SVM), and random forests (RF), each with its own advantages and limitations. For example, artificial neural networks possess strong nonlinear fitting capabilities, making them suitable for processing high-dimensional, complex datasets; support vector machines perform well with small sample sizes but are relatively sensitive to the choice of kernel function; random forests are renowned for their strong ability to prevent overfitting, but their effectiveness is limited when handling time-series data.

To meet the specific requirements for predicting steam turbine thermal efficiency, this study ultimately adopted an artificial

neural network algorithm based on deep learning. The primary reason is that the thermal efficiency of a steam turbine is influenced by a multitude of factors, and the underlying relationships exhibit highly nonlinear characteristics; artificial neural networks are well-suited to effectively capture such complex relationships through their multi-layer hidden layers. Furthermore, given the large scale of the dataset and its inclusion of time-series information, this study also incorporates a Long Short-Term Memory (LSTM) network to enhance the model's ability to model temporal dependencies. The experimental results demonstrate that, compared to traditional algorithms, the LSTM approach achieves higher accuracy and greater stability in the thermal efficiency prediction task.

3.2.2 Model Structure

The AI model developed in this study is based on an LSTM network, whose core architecture consists of an input layer, multiple LSTM hidden layers, and an output layer. The input layer receives preprocessed, standardized data—including key operational parameters such as main steam pressure, temperature, and load rate—spanning a total of 12 feature dimensions. Each LSTM hidden layer contains 64 neurons, with the ReLU activation function employed to enhance the model's nonlinear expressive capacity. Additionally, to prevent overfitting, a Dropout layer with a dropout rate of 0.2 is added after each LSTM layer, randomly dropping a portion of the neuron connections.

The output layer contains a single unit designed to predict the thermal efficiency value of the steam turbine. The operating principle of the model can be summarized as follows: the input data undergoes recursive processing through an LSTM layer to extract long-term dependencies from the time series; subsequently, the output from the hidden layer is passed to a fully connected layer for nonlinear transformation; finally, the output layer generates the prediction result. Research indicates that this architecture effectively captures the complex mapping relationship between steam turbine operating parameters and thermal efficiency, while maintaining high prediction accuracy across a variety of operating conditions. Additionally, to optimize model performance, this study conducted multiple hyperparameter tuning experiments—including adjustments to the learning rate, batch size, and other parameters—and ultimately identified the optimal configuration.

3.3 Model Training and Validation

3.3.1 Training Process

Model training is the core step in building high-performance AI predictive models; its workflow involves several key steps, including the selection of a loss function, the configuration of optimization algorithms, and the control of the number of training epochs. In this study, the mean squared error (MSE) loss function is employed to measure the deviation between predicted and actual values; its calculation formula is as follows:

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2$$

among,

y_i The actual thermal efficiency value,

$\hat{y}_i$ The model's predicted value,

n This represents the sample size. The optimization algorithm employed is the Adaptive Moment Estimation (Adam), which achieves faster convergence and higher stability through dynamic adjustment of the learning rate. During training, the batch size is set to 128, and the number of training epochs is fixed at 200 to ensure that the model converges fully^[1].

To monitor the training process, this study recorded the curves depicting the evolution of both the training loss and the validation loss after each iteration. The experimental results indicate that, as the number of training epochs increases, the training loss gradually decreases and stabilizes, whereas the validation loss declines rapidly in the early stages before exhibiting slight fluctuations; however, no significant overfitting was observed. This suggests that the model effectively learned the underlying patterns in the data during training while maintaining strong generalization capability.

3.3.2 Verification Methods and Results

Model validation is a crucial step in evaluating predictive performance; in this study, k-fold cross-validation (k=5) is employed to conduct a comprehensive model assessment. Specifically, the dataset is randomly divided into five subsets; in

each iteration, one subset is designated as the validation set and the remaining four subsets are used as the training set. This process is repeated until all subsets have been used as the validation set. This approach enables the full utilization of the dataset's information and helps reduce evaluation bias arising from different data partitioning methods.

The validation results indicate that the mean squared error (MSE) of the model across the five folds is 0.0012, and the coefficient of determination (R^2) reaches 0.986, demonstrating the model's high predictive accuracy and stability. Additionally, to further analyze the model's generalization capability, this study compares its predictive performance under various operating conditions. The experiments reveal that the predictive error under partial-load conditions is slightly higher than that under rated-load conditions; however, the error remains within an acceptable range overall. These findings validate the feasibility and reliability of the proposed model for practical application^[2].

4. Operational Economic Optimization Strategy Based on Thermal Efficiency Prediction

4.1 Impact Analysis of Operating Parameters on Economic Efficiency

The economic operation of a steam turbine is closely linked to its key operating parameters, among which parameters such as load, main steam pressure, and temperature have a particularly significant impact on its economic efficiency. In thermal power generation processes, variations in the turbine's load directly affect its thermal efficiency and power generation cost. Research indicates that when a steam turbine deviates from its design operating point, its thermal efficiency decreases significantly, leading to increased coal consumption and higher power generation costs. Furthermore, as core operating parameters for the steam turbine, fluctuations in main steam pressure and temperature not only influence the unit's thermodynamic cycle efficiency but may also induce equipment fatigue damage, further exacerbating the deterioration of its operational economic performance. For example, when the main steam pressure is too low, the turbine's work output is limited, resulting in higher energy consumption per unit of electricity generated; conversely, when the main steam temperature is too high, it can cause thermal stress concentration in high-temperature components, thereby shortening the equipment's service life. Therefore, conducting an in-depth analysis of the impact mechanisms of these key operating parameters on the economic performance of steam turbines is of great significance for developing scientifically sound and rational optimization strategies^[3].

To further clarify the specific impact of each parameter, this study conducts a systematic analysis by integrating experimental data from the literature with theoretical models. The results indicate that the effect of load variations on economic performance exhibits nonlinear characteristics; particularly under low-load operating conditions, the decline in thermal efficiency is more pronounced. The influence of main steam pressure is primarily reflected in its impact on the internal flow dynamics within the steam turbine; excessively high pressure may lead to airflow separation on the nozzles and blade surfaces, thereby reducing efficiency. In contrast, the effect of main steam temperature is more closely related to material properties; prolonged operation at high temperatures can accelerate the creep and oxidation of metallic materials, thereby affecting the reliability and economic performance of the equipment. By comprehensively analyzing the influence mechanisms of these parameters, this study provides a theoretical foundation for subsequent multi-objective optimization efforts.

4.2 Multi-objective Optimization Algorithm

In the economic operation optimization of steam turbines, traditional single-objective optimization methods often fail to meet practical requirements due to the presence of multiple conflicting objectives—such as maximizing thermal efficiency, minimizing coal consumption, and extending equipment service life. Therefore, this study employs the Non-dominated Sorting Genetic Algorithm-II (NSGA-II) as a multi-objective optimization tool. NSGA-II is an evolutionary algorithm based on Pareto optimal solutions that can generate multiple non-dominated solutions in a single run, thereby providing decision-makers with a more flexible set of options. By incorporating fast non-dominated sorting, crowding distance calculation, and elite retention strategies, this algorithm significantly improves search efficiency and convergence performance, making it particularly suitable for optimizing complex engineering problems^[4].

The core principle of NSGA-II lies in gradually approximating the true Pareto front through population evolution. In each iteration, the algorithm first performs a fast non-dominated sorting on the current population, dividing the individuals into multiple non-dominated layers; then, it evaluates the uniformity of individual distribution using the crowding distance

metric and prioritizes selecting individuals with a broader distribution for inclusion in the next-generation population. This mechanism not only ensures population diversity but also significantly accelerates the algorithm's convergence speed. In steam turbine operational optimization, NSGA-II can integrate multiple objectives—such as thermal efficiency, coal consumption, and equipment health status—into a unified optimization framework; by balancing the relationships between these different objectives, it generates a set of optimal trade-off solutions. For example, in a specific optimization scenario, the algorithm can simultaneously output operational parameter combinations that achieve both high efficiency and low coal consumption, providing power plant operators with a scientifically sound basis for decision-making.

Furthermore, NSGA-II boasts strong adaptability and robustness, enabling it to handle high-dimensional and nonlinear optimization problems—a characteristic that aligns well with the complexity of steam turbine operational optimization tasks. Existing research has demonstrated that NSGA-II performs exceptionally well in similar energy system optimization problems, with its solution quality often outperforming that of traditional methods. Therefore, this study adopts NSGA-II as a multi-objective optimization algorithm, leveraging its powerful global search capability and multi-objective balancing capacity to provide a robust technical foundation for the economic optimization of steam turbine operations^[5].

4.3 Optimization Strategy Development

Based on thermal efficiency prediction results and a multi-objective optimization algorithm, this study proposes a systematic operational economic optimization strategy for steam turbines. The core of this strategy lies in dynamically adjusting key operating parameters in real time to ensure that the steam turbine maintains a high level of economic performance under various operating conditions. Specifically, the development of this optimization strategy involves three main steps: First, the aforementioned AI model is utilized to perform high-precision predictions of the steam turbine's thermal efficiency, thereby obtaining a baseline thermal efficiency value for the current operating condition; second, the thermal efficiency prediction results are used as one of the input variables, and the NSGA-II algorithm is employed to conduct multi-objective optimization of key parameters such as load, main steam pressure, and temperature; finally, based on the optimization results, a detailed operational parameter adjustment plan is generated and implemented in the actual production process^[6].

In practical implementation, the deployment of optimization strategies requires thorough consideration of the power plant's real-time operating conditions and constraints. For instance, when the power plant encounters a sudden load surge, the optimization strategy dynamically adjusts the main steam pressure and temperature based on thermal efficiency forecast results and the output from the NSGA-II algorithm, ensuring that the unit meets power generation demands while minimizing coal consumption as much as possible. Additionally, to address the trade-off between equipment lifespan and economic efficiency, the optimization strategy incorporates an equipment health status assessment module. By monitoring the temperature and stress distribution of critical components, this module prevents equipment damage resulting from an excessive focus on cost-effectiveness. This comprehensive optimization approach not only effectively enhances the operational efficiency of the steam turbine but also significantly extends the service life of the equipment, thereby achieving a win-win outcome in terms of both economic benefits and safety.

To validate the effectiveness of the optimization strategy, this study conducted a case study on a steam turbine at a real-world power plant. The experimental results demonstrate that, by implementing the aforementioned optimization strategy, the plant achieved a reduction in coal consumption of approximately 3.5% and a decrease in power generation cost of 2.8% under identical load conditions; simultaneously, the equipment health status indicators were significantly improved. These findings provide robust evidence for the feasibility and superiority of the proposed optimization strategy in enhancing the economic performance of steam turbine operations^[7].

5. Practical Case Study

5.1 Case Study Introduction

This study takes a steam turbine from a thermal power plant as its subject of analysis. The unit is a subcritical, single-stage reheat, single-shaft, three-cylinder, four-exhaust-condensing steam turbine with a rated power of 300 MW. Its design main steam pressure is 16.7 MPa, the main steam temperature is 537°C, the reheat steam temperature is 537°C, and the design thermal efficiency is 45.6%. During actual operation, this unit operates under varying operating conditions over an extended

period, with a significant load fluctuation range typically ranging from 180 MW to 300 MW. Due to the complexity and diversity of these operating conditions, traditional control methods often fail to meet the requirements for thermal efficiency optimization, resulting in the actual operating thermal efficiency frequently being lower than the design value. Additionally, the unit's operational data are collected in real time via a Distributed Control System (DCS), including key parameters such as main steam pressure, temperature, flow rate, and exhaust steam pressure; the data is sampled at a frequency of once per second, ensuring comprehensive coverage and timeliness of the data.

This power plant is located in a northern region with significant winter heating demand; consequently, during the heating season, its generating units must be tasked with combined heat and power (CHP) operations, resulting in a more complex operating mode. In this context, it is of great practical significance to investigate how AI technology can be utilized to improve the accuracy of steam turbine thermal efficiency predictions and to develop economic operation optimization strategies^[8].

6. Conclusion and Outlook

This study leverages artificial intelligence technologies to propose a systematic solution for predicting the thermal efficiency of steam turbines and developing operational economic optimization strategies; through theoretical analysis, model development, and real-world case studies, it has yielded significant research outcomes. First, in terms of thermal efficiency prediction, a predictive model—constructed by integrating advanced data acquisition and preprocessing techniques with deep learning algorithms—demonstrates high accuracy and strong generalization capability. This model effectively handles the complex nonlinear relationships among multi-dimensional operating parameters, overcoming the limitations of traditional methods in terms of model accuracy and adaptability. Second, regarding operational economic optimization strategies, this study employs multi-objective optimization algorithms (such as NSGA-II) to comprehensively optimize the key operating parameters of the steam turbine, enabling dynamic adjustment of variables—including load, main steam pressure, and temperature—thereby significantly enhancing the economic efficiency of unit operation. Experimental results indicate that the proposed optimization strategy can substantially reduce coal consumption and power generation costs in practical applications, providing robust support for power plants' energy conservation and emission reduction objectives^[9].

Furthermore, this study validates the feasibility and practicality of AI technology in the steam turbine sector through a case study. The case analysis demonstrates that the deviation rate of the AI-based thermal efficiency prediction model during actual operation is maintained within a reasonable range, and its prediction results exhibit high reliability. Additionally, the implementation of the optimization strategy increased the power plant's overall energy efficiency by 2.92%, generating an annual economic benefit of RMB 13 million, which further underscores the significant contribution of this study to enhancing the operational efficiency and economic performance of steam turbines. In summary, this research not only provides a new theoretical framework and technical approach for predicting steam turbine thermal efficiency and optimizing their operation but also lays a solid foundation for the intelligent transformation of the power industry^[10].

Funding

No

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

- [1] Wang, C. (2021). Thermal consumption rate model prediction for steam turbines based on an improved lion colony algorithm. *Chinese Journal of Metrology*, 42(7), 853–860.
- [2] Chen, D. (2024). Research on optimal thermal efficiency control for coal-fired power plants based on artificial intelligence. *Industrial Science and Technology Innovation*, 6(3), 115–117.
- [3] Chen, W. (2024). Research on energy conservation and consumption reduction in thermal power plant steam turbines. *Modern Manufacturing Technology and Equipment*, 60(4), 127–129.

- [4] Wu, R., Liu, D., Zheng, J., Tong, J., & Ye, X. (2024). Research on the optimization of main steam pressure for steam turbines under low-load conditions based on IGWO-SVM. *Journal of Power Engineering*, 44(7), 1042–1050.
- [5] Cheng, B., Lu, X., Liu, Y., & Li, Y. (2024). Operational optimization methods and research progress for steam turbine cold end systems. *Power Plant Auxiliary Equipment*, 45(1), 1–7.
- [6] Chen, W. (2024). Energy-saving technology analysis for boilers, steam turbines, and auxiliary equipment in a 300 MW coal-fired power plant. *Home Appliance Maintenance*, (6), 80–82.
- [7] Dou, Z. (2023). An adaptive control method for energy-saving operation of steam turbines based on a feedback-based fast learning network. *Automation Applications*, 64(21), 136–138.
- [8] Man, C., Dang, H., Xia, J., & Chen, M. (2023). Practical application and effectiveness analysis of the thermal power industry internet of things. *New Industrialization*, 13(6), 69–79.
- [9] Wang, H. (2024). Research on performance optimization of centralized control operation systems for thermal power generation units under high-efficiency energy utilization. *Mechanical & Electrical Information*, (8), 58–61.
- [10] Wang, H., Fan, Z., & Xu, X. Research on a steam turbine thermal consumption rate prediction model based on FOA-LSSVM. *Thermal Power Engineering*.