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An advanced framework for net electricity consumption prediction: Incorporating novel machine learning models and optimization algorithms

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A B S T R A C T

In recent years, the escalating demand for electric energy has underscored the need for robust prediction models capable of accurately anticipating consumption patterns. The imperative lies in enabling utilities and policymakers to optimize resource allocation, strategically plan infrastructure development, and ensure the stability and efficiency of the power grid. This study undertakes a comprehensive comparative analysis of machine learning techniques employed in predicting net electricity consumption in Turkey. The primary goal is to augment the accuracy and performance of electricity load forecasting, thereby contributing to effective energy management and fostering sustainable development within the power sector. Two machine learning models, including CatBoost and Extreme Gradient Boosting (XGBoost), are strategically integrated with optimization algorithms such as Sparrow Search Algorithm (SSA), Phasor Particle Swarm Optimization (PPSO), and Hybrid Grey Wolf Optimization (GWO). The core analysis centers on evaluating the performance of these integrated models based on key accuracy metrics and runtime efficiency. Notably, the results underscore that the XGBoost-SSA model emerges as the superior performer, exhibiting heightened accuracy and superior performance in predicting electricity consumption. This model showcases the highest coefficient of determination (R^2) value and demonstrates lower errors during the testing phase, thereby presenting a promising and effective approach for electricity consumption prediction in the specific context of Turkey.

1. Introduction

Electricity consumption profoundly affects the operation, strategic planning, and maintenance of power grid infrastructure. The efficiency and optimal performance of power systems depend on prudent management, shaped by the patterns and intensity of electricity usage [1].

The socio-economic impacts of electricity usage are substantial. It is a key driver of economic development, enabling industrial activities, commercial operations, and fulfilling residential needs. In industrial sectors, electricity powers machinery and manufacturing processes, thereby boosting productivity and economic growth. Commercial establishments rely on electricity for business transactions, supporting information technology infrastructure, and delivering essential customer services [2]. For individuals, electricity is essential for daily life, powering lighting, heating and cooling systems, communication devices, and various household appliances [3].

Power Electricity Consumption (PEC) is a reliable indicator of economic activity. Developed economies depend on significant amounts of electricity to support industries, households, agriculture, and government functions [4]. Many countries, with limited domestic energy resources, depend heavily on foreign energy supplies [5]. Effective planning in such contexts involves sourcing energy from abroad. However, electricity poses unique investment challenges due to its volatile consumption patterns and the difficulty in measuring its physical flow. Therefore, governments need robust models to forecast electricity demand, particularly in unstable situations. Such forecasting aids decision-making, helping governments to manage fluctuations in electricity consumption and ensure a stable, efficient energy supply under uncertain conditions. Accurate PEC forecasting is crucial for effective planning in the electrical power industry and for the reliable operation of power systems [6]. Since electricity cannot be stored easily, precise forecasts are vital for balancing supply and demand. These forecasts are influential in future energy management decisions, reducing operational

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Abbreviations

AI	Artificial intelligence
ALO	Ant Lion Optimizer
ANOVA	Analysis of Variance
ANN	Artificial Neural Networks
AOA	Arithmetic Optimization Algorithm
ARIMA	Autoregressive Integrated Moving Average
a	calculated using Equation (2), and it linearly decreases from 2 to 0
BOA	Butterfly optimization algorithm
CatBoost	Categorical Gradient Boosting
c_1 and c_2	are acceleration coefficients
DEA	Data Envelopment Analysis
EC	Energy Consumption
EECP	Electric Prediction
ELM	Extreme learning machine
$\exp(j \times \theta_i)$	Is the phase angle, and j is the imaginary unit
fk(xi)	is the output of a regression tree
f (x)	the weight of leaves
GA	Genetic Algorithm
GBDT	Gradient boosting decision tree
GM	Grey model
GWO	Grey Wolf Optimizer
HHO	Harris Hawks Optimization
IAOA	Improved Arithmetic Optimization Algorithm
i	dataset's sample size
it	the current number of iterations
$iter_{max}$	maximum number of iterations
JS	Jellyfish Search
j	representing the dimensions of the sparrow's position
φ	symbolizes the set of regression tree
γ and λ	the complexity of the tree
ρ_1 and ρ_2	random numbers ranging between 0 and 1
LSSVR	least square support vector regression
LSTM	Long Short-Term Memory
m	amount of data utilized in the kth tree
MAPE	Mean Absolute Percentage Error
MAX_{IT}	The maximum number of iterations
MBE	Mean Bias Error
MLP	Multilayer perceptron model
P	prior value
PCA	Principal Component Analysis
PCD	Prediction of Change in Direction
PEC	Power electricity consumption
PPSO	Phasor particle swarm optimization
Q	random number used to enforce normal distribution
Q(t)	represents the position vector of the current grey wolf
$Q_p(t)$	denotes the position vector of the prey
Q(t + 1)	The position of the grey wolf in the next iteration
R_2	the fap value
R^2	Coefficient of Determination
R_i	is the magnitude of the phasor
RMSE	Root Mean Squared Error
SARIMA	Seasonal ARIMA
SOS	Symbiotic Organisms Search
SSA	Sparrow Search Algorithm
ST	solidity threshold
SVM	Support Vector Machines
SVR	Support Vector Regression
TLBO	Teaching-Learning-Based Optimization
t	is the number of iterations
$V_i(t)$	is the velocity of the ith particle at time t
w	number of leaves
XGBoost	Extreme Gradient Boosting
x_i	one of the samples
X_i	is the position of the ith particle
$X_{i,j}^{t+1}$	the updated value of the jth dimension of the ith sparrow
$\hat{y}_i$	Is the predicted label
α	a random number between 0 and 1

and maintenance costs, and enhancing power system optimization and sustainable energy management practices [7].

Predicting electricity consumption accurately is complex due to various influencing factors such as population size, economic development, electricity infrastructure, and climate conditions. Numerous studies have been conducted to develop models for forecasting electricity consumption, typically classified into three categories: non-linear intelligent models, statistical analysis models, and grey prediction models.

The category of non-linear models primarily consists of techniques such as Artificial Neural Networks and Support Vector Machines. For example, Bouzerdoum et al. [8] introduced an innovative approach for short-term power prediction in photovoltaic facilities, combining SARIMA and SVM models. This hybrid model demonstrates superior accuracy, surpassing individual SARIMA and SVM models, and effectively estimates power production in small-scale plants without relying on forecasted meteorological parameters. However, its accuracy hinges on sufficient training data and expertise. ANN was used by Ekonomou [9] employed ANN to predict Greece's long-term energy consumption. The study evaluated various ANN architectures, finding that the Multilayer Perceptron model (MLP) outperformed linear regression and SVM methods. This ANN model proved to be a precise tool for predicting energy consumption, offering significant benefits for energy policy, investment decisions, and environmental analysis. These studies highlight the importance of advanced modeling techniques in accurately forecasting electricity consumption, which is crucial for efficient energy management and planning.

In addition to non-linear intelligent models and the previously mentioned statistical analysis models, regression analysis methods, Autoregressive Integrated Moving Average (ARIMA), and Kalman filter-based techniques have also gained prominence in electricity consumption (EC) prediction [10]. These statistical models provide alternative approaches for forecasting EC and are extensively used in the field.

Yuan et al. [11] conducted a study on forecasting China's primary EC, which holds significant implications for the nation's sustainable development and the global energy market. The research utilized two univariate models: the ARIMA model and the Grey Model (GM). The findings showed that both models were effective, with the ARIMA model displaying less sensitivity to fluctuations and the GM model exhibiting higher responsiveness by using more recent data. To improve accuracy, a hybrid model combining these two was created, achieving a smaller Mean Absolute Percentage Error (MAPE) than the individual models. The study projected that the growth rate of China's primary EC from 2014 to 2020 would be considerable, though lower than the previous decade. Ediger et al. [12] focused on energy demand forecasting in emerging markets, particularly Turkey. They compared econometric modeling with time-series forecasting methods, namely ARIMA and Seasonal ARIMA (SARIMA), and found that the latter provided better results. The research applied these methods to predict Turkey's primary energy demand from 2005 to 2020, indicating a potential decrease in average annual growth rates. This suggested an approaching peak in energy intensity and underscored the need for inter-fuel substitution and policy recommendations to optimize Turkey's energy system. Hou et al. [13] aimed at forecasting wind power demand in China. They developed a sophisticated hybrid model comprising Complete Ensemble Empirical Mode Decomposition with Adaptive Noise, Variational Mode Decomposition, Kernel Principal Component Analysis, an Enhanced Arithmetic Optimization Algorithm, and a Bidirectional Long Short-Term Memory Neural Network. This combination represents a cutting-edge approach in the field of energy forecasting, integrating advanced statistical and machine learning techniques to improve prediction accuracy.

Predicting electricity consumption is a complex task due to the significant uncertainties involved. Factors like urbanization, economic development, and others influence the accuracy of forecasts. These elements create a complex system where variables interact in intricate ways, complicating precise prediction efforts. The exact impact of these factors on electricity consumption is often unclear. This challenge is particularly pronounced in rapidly developing countries like China, where electricity consumption is growing swiftly, and data may be scarce. In such scenarios, the Grey Model (GM) provides a viable alternative for forecasting electricity consumption, especially given the prevailing uncertainties and limited data [3].

Ding et al. [14] developed an adapted grey prediction model to enhance the accuracy of predicting electricity consumption (EC) in China at both overall and industrial levels. This model introduced a novel initial condition and a rolling mechanism prioritizing new information, outperforming benchmark models in precision. The study underscores the significance of EC forecasting for power system development and economic growth, suggesting future model applications and improvements. Zhao et al. [15] created a Rolling GM model for forecasting electricity loading in China and Shanghai. Bahrami et al. [16] proposed an innovative method for short-term electricity load forecasting, integrating a grey model with wavelet transform. Jin et al. [17] used a modified Markov chain state transition matrix for long-term electricity demand prediction in China, focusing on low-carbon emission methods like nuclear, solar, hydro, and wind energy. Hamed et al. [18] explored annual power consumption forecasting using three models: a random parameter linear regression model, a correlated random parameter linear model, and a random parameter linear model with heterogeneity in means and variances. Meria et al. [19] proposed a hierarchical forecast reconciliation approach to provide accurate forecasts of energy demand across all divisions of Brazil's power system, aiming for long-term forecasting that could potentially save 900,000 MWh in the Brazilian power system. Bilgili and Pinar [20] employed a long short-term memory neural network to forecast the growth of power consumption in Turkey. They compared this model with a seasonal autoregressive integrated moving average model, achieving a lower mean absolute percentage error of 2.42 %.

The research community has increasingly focused on hybrid methods to enhance energy modeling. These methods combine different approaches or strategies, leveraging the strengths of each to improve the accuracy and performance of energy models. Additionally, researchers have employed metaheuristic techniques, which involve sophisticated, intelligent algorithms, to fine-tune the parameters of these models, optimizing them for superior results. This synergy of hybrid methodologies and AI-based techniques is paving the way for advancements in energy modeling. Kheirkhah et al. developed a novel algorithm that integrates Artificial Neural Networks (ANN), Principal Component Analysis (PCA), Data Envelopment Analysis (DEA), and ANOVA methods for assessing and forecasting electricity demand. This algorithm addressed seasonal and monthly variations, using pre-processing and post-processing to enhance ANN model performance. The effectiveness of this approach was demonstrated using data on Iranian electricity consumption, yielding accurate estimates. Aslan et al. [21] focused on energy demand estimation in Turkey, presenting an improved version of the Arithmetic Optimization Algorithm (AOA), termed IAOA. This enhanced algorithm improved exploration and exploitation capabilities for solving energy demand problems. Utilizing a linear regression model and data from 1979 to 2011, the study successfully forecasted Turkey's long-term energy demand from 2012 to 2030, showcasing the IAOA method's effectiveness. Chou et al. [22] introduced a forecasting system that combined linear time-series modeling (SARIMA) with non-linear machine learning (LSSVR). They evaluated various optimization algorithms, including Teaching-Learning-Based Optimization (TLBO) and Symbiotic Organisms Search (SOS), with the Jellyfish Search (JS) algorithm performing optimally. This system excelled in predicting multi-step energy consumption with fewer inputs, demonstrating its efficiency for energy forecasting and management in sustainable cities. Hora [23] developed a model using LSTM and BOA for accurate Electric Energy Consumption Prediction (EECP) with a minimum error rate. Musa et al. [24] proposed hybrid algorithms (SVR-HHO and SVR-PSO) for load forecasting, which outperformed traditional SVR. They also optimized a hybrid renewable energy system using SVR-HHO predictions. Li and Qi [25] developed a hybrid grey system model for seasonal power consumption forecasting, focusing on Australia. Their model achieved a mean absolute percentage error of 6.02 %. Zhao et al. [26] utilized a hybrid grey model-least squares SVM to forecast power consumption in Beijing, considering the spatial-temporal distribution characteristics and levels of electric consumption intensity, which revealed a positive spatial correlation and low electric consumption intensity. Afzal et al. [27] focused on improving energy efficiency in buildings through accurate predictions of heating and cooling loads. The study compared three artificial neural network models and a regression model, ultimately enhancing the chosen model with four optimization techniques. The best-performing model, an Extreme Learning Machine enhanced by the Biogeography-Based Optimization algorithm (ELM-BBO), significantly improved the accuracy of load predictions. The ELM-BBO model outperformed others, achieving a correlation coefficient of 0.9969 for cooling and 0.9993 for heating load estimation, demonstrating the effectiveness of the selected optimization methods in achieving precise results. Afzal et al. [28] aimed to enhance building energy efficiency by predicting cooling and heating loads using a multilayer perceptron neural network. The network is combined with eight meta-heuristic algorithms to optimize its hyper-parameters. Performance is evaluated through statistical analysis, revealing that the Perceptron combined with Particle Swarm Optimization and Grey Wolf Optimizer model outperforms others. It achieves the highest R^2 values of 0.966 for cooling and 0.998 for heating loads, demonstrating superior accuracy and efficiency over other hybrid models. The study highlights the effectiveness of the chosen optimization methods in providing accurate predictions.

The demand for electric energy has witnessed a significant surge in recent years, underscoring the urgent need for robust and accurate Electricity Consumption Prediction models. As electricity remains a fundamental driver of economic development, industrial activities, and daily life, its availability and efficient utilization are paramount. Inadequate prediction of electricity consumption can result in inefficient resource allocation, inadequate infrastructure planning, and grid instability. Moreover, in regions heavily reliant on foreign energy supplies, precise ECP becomes even more crucial to ensure reliable energy sourcing. With the complex interplay of factors such as population growth, economic development, and climatic variations affecting consumption patterns, accurate Electricity Consumption Prediction models are indispensable for governments, utilities, and policymakers. Therefore, this research addresses the pressing need for advanced ECP techniques and contributes novel machine learning models and optimization algorithms to enhance the accuracy and efficiency of electricity load forecasting, paving the way for improved energy management and sustainable development in the power sector. Accordingly, this research aims to address the following main research gaps and contributions:

- **Research Gaps**

Despite the growing importance of accurate Electricity Consumption

Prediction, several research gaps exist in the field. First, existing models often lack the ability to handle the intricate and dynamic factors that influence electricity consumption, such as population size, economic development, and climate conditions, leading to suboptimal predictions. Second, there is a need for more comprehensive and localized studies, especially in regions like Turkey, where unique socio-economic and climatic factors can significantly impact consumption patterns. Third, previous research predominantly relies on traditional models or isolated machine learning techniques, and there is a gap in exploring the potential synergies between advanced machine learning models and optimization algorithms for ECP. Lastly, the lack of empirical evaluations comparing the performance of various ECP models leaves a gap in understanding which approaches offer the best accuracy and runtime efficiency.

- **Research Contributions and Novelties**

These research gaps are addressed in this study, and several noteworthy contributions are made to the field of Electricity Consumption Prediction. Firstly, a comprehensive analysis of machine learning techniques, including CatBoost and Extreme Gradient Boosting (XGBoost), in conjunction with optimization algorithms like Sparrow Search Algorithm (SSA), Phasor Particle Swarm Optimization (PPSO), and Hybrid Grey Wolf Optimization (GWO), is presented. This novel approach combines the strengths of advanced machine learning and optimization, offering a more holistic and effective solution for ECP. Secondly, a localized case study in Turkey is provided, shedding light on the unique challenges and opportunities in this region, which have been relatively unexplored in the literature. Thirdly, the performance of these models is compared based on accuracy metrics and runtime efficiency through an empirical evaluation conducted in this study, ultimately identifying the XGBoost-SSA model as the most promising approach for ECP in Turkey. The state-of-the-art in ECP is advanced through these contributions, offering a more accurate, efficient, and localized solution to address the pressing need for reliable electricity consumption predictions.

2. Methodology

This study employs machine learning methods, notably CatBoost and XGBoost, for predicting electricity consumption. These methods are renowned for their effectiveness in handling complex datasets and their ability to provide accurate predictions in various applications, including energy forecasting.

To further enhance the performance of these models, the study involves the optimization of hyperparameters. Hyperparameter optimization is a crucial step in machine learning that involves fine-tuning the parameters of a model to improve its accuracy and efficiency. The optimization algorithms used in this study are the Salp Swarm Algorithm (SSA), Particle Swarm Optimization (PPSO), and Grey Wolf Optimizer (GWO).

The study constructs six different models by combining CatBoost and XGBoost with each of the three optimization algorithms. These models are then utilized to predict electricity consumption. To evaluate and compare the performance of these models, statistical evaluation techniques are employed. These techniques assess the accuracy, reliability, and predictive power of the models, providing insights into which model or combination of models performs best for forecasting electricity consumption.

In the subsequent section, the study provides comprehensive explanations of the algorithms used, detailing their mechanics, the rationale behind their selection, and how they contribute to the overall predictive capability of the models. This detailed examination aids in understanding the strengths and limitations of each approach and the reasoning behind the final model choices for accurate electricity consumption forecasting.

2.1. CatBoost

CatBoost, a powerful machine learning framework developed by Yandex [29], stands out for its application of gradient boosting to a range of tasks, particularly excelling in both classification and regression problems. It is available as a comprehensive open-source library specifically designed for gradient boosting. CatBoost distinguishes itself through its efficient execution time and optimized memory usage, making it a competitive choice among machine learning algorithms [29]. One of the key strengths of CatBoost is its exceptional handling of categorical attributes. Unlike some other algorithms that may struggle with categorical data or require extensive preprocessing, CatBoost inherently manages categorical features effectively, often delivering superior results compared to other methodologies.

In terms of its core functionality, CatBoost introduces significant advancements in parallel processing. This enhancement enables faster training times and facilitates easier implementation, particularly in Internet-based network environments. Such improvements in parallelism are crucial for handling large datasets and complex modeling tasks efficiently.

Moreover, CatBoost addresses a common challenge in machine learning: overfitting. Overfitting occurs when a model learns the details and noise in the training data to the extent that it negatively impacts the performance of the model on new data. To combat this, CatBoost implements several mechanisms. One notable technique involves a unique approach to handling categorical data:

In CatBoost, a random permutation of the dataset is performed. For each example in the dataset, the algorithm calculates the average label value among the examples that share the same category value and precede the given example in the permutation. This method effectively utilizes the ordering in the data to generate new features, reducing the risk of overfitting and improving the model's generalization ability. This is mathematically represented as [29]:

$$\Theta = [\sigma_1, \ldots, \sigma_n]_n^T \tag{1}$$

Here, Θ is a vector of calculated averages for each category, $\sigma_i = [\sigma_1, \sigma_2, \ldots, \sigma_n]$ is random permutation. The average label value calculation is defined as follows [29]:

$$X_{\sigma_{p,k}} = \frac{\sum_{j=1}^{p-1} \left[X_{\sigma_{j,k}} = X_{\sigma_{p,k}}\right] Y_{\sigma_j} + \beta.P}{\sum_{j=1}^{p-1} \left[X_{\sigma_{j,k}} = X_{\sigma_{p,k}}\right] + \beta} \tag{2}$$

where, $X_{\sigma_{p,k}}$ is a target variable statistic, $X_{\sigma_{j,k}}$ is a category feature, Y_{σ_j} is the label value of the corresponding feature, $[X_{\sigma_{j,k}} = X_{\sigma_{p,k}}]$ takes the value 1 when the condition is satisfied, P is a prior value and β is the weight of the prior. This formula considers all the examples preceding the current example in the permutation that share the same category value [29]. In regression tasks, the prior value (*P*) is typically set as the average label value from the entire dataset. This value provides a baseline or starting point for the regression model. The weight (β) assigned to this prior value helps in determining its influence or significance in the regression model. The inclusion of this prior value and its corresponding weight is crucial as it ensures that the model does not overly rely on the specific order or composition of the training data, thereby improving robustness and prediction accuracy [29].

2.2. XGBoost

XGBoost (eXtreme Gradient Boosting) is a highly efficient algorithm built on the principles of gradient-boosting decision trees (GBDT). It has become an essential tool in the fields of machine learning and data science for addressing complex problems in both regression and classification tasks. The efficiency and versatility of XGBoost, stemming from its foundation in classification and regression trees, have earned it considerable recognition and popularity in the research community [30].

XGBoost stands out not only as a practical algorithm but also as a part of a soft computing library that combines innovative techniques with GBDT methodologies. The strength of XGBoost lies in its objective function, which is composed of two key components:

- **Model's Deviation:** This component measures the model's fit to the training data. The goal is to minimize this deviation, indicating a better fit to the data. A lower deviation means the model is accurately capturing the patterns and relationships in the training data.
- **Regularization Term:** This term is crucial for preventing overfitting, a common problem in machine learning where a model becomes too complex and starts to memorize the training data instead of generalizing from it. Overfitting impairs the model's predictive performance on new data. The regularization term in XGBoost introduces a penalty for complexity, promoting simpler models that are more likely to generalize well to unseen data.

By balancing these two aspects, XGBoost effectively minimizes model deviation while controlling complexity. This dual objective enables XGBoost to achieve optimized performance and generalization capability, as outlined in the following equations [31]:

- The predicted label for a sample x_i is given by:

$$\widehat{y}_i = \varphi(x_i) = \sum_{k=1}^{k} f_k(x_i), f_k \in F, \tag{3}$$

where $\widehat{y}_i$ represents the predicted value, $f_k(x_i)$ represents the output of the kth regression tree for the input sample x_i, φ is the set of regression trees with the tree structure parameters *s* and leaf weights *w*, and k is the total number of samples.

- The objective function of XGBoost evaluates performance by considering both the traditional loss function and model complexity [31]:

$$L(\varphi) = l(\varphi) + \Omega(\varphi) = \sum_{i=1}^{n} l(y_i, \widehat{y}_i) + \sum_{i=1}^{k} \Omega(f_k) \tag{4}$$

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2 \tag{5}$$

In this context, y_i denotes the observed value, while *l* refers to a loss function. The primary purpose of the loss function is to quantify the discrepancy between the observed value (y_i) and the predicted value ($\widehat{y}_i$). The second term, Ω, represents the regularization term, which serves to penalize model complexity, thereby mitigating the risk of overfitting. Within this term, γ signifies the complexity associated with each leaf in the decision tree, and *T* denotes the total number of leaves. The parameter λ acts as a balancing factor, adjusting the scale of the penalty to ensure appropriate regularization. Lastly, symbolizes the score attributed to the jth leaf, highlighting its contribution to the model's predictive capability.

Through this intricate balance of fitting the model to the data, while controlling its complexity, XGBoost achieves an effective and robust predictive performance. The algorithm's ability to handle large datasets, along with its flexibility in tuning for different applications, makes XGBoost a widely used tool in various machine learning tasks.

2.3. Grey wolf optimization

The Grey Wolf Optimizer (GWO) is an innovative metaheuristic algorithm inspired by the social hierarchy and hunting behavior of grey wolves in nature. This algorithm is designed to solve optimization problems by mimicking the way grey wolves hunt and interact within their packs. The essential components of the GWO algorithm can be summarized as follows [30].

(1) Social Hierarchy Simulation (Fig. 1)
  - Alpha Wolves (α): Represent the best solution found so far.
  - Beta Wolves (β): Second in the hierarchy, representing the second-best solution.
  - Delta Wolves (δ): Third in the hierarchy, holding the third-best solution.
  - Omega Wolves (ω): The rest of the pack, following the lead of α, β, and δ wolves.

(2) Iterative Process

The algorithm progresses through iterations, updating the positions of the wolves in the solution space.

(3) Key Steps in GWO
  - Exploration: Wolves explore the vicinity of the alpha wolf (the best current solution). This is achieved by randomly adjusting their positions towards the alpha, allowing for a broad exploration of the solution space.
  - Exploitation: Beta and delta wolves, representing other potential solutions, guide the pack. The rest of the wolves adjust their positions towards these wolves, exploiting promising regions of the solution space.
  - Update: Positions of wolves are updated using mathematical models that simulate the encircling behavior and the dynamic of closing in on the prey.

(4) Encircling Prey Strategy

Grey wolves are known for their strategy of encircling prey during a hunt. This behavior is modeled mathematically in GWO to guide the search for the optimal solution.

(5) Mathematical Formulation

The position update equation (Eq. 6) models the encircling behavior:

$$Q(t+1) = Q_P(t) - (2a.\rho_1 - a)\left(2\rho_2.Q_p(t) - Q(t)\right) \tag{6}$$

Here, $Q_P(t)$ is the position vector of the prey (best solution), $Q(t)$ is the current position vector of a wolf, and $Q(t+1)$ is its position in the next iteration [31]. ρ_1 and ρ_2 are random numbers in the range [0,1]. The coefficient a decreases linearly from 2 to 0 over the course of iterations, as calculated by Eq. (8):

$$a = 2 - 2.it/MAX_{IT} \tag{7}$$

(6) Implementation Details

The GWO algorithm iteratively refines the positions of the wolves (solutions), with each iteration representing an attempt to improve upon the current best solution. The algorithm is terminated after a predefined number of iterations (MAX_{IT}) or when a satisfactory solution is found.

By incorporating the principles of grey wolf social structure and hunting patterns, the GWO algorithm offers a robust and efficient method for finding optimal solutions to complex optimization problems. The algorithm's ability to balance exploration and exploitation makes it suitable for a wide range of applications in various fields.

2.4. Sparrow Search Algorithm

The Sparrow Search Algorithm (SSA) is a novel metaheuristic optimization algorithm inspired by the foraging behavior and anti-predation

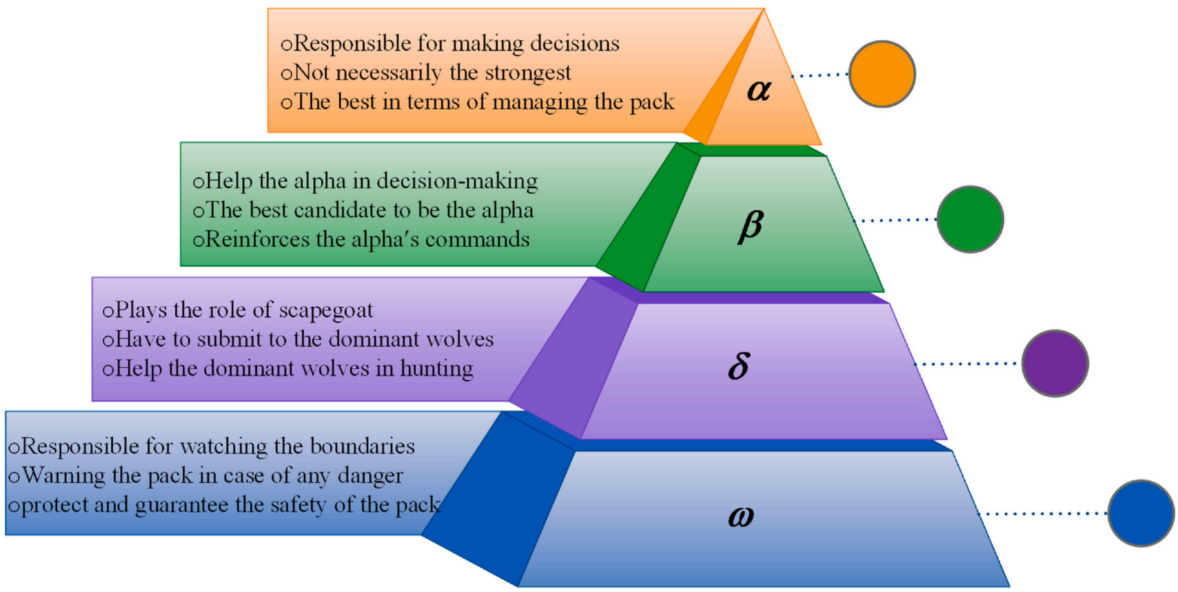

Fig. 1. Leadership hierarchy of grey wolves in nature.

tactics of sparrows. Developed by Xue and Shen [32], the SSA models the interactive behaviors of sparrows, specifically focusing on the roles of producers and scroungers within their social structure.

An overview of the key components and operational mechanics of the SSA can be described as follows [32]:

(1) Producers and Scroungers

- **Producers:** These sparrows actively search for food and determine the foraging direction for the group. They play a pivotal role in locating areas with rich food sources.
- **Scroungers:** They depend on the producers to find food, following their lead to the food sources.

(2) Position Update Mechanism

The position update in SSA is based on the behavior of both producers and scroungers. The algorithm incorporates randomness and adaptability in the search process, reflecting the unpredictable nature of food sources and predator threats.

(3) Mathematical Formulation

The position of a sparrow (solution) in the next iteration is updated using the following equations [32]:

$$\begin{cases} X_{i,j}^{t+1} = X_{i,j}^{t}.\exp\left(-\dfrac{1}{\alpha.\mathrm{iter}_{max}}\right) & \text{if } R_2 < ST \\ X_{i,j}^{t+1} = X_{i,j}^{t} + Q.L & \text{if } R_2 \geq ST \end{cases} \tag{8}$$

where t indicates the current iteration, $X_{i,j}^{t+1}$ represents the updated position of the jth dimension of the ith sparrow in the next iteration. α is a random number in the range [0, 1], and iter_{max} is the maximum number of iterations. R_2 and ST are parameters related to predator detection, with R_2 being a random number between 0 and 1 and ST representing the solidity threshold, typically between 0.5 and 1.0. Q is a random number for enforcing a normal distribution, and L is a $1\times d$ matrix with each element set to 1 [33].

(4) Predator Detection and Response

When the value of R_2 is less than ST, it indicates the absence of predators, and the producer adopts a broad search strategy. Conversely, if R_2 is greater than or equal to ST, signifying the presence of predators, all sparrows move swiftly to safer areas.

(5) Algorithm Dynamics

The SSA dynamically adjusts the search strategy based on the perceived threat level. This mimics the real-world behavior of sparrows, who must constantly balance the need to find food with the risk of predation. The algorithm's flexibility allows for efficient exploration and exploitation of the search space, aiming to find the global optimum in complex optimization problems.

The SSA's approach, which combines exploration (search for new solutions) with exploitation (refinement of known good solutions), makes it a versatile and effective tool for various optimization tasks. The incorporation of producer and scrounger roles adds a unique dimension to the algorithm, enhancing its ability to navigate and adapt within the solution space.

2.5. Phasor particle swarm optimization

Phasor Particle Swarm Optimization (PPSO) is an innovative adaptation of the classic Particle Swarm Optimization (PSO) algorithm, integrating the concept of phasors commonly used in electrical engineering. In PPSO, particles are represented as phasors, which are complex numbers used to represent sinusoidal functions. This representation allows for a more dynamic and flexible exploration of the solution space [34]. The key aspects of the PPSO algorithm can be described as follows:

(1) Phasor Representation

Each particle in PPSO is represented by a phasor in a two-dimensional space. The position of the ith particle is given by Ref. [34]:

$$X_i = R_i \times \exp(j \times \theta_i) \tag{9}$$

Here, X_i is the position of the ith particle, R_i represents the magnitude of the phasor, θ_i is the phase angle, and j is the imaginary unit.

(2) Velocity Update

The velocity of each particle is adjusted based on its own best-known position (P_i), the global best position found by the swarm (G), and its current velocity. The velocity update equation is [34]:

$$V_i(t+1) = w \times V_i(t) + c_1 \times \text{RandomValue} \times (P_i - X_i(t)) + c_2 \times \text{RandomValue} \times (G - X_i(t)) \tag{10}$$

In this equation, $V_i(t)$ is the velocity of the ith particle at time t, w is the inertia weight, and c_1 and c_2 are acceleration coefficients. " RandomValue" generates a random number within [0,1].

(3) Position Update:

The position of each particle is updated considering its current position and new velocity. The position update equation is [34]:

$$X_i(t+1) = X_i(t) + V_i(t+1) \tag{11}$$

(4) Iterative Process

The process of updating velocities and positions is repeated iteratively. The algorithm continues until a termination criterion is met, which could be reaching a maximum number of iterations or achieving a desired solution accuracy.

(5) Exploration and Convergence:

PPSO leverages the collective behavior of particles to effectively explore the search space. The phasor representation allows for a unique movement pattern in the solution space, enhancing the algorithm's ability to avoid local optima and converge towards the global optimum.

(6) Application:

PPSO can be applied to a wide range of optimization problems. Its unique approach makes it suitable for complex problems where the solution space might be difficult to navigate using traditional methods.

In summary, PPSO adds an extra layer of sophistication to the classic PSO by incorporating phasors, leading to potentially more effective search strategies and solution convergence in optimization problems [32].

2.6. Data description

The case study presented aims to forecast the net electricity consumption (EC) in Turkey, utilizing a dataset from previous research conducted by Tutun et al. [35]. Table 1 provides a comprehensive view of the factors influencing electricity consumption in Turkey, making it a valuable resource for understanding and predicting future energy needs. The detailed analysis of the data according to Table 1 can be presented as follows:

- **Dataset Overview**

The dataset covers a period from January 1990 to December 2010. Data is sourced from the Turkish electricity transmission company [35]. The dataset includes variables such as Gross Income, Transmitted Energy, Export, and Import, which are identified as significant factors impacting net EC in Turkey.

- **Data Analysis Approach**

The dataset is divided with 80 % dedicated to training (336 monthly data points) and 20 % for testing and validation (84 monthly data points). The study emphasizes the importance of examining indicators like imports, gross generation, exports, and transmitted energy to understand Turkey's energy scenario.

- **Significance of Key Indicators**
  (a) Imports and Exports: These indicators represent financial transactions in international trade, particularly in the energy sector. They are robust indicators of the country's manufacturing activity and economic vitality. (b) Transmitted Energy: The efficient transmission of electricity is crucial for maintaining high living standards, as it ensures a consistent and reliable electricity supply to households and businesses. (c) Gross Generation: This metric is vital for the country's ability to provide electrical energy promptly, contributing to the reliability and stability of the energy supply system.
- **Implications of the Study:**

By analyzing these variables, the study aims to predict future trends in electricity consumption, which is essential for strategic energy planning and policy-making. The dynamics of exports and imports in the energy sector offer insights into Turkey's economic health and manufacturing activities. Understanding the patterns of electricity consumption and generation can guide the development of energy policies and infrastructure projects to meet future demands.

- **Methodology:**

The study likely employs hybrid machine learning techniques to model and forecast electricity consumption based on the identified variables. The methodology's effectiveness is evaluated based on the performance of the model in the testing and training phases.

2.7. Model verification and evaluation

When evaluating the performance of predictive models, particularly hybrid models in your study, it is crucial to use various error metrics to accurately assess their accuracy and reliability. These metrics help in quantifying how well the models predict compared to the actual data [36–38].

Table 1
The input variables and their statistical details.

Parameters	ID	Statistical Details							
		Count.	Mean.	Std.	Min.	25 %	50 %	75 %	Max.
Gross Income	0	420	4932824.80	1955774.43	2490453.59	3082548.6	4601098.69	6043319.25	8811567.75
Population	1	420	56820195	9651429.60	40446729	48360679	56959988	65446165	72752325
Hourly load [MWh]	2	420	12690.103	8300.98708	2335.1	5187.95	10574.5	18809	33191
Immediate load [MWh]	3	420	12850.518	8371.6050	2125.4	5273.775	10795	19049.4	33391.9
Import [GWh]	4	420	106.38834	105.03728	0	36.425	61.65	164.25	490.3
Export [GWh]	5	420	44.90102	62.721372	0	0	22.1	66.425	314.18559
Gross Production [GWh]	6	420	7311.020	5053.4298	1139.8	2395.25	5996	10893.65	20620.807
Transmitted energy [GWh]	7	420	6124.715107	4247.37659	1118	2274.025	5157.75	8827.925	18139.262
Net Electricity Consumption [kWh]	8	420	5936159699	3981060220	1234451853	2299504640	4772075424	8629348344	1636250673

$$\mathrm{RMSE}=\sqrt{\frac{\sum_{i=1}^{n}(y_i-\hat{y}_i)^2}{T}} \tag{12}$$

$$\mathrm{MAPE}=\frac{1}{T}\sum_{i=1}^{n}\left|\frac{y_i-\hat{y}_i}{y_i}\right| \tag{13}$$

$$R^2=1-\frac{\sum_{i=1}^{T}(y_i-\hat{y}_i)^2}{\sum_{i=1}^{T}(y_i-\overline{y})^2} \tag{14}$$

$$\mathrm{MBE}=\frac{\sum_{i=1}^{T}(y_i-\hat{y}_i)}{T} \tag{15}$$

$$\mathrm{A10}(y,\hat{y})=\frac{1}{T}\sum_{i=1}^{T}\begin{cases}1 & \text{if } \frac{|\hat{y}_i-y_i|}{y_i}\le 0.1\\ 0 & \text{otherwise}\end{cases} \tag{16}$$

$$\mathrm{PCD}(y,\hat{y})=\frac{1}{T-1}\sum_{i=2}^{T}I((f_i-f_{i-1})(y_i-y_{i-1})>0) \tag{17}$$

In these formulas, T represents the total number of observations. y_i is the ith observed value. $\hat{y}_i$ is the ith predicted value. $\overline{y}$ is the mean of the observed values. I is an indicator function, yielding 1 if the condition is true and 0 otherwise.

3. Results and discussion

This section presents the results for the hybrid models CatBoost and XGBoost. Figs. 2 and 3 illustrate the predicted data alongside the target values for these models during both the training and testing phases. An analysis of these results yields intriguing insights into the performance of the two models.

The results indicate that the CatBoost hybrid models face challenges in accurately predicting the target values. These limitations are particularly noticeable during the testing phase and at peak data points. In contrast, the XGBoost models demonstrate a markedly superior performance in the testing phase. They show a better alignment with the target values, especially at peak points, indicating a more robust predictive capability.

To provide a detailed and precise evaluation, a wide array of statistical indicators has been thoroughly analyzed. These indicators, to be detailed in the subsequent sections, offer a comprehensive evaluation of the strengths and weaknesses of each model. This thorough analysis is critical to understanding the models' performance and guiding future improvements in predictive modeling.

Fig. 4 employs the coefficient of determination (R^2) to compare the performance of the CatBoost and XGBoost hybrid models. The plot illustrates the prediction-observation relationship, with the x = y line serving as a benchmark for perfect alignment between predicted and observed values. A closer proximity of the data points to this line indicates a stronger correlation and proportional association between the observed and predicted values.

The analysis reveals that, for the training dataset, the CatBoost hybrid models surpass the XGBoost models in terms of R^2 values, suggesting superior training efficacy. However, when evaluating the test dataset, the XGBoost hybrid models exhibit a higher performance based on their R^2 values. Among the models assessed, the XGBoost-SSA model stands out with the highest performance in the test phase, achieving an R^2 value of 0.9984. On the other hand, the CatBoost-PPSO model shows the weakest performance during the test phase, with an R^2 value of 0.9802. These findings indicate a notable difference in the predictive accuracy of the models across training and testing phases, with each model displaying distinct strengths in different contexts.

Fig. 5 features box plots that illustrate the error values during the test and training periods for all hybrid models. These plots are instrumental in analyzing various characteristics of the data, such as the compactness of distribution, symmetry, and the presence of outliers. Within each box, the median value is depicted by the central line. The length of the box itself represents the data's variability or spread, with a non-central median indicating a deviation from a normal distribution.

Upon examining the training dataset, the box plots reveal that the data trained using XGBoost hybrid models exhibit positive skewness, suggesting a non-normal distribution. In contrast, the training data for CatBoost hybrid models appear to follow a normal distribution, indicating their enhanced performance in the training phase.

For the test dataset, the data predicted by the XGBoost-SSA and CatBoost-SSA hybrid models show more normal distributions and lower error values compared to other models. When considering the range of

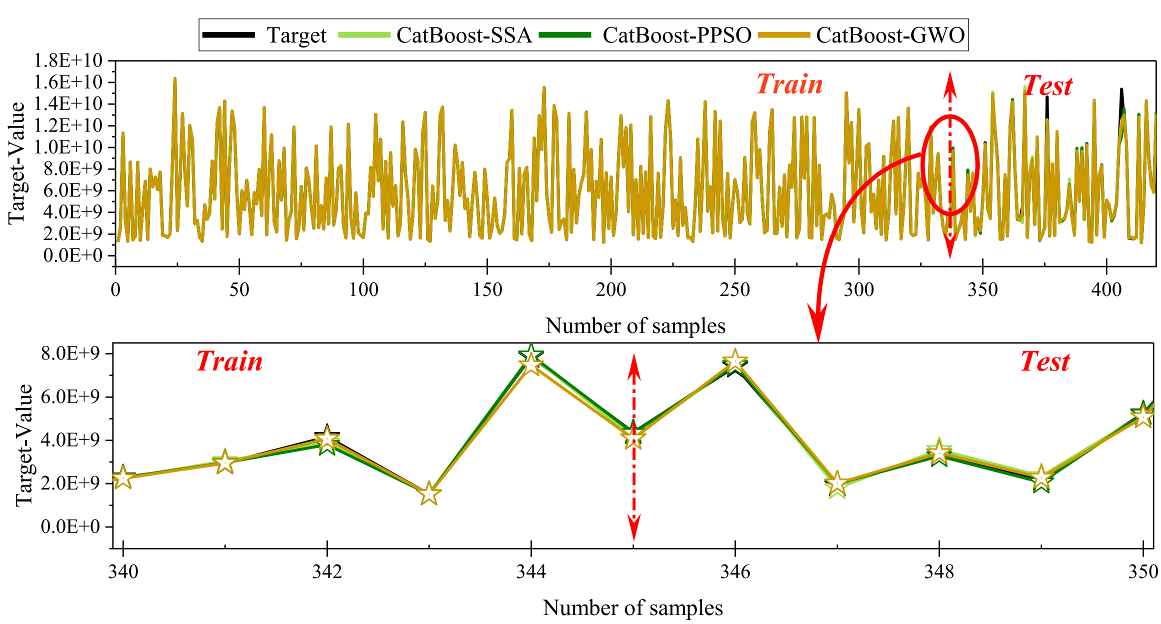

Fig. 2. Time series of the observed and predicted by hybrid CatBoost models.

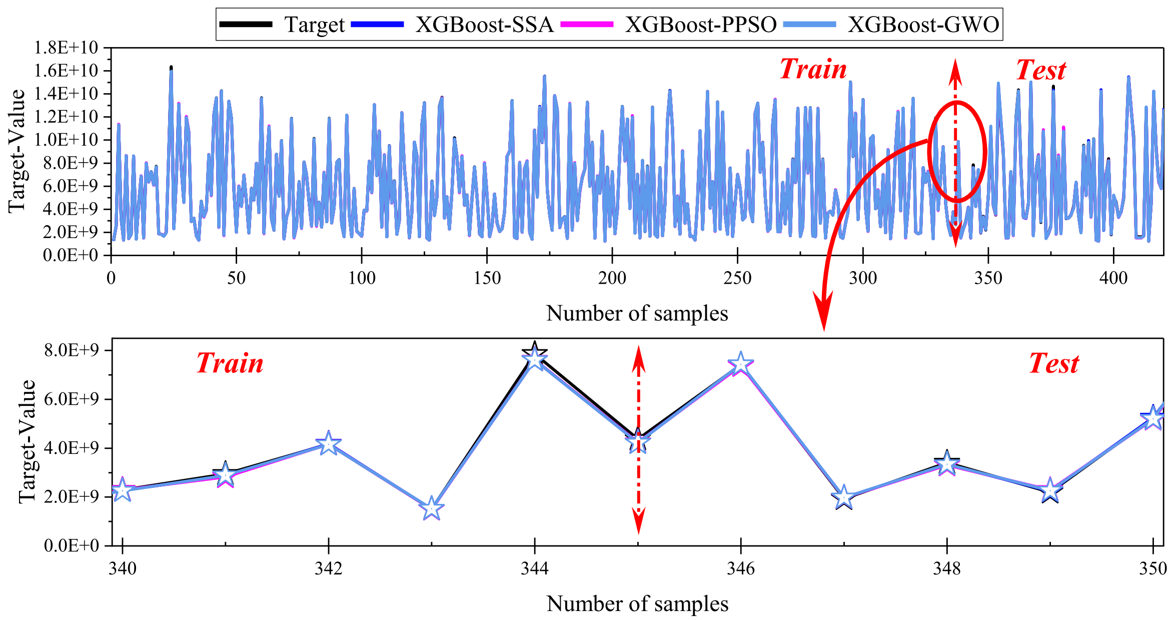

Fig. 3. Time series of the observed and predicted by hybrid XGBoost models.

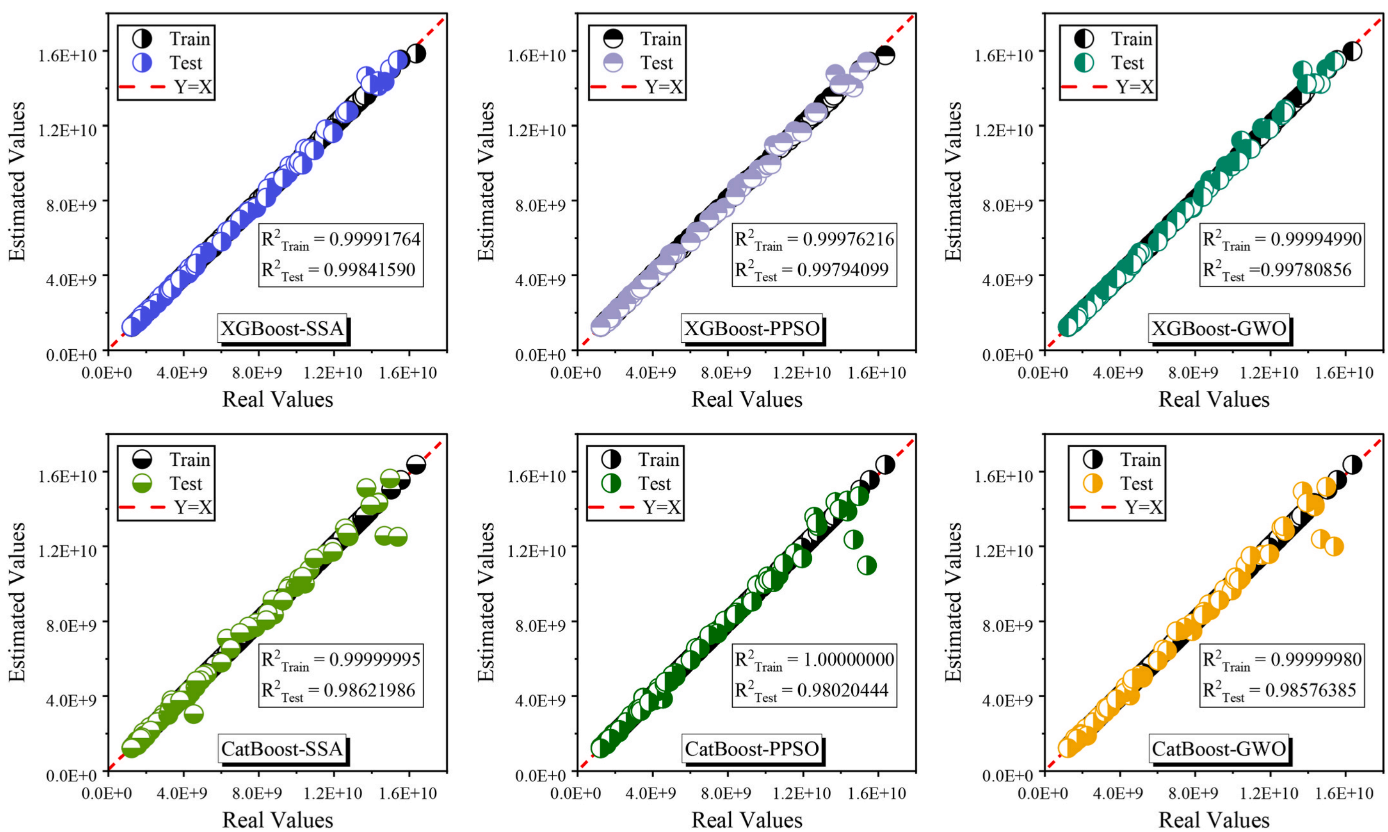

Fig. 4. Scatter plot of the observation-prediction for all hybrid models.

error values, including maximum and minimum errors, and the overall spread of errors, the XGBoost-SSA model emerges as exhibiting a more favorable performance. This analysis of box plots provides a comprehensive understanding of the error characteristics and distribution tendencies of the different models, highlighting the nuances in their performance.

Fig. 6 displays the runtime calculations for the six hybrid models utilized in this study. The analysis reveals a variation in runtime durations for models combined with the CatBoost algorithm, with some models exhibiting shorter runtimes and others, notably the CatBoost-SSA, requiring significantly more time. In comparison, models combined with the XGBoost algorithm generally demonstrate shorter runtimes than their CatBoost counterparts. Among all models, CatBoost-PPSO and XGBoost-PPSO are observed to have the shortest runtimes.

While runtime is an important factor in model evaluation, it is not the sole criterion. Considering the error analysis and other performance

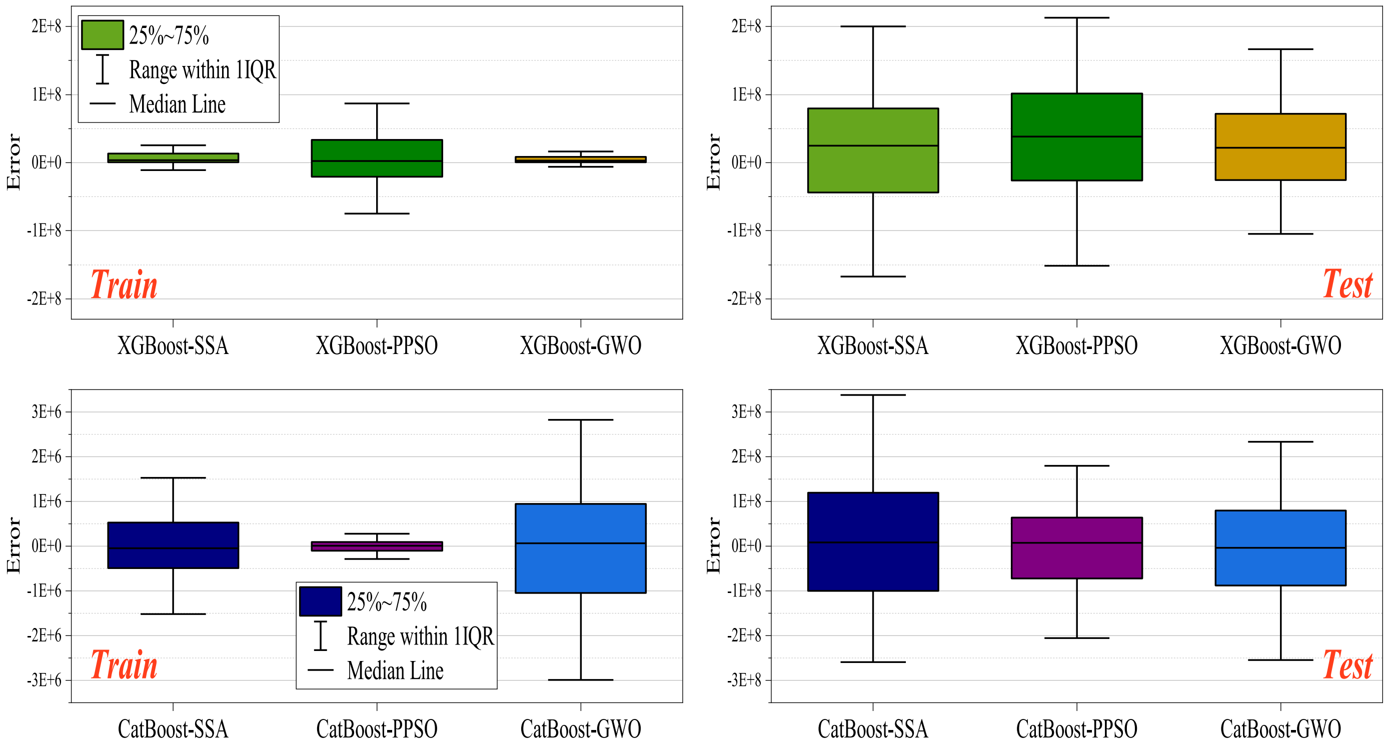

Fig. 5. Box plots of the error values for all hybrid models during the test and training periods.

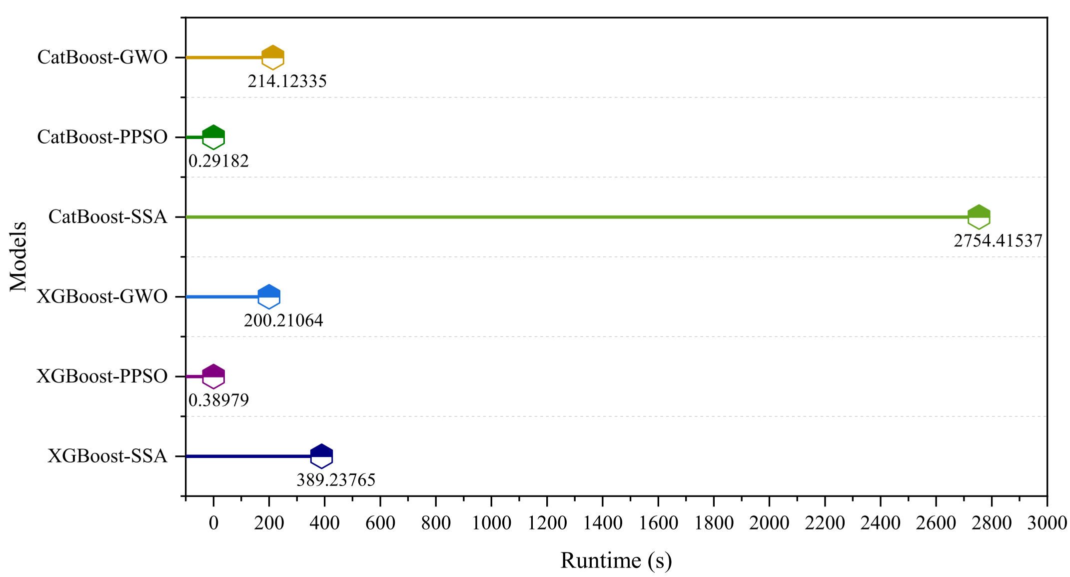

Fig. 6. Comparison of runtime for the six hybrid models.

metrics previously discussed, the XGBoost-SSA model stands out as a favorable option. It strikes a balance between reasonable runtime and efficient performance, making it a recommended choice for predictive analysis in this study's context.

Table 1 lists the input and output data for the model, with each parameter assigned a specific ID for systematic analysis. To explore the interrelationships among these parameters, a correlation matrix is presented in Fig. 7. This matrix is a tabular representation of correlation coefficients, indicating the strength and direction of linear relationships between variables in the dataset.

The correlation coefficients, which range from −1 to 1, reveal the degree of association between variables. A coefficient of 1 implies a perfect positive linear relationship, where variables increase together proportionally. In contrast, a coefficient of −1 indicates a perfect negative linear relationship, with one variable increasing as the other decreases. A coefficient of 0 suggests no linear correlation, although non-linear relationships might still exist.

An analysis of the matrix shows that most features positively correlate with the target variable, indicating a reinforcing relationship. Notably, ID-4 has the weakest correlation with the target, while ID-6 has the strongest. These patterns in the correlation matrix provide key insights into how the input variables are interdependent with the desired output, thereby enhancing our understanding of the model's dynamics.

Fig. 8 presents a bar plot of various metric errors, including RMSE (Root Mean Square Error), MBE (Mean Bias Error), PCD (Percentage of Change in Direction), R^2 (Coefficient of Determination), A10 (A10 Error

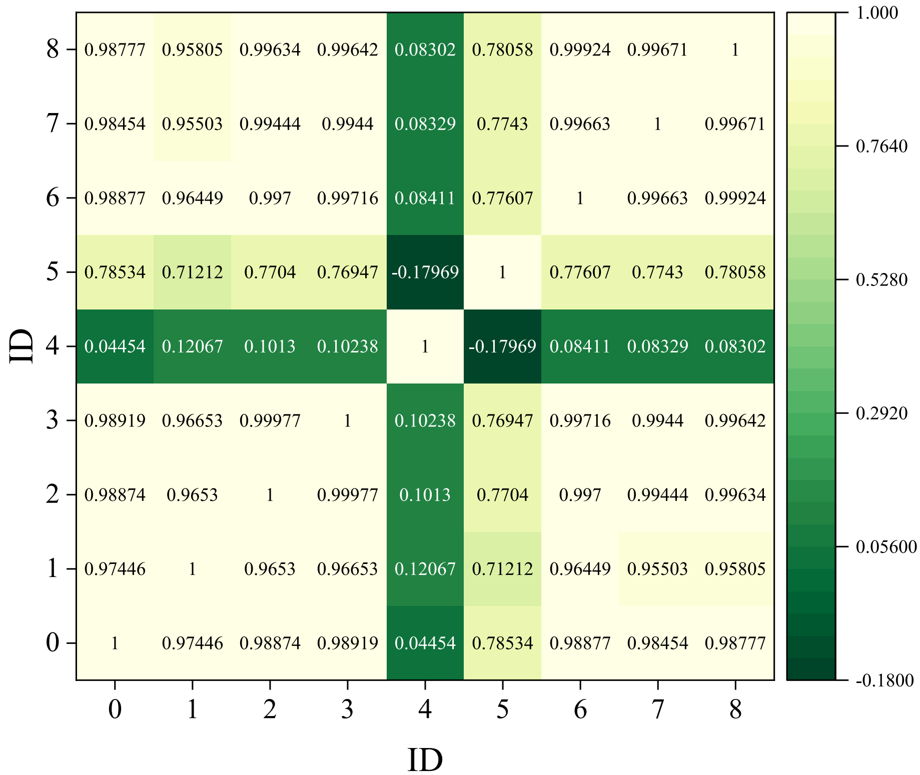

Fig. 7. The correlation matrix of features.

Metric), and MAPE (Mean Absolute Percentage Error), for both training and testing datasets.

In the training dataset, the CatBoost variants (CatBoost-GWO, CatBoost-PPSO, CatBoost-SSA) show very low values for RMSE, MBE, and MAPE, indicating effective training performance with these models. Conversely, the XGBoost models (XGBoost-GWO, XGBoost-PPSO, XGBoost-SSA) display slightly higher error values, suggesting some degree of error in their performance.

Although R^2 values for all models are close to 1, the CatBoost-PPSO model stands out for its superior performance during training. Similarly, for PCD and A10 metrics, this model again shows the best results among all the tested models. On the other hand, considering all the error metrics collectively, the XGBoost-PPSO model ranks as the least effective among the hybrid models.

In the testing dataset, the XGBoost models notably outshine the others. According to the RMSE, MAPE, and MBE metrics, the XGBoost variants (XGBoost-GWO, XGBoost-PPSO, and XGBoost-SSA) show significantly better performance, as evidenced by their lower error values compared to the other models. While the R^2 values for all models are similar, the XGBoost models achieve slightly higher scores, indicating better fit and prediction accuracy. Specifically, the XGBoost-SSA model stands out with the highest R^2 value among all tested models, contrasting with the CatBoost-PPSO model, which has the lowest R^2 value.

Regarding the PCD metric, the XGBoost-GWO model scores the highest, while the CatBoost-SSA model ranks the lowest. For the A10 metric, values for the XGBoost hybrid models are close to 1, suggesting superior performance in comparison to the other models. A comprehensive evaluation of these error metrics and comparisons leads to the conclusion that, for the testing dataset, the XGBoost-SSA model exhibits the most outstanding performance among all the hybrid models.

Table 2 complements the charts by providing detailed error metric values for all the hybrid models. A focused analysis on the MAPE reveals distinct performance patterns across these models. During the training phase, the CatBoost-PPSO model stands out for its exemplary performance, recording the lowest MAPE and thus outperforming the other models. In contrast, the XGBoost-PPSO model exhibits the least favorable performance based on MAPE in this phase.

In the testing dataset, the performance dynamics shift. Here, the XGBoost-SSA model emerges as the top performer, achieving the lowest MAPE and thereby surpassing the other models. On the other hand, the CatBoost-SSA model shows a comparatively lower performance in the testing phase, as indicated by its higher MAPE values compared to its counterparts. These findings highlight the varying strengths of each model in different phases of application, underscoring the importance of model selection based on the specific phase of usage.

Fig. 9 graphically illustrates the balance between exploration and exploitation in the hybrid models, as tracked across iteration numbers. Exploration entails searching new areas of the solution space to find potentially superior solutions, while exploitation focuses on leveraging the best-known solutions for immediate benefits. This balance is crucial in optimization algorithms, as it impacts the efficiency and effectiveness of finding optimal solutions.

From the analysis of Fig. 9, distinct patterns emerge in how the models approach this balance. The CatBoost-PPSO and XGBoost-PPSO models demonstrate a lack of convergence from the initial stages, resulting in their significantly shorter runtimes. In contrast, the CatBoost-GWO and XGBoost-GWO models show a trend toward eventual convergence, but they require a longer duration to reach the optimization objective.

Notably, the CatBoost-SSA and XGBoost-SSA models exhibit rapid convergence, attaining the optimization objective much quicker than other models. Among these, the XGBoost-SSA model stands out, displaying the most favorable performance in terms of convergence speed and computational efficiency. These observations from Fig. 9 shed light on the varying convergence rates and runtime efficiencies among the hybrid models, with the XGBoost-SSA model demonstrating superior performance.

The convergence plots in Fig. 10, illustrating the performance of various hybrid models over 500 iterations, are based on the Mean

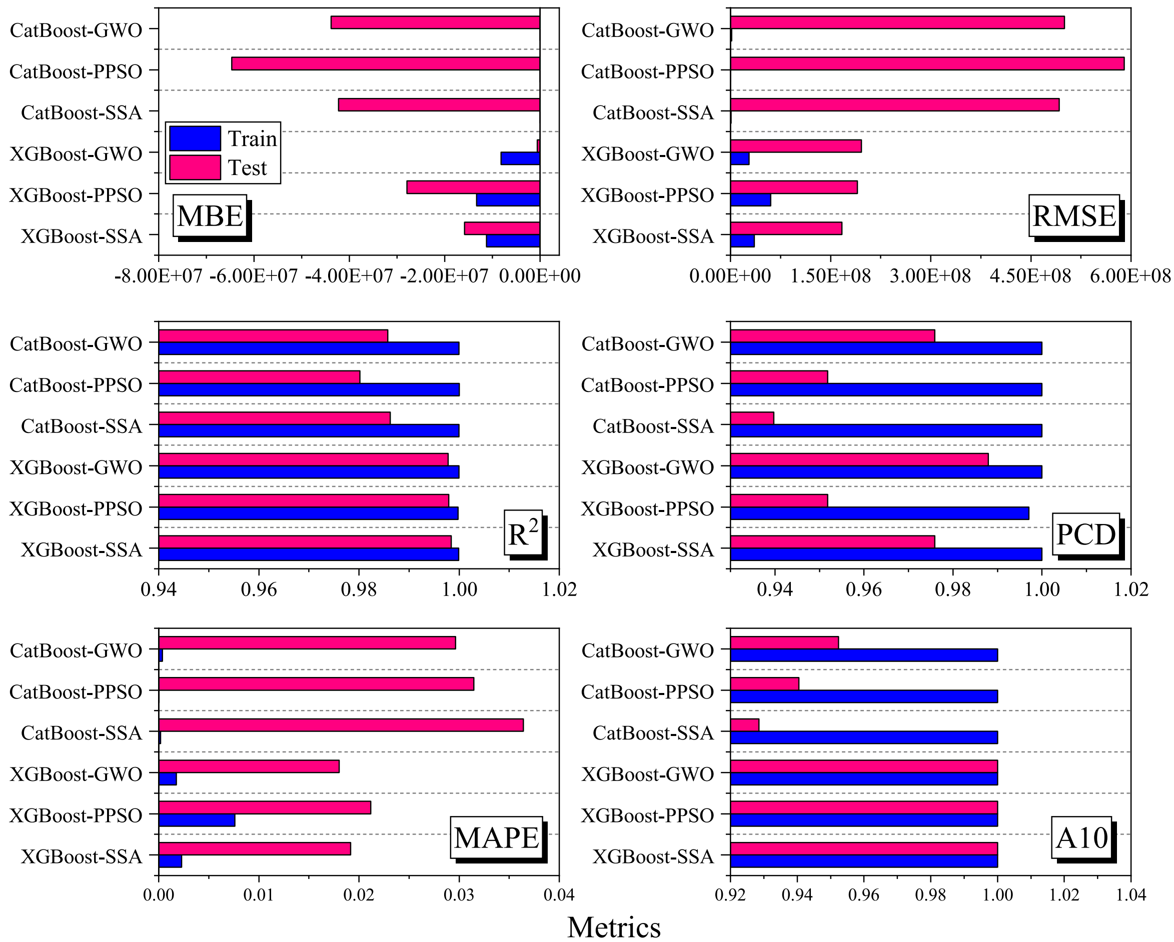

Fig. 8. The obtained Error metrics values for proposed hybrid models.

Table 2
The obtained error metric values for CatBoost and XGBoost hybrid models.

Error metrics	XGBoost-based hybrid models			CatBoost-based hybrid models		
	SSA	PPSO	GWO	SSA	PPSO	GWO
	Train					
MBE	−11226488	−13354365	−8189121	2344	216	91
RMSE	35575295	60455421	27746676	883882	159145	1765543
MAPE	0.00229	0.00760	0.00176	0.00018	0.00003	0.00037
R^2	0.99991764	0.99976216	0.99994990	0.99999995	1.00000000	0.99999980
PCD	1.0000	0.9970	1.0000	1.0000	1.0000	1.0000
A10	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
	Test					
MBE	−15881535	−27942893	−614136	−42284320	−64660112	−43817197
RMSE	166906101	190287310	196311093	492274357	590016650	500353090
MAPE	0.01915	0.02119	0.01801	0.03641	0.03148	0.02964
R^2	0.99841590	0.99794099	0.99780856	0.98621986	0.98020444	0.98576385
PCD	0.9759	0.9518	0.9880	0.9398	0.9518	0.9759
A10	1.0000	1.0000	1.0000	0.9286	0.9405	0.9524

Squared Error (MSE) index. The MSE values provide insights into the convergence efficiency of each model.

Upon examining these plots, the CatBoost hybrid models are observed to have higher MSE values, signaling a less efficient convergence and thereby indicating a relatively lower performance. In contrast, the XGBoost models, when paired with GWO, PPSO, and SSA optimizers, show lower MSE values, signifying better convergence.

Of particular note is the XGBoost-GWO hybrid model, which demonstrates the fastest convergence, achieving it with a relatively small number of iterations. However, this rapid convergence might hint at some limitations in its overall performance. The XGBoost-SSA model, on the other hand, presents a more balanced convergence pattern. It reaches convergence around the 50th iteration and maintains significantly lower MSE values throughout the process. This pattern indicates a more stable and effective performance, making the XGBoost-SSA model a preferable choice based on convergence behavior.

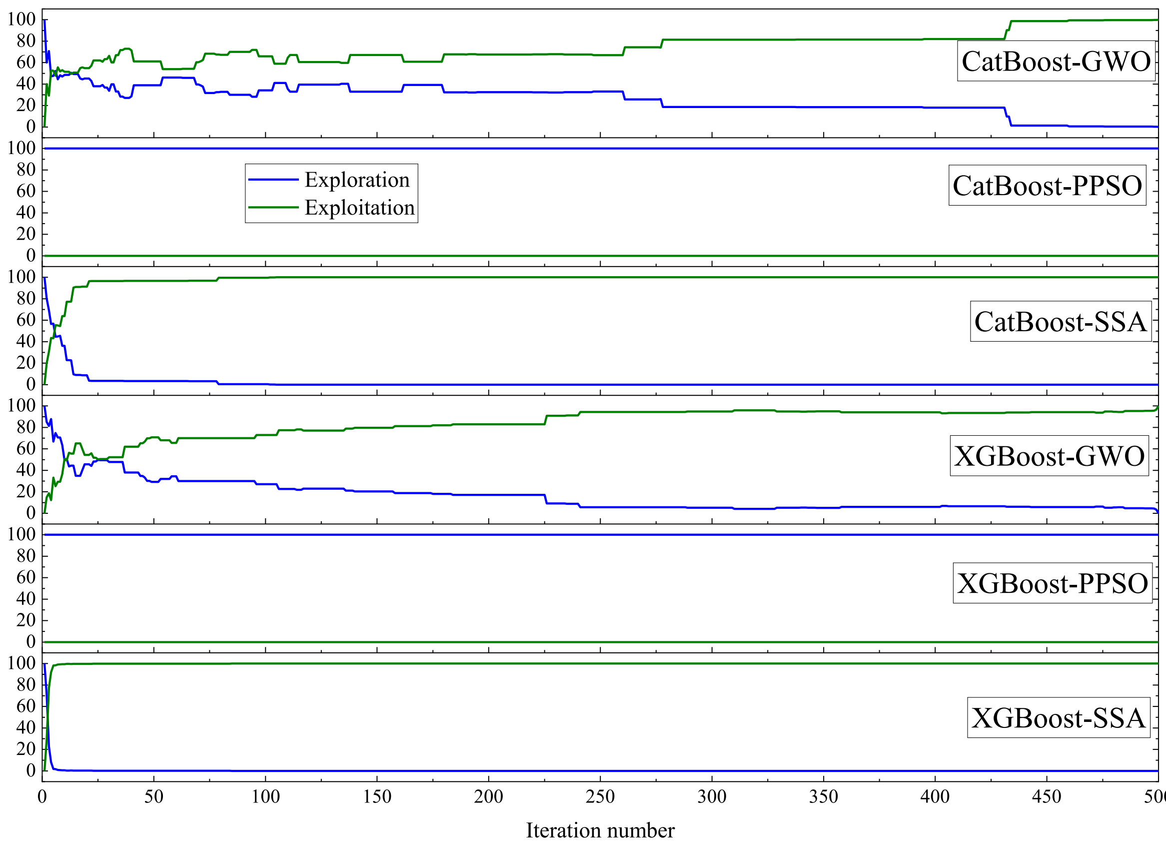

Fig. 9. The trade-off between exploration and exploitation for the hybrid models.

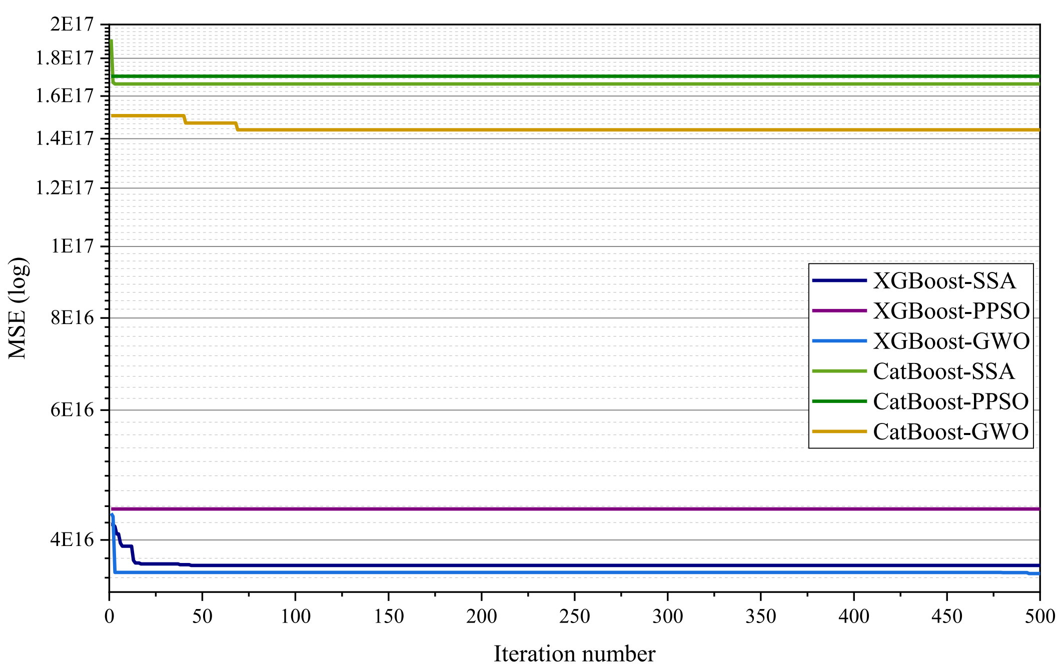

Fig. 10. The convergence plots of the hybrid models based on the Mean Squared Error (MSE) statistical index.

3.1. Comparative study

This section comprises two comparative studies designed to underscore the superiority of the proposed hybrid models. The first study involves a comparison of the proposed hybrid models with the same machine learning methods combined with benchmark optimizers like the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). The findings from this assessment are detailed in Table 3. They reveal that the proposed hybrid models demonstrate significantly higher accuracy compared to their benchmark counterparts.

Table 3
The comparison of the proposed hybrid models' accuracy with the benchmark optimizers-based hybrid models.

Error metrics	XGBoost-Based Hybrid Models				
	XGBoost-GA	XGBoost-PSO	XGBoost-SSA	XGBoost-PPSO	XGBoost-GWO
	Train				
MBE	−139.687838	−0.27843495	−13354365	−8189121	−8189121
RMSE	22644.45327	3895.751579	60455421	27746676	27746676
MAPE	0.00000492	0.00000089	0.00760	0.00176	0.00176
R^2	1	1	0.99976216	0.99994990	0.99994990
PCD	1	1	0.9970	1.0000	1.0000
A10	1	1	1.0000	1.0000	1.0000
	Test				
MBE	−96178001.55	−76879780.55	−15881535	−27942893	−614136
RMSE	809829895.6	789432996.6	166906101	190287310	196311093
MAPE	0.03513547	0.03851326	0.01915	0.02119	0.01801
R^2	0.96270703	0.96456195	0.99841590	0.99794099	0.99780856
PCD	0.96385542	0.92771084	0.9759	0.9518	0.9880
A10	0.95238095	0.94047619	1.0000	1.0000	1.0000
Error metrics	**CatBoost-Based Hybrid Models**				
	CatBoost -GA	CatBoost-PSO	CatBoost-SSA	CatBoost-PPSO	CatBoost-GWO
	Train				
MBE	−653681988.7	−575362294.6	2344	216	91
RMSE	830219042	738405717	883882	159145	1765543
MAPE	0.10781431	0.0945392	0.00018	0.00003	0.00037
R^2	0.95514649	0.96451856	0.99999995	1.00000000	0.99999980
PCD	0.9880597	0.99402985	1.0000	1.0000	1.0000
A10	0.27380952	0.45535714	1.0000	1.0000	1.0000
	Test				
MBE	−713462440.3	−638966691.7	−42284320	−64660112	−43817197
RMSE	937599229.1	843145950.4	492274357	590016650	500353090
MAPE	0.11615152	0.1039163	0.03641	0.03148	0.02964
R^2	0.95001107	0.95957548	0.98621986	0.98020444	0.98576385
PCD	0.93975904	0.93975904	0.9398	0.9518	0.9759
A10	0.19940476	0.38095238	0.9286	0.9405	0.9524

The second study provides a comparison of the hybrid model selected in this research with models from previous studies. The results of this comparative analysis are presented in Table 4. This study is instrumental in positioning the selected hybrid model in the context of existing research, further highlighting its performance and advantages.

4. Conclusion

This study delves into the realm of electricity consumption prediction in Turkey, employing machine learning methodologies, specifically CatBoost and Extreme Gradient Boosting (XGBoost), in tandem with optimization algorithms like SSA, PPSO, and GWO. The overarching goal is to refine the accuracy and performance of electricity load forecasting, with a keen eye toward bolstering effective energy management and steering the power sector towards sustainable development.

The empirical findings underscore the prowess of hybrid models, particularly those intertwining XGBoost with optimization algorithms, and notably, the XGBoost-SSA configuration. This hybrid outperformed its CatBoost counterparts, exhibiting superior precision in predicting net electricity consumption. During the testing phase, XGBoost models excelled, showcasing a superior alignment with target values, particularly at peak consumption intervals. A rigorous statistical evaluation, incorporating metrics like the coefficient of determination (R^2), error analysis, and convergence plots, revealed the XGBoost-SSA model's preeminence.

The culmination of these evaluations witnessed the XGBoost-SSA model securing the highest R^2 value during the testing phase, indicative of its unparalleled performance. Additionally, lower error values were observed, attesting to the model's enhanced accuracy in forecasting electricity consumption. The convergence plot analysis further underscored the XGBoost-SSA model's efficiency, converging at a reasonable number of iterations, reinforcing its suitability for predictive applications.

The proposed methodology, orchestrating a synergy between machine learning algorithms and optimization techniques, presents an innovative paradigm for accurately forecasting electricity load, transcending the limitations of traditional models in comprehending intricate consumption patterns. The superior accuracy and performance achieved by the XGBoost-SSA model hold promising implications for proactive planning in the electrical power industry, ensuring the steadfast operation of power systems. Future research endeavors could explore the transferability of this methodology to other regions and contemplate expanding the dataset temporally to encompass a more prolonged period, thereby accommodating the evolving dynamics of electricity consumption. This holistic approach ensures the robustness and applicability of the proposed methodology in diverse contexts within the realm of energy forecasting.

Table 4
The comparison of attained R^2 and MAPE values in the current investigation and previous publications.

Investigation	Model	R^2	MAPE
Ding et al. [14]	Adapted grey prediction model-PSO	N/A	0.03381
Hou et al. [13]	Kernel principal component analysis-arithmetic optimization algorithm	0.7521	1.2717
Zhao et al. [15]	Grey model- Ant Lion Optimizer	N/A	0.0323
Xu et al. [20]	Grey model-PSO	N/A	0.06826
Jin et al. [17]	Markov chain state transition matrix	N/A	0.075
Kheirkhah et al. [39]	ANN-PCA-DEA-ANOVA	N/A	0.045
Musa et al. [24]	SVR-HHO	0.9951	0.1311
Li and Qi [25]	Grey model	N/A	0.0602
This study	**XGBoost-SSA**	**0.998**	**0.01915**

CRediT authorship contribution statement

Xuetao Li: Conceptualization, Resources, Validation, Visualization, Writing – review & editing. **Ziwei Wang:** Data curation, Formal analysis, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Chengying Yang:** Investigation, Resources, Software, Validation, Writing – review & editing. **Ayhan Bozkurt:** Conceptualization, Data curation, Investigation, Methodology, Project administration, Software, Visualization, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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