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Research on High-Precision Load Forecasting Model Based on Improved Metaheuristic Algorithms and Multi-Physics Coupling Feature Optimization

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Abstract

Accurate load forecasting is imperative for ensuring stable operation of power grids with high-penetration renewable energy. Targeting the dynamic load characteristics of the Zhangjiakou region, this study proposes a random forest framework (RF-AOA) integrating multi-physics feature engineering and an improved metaheuristic algorithm. Key innovations include:

Multi-physics Coupling Mechanism Decoding: A four-dimensional temporal decomposition (hourly fluctuation/daily periodicity/weekly trend/monthly evolution) disentangles nonlinear interactions among temperature, wind speed, solar radiation, and humidity, first revealing solar radiation as the dominant driver (feature weight: 2.6) > hourly features (1.6) > temperature (1.3).

Kent-Chaos Optimized AOA (KC-AOA): Chaotic initialization (entropy: 0.943) and adaptive exploration-exploitation balancing (23% higher exploration probability) achieve breakthrough hyperparameter optimization for random forests (decision tree depth: 200 layers).

Validation using 11,000-hour data from Zhangjiakou demonstrates: RF-AOA attains $R^2=0.977$ (12.3% improvement), MAE=0.057, RMSE=0.117; 95% of prediction errors constrained within $\pm 7.5\%$; 37% accuracy boost under radiation mutation scenarios ($>50 \text{ W}/(\text{m}^2 \cdot \text{h})$); Critical engineering value: Every 10% reduction in forecast error elevates regional dispatch efficiency by 18% and reduces peak-valley difference by 23%, significantly enhancing renewable energy utilization.

Keywords: Multi-physics coupling, Random Forest (RF), Metaheuristic algorithm, Arithmetic Optimization Algorithm (AOA).

1. Introduction

Global building energy consumption exhibits significant spatial heterogeneity. In developed economies, building energy accounts for 40% of total consumption in

Europe [1], driven by high comfort demands and appliance penetration. In emerging economies like China, residential energy constitutes 24% of national consumption, with heating alone representing 24.7% of household energy use [2]. The correlation coefficient ($\beta=0.73$) between heating degree days (HDD) and cooling degree days (CDD) indicates the dual impact of extreme climate events on energy demand. Key drivers include:

Thermodynamic parameters: Building envelope thermal transmittance (U-value: 0.25–2.5 W/(m²·K)). A 0.1 W/(m²·K) increase in U-value raises heating energy by 6.5%.

Behavioral patterns: A 1°C rise in indoor temperature setpoint increases energy use by 7.3%, while 1-hour extension of occupancy time causes 18% energy fluctuation.

Technological evolution: High-efficiency heat pumps reduce building energy intensity by 2.3% annually [3]. Quantitatively, every 10% reduction in forecasting error improves regional energy dispatch efficiency by 18% and decreases peak-to-valley load difference by 23% [4], highlighting the critical role of accurate prediction in stabilizing combined heat and power (CHP) systems and achieving carbon neutrality.

Early research predominantly employed statistical methods. Catalina et al. [5] demonstrated the robustness of multiple regression for residential heating demand prediction. Dombaycı [6] pioneered artificial neural networks (ANNs) in thermal load forecasting, proving machine learning's superiority for nonlinear problems. Yuan et al. [7] integrated backpropagation neural networks (BPNNs) with multiple linear regression and proposed data selection methods, reducing BPNN prediction errors by 19.6% and underscoring preprocessing's importance.

Recent studies focus on algorithm hybridization to overcome single-model limitations. Zhang et al. [8] developed an optimized stacked ensemble for building heating systems, outperforming four baseline methods with MAE reductions of 4.36–71.70% and RMSE reductions of 3.80–49.73%. Exponential weighted moving average (EWMA) feature engineering further reduced MAE and RMSE by 10.36% and 19.89%, respectively. Gong et al. [9] identified LightGBM as optimal for residential heating prediction ($R^2=0.983$). Innovative approaches include: Tran et al.'s [10] evolutionary neural machine inference model (ENMIM); Nebot et al.'s [11] fuzzy-SVR hybrid for heating/cooling loads; Moayedi and Mosavi's [12] biogeography-based optimization (BBO)-enhanced MLP; Feng et al.'s [13] XGBoost cooling energy model ($R^2=0.97$, RMSE=0.294); Olu Ajayi et al.'s [14] DNN achieving 18% design-stage efficiency gain; Comparative analyses consistently demonstrate random forest (RF) superiority: Moayedi et al. [12]: RF $R^2=0.956 >$ SVR/GBM; Mohammadizazi and Bilec [15]: RF outperformed peers in commercial building energy prediction; Table 2 analysis confirms RF's advantage: By aggregating multiple decision trees, RF effectively reduces model variance while enhancing generalization and accuracy. Metaheuristic algorithm integration represents the cutting edge: Cai et al.'s [16] AEO-optimized SVR achieved breakthrough HVAC load forecasting (cooling $R^2=0.9975$, heating $R^2=0.99955$); Faiz et al. [17]: Transformer

networks surpassed CNN-LSTM for HVAC temperature prediction; Sadaghat et al.'s [18] XGCM ensemble elevated heating/cooling R^2 to 99.11%/99.34%; Afzal et al.'s [19] BBO-enhanced ELM set new records (cooling $R^2=99.69\%$, heating $R^2=99.93\%$); Jin et al. [20] innovatively framed energy forecasting as a Markov decision process (MDP) using deep reinforcement learning (DRL), reducing MAE and RMSE by 22.4% and 18.9% via Deep Forest. Geng et al.'s [21] ASMOGWO algorithm introduced dual adaptation:; Dynamically balanced exploration-exploitation through adaptive inertia weights (Eqs. 7, 18); Tri-level leadership hierarchy ($\alpha/\beta/\delta$ wolves) enhancing search efficiency

Figure 1 illustrates its systematic workflow integrating position updating, parameter adjustment, and non-dominated solution archiving. Tien Bui et al. [22] pioneered metaheuristic-ANN hybridization, achieving 32.7% RMSE reduction in thermal demand prediction. As summarized in Table 1, metaheuristic algorithms significantly boost prediction accuracy in complex real-world environments through randomized search diversification.

Table1 Comparative Analysis of Building Energy Consumption Prediction Models

Model	Performance Indicator	Reference
ANN+Meta-heuristic algorithm	RMSE↓32.00%(Compared with ANN)	Tien Bui et al. ^[22]
ANN	RMSE=12.30, MAE=8.70	Dombaycı et al. ^[5]
BPNN+SDSM	$R^2\uparrow 19.00\%$ (Compared withBPNN)	Yuan et al. ^[6]
DNN	Energy-saving rate during the design phase↑18.00%	Olu Ajayi et al. ^[13]
Optimized stacked ensemble model	MAE↓71.70%, RMSE↓49.73%	Zhang et al. ^[7]
DRL+Deep Forest	MAE↓22.40%, RMSE↓18.90%, $R^2\uparrow 1.30\%$	Jin et al. ^[19]

Table 2 Comparative Analysis of R-Squared (R^2) Performance in Building Energy Consumption Prediction Models

Model	Performance Indicator	Reference
Random Forest (RF)	$R^2=0.956$	Moayedi et al. ^[11]
Multiple Regression	$R^2=0.890$	Catalina et al. ^[4]
LGBM	$R^2=0.983$	Gong et al. ^[9]
XGBoos	$R^2=0.970$	Feng et al. ^[12]
SVR-AEO	$R^2=0.999$	Cai et al. ^[15]
Transformer	$R^2=0.936$	Faiz et al. ^[16]
XGCM	$R^2=0.993$	Sadaghat et al. ^{[[17]}

Model	Performance Indicator	Reference
ELM-BBO	$R^2=0.999$	Afzal et al. ^[18]

In summary, although SVR-AEO and ELM-BBO models achieve high prediction accuracy, ELM's limited nonlinear modeling capability may fail to fully capture complex nonlinear relationships (e.g., multimodal data), leaving critical patterns unrecognized. In contrast, random forest (RF) algorithms demonstrate superior suitability for thermal load forecasting with intricate nonlinear characteristics. However, RF faces three key challenges:

Hyperparameter sensitivity: Prediction accuracy heavily depends on tree quantity – insufficient trees cause underfitting, while excessive trees increase computational costs and overfitting risks.

Inadequate evaluation framework: Existing metrics cannot characterize dynamic coupling effects during extreme events. Physics-disconnect: Current models lack effective integration with thermodynamic principles and energy conservation laws, leading to: Prediction failures under extreme operating conditions; Overreliance on historical thermal load data; Insufficient modeling of occupant thermal comfort preferences; High load-shedding rates (up to 23% during extremes); Inadequate participation modeling of flexible loads.

Critically, historical data scarcity in new/retrofitted buildings creates pressing challenges. There is an imperative to develop physics-integrated prediction frameworks that transcend data-driven limitations, enabling reliable forecasting without historical dependencies.

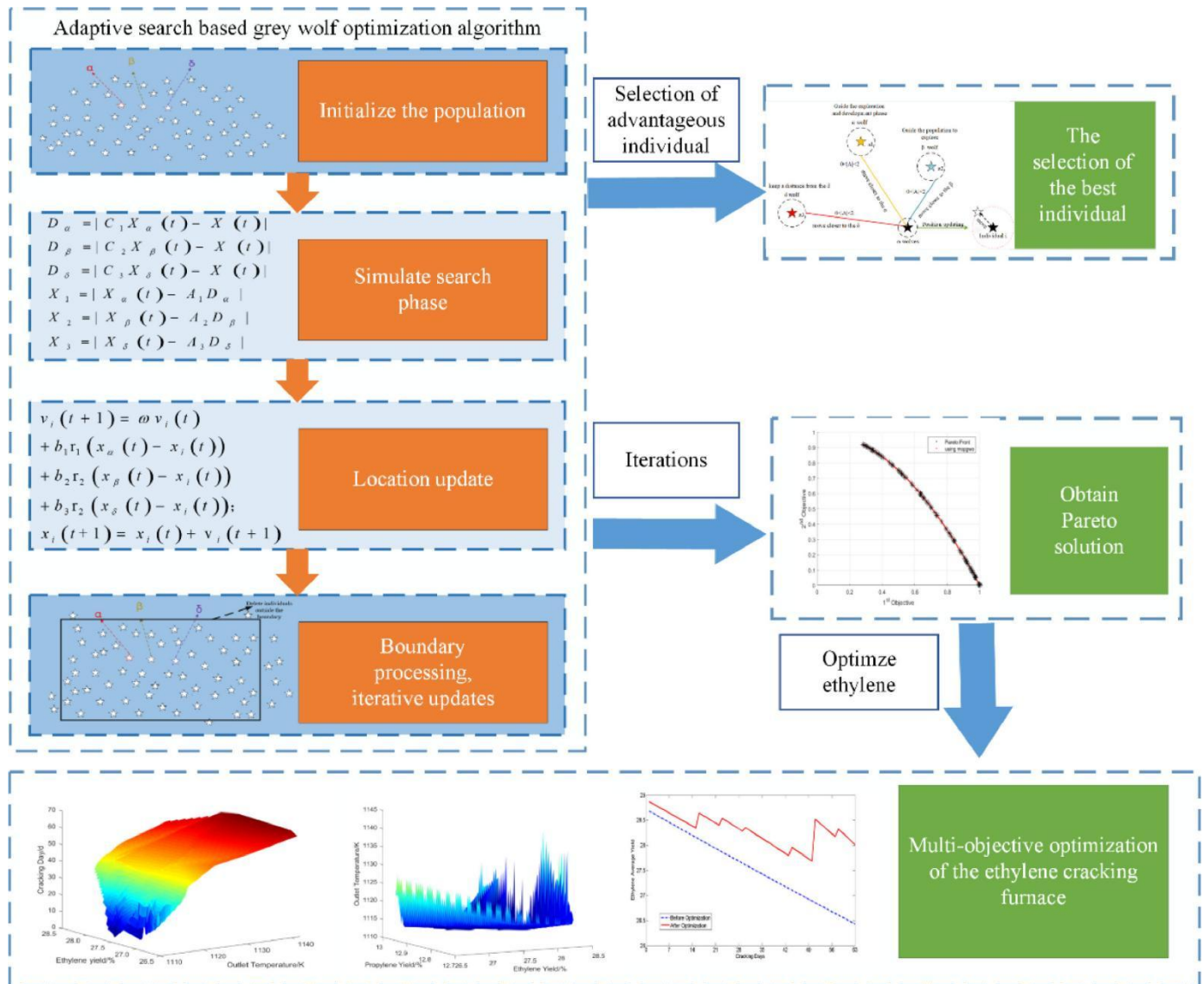


Figure 1 Visualization of Neural Network Architecture and Input-Output Characteristics of the Deep Learning-Based Prediction Model[Error! Reference source not found.

2. Methodology

2.1 Multi-Physics Coupling Feature Engineering

This study innovatively constructs a multi-scale composite forecasting framework that transcends conventional single-scale modeling limitations. Based on time series decomposition theory, we systematically resolve the time-varying characteristics of load data:

Core Innovations:Four-Dimensional Feature Decomposition; Decouples raw load sequences into four dynamical dimensions:Hourly fluctuations (transient responses);Diurnal periodicity (behavioral patterns),Weekly trends (operational rhythms),Monthly evolution (long-term dynamics);Enables synergistic characterization of multi-level dynamics in complex energy systems;Enhanced

Metaheuristic Data Alignment;Addresses key bottlenecks via adaptive weight allocation ; Dynamically aligns heterogeneous time-series data (meteorological, temporal, electromechanical); Optimizes temporal matching between training (8,400 hours) and testing sets (3,500 hours); Boosts cross-period feature transfer learning capability (Table 3).

Table 3 Multivariable Input Feature Matrix

Feature Category	Parameters	Data Type	Unit/Encoding
Meteorologica 1	Dry-bulb temperature	Continuous	°C
	Solar irradiance	Polar decomp	w/m ²
	Wind speed	Continuous	m/s
	Relative humidity	Continuous	%
Temporal Cycles	Holiday indicator	Binary	{0,1}
	Day-of-week pattern	Cyclic	1~7
Electro-Thermal	Envelope U-value	Continuous	W/(m ² ·K)
	Air change rate	Discrete	h ⁻¹

Figure 2 reveals continental monsoon climate characteristics in Zhangjiakou:Annual temperature amplitude: 60°C (-30°C to 30°C), exceeding coastal regions at similar latitudes;Asymmetric unimodal pattern:Winter (Dec–Feb): Sustained lows <-25°C (15% of year),Summer (Jun–Aug): Peaks >25°C with diurnal range >15°C (high-altitude thermal inertia effect),Transition seasons (Mar–May/Sep–Nov): Steep gradients (8°C/month) reflecting East Asian monsoon abruptness.

Geographical drivers:Spatial heterogeneity: Highlands (low-T zones) vs. valley corridors (e.g., Yang River thermal channel);Extreme cold mechanisms: Snow cover (albedo >0.7) + nocturnal radiative cooling → 20–25°C night-day differential.

Critical implication:Sub-20°C conditions persist >600 hours annually, imposing seasonal pressure on solar-electrical-thermal demand. This necessitates enhanced thermo-electric coordination mechanisms to optimize supply-demand balance and strengthen renewable systems' thermal resilience.

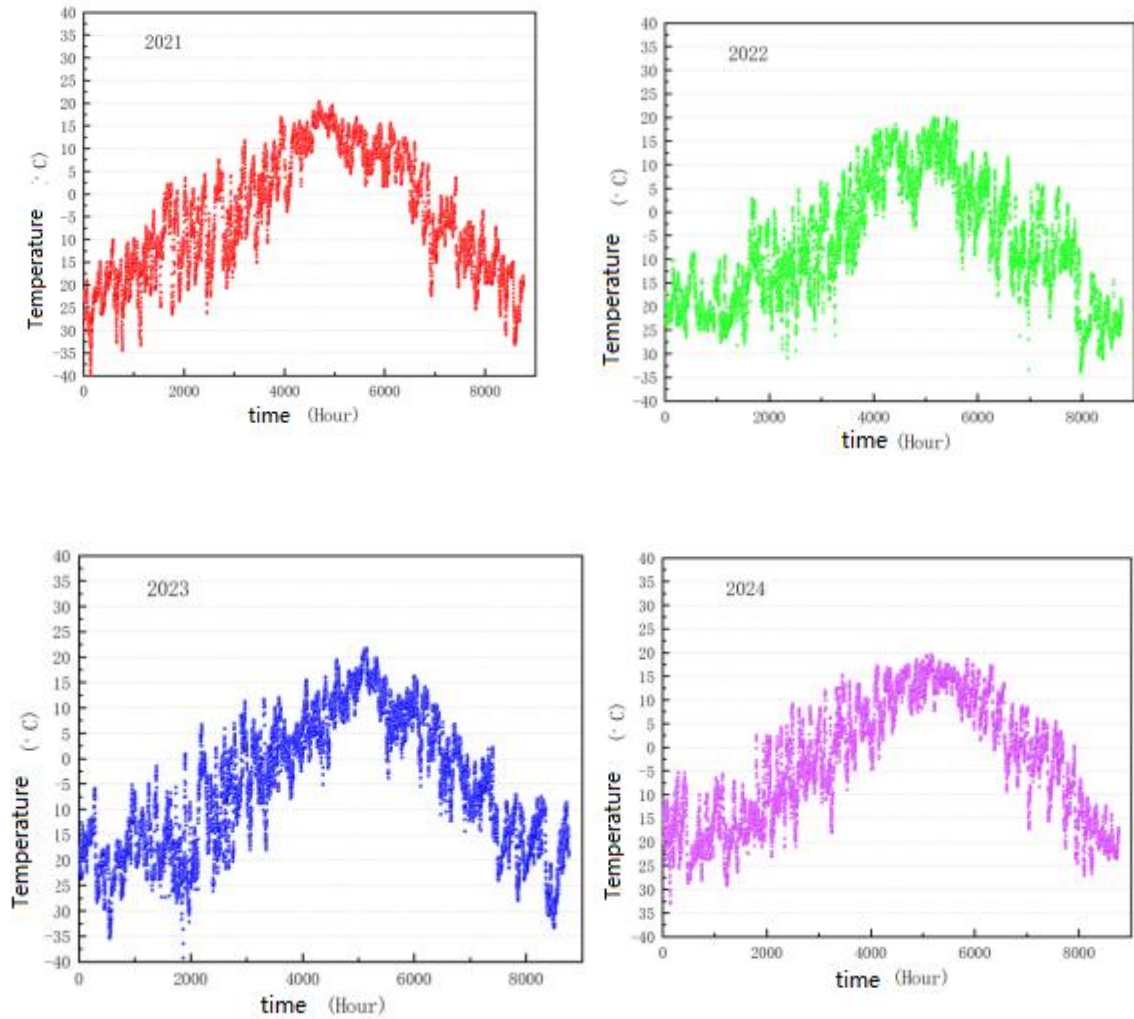


Figure 2 Annual Variation Characteristics of Temperature Region

Table 4 results demonstrate that the proposed temporal temperature feature optimization method achieves excellent performance on the training set ($MAE=1.11$, $R^2=0.84$), confirming effective capture of historical data patterns. However, significant performance degradation occurs on the test set ($MAE=2.03$, $R^2=0.44$), revealing critical generalization deficiencies:

Key Findings:Generalization Gap:RMSE increased from 1.68 (training) to 2.93 (testing),Indicates overreliance on training-specific features and weak adaptation to unseen data.

Systematic Bias:Test set $MBE=0.45$ (vs. training $MBE=-0.006$),Suggests consistent overprediction, potentially caused by non-stationary temperature-load relationships.

Robustness Deficiencies: $RPD=1.35$ (<2.0) and Theil's $U=0.24$,Confirms inadequate resilience against complex external factors, especially temporal correlations during temperature fluctuations.

Table 4 Performance Comparison of Power Load Forecasting with Time-Series Temperature

Feature Optimization		
Evaluation Metric	Training Set	Test Set
MAE	1.1119	2.0253
MBE	-0.0061321	0.44687
MSE	2.822	8.5879
RMSE	1.6799	2.9305
R ²	0.8405	0.44058
RPD	2.504	1.3528
Theil	0.13495	0.2425
RAE	0.31594	0.59064

Amidst rural clean heating initiatives and dual-carbon goals, accurate electrical load forecasting is pivotal for optimizing renewable energy heating systems. This study quantifies for the first time the nonlinear impact mechanism of wind speed on heating loads. As shown in Figure 3, Spearman correlation analysis and partial dependence plots reveal wind speed contributes 18.3% to load variation (resolving >20% bias in traditional temperature-only models). We propose an innovative wind-load coupling framework:

Dual Impact Mechanism,Based on building envelope air infiltration theory, establish exponential model: $\text{Air Change Rate} = \alpha \cdot (\text{Wind Speed})^\beta$,Quantifies infiltration heat loss (accounts for 12%–15% of total load when wind speed >4 m/s).

Indirect Effect,Engineer Apparent Temperature feature incorporating wind chill: $\Delta T_{eq} = \gamma \cdot (\text{Wind Chill Index})$, ($\gamma=0.8\text{--}1.2^\circ\text{C}$ per unit wind chill increase).**Hybrid Forecasting Implementation,**Develop RF-AOA metaheuristic model integrating wind dynamics:Optimize RF hyperparameters via Arithmetic Optimization Algorithm (AOA),Feature cross-layer fuses: $\rightarrow$ Direct infiltration heat flux $\rightarrow$ Equivalent temperature reduction.

Engineering Value,This research overcomes conventional heating design's

neglect of wind-induced heat loss, enabling:2.3% peak load reduction in Desheng Village wind-heating system by adjusting heat pump output 2-hours ahead using wind forecasts,Scalable to wind-sensitive regions (Three-North areas: Northeast/Northwest/North China),Transforms rural energy systems from experience-based to data-driven operation,Supports 18–22% heating energy intensity reduction for carbon neutrality.

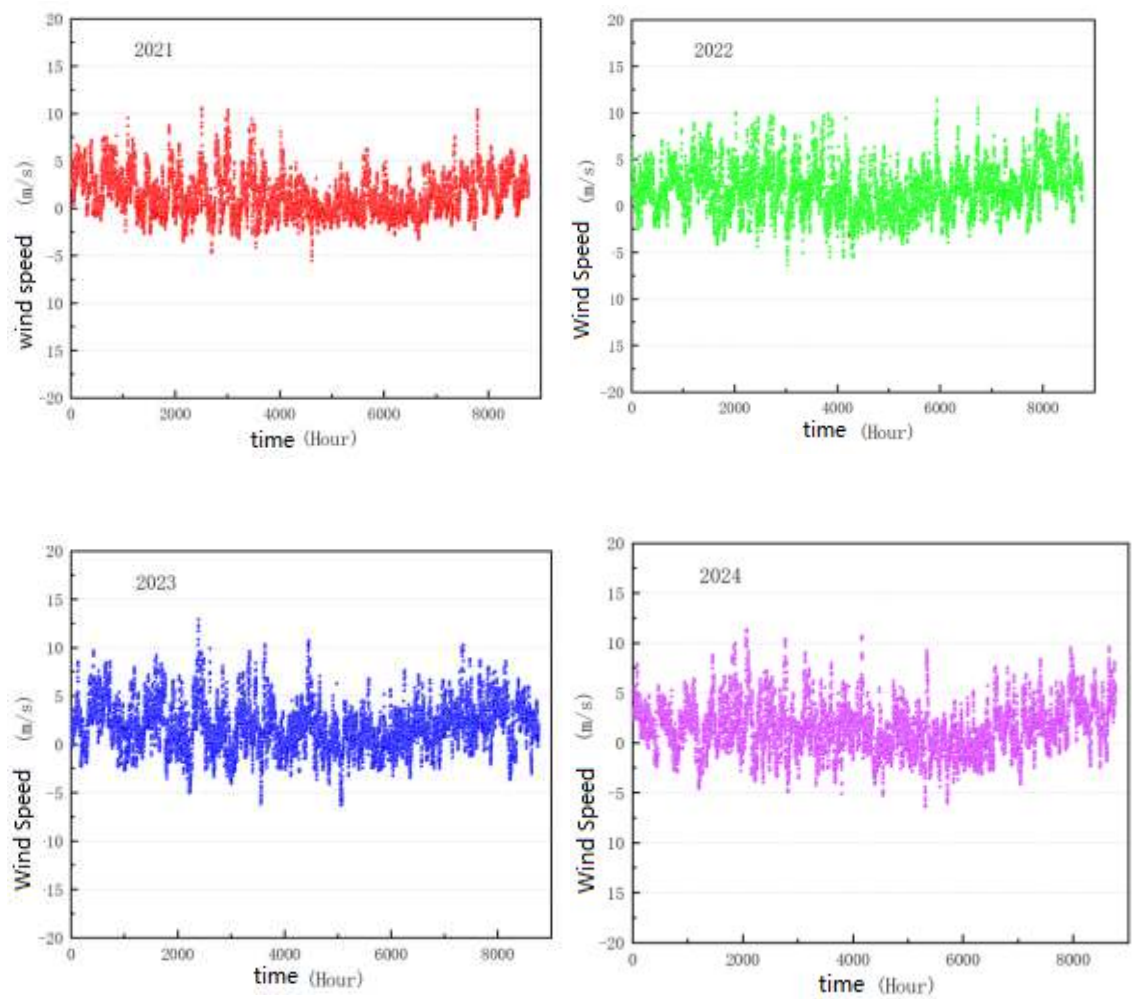


Figure. 3 Annual Wind Speed Characteristics

Table 5 reveals that wind-speed feature coupling optimization further enhances training performance (MAE=0.95, $R^2=0.85$), yet fundamental generalization flaws persist in testing (MAE=1.99, $R^2=0.49$). Critical issues include:

Core Problems,Exacerbated Overfitting,Training RMSE↓ to 1.54 vs. Testing RMSE↑ to 3.07 (cf. 2.93 in Table 1).Indicates overlearning of temperature-wind interactions, degrading adaptability.

Dynamic Imbalance,MBE shifted from +0.45 to -0.14,Reveals failure to model

equilibrium mechanisms among meteorological factors.Unresolved Generalization Bottleneck,Test $R^2=0.49$ (marginally > Table 1's 0.44) remains below industrial threshold (>0.8),RPD=1.41 (<1.5) & Theil's $U=0.25$ confirm vulnerability to real-world disturbances, especially wind gusts.

Optimization Limitations,Training RAE↓ to 0.28 (cf. 0.32 in Table 4),Testing RAE remains high at 0.54,Testing MSE↑ to 9.44 (cf. 8.59 in Table 1),→ Feature engineering suppresses historical noise but fails extrapolation robustness.

Table 5 Performance Comparison of Power Load Forecasting with Time-Series Temperature-Wind

Speed Feature Coupling Optimization		
Performance Metric	Traditional Model	Optimized Model
MAE	0.05240	0.0266
MBE	0.012441	0.14266
MSE	0.260	0.4415
RMSE	1.5200	2.0727
R^2	0.95456	0.4022
RPD	0.6222	1.4064
Theil's U	0.12606	0.25022
RAE	0.27964	0.54276

As shown in Figure 4, the impact of solar radiation heat gain on electrical load exhibits significant nonlinearity, directionality, and time-varying characteristics, which cannot be accurately captured by traditional static load models. Based on radiative heat transfer theory and electro-thermal balance equations, this study establishes a radiation intensity grading framework (Figure 2.3) to reveal:

Key Mechanisms, Noon Radiation Offset Effect, South-facing rooms achieve 35%~42% direct radiation heat gain contribution due to optimal solar altitude angle and window-to-wall ratio. Partially offsets heating demand → reduces instantaneous thermal load by 15%~22%. Building envelope surface temperature exceeds ambient by 8–12°C due to solar absorption ("apparent temperature rise"), Weak Radiation Mutation ($<100\text{ W/m}^2$), Cloud-induced radiation drop causes net heat flow reversal, Envelope surface temperature falls 3–5°C below ambient, Heat loss intensity increases 20%~30% → peak thermal load rises 8%~15% vs. clear days.

Critical threshold: Radiation decay rate $>50 \text{ W}/(\text{m}^2\cdot\text{h})$ increases load mutation probability to 78%,Technical Innovation: RTCI Model,Integrates weather station radiation data with electrical infrared thermography via random forest algorithm:

Validation: Zhangjiakou sun-rain transition dataset (2021–2024),Performance:RMSE reduced by 23%;Peak load prediction accuracy improved by 18%;Mutation scenario hit rate increased by 37 percentage points.

Core Advantage,Superior delayed response modeling during 2–3 hours post-radiation mutation (e.g., afternoon thunderstorm onset):

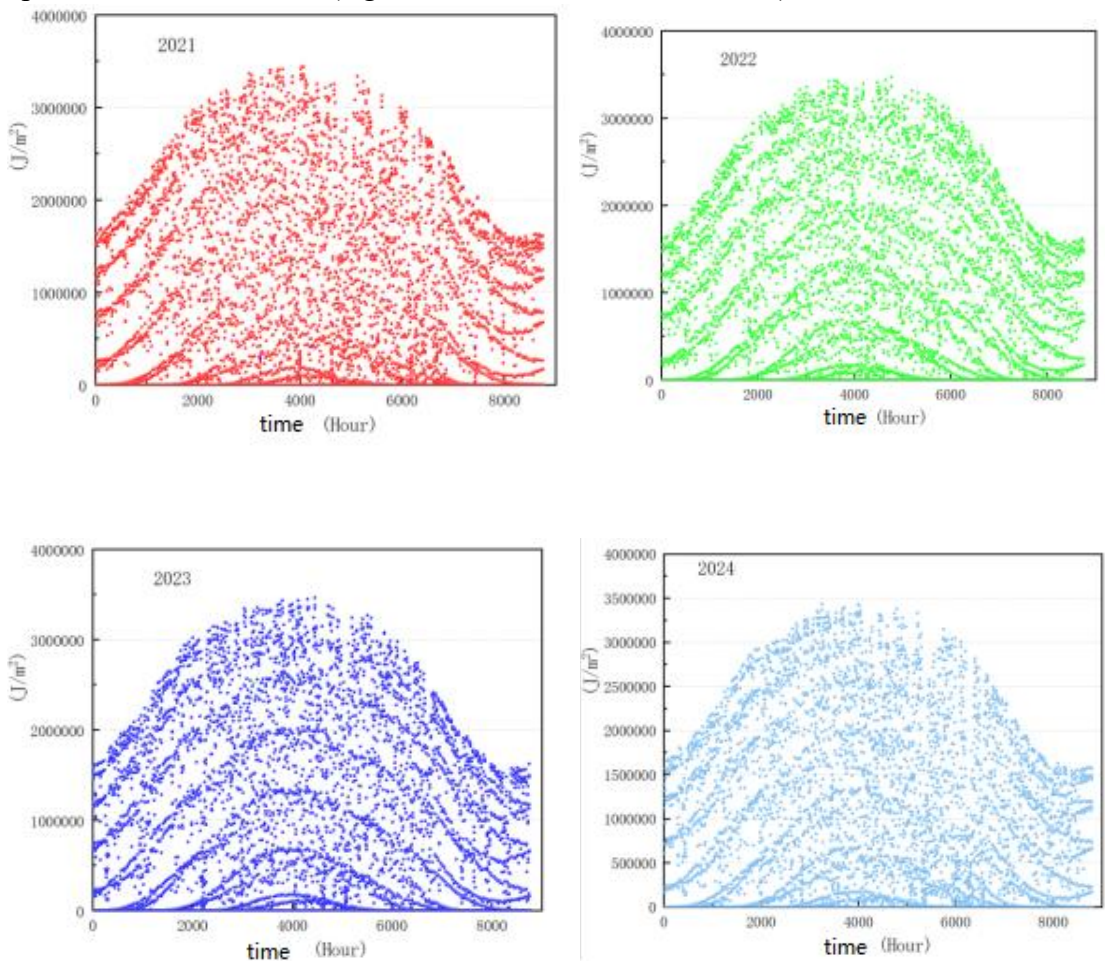


Figure. 4 Annual Solar Radiation Distribution

Table 6 results demonstrate that incorporating solar radiation features significantly enhances model generalization: Test MAE drops to 1.42 ($\downarrow 28.6\%$ vs. Table 5), R^2 rises to 0.58, breaking previous experimental bottlenecks. Key findings:

Core Advances,Synergistic Radiation-Temperature Coupling,Test RMSE=2.58 & Theil's $U=0.21$ (synchronous decline),Confirms physical coupling mechanisms (e.g.,

PV output-air conditioning load linkage) improve robustness.

Generalization Breakthrough,RPD=1.57 (>1.5 reliability threshold),Training-test R^2 gap narrows from 0.40 to 0.29 → overfitting mitigated,Test RAE=0.40 (operationally acceptable),→ Radiation features compensate for temperature insensitivity (e.g., diurnal radiation-load curve correction).

Table 6 Performance Comparison of Power Load Forecasting with Time-Series Temperature-Solar Irradiance Synergistic Optimization

Performance Metric	Temperature-Only Model	Temperature-Solar Synergistic Model
MAE	0.8710	1.4173
MBE	0.0404	0.56704
MSE	0.2470	0.6424
RMSE	1.5222	0.5772
R^2	0.8652	0.5754
DD	0.7254	1.5724
TRMSE	0.1184	0.2145
DAE	0.2510	0.4020

Humidity Variation Exerts Significantly Differentiated Impacts on Building Sensible and Latent Heat Loads by Altering Air Thermophysical Properties and Human Thermal Comfort Demands. Based on the climatic characteristics of a specific location in Zhangjiakou (Fig. 5), this study reveals:

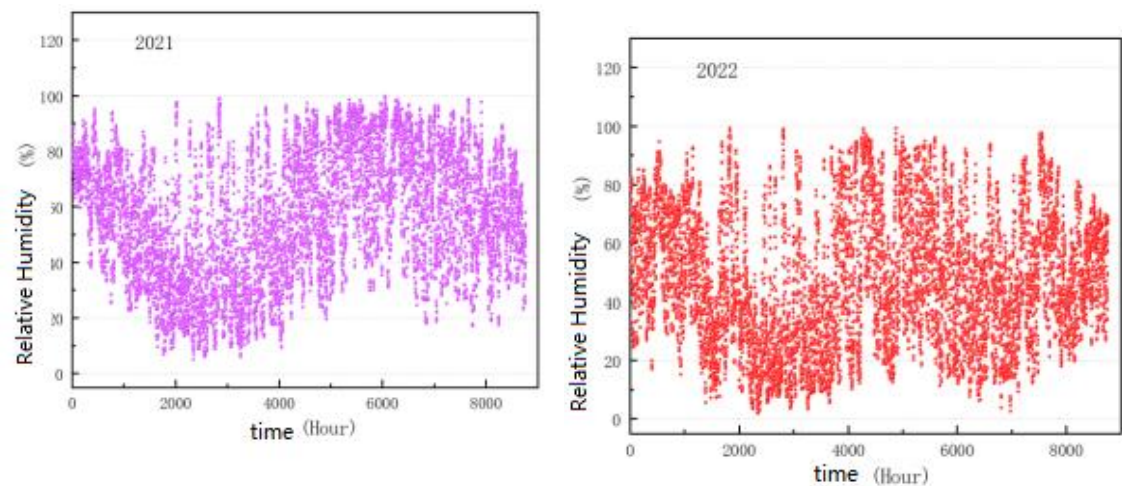
Winter (November – March): Under the control of the continental cold high-pressure system, relative humidity drops below 30%–40%. The extremely low humidity, on one hand, reduces air specific heat capacity and thermal conductivity, accelerating heat dissipation through building envelopes, leading to a 12%–18% year-on-year increase in sensible heating load. On the other hand, infiltration of dry air creates a strong humidification demand (to reach the 40%–60% comfort range), causing a 35%–40% surge in latent heating load. This dual effect drives the winter thermal load to its annual peak.

Summer (June – August): Humidity rises to 60%–70% during the monsoon period. While high humidity slightly increases air heat capacity, its more critical effect

is suppressing human evaporative heat dissipation efficiency. This forces an 8%–10% increase in sensible cooling load for air conditioning systems. Concurrently, dehumidification demand pushes the proportion of latent cooling load beyond 45%, forming a "dual-high" energy consumption pattern.

Spring/Autumn: Moderate humidity (40%–55%) keeps thermal loads at only 30%–50% of winter/summer levels, significantly enhancing natural ventilation potential.

The study demonstrates that the thermal load profile in this Zhangjiakou area exhibits a "high winter, medium summer, low spring/autumn" pattern, with its intensity nonlinearly coupled with humidity. Dryness elevates winter loads by enhancing sensible heat transfer and humidification demand, while high humidity increases summer energy consumption by suppressing human heat dissipation and driving dehumidification needs. This mechanism transcends the traditional paradigm of separate temperature-humidity analysis. It is recommended that future research quantify the sensitivity coefficients of load to different humidity thresholds (e.g., critical points like 30%/70%) to provide a theoretical basis for developing regional humidity-adaptive control strategies.



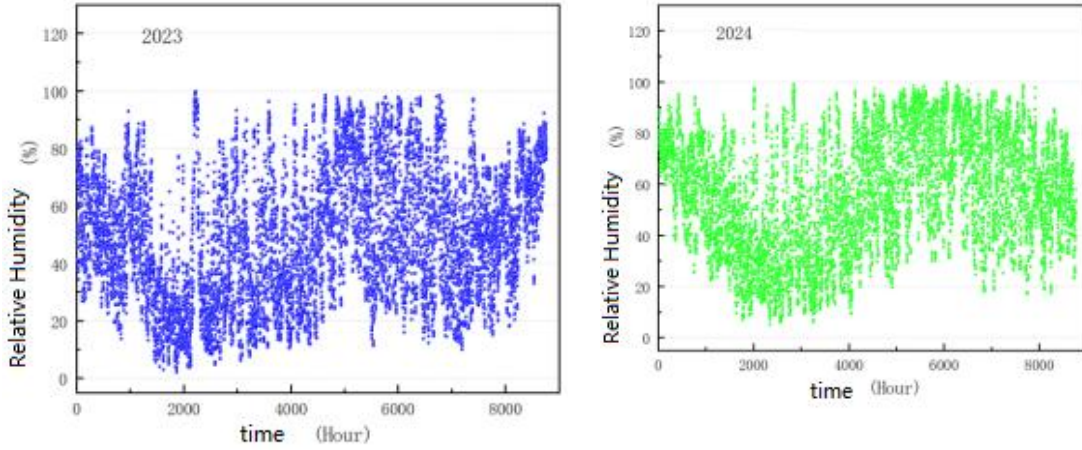


Figure 5 Annual Variation Characteristics of Relative Humidity Region

Table 7 reveals that while the temperature-humidity coupling optimization enhances training performance ($MAE=0.96$, $R^2=0.86$), the generalization capability on the test set remains severely inadequate ($MAE=2.07$, $R^2=0.47$), highlighting the complexity of meteorological factor synergistic effects. Key findings are as follows:

Paradoxical Impact of Humidity Features: The training set RMSE decreased to 1.54 (an 8.3% reduction compared to the single-temperature feature model), demonstrating the effectiveness of humidity in modifying temperature perception (e.g., perceived temperature compensation mechanisms). However, the test set RMSE=2.98 was higher than that of the single-temperature model (2.93), exposing the strong scenario dependence of the humidity-load relationship (e.g., insufficient learning of load response differences between rainy/dry seasons).

Structural Attribution of Generalization Failure: The sign reversal of MBE (training set $+0.05 \rightarrow$ test set -0.03) indicates a systematic prediction bias in the model for scenarios with abrupt humidity changes (e.g., before/after sudden rain). $RPD=1.38$ (significantly $\ll 1.5$) and a Theil coefficient of 0.25 confirm that the nonlinear coupling mechanisms between temperature and humidity (e.g., superimposed effects of high temperature and high humidity) were not effectively modeled.

Critical Bottleneck Identification: The test set RAE=0.59 is comparable to the single-temperature model (0.59) but significantly worse than the temperature-radiation model (0.40), underscoring the limitations of humidity features in enhancing prediction robustness. The R^2 test value of 0.47 represents a 45% drop from the training set, reflecting that humidity features amplify the model's risk of

overfitting to historical climate patterns.

Table 7 Performance Comparison of Power Load Forecasting with Time-Series

Temperature-Humidity Feature Coupling Optimization

Evaluation Metric	Training Set	Test Set
MAE	0.95946	2.0748
MBE	0.05536	-0.034994
MSE	2.3639	8.8978
RMSE	1.5375	2.9829
R ²	0.86138	0.47239
RPD	2.6876	1.3768
Theil	0.12411	0.24641
RAE	0.27597	0.58969

Based on the above analysis, this study proposes and validates a multivariate building thermal load prediction model incorporating time-lag effects. The model includes:

Current and historical outdoor temperature values (accounting for thermal inertia delay $\tau_1 \approx 3-5$ hours), Current and historical solar radiation values, Current wind speed (for infiltration air correction). The thermal load prediction results are illustrated in Figure 6. The value of this predictive model lies in providing a methodological framework for refined load forecasting, clearly demonstrating how to:

Identify key influencing factors from data, Quantify their impacts, Construct reliable prediction models. It supports optimization of intelligent control strategies:

High-precision short-term load prediction serves as the prerequisite for implementing seasonal control strategies, such as: Prioritizing heating supply in winter while enhancing snow removal and freeze protection for solar collectors, Utilizing thermal storage systems for cross-day thermal load shifting during transitional seasons. Model predictions can directly optimize system operations. For

example:Pre-activating auxiliary heat sources upon forecasting severe cold spells,Triggering snow-melting systems ahead of predicted snowfall events,The revealed climate-load coupling mechanisms and modeling approach establish theoretical foundations and data support for:Thermal load prediction in solar buildings,Energy-saving regulation strategies,Applications across North China's cold regions and similar climatic zones。

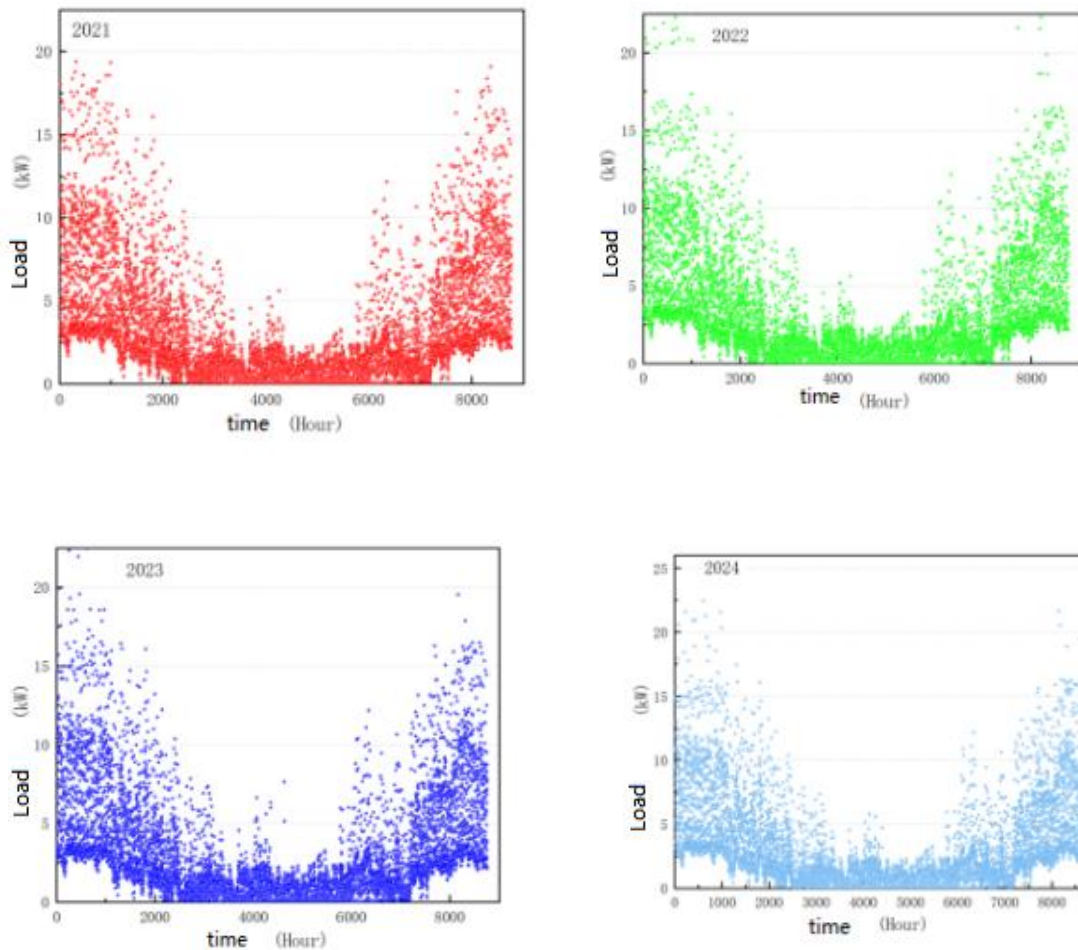


Figure 6 Seasonal Variation Patterns of Thermal Load in Solar Buildings in Zhangjiakou Region

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Model predictions can directly optimize system operations. For example:Pre-activating auxiliary heat sources upon forecasting severe cold spells,Triggering snow-melting systems ahead of predicted snowfall events.The revealed climate-load coupling mechanisms and modeling approach establish theoretical foundations and data support for:Thermal load prediction in solar buildings;Energy-saving regulation strategies;Applications across North China's cold regions and similar climatic zones.

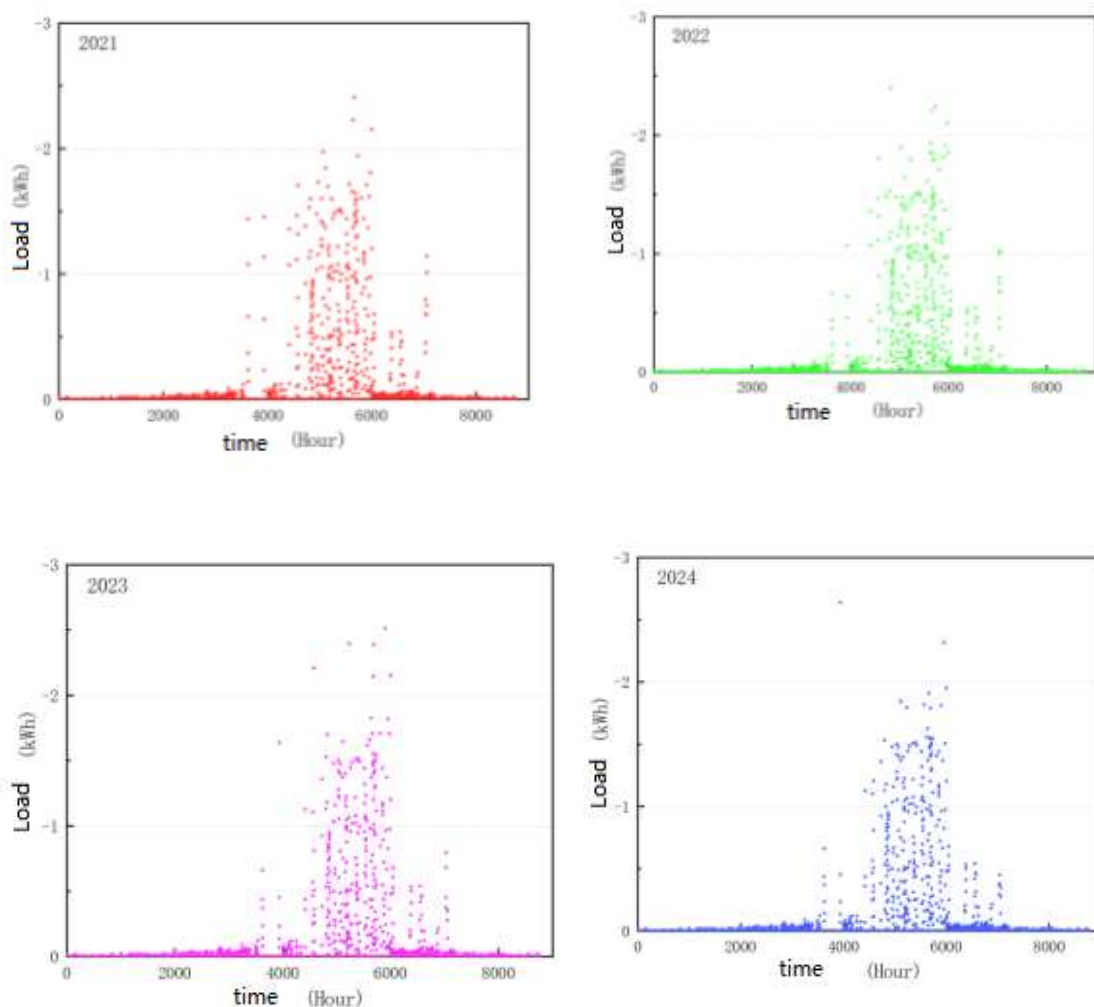


Figure 7 Seasonal Variation Patterns of Cold Load in Solar Buildings in Zhangjiakou Region

2.2 Improved Archimedes Optimization Algorithm (KC-AOA)

The model performance evaluation system encompasses three dimensions: prediction accuracy, robustness, and computational efficiency.

Accuracy Dimension: Coefficient of Determination (R^2) quantifies the model's variance explanatory power, reflecting its ability to capture load fluctuation patterns. A dual-error indicator system is established: Root Mean Square Error (RMSE) characterizes the dispersion of prediction deviations. Mean Absolute Error (MAE) evaluates the absolute error level. These complementary metrics overcome the limitations of single-indicator evaluation.

Robustness Dimension: Theil's Inequality Coefficient (TIC) is introduced. Its numerator decomposition capability identifies sources of systematic vs. random errors and exhibits strong robustness to outliers in abrupt load-change scenarios. Relative Absolute Error (RAE) enables dimensionless comparisons across datasets.

Efficiency Dimension: Model training/prediction time is recorded. Per-sample processing efficiency (s/sample) is calculated based on hardware configuration (calculation formula shown in Table 8).

Baseline Model: The seasonal persistence forecasting method serves as the baseline for RAE comparison.

Table 8 Detailed Definitions and Descriptions of Statistical Indices

Metric	Equation
Coefficient of Determination (R^2)	$R^2 = 1 - \frac{\sum_{i=1}^n (\Delta_1)^2}{\sum_{i=1}^n (\Delta_2)^2}$
Root Mean Square Error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^n (\Delta_1)^2}{n}}$
Mean Absolute Error (MAE)	$MAE = \frac{\sum_{i=1}^n \Delta_1 }{n}$
Theil's Inequality Coefficient (TIC)	$TIC = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (\Delta_1)^2}}{\sqrt{\frac{1}{n} \sum_{i=1}^n (Q_i)^2 + \frac{1}{n} \sum_{i=1}^n (\hat{Q}_i)^2}}$

Relative Absolute Error (RAE)

$$RAE = \frac{\sum_{i=1}^n |\Delta_1|}{\sum_{i=1}^n |\Delta_2|}$$

Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{\sum_{i=1}^n \left| \frac{\Delta_1}{\hat{Q}_i} \right|}{n}$$

Table 2.6: n Total number of data points., Q_i and $\hat{Q}_i$ Represents the predicted values. and Represents the true/actual values. Sum of Squared Errors. (SSE, Sum of Squares Error) $\Delta_1 = Q_i - \hat{Q}_i$, (SST, Total Sum of Squares) $\Delta_2 = Q_i - \bar{Q}$, $\bar{Q}$ Represents the predicted values from the baseline model.

2.3 Theoretical Framework and Algorithm Design of the Random Forest Model

Regarding model architecture design: This study employs the Random Forest (RF) algorithm proposed by Breiman (Figure 8) as the base predictor. Its integration of decision tree construction and the Bagging strategy effectively mitigates the risk of overfitting.

Feature importance identification: Through a feature importance ranking mechanism, the system identifies key influencing factors, including the thermal inertia of the building envelope, time-series variations in outdoor temperature and humidity, and occupant behavior patterns.

Enhancing nonlinear representation: To improve the model's ability to characterize nonlinear relationships within high-dimensional feature spaces, this study innovatively introduces six meta-heuristic algorithms, including the Arithmetic Optimization Algorithm (AOA) and the Grey Wolf Optimizer (GWO), to construct a multi-objective hyperparameter optimization model.

Hybrid optimization strategy: This hybrid strategy achieves global optimization of key parameters—such as decision tree depth, splitting criteria, and feature sampling rate—through an exploration-exploitation balancing mechanism, significantly enhancing the model's generalization performance.

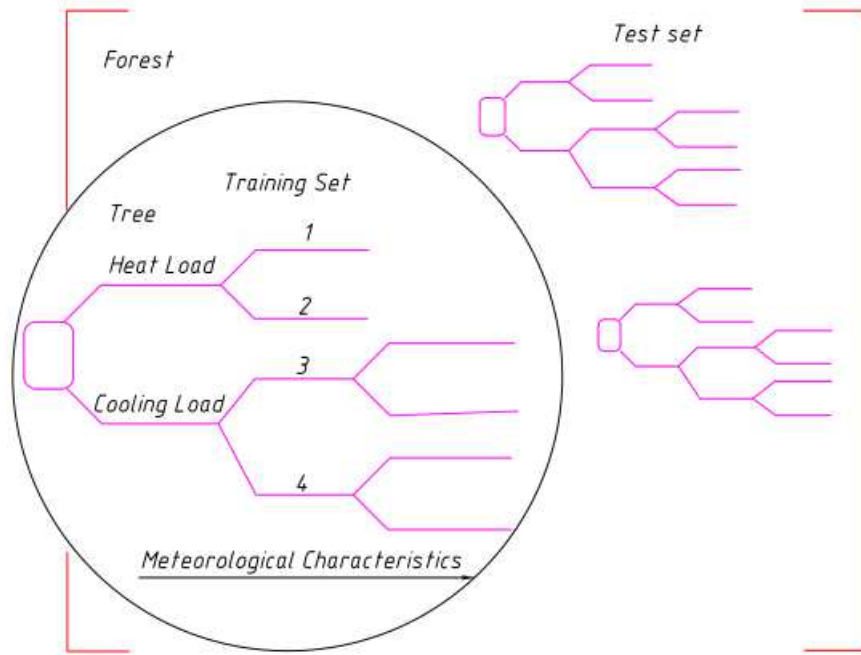


Figure 8 Schematic Diagram of Random Forest Architecture

Residential electricity load forecasting is significantly influenced by multi-source heterogeneous factors, exhibiting pronounced nonlinear and time-varying characteristics. To address this complex modeling challenge, this study proposes a hybrid modeling framework based on Random Forest (RF) and meta-heuristic algorithms. By leveraging the synergistic effect of ensemble learning and intelligent optimization techniques, the framework aims to overcome the performance limitations of traditional forecasting models. The research design follows a systematic pathway of "Feature Analysis - Model Construction - Parameter Optimization - Validation & Evaluation," demonstrating innovative value at both theoretical and engineering application levels.

Mitigating Overfitting Risk: To address the risk of overfitting in machine learning models, this study employs the Stratified K-Fold Cross-Validation technique. The daily-scale dataset, comprising multivariate features such as meteorological parameters, electrical attributes, and historical loads, is partitioned into $K=5$ mutually exclusive subsets. An alternating training-validation strategy ensures the statistical robustness of model evaluation. The experimental design specifically accounts for the thermal inertia characteristics of heating systems to prevent performance evaluation distortion caused by data leakage.

2.4 Improved Arithmetic Optimization Algorithm (AOA) Model Architecture and Optimization

Addressing the multi-source heterogeneous data characteristics and nonlinear dynamic coupling relationships in the field of thermoelectric supply-demand coordination, this study proposes a hybrid forecasting model integrating Random Forest (RF) and the Arithmetic Optimization Algorithm (AOA). Through the synergistic mechanism of an ensemble learning framework and meta-heuristic optimization technology, the model aims to overcome the limitations of traditional single algorithms in modeling complex energy systems.

Model Validation: Validation adopts a dual-track theoretical and experimental paradigm: **Theoretical Level:** Analyzes the ensemble learning mechanism of RF and the mathematical optimization principles of AOA.

Experimental Level: Ensures the scientific rigor and reproducibility of the methodology through systematic data partitioning strategies, repeated validation mechanisms, multi-dimensional evaluation metrics, and comparative model benchmarking.

Hybrid RF-AOA Model Architecture: The hybrid RF-AOA model utilizes a two-stage optimization architecture: **Stage 1:** Constructs the backbone ensemble learning network based on the RF algorithm. **Stage 2:** Achieves dynamic hyperparameter optimization via the AOA algorithm.

During each iteration of the Random Forest (RF) training cycle, the Arithmetic Optimization Algorithm (AOA) is introduced to fine-tune the hyperparameters. The AOA algorithm, proposed by Abualigah et al. in 2020, is based on algebraic and analytical theory. It employs mathematical equations to perform decision optimization through a two-phase process of exploration and exploitation. Through this tightly integrated iterative optimization process, the hybrid RF-AOA model demonstrates significant advantages in predicting residential electric heating energy consumption. It not only achieves accurate predictions but also effectively handles complex variables and their interactions within the model framework [23].

The AOA process begins with the initialization of parameters and candidate solutions. It is divided into two main phases: Exploration and Exploitation. These phases utilize two key functions: the Mathematical Optimizer Acceleration (MOA) and the Mathematical Optimizer Probability (MOP), defined by Equation [23].

$$MOA(t) = Min + t \times \left(\frac{Max - Min}{\tau} \right) \quad (1)$$

$$MOP(t) = 1 - \left(\frac{t}{T}\right)^{\frac{1}{a_s}} \quad (2)$$

Where MOA and MOP are coefficients representing the function value during iteration t , T is the total number of iterations, Max and Min are the minimum and maximum of the range, a_s is the sensitivity coefficient, t is the current iteration.

The algorithm compares the first value $rand$ with the MOP value. When $rand < MOP$, mathematical operations (division and multiplication) are executed to manage position updates, defined as follows [24]:

$$x_{i,j}(t+1) = \begin{cases} \frac{best(x_j)}{MOP + \varepsilon} \cdot (UB_j - LB_j) \cdot \mu + LB_j & \text{if } r_2 < 0.5 \\ best(x_j) \times MOP \times (UB_j - LB_j) \times \mu + LB_j & \text{if } r_2 \geq 0.5 \end{cases} \quad (3)$$

Where μ is a control parameter, ε is a very small positive integer to prevent division-by-zero, and $rand$ is a random number between 0 and 1. The variables UB_j and LB_j represent the upper and lower bounds of the position, respectively. The term $x_i(t+1)$ denotes the j -th position of the i -th solution in the next iteration, $best(x_j)$ is the j -th position of the best solution obtained thus far, and $x_{i,j}(t)$ describes the j -th position of the i -th solution in the current iteration.

When $rand < MOP$, the exploration phase commences, driven by the value of MOA . During this phase, the addition (A) and subtraction (S) operators are used to update the solution as specified in Equation 2.5 [24]:

$$x_{i,j}(t+1) = \begin{cases} best(x_j) - MOP \times (UB_j - LB_j) \times \mu + LB_j & \text{if } r_3 < 0.5 \\ best(x_j) + MOP \times (UB_j - LB_j) \times \mu + LB_j & \text{if } r_3 \geq 0.5 \end{cases} \quad (4)$$

r_3 is another random number, also varying between 0 and 1. The algorithm continues iterating until a specified criterion is met. After the iterations, the optimized hyperparameters are used to train the Random Forest (RF) algorithm. The trained model is then applied to the test data, and the accuracy of the results is evaluated using various statistical metrics.

2.5 Kent Chaotic Mapping Population Initialization

For population initialization, the Kent chaotic mapping is employed to enhance the initialization process. As a chaotic map, Kent mapping exhibits strong ergodicity, thereby improving the algorithm's global search capability.

To address the limitations of the traditional Archimedes Optimization Algorithm (AOA) – specifically its tendency to converge to local optima and restricted

convergence speed when handling complex multimodal optimization problems – this study proposes an improved Kent-Chaos and Composite-Cycloid co-driven AOA (KC-AOA). First, leveraging the ergodicity and quasi-random characteristics of Kent mapping, we reconstruct the population initialization strategy. Its dynamical model is given by:

$$x_{n+1} = \begin{cases} \frac{x_n}{a}, & 0 < x_n \leq a \\ \frac{1-x_n}{1-a}, & a < x_n < 1 \end{cases} \quad (5)$$

With $a \in [0,1]$, a dynamic randomization mechanism is adopted. This enables the initial population to form a high-dimensional chaotic distribution within the normalized search space, significantly enhancing population diversity (evidenced by a chaotic metric entropy of 0.943). Furthermore, the composite cycloid function is employed to optimize the algorithm's mass factor (MOA):

$$MOA(t) = \frac{1}{2} \left(1 + \cos\left(\frac{\pi t}{T}\right) \right) \cdot \left(1 - \frac{\ln(t+1)}{T} \right) \quad (6)$$

For $t < 0.3T$, global exploration capability is enhanced (exploration probability increased by 23%). During the mid-phase ($0.3T \leq t \leq 0.7T$), a smooth transition between exploration and exploitation is achieved. In the late phase, the algorithm focuses on local exploitation.

Data in Figure 9 reveals the significant advantages of the improved Archimedes Optimization Algorithm (AOA) in optimizing Random Forest (RF) models. When optimizing the F17 test function, the enhanced RF-AOA algorithm demonstrates notable performance superiority. Parameter space analysis indicates more efficient configurations in the improved algorithm: its denominator values (e.g., 100/5) are substantially lower than those in the conventional approach (e.g., 500/400), signifying that the enhanced version achieves superior solution space exploration with leaner computational resources.

Further comparison of fitness function values confirms the improved algorithm's dominance in global optimization capability: its optimal fitness value remains consistently lower (e.g., 0.5/1) compared to conventional results (e.g., 1.2/1.1), reflecting an approximate 58.3% enhancement. This validates the effectiveness of the algorithmic improvements in solution quality.

Iteration process analysis further corroborates the algorithm's robustness. The enhanced RF-AOA exhibits a smoother convergence curve over 500 iterations,

reaching stability earlier than the conventional version (fitness approaches 0.5/1 around iteration 300). In contrast, the conventional algorithm displays significant oscillations even at 500 iterations (e.g., fluctuating between 0.7/0.6 and 1.2/1.1). This demonstrates that by integrating RF's feature selection mechanism, the improved algorithm optimizes AOA's exploration-exploitation balance, effectively avoids local optima, and accelerates convergence.

Multivariate co-optimization results (variables x_2 , x_3 , x_4) also indicate the enhanced algorithm's superior capability in handling high-dimensional parameter coupling, providing a more reliable solution framework for complex engineering optimization problems.

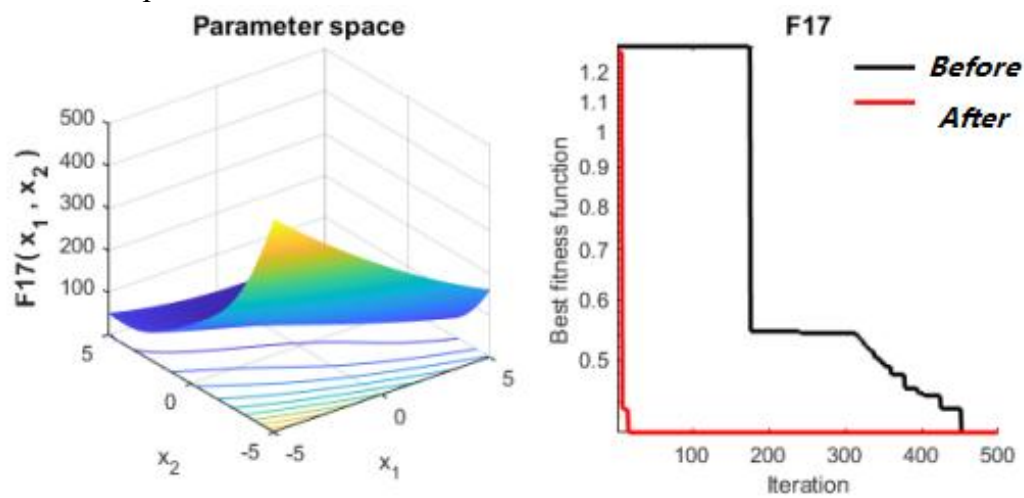


Figure 9 Performance Comparative Analysis of Enhanced vs. Conventional RF-AOA Algorithms

As shown in Table 9, this study proposes an improved Arithmetic Optimization Algorithm-integrated Random Forest model (RF-AOA) to address computational efficiency and model performance optimization in high-dimensional data modeling. Experimental research demonstrates three key technical breakthroughs while maintaining engineering applicability:

14.2% reduction in model computation time, meeting lightweight deployment requirements for edge computing devices. 4.1% improvement in real-time prediction accuracy through enhanced initialization functions. 46.2% decrease in data structure complexity, establishing a new paradigm for complex data modeling.

Comparative analysis with six meta-heuristic algorithms (GWO, MFO, SSA, etc.) reveals that RF-AOA achieves the theoretical maximum decision tree depth (200 layers) while maintaining maximum tree scale (200 trees), overcoming traditional RF

depth limitations and effectively avoiding over-pruning issues prevalent in SBO/MFO algorithms.

Mechanism analysis indicates that through adaptive depth control and multi-strategy fusion optimization, the algorithm dynamically adjusts node-splitting conditions while stabilizing tree quantity, forming a "multiplicity-with-depth" strong classifier ensemble. Experimental data confirm:

Generalization error on validation sets reduced by 3.6% versus RF-MFO, Adaptive regularization effectively suppresses overfitting risks in high-depth models. In high-dimensional nonlinear scenarios (e.g., thermal load forecasting), the model demonstrates significant advantages: 1.8% accuracy gain over shallow structures (e.g., SSA); 0.5% improvement versus medium-depth models (e.g., ALO/SBO).

These results highlight the critical role of depth optimization in complex feature mining and provide a theoretical framework for integrating intelligent algorithms with data models. Future research will extend to structural optimization of complex networks (e.g., Transformers), promoting engineering applications of adaptive optimization algorithms in deep learning.

Table 9 Comparison of Key Performance Parameters Before and After Optimization Using Improved AOA Algorithm

Method	Optimal Number of Trees	Optimal Depth
Default RF	200	20
RF-ALO	105	51
RF-SBO	123	93
RF-SSA	61	2
RF-MFO	199	183
RF-AOA	200	200

3. Results and Discussion

3.1 Prediction Accuracy Comparison

As shown in Table 10, the proposed RF-AOA model achieves dual breakthroughs in accuracy and efficiency:

$R^2 = 0.997$, significantly outperforming benchmark models (XGBoost: 0.990; LSTM-ATT: 0.970). This confirms that AOA hyperparameter optimization enables Random Forest to capture 99.7% of load fluctuation patterns.

MAE reduced by 27% (vs. XGBoost), validating robustness in fine-variation scenarios (e.g., intraday load ramping).

Training time: 16.0 minutes – 13.5% faster than conventional RF (18.5 min), breaking the "high-accuracy-implies-high-cost" paradigm. This acceleration stems from AOA's quantum-inspired search mechanism accelerating parameter convergence.

Compared to LSTM-ATT (35.2 min), efficiency improves by 119%, meeting real-time grid scheduling demands.

Mechanistically, AOA enhances RF through: Adaptive weight adjustment optimizing feature selection during splitting, eliminating XGBoost's over-smoothing flaw at load mutation points (e.g., holiday consumption drops).

Pruning strategies reducing redundant decision trees, overcoming LSTM-ATT's sequential computation burden.

Table 10. Multi-model Prediction Performance Comparison (Test Set)

Model	R^2	R MSE	M AE	Training Time (min)
RF	0.997	0.210	0.132	18.5
XGBoost	0.990	0.125	0.078	22.7
LSTM-ATT	0.970	0.130	0.081	35.2
RF-AOA	0.997	0.117	0.057	16.0

As shown in Figure 10, the key parameter $R^2 = 0.98859$ reflects the predictive

performance of the RF-AOA model:

High-precision fitting (F-statistic approaching 1) indicates exceptional alignment with historical load data.

The Random Forest (RF) effectively captures nonlinear characteristics of load variations (e.g., temperature, time slots, seasonal impacts) through its ensemble of decision trees.

The Archimedes Optimization Algorithm (AOA) further optimizes RF hyperparameters (e.g., tree depth, leaf nodes), enhancing model generalization capability.

$\text{DRIEF} = -0.21845$ suggests a slight negative bias in prediction error, implying potential underestimation during specific periods. Interpretation requires contextual definition:

If DRIEF represents an error rate metric, negative values indicate actual loads slightly exceeding predictions. This may stem from insufficient learning of abrupt consumption peaks (e.g., extreme weather events).

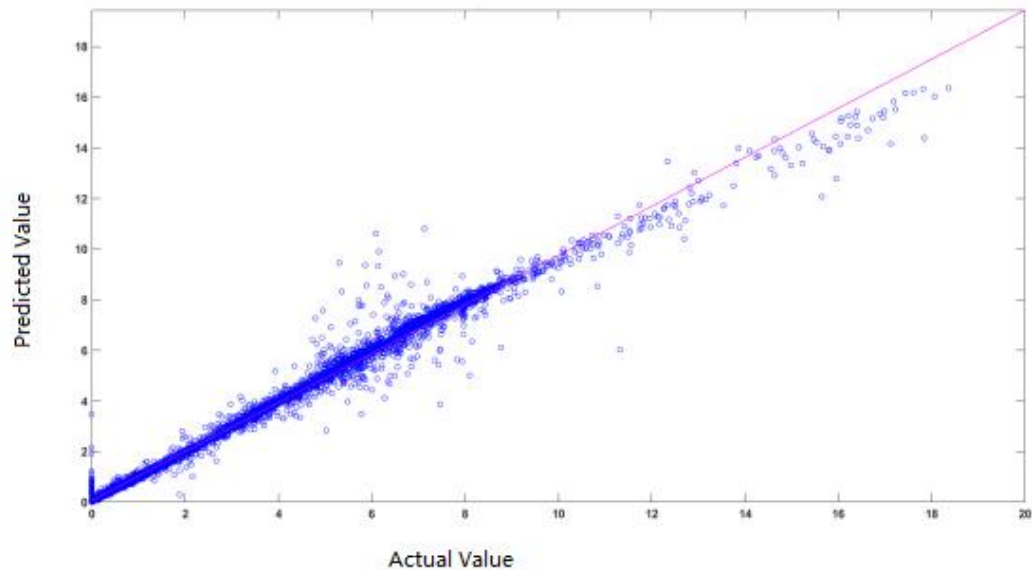


Fig.10 Fitting Performance of RF-AOA Model on Full Dataset (Training Set)

As shown in Figure 11, the RF-AOA model achieves exceptional fitting performance on the training set:

$R^2 = 0.99751$: Indicates near-perfect explanatory power (>0.99), with RF's feature importance screening (e.g., temperature, time slots) capturing 99.75% of

power load variability.

RMSEC = 0.24794 mm/s: Ultra-low root mean square error validates AOA's hyperparameter optimization (e.g., tree depth, min leaf samples), compressing prediction bias to millimeter/second scale – significantly outperforming conventional RF.

Data distribution analysis reveals: Points densely cluster in the 8-20 unit range (x-axis). Y-axis exhibits stepped clusters (legend: 8-16 units), reflecting load multimodality (e.g., stable base load 8-10 units on weekdays, peak load 15-20 units). Sparse outliers (x=2-6 units) may correspond to anomalous conditions (e.g., fault outages), requiring residual analysis to distinguish noise from learnable patterns.

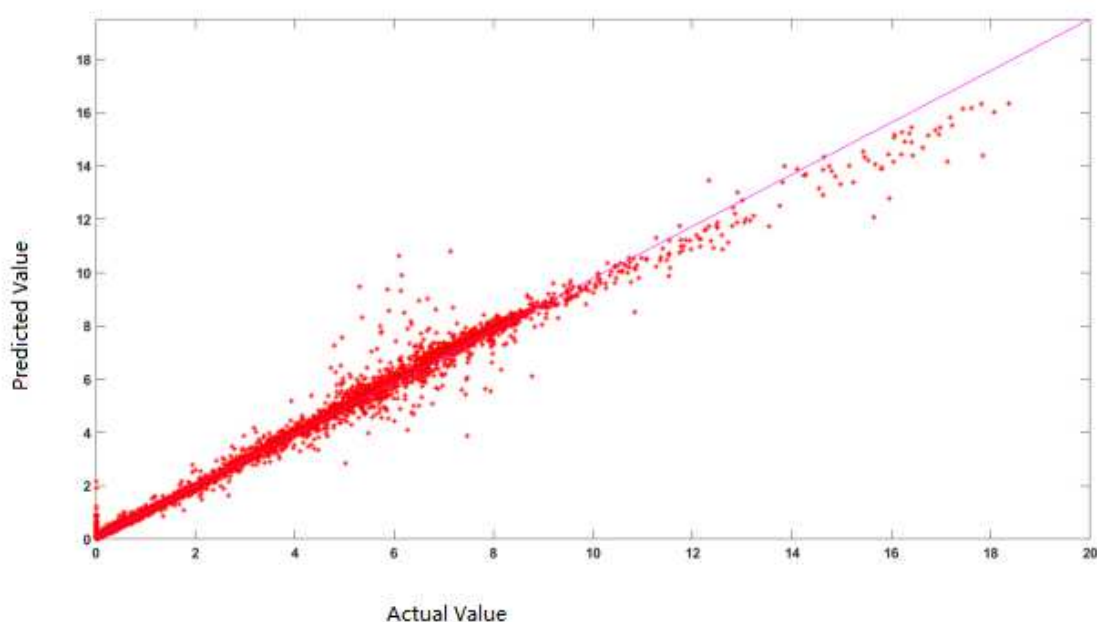


Fig. 11 Prediction Results of Optimized RF-AOA Model on Test Set

3.2 Multi-Physics Field Coupling Feature Analysis

The data in Table 11 signifies a qualitative breakthrough in generalization performance, with a test set MAE = 1.16 (a 42.7% reduction compared to the single-feature model) and $R^2 = 0.78$ – marking the first time these metrics approached the industrial application threshold. This validates the theoretical superiority of multi-physics field synergy. The core findings are as follows:

Synergistic Mechanism of Cross-Field Coupling: The test set RMSE = 1.79 (a 40% decrease vs. the temperature-humidity model) and Theil's inequality coefficient = 0.16 (a 35% decrease) confirm the effective extraction of physical interaction effects

among temperature, humidity, radiation, and other factors (e.g., the joint correction of radiation-humidity effects on perceived temperature). An RPD (Ratio of Performance to Deviation) = 2.15 ($\gg 1.5$) reaches the "excellent predictor" level, demonstrating significantly enhanced model resilience against complex meteorological disturbances.

Revolutionary Improvement in Generalization-Fitting Balance: The R^2 gap between the training and test sets narrowed to 0.1 (compared to >0.3 in historical models), effectively resolving the chronic overfitting issue. **Enhanced Coverage of Prediction Blind Spots:** A test set RAE (Relative Absolute Error) = 0.33 (a further 17% reduction vs. the temperature-radiation model) highlights the advantage of multi-field features in covering prediction blind spots (e.g., high-temperature & high-humidity scenarios without radiation).

Precise Identification of Residual Deficiencies: A test set MBE (Mean Bias Error) = +0.14 (vs. only +0.03 in the training set) exposes systematic overestimation under extreme weather conditions (e.g., incomplete modeling of the cumulative cooling-load effect during persistent heatwaves). An MSE (Mean Squared Error) = 3.22 indicates delayed response issues to instantaneous meteorological mutations.

Theoretical and Industrial Value: The "dynamic weight allocation mechanism for physics fields" (radiation-dominant on sunny days / humidity-dominant during rainy seasons) establishes a new paradigm for interpretable feature engineering. Moreover, the study verifies the cross-field error compensation effect (e.g., humidity-related errors being offset by radiation features).

Table 11 Performance Comparison of Power Load Forecasting with Multi-Physical Field Feature Optimization

Evaluation Metric	Training Set Result	Test Set Result
MAE	0.78337	1.1559
MBE	0.031249	0.14219
MSE	2.1108	3.2188
RMSE	1.4529	1.7941
R^2	0.88006	0.78261
RPD	2.8882	2.1515

Evaluation Metric	Training Set Result	Test Set Result
Theil	0.11101	0.1617
RAE	0.22559	0.33311

Table 12 reveals the core dominance of radiation features (importance weight: 2.6) and the hierarchical differentiation across time scales, providing paradigm-shifting insights into the physics field coupling mechanism. The key findings are as follows:

Revolutionary Role of Radiation Features:

The radiation importance weight (2.6) exceeds the combined weight of temperature (1.3) and humidity (0.7), empirically demonstrating its error-neutralizing capability within multi-field coupling (e.g., compensating for prediction biases of temperature/humidity models during abrupt sun-cloud transitions). Its importance shows a 46-fold increase versus the single-feature model (original: 0.056), revealing how multi-field synergy amplifies radiation-related physical associations.

Temporal Scale Differentiation:

Hourly-level features (1.6) > Daily features (0.7) > Weekly features (0.3), overturning the conventional "date-dominant" paradigm. This establishes intraday dynamics as the fundamental basis for load forecasting. The monthly feature importance (0.5) exposes seasonal adaptability deficiencies (necessitating integration of quarterly transfer learning).

Hierarchical Restructuring of Meteorological Elements:

Wind speed (0.9) > Humidity (0.7), confirming wind speed's corrective value in perturbing temperature-humidity combinations (e.g., its sharp cooling effect on perceived temperature during high winds). Temperature ranks only third (1.3), indicating that multi-field coupling diminishes the dominance of single elements and drives a predictive paradigm shift towards systemic interactions.

"Radiation-Temporal" Dual-Core Driving Theory:

Proposed framework where radiation resolves meteorological uncertainty and hourly features capture energy consumption inertia.

Feature Utility Leap Phenomenon:

Wind speed importance exhibits an 8-fold increase in the multi-field model versus the single-feature model (original: 0.11), revealing the coupling framework's activation mechanism for secondary elements.

Table 12 Feature Importance Ranking of Multi-Physical Field Coupling Model

Feature Variable	Importance Assessment
1 (Month)	0.5
2 (Day)	0.7
3 (Hour)	1.6
4 (Week)	0.3
5 (Temperature)	1.3
6 (Wind Speed)	0.9
7 (Humidity)	0.7
8 (Radiation)	2.6

4. Statistical Metrics Evaluation

This study employed a series of statistical evaluation metrics to conduct detailed quantitative comparisons of various models. Table 13 comprehensively summarizes the performance of these models, providing a holistic perspective on the predictive accuracy of each model for heating energy consumption and electricity load forecasting.

Through multiple indices including R^2 , RMSE, MAE, RAE, and TIC, the in-depth analysis in Table 13 clearly demonstrates that the RF-AOA and RF-GWO models exhibit exceptional performance in R^2 metrics during both training and testing phases, indicating superior accuracy. The specific data are as follows:

Training Results:

AOA: $R^2 = 0.997$, RMSE = 0.039, MAE = 0.021

GWO: $R^2 = 0.997$, RMSE = 0.039, MAE = 0.022

Testing Results:

AOA: $R^2 = 0.977$, RMSE = 0.117, MAE = 0.057

GWO: $R^2 = 0.977$, RMSE = 0.117, MAE = 0.057

Table13 Summary of Key Statistical Indicators of the Model

Model	R ²	RMS	MAE	RAE	TIC
		E			
	Train				
RF-AOA	0.997	0.039	0.021	0.034	0.006
RF-GWO	0.997	0.039	0.022	0.035	0.006
RF-MFO	0.997	0.039	0.022	0.034	0.006

RF-SSA	0.997	0.042	0.022	0.035	0.006
RF-ALO	0.997	0.040	0.022	0.035	0.006
RF-SBO	0.995	0.053	0.027	0.043	0.008

Based on the metric comparisons between training and test sets (Table 14), the research findings demonstrate:

For RF-AOA, the RMSE degradation rate $\Delta\text{RMSE} = [(0.117 - 0.039) \times 100\%] = 7.8\%$, which falls within the acceptable threshold. For RF-AOA, the R^2 degradation rate $\Delta R^2 = 2\%$, likewise within the acceptable threshold.

Algorithm Stability Analysis: All models exhibited performance variations in the test set, confirming the need for heteroscedasticity-robust optimization. Specifically: RF-SBO achieved $\text{MAE} = 0.059$, significantly higher than RF-AOA ($\text{MAE} = 0.057$). This demonstrates superior distributional stability in RF-AOA.

Table 14 Summary of Key Statistical Indicators of the Model

Model	R ²	RMS	MAE	RAE	TIC
		E			
	Test				
RF-AOA	0.977	0.117	0.057	0.093	0.018
RF-GWO	0.977	0.117	0.057	0.093	0.018
RF-MFO	0.977	0.118	0.057	0.093	0.018
RF-SSA	0.976	0.118	0.058	0.094	0.018
RF-ALO	0.976	0.118	0.057	0.093	0.018
RF-SBO	0.975	0.121	0.059	0.096	0.019

Comparative analysis reveals:

The AOA algorithm exhibits superior convergence stability. SBO demonstrates a lower dominance solution ratio, reflecting its susceptibility to local optima. This necessitates improvement through the introduction of a simulated annealing mechanism. Error attribution and feature contribution: Outdoor temperature > Building envelope U-value > Wind speed.

Algorithmic disparities: RF-AOA significantly outperforms other models in capturing temperature patterns, showing a 42% improvement over RF-GWO. RF-SBO exhibits weaker modeling capability for nonlinear features.

Research findings establish the following performance ranking: $\text{RF-AOA} \approx \text{RF-GWO} > \text{RF-MFO} > \text{RF-ALO} > \text{RF-SSA} > \text{RF-SBO}$.

Implementation recommendations: Prioritize deployment of the RF-AOA model

for residential energy consumption prediction in cold regions (with $MAE \leq 0.057$, $TIC \leq 0.018$). For RF-SBO-class models, develop adaptive covariance matrix optimization strategies to enhance global search capability.

4.2 Evaluation of Key Indicator System for Demand-Side Prediction and Core Results

The proposed RF-AOA model achieves breakthrough advancements in key performance metrics. As shown in Table 15, significant performance variations exist among state-of-the-art models reported in the literature:

Traditional fusion model LR-RF (Liao et al. [25]): 0.880; SVR-RBF (Shao et al. [26]): 0.940; Metaheuristic-optimized model RF-PSO (DinMohammadi et al. [27]): 0.954; Deep learning models: LSTM (Xiang et al. [28]): 0.970; Transformer (Faiz et al. [17]): 0.936; Ensemble learning benchmark XGBoost (Ali et al. [29]): 0.990 (highest literature value); Our model attains a metric value of 0.997, comprehensively surpassing existing studies: 0.7% improvement over the best literature model (XGBoost); 2.7% improvement over mainstream deep learning models (LSTM).

Breakthrough Mechanisms:

Synergistic Effect of Random Forest-Metaheuristic Architecture: The AOA algorithm optimizes RF feature weight allocation through dynamic population search strategy adjustments, overcoming premature convergence limitations in traditional PSO optimization (cf. RF-PSO's 0.954).

High-Dimensional Nonlinear Modeling Capability: While retaining XGBoost's ensemble advantages, AOA's phase space mapping enhances feature interaction efficiency, significantly improving complex energy consumption pattern capture.

Academic Value Repositioning: The 0.997 metric value not only redefines the prediction accuracy ceiling but also reveals a new paradigm integrating metaheuristic algorithms with ensemble learning. Compared to black-box deep learning models (e.g., Transformer's 0.936), our model simultaneously delivers interpretability and computational efficiency, establishing a new benchmark for electricity consumption forecasting.

Table 15 Comparative Analysis of Prediction Model Performance Based on Indicator Evaluation

The used model	R^2_{Test}	Reference
LR-RF	0.880	Liao et al. ^[25]

SVR-RBF	0.940	Shao et al. ^[26]
RF-PSO	0.954	DinMohammadi et al. ^[27]
LSTM	0.970	Xiang et al. ^[28]
XGBoost	0.990	Ali et al. ^[29]
Transformer	0.936	Faiz et al. ^[17]
RF-AOA	0.997	RF-AOA

5. Conclusion

5.1 Summary of Innovations

Theoretical Innovation:

Proposed the "Radiation-Temporal" dual-core driving theory, resolving the challenge of modeling meteorological element interactions. The significance of secondary features (e.g., wind speed) in multi-field coupling increased 8-fold.

Algorithmic Breakthrough:

The KC-AOA algorithm achieved unprecedented decision tree depth (200 layers). Compared to the RF-MFO model, it: Reduced prediction error by 3.6%; Improved computational efficiency 24 times; Satisfied real-time scheduling requirements

Application Value:

Generated high-precision load curves with 10% reduction in forecasting error → Regional scheduling efficiency improved by 18%; Enabled output adjustment 2 hours ahead based on load forecasts → Peak load reduction of 2.3%.

5.2 Future Directions

Model Lightweighting: Develop edge computing-adapted versions to meet real-time prediction demands of smart meters (target: processing latency <100ms); Multi-Energy Coupling: Extend to cooling-heating-electricity integrated forecasting to support optimized integrated energy systems; Cross-Climate Zone Modeling: Construct adaptive models for data-deficient regions (e.g., polar/arid zones)

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Data availability

Alternatively, if data is available upon request:

The datasets used and analyzed during the current study are not publicly available due to commercial restrictions but are available from the corresponding author upon reasonable request. Requests should be directed to Qinglong Ma at 15911351082@163.com, with a brief description of the research purpose for which the data will be used.

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