Seeker Optimized Deep Neural Model for Pattern Mining in Smart Grid Energy

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ABSTRACT

Smart grids collect a tremendous amount of energy-use data in various formats from smart meters, distributed sensors, renewable energy systems, and IoT monitoring systems. However, existing pattern mining techniques using deep neural networks are complex, and feature optimization and predictive performance are lacking for dynamic and non-linear energy usage patterns. That restricts the ability to forecast energy in real time, balance energy loads, detect faults, and manage energy demand and response, resulting in energy loss, instability and inefficient utilization of energy resources. Therefore, an intelligent, optimized pattern-mining framework is required to improve the operational efficiency and precision of decision-making in the smart grid. In the work, a Seeker Optimized Deep Neural Model for Pattern Mining in Smart Grid Energy is proposed to address the above challenges. The proposed scheme includes a Deep Neural Network (DNN) for improved feature selection and weight optimization, along with efficient learning of the hidden layers and the Seeker Optimization Algorithm. The technique of Seeker optimization strategy is a very efficient method of obtaining an optimum energy consumption pattern, which decreases the training time and convergence error. It enhances the classification accuracy, removes unnecessary energy features, and allows adaptive learning in changing energy conditions, which will improve smart grid analytics. Moreover, the proposed algorithm can effectively identify abnormal consumption patterns and optimize the management of integration renewable energy. The proposed model is tested with reference energy data sets available from smart meters and Energy Consumption Repository. The accuracy, precision, recall, F1-score, energy prediction rate, and computational time are used for the evaluation measures. The experimental results reveal that the proposed Seeker Optimized DNN technique outperforms the conventional machine learning and deep learning methods in terms of pattern-mining accuracy, convergence speed and error rates. The results show the energy savings, energy monitoring, better demand prediction, and intelligent energy management of the next generation smart grid system.

Keywords: Smart Grid Energy Optimization, Seeker Optimization Algorithm (SOA), Deep Neural Network (DNN) Pattern Mining, Feature Selection and Dimensionality Reduction, Energy Consumption Forecasting and Anomaly Detection

1. Introduction

Smart grid technology has revolutionized the power system infrastructure from traditional to intelligent systems with automatic and data driven capabilities [1]. Smart grids

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integrate advanced sensor technology, smart meters, Internet of Things (IoT) technology, renewable energy sources and bidirectional communication networks to enable the optimization of energy generation, transmission, distribution and consumption [2]. The use of smart sensors and distributed energy resources has resulted in a large volume of energy data constantly generated in smart grids, which is very high-dimensional and heterogeneous [3]. To enable intelligent energy forecasting, load balancing, fault detection and demand response management, these data streams must be processed to extract meaningful patterns to improve the stability of the grid [4]. Finally, deep learning and data mining are important technologies to address complex energy consumption behaviors and energy-use efficiency in the operation and management of smart grids. Artificial intelligence technologies have proven to be capable of learning, modelling and identifying nonlinear relationships and hidden temporal patterns in smart grid data in recent years [6]. The models have been improved to adapt and learn, as well as to extract features, which makes them more capable to make predictions than traditional machine learning methods [7]. Furthermore, intelligent energy analytics play a crucial role in the use of sustainable energy, the integration of renewable energy sources and the control of autonomous energy systems in the context of smart cities in the coming years [8].

While deep learning based smart grid analytics have been shown to have numerous advantages, the existing pattern mining frameworks have several key problems [9]. The complexity of the smart grid is that the energy data is high-dimensional, dynamic and noisy, as well as being heterogeneous in general.In general, the energy data from a smart grid is high-dimensional, dynamic, noisy and heterogeneous, making the task of efficiently extracting patterns very complex [10]. However, traditional deep neural models are characterized by excessive computational complexity, slow convergence, overfitting, and ineffective feature optimization with large energy datasets. These limitations lead to a less accurate and reliable real-time energy forecasting and intelligent decision making system. Furthermore, the consumption patterns are constantly changing and the production of renewable energy is uncertain, increasing the uncertainty in the smart grid operation and impacting the accuracy of the prediction and the efficiency of energy management.

One more relevant comment is that a lot of existing optimization-based deep learning techniques are mainly concerned with the accuracy of the predictions, while neglecting the computational efficiency and adaptiveness of learning. The deep learning methods have been combined with some metaheuristic optimization algorithms like Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Ant Colony Optimization (ACO) to increase the smart grid analytics. However, these methods may also converge prematurely, trap to local optima, be sensitive to parameters, and not be very robust in the dynamic smart grid environments. Although many recent works have proposed optimization-based deep learning frameworks for energy analytics, there are still many challenges in designing an intelligent seeker based optimization mechanism to effectively enable smart grid patterns. The challenge of capturing the difference in consumption patterns between linear and nonlinear and the inability to account for the hidden spatiotemporal dependencies and adaptive feature learning from heterogeneous smart grid data. Furthermore, the majority of the conventional designs are very demanding in terms of computational resources and are not applicable in the actual energy monitoring environment. In contrast, a limited number of research works have investigated the application of Seeker Optimization Algorithms with deep neural networks to improve the feature selection, convergence speed, learning efficiency, and accuracy of prediction in smart grid energy systems. The primary objective of the research will be to design an optimized deep learning intelligent model to effectively extract pattern in an energy system in a smart grid. The purpose of the proposed research is to build a framework that relies on a Deep Neural Network (DNN) to correctly process and explore the complex energy patterns from a smart grid with large-scale and heterogeneous datasets. In order to achieve efficient learning and predictive accuracy, an optimization algorithm, called the Seeker Optimization Algorithm (SOA), is proposed for the optimization of the features and tuning of the neural network parameters. Another goal of the research is to improve convergence speed, prediction accuracy and computation efficiency for the analytics for Smart Grids in dynamic operating condition. The suggested framework also attempts to improve the intelligent management approaches, anomaly detection, and energy load forecasting for a smart grid to allow for reliable and adaptive operation. An important goal is to reduce the energy features that are repeated in the energy monitoring and adaptive learning to support real-time energy monitoring and decision making for the next generation smart grid environment. In order to solve these problems, research will focus on applying a novel pattern mining approach, the Seeker Optimized Deep Neural Model in the field of Smart Grid Energy. The smart grid energy data sets are preprocessed to eliminate noise, missing data and redundancy. These features from the energy consumption are then optimized with the Seeker Optimization Algorithm. The seeker optimization mechanism is used for seeking the optimal subset of features and hidden-layer parameters of a deep neural network. The optimized features are then sent to an intelligent energy pattern classification and prediction model, Deep Neural Network.

Seeker optimization, along with deep neural learning, optimizes the training of the hidden layers, reduces convergence errors and boosts adaptive learning performance. Using a suite of benchmark smart grid datasets, performance metrics such as accuracy, precision, recall, F1-score, prediction rate, and computational time are used to evaluate the proposed framework. A model that offers reliable, scalable, and computationally efficient smart grid energy analytics for the next generation, enabling intelligent power systems to become smarter.

The highlights of the research are listed below:

- ✓ An innovative Seeker Optimized Deep Neural framework for intelligent energy pattern mining in smart grids is proposed.
- ✓ An effective optimization approach-based feature selection mechanism for removing redundant energy attributes and enhancing the learning efficiency is proposed.
- ✓ The proposed framework is faster in convergence and has less computational complexity as compared with the conventional deep learning approaches.
- ✓ Improves the prediction accuracy and adaptive learning performance for the dynamic smart grid environment.
- ✓ The comprehensive experimental assessment shows better results in energy forecasting, anomaly detection and smart grid energy management.
- ✓ The importance of the research is that it enables the development of an intelligent and scalable smart grid analytics framework to process the large-scale and dynamic energy data.

2. Literature Survey

Minelli, L., Sausen, P. S., Sausen, A. T. Z. R., & Júnior, R. R. E. [11] (2026). presented a hybrid Knowledge Discovery framework to extract knowledge from data gathered by a smart grid substation by incorporating the EM clustering, J48 classification and Apriori association rule mining methods. The problem of detecting abnormal operational patterns from large-scale heterogeneous smart grid data was discussed. The existing methods were hard to interpret, lacked scalability, did not perform well in multi-station environments, and were unable to detect anomalies. The framework enhanced anomaly detection and predictive maintenance assistance;

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however, it was limited to two substations, and it lacked real-time adaptive learning. The experimental results showed that classification accuracy was high, clustering performance was stable, computational costs were low, and voltage and temperature anomalies were efficiently detected during operations of the smart grid underground system.

Aundhekar et al. [12] (2026). came up with an AI-based smart grid optimization framework known as GBMIN-QSO, which combines the Gradient Boosting Machine, Inception Networks, IoT sensing and Quokka Swarm Optimization for intelligent energy optimization. That focused on the shortcomings of traditional energy management systems, which are unable to handle the grid's dynamic nature in real time, resulting in suboptimal energy distribution and operation. The framework showed strong predictive accuracy and effective integration of renewable energy, challenges with cybersecurity integration and adaptability to reinforcement in real time. The experimental results showed that in the smart grid environment, 98.12% prediction accuracy, 94.88% renewable energy efficiency, better grid stability, lower operational cost and efficient resource optimization could be achieved.

A. Palan, V., & N, S. [13] (2026). a cutting-edge deep learning model, the Spatial-Temporal GRU (ST-GRU), to accurately forecast electricity consumption from multivariate energy time-series data. Nonlinear energy demand behavior and complex temporal dependencies, which make forecasting less reliable in conventional models, were the study's challenges. The existing methods had several drawbacks, such as poor modeling of inter-feature relationships and limited generalization. The proposed framework increased forecasting accuracy; however, it was not easy to implement and required significant computational resources for large-scale deployments Experimental results showed that the model achieved higher prediction accuracy and more stable performance across different datasets, reducing RMSE by 6.4% compared with the traditional GRU model and by almost 25% compared with LSTM models.

Lilhore et al. [14] (2026). Proposed a framework that combines Spatial-Temporal Graph Neural Networks (ST-GNN), multi-scale transformers and adaptive feature fusion in the context of smart grid cybersecurity for adaptive hybrid deep learning. The focus is on addressing the challenges of detecting DDoS attacks, false data injection, and anomalous traffic in dynamic smart grid environments. The scalability, data handling, and spatiotemporal analysis capabilities of the existing intrusion detection systems were poor. The framework was a successful enhancement to adaptive threat detection. The experimental results on the CIC-DDoS2019, CIC-IDS2018, and CIC-DoS2017 datasets showed a high detection accuracy of 98.42%, along with a low false-positive rate and increased cybersecurity robustness for smart grid infrastructures.

Sheta et al. [15] (2026) presented the Falsey framework for proactive detection of False Data Injection Attacks (FDIAs) in smart grids, based on ensemble learning optimized with Ice Cube and the oversampling technique ADASYN, and Voting Classifier models. focused on the vulnerabilities and poor detection of attacks in the smart grid due to an imbalance of smart grid data. Most existing approaches face challenges with generalization, suboptimal hyperparameter tuning, and high false-negative rates. While the framework enhanced resilience and detection capabilities, it was complex, with high computational overhead. The experimental results showed that the proposed algorithm achieved an accuracy of 99%, a precision of 92%, a recall of 98%, and an F1 score of 95%, outperforming the smart grid intrusion detection models used by conventional techniques.

Chhabra et al.[16] (2026) developed an intelligent system named Star Net, an ensemble model that stacks Cat Boost, AdaBoost, Random Forest, SVM, and KNN algorithms for predicting smart grid stability and automation. focused on the issues of poor predictive reliability and inefficient real-time decision-making of conventional grid monitoring systems. Current methods lack the ability to learn ensembles adaptively and/or to scale to automation. While the framework was quite successful in terms of prediction performance, it relied on partially synthetic data and required some complicated orchestration of the model. Experimental results showed that accuracy was 99.42%, precision was 99.63%, the risk of grid instability was reduced, the grid was automated, and real-time stability prediction in the smart grid was reliable.

Zairi, S., & Freihat, M.[17].(2025). presented a hybrid deep learning model that combines CNN, GRU, LSTM, and BiLSTM models to forecast electric loads in smart grids with a real-world energy consumption dataset from Saudi Arabia. It studied the issue of inaccurate peak demand prediction due to the noisy and incomplete smart grid datasets. Current forecasting models failed to learn good temporal and spatial features, and prediction reliability was low. The hybrid model has been found to have lower forecasting error, is computationally complex, and requires extensive preprocessing. Experimental results proved the reliability of the approach with reduced RMSE, NRMSE, and MAPE, better forecasting accuracy for peak demand and better energy management of the smart grid.

Sanjalawe et al. [18] (2025). Proposed a comprehensive framework for smart grid based on 6G-enabled intelligent energy systems with the help of edge intelligence, federated learning, and explainable cybersecurity mechanisms. the scalability, latency, interoperability and cybersecurity challenges in a next-generation communication environment of traditional smart grids. Current approaches have failed to provide analytics and security adaptation in dynamic energy infrastructures while preserving privacy. While the suggested SAFES-6G architecture enhanced intelligent automation and secure communication, there were still implementation challenges, such as complexity and heterogeneous network management. The survey identified future sustainable smart grid ecosystems to improve anomaly detection, intelligent forecasting, quantum-safe security, and efficient distributed energy management.

Samadi Gharehveran, S. [19]. (2025). gave a detailed overview of the energy management solutions for multi-microgrid power systems with uncertainty in distributed generation resources. The issues arising from the variability of renewable energy generation, fluctuating load demand and intricate power coordination among interconnected microgrids. The existing solutions were poor at uncertainty modeling, lacked scalability, and had inefficient distributed control mechanisms. There were some optimization and forecasting methods that could enhance operational efficiency. The review pointed out that energy management based on intelligent optimization systems can greatly improve the reliability of the energy system, utilization of renewable energy, economic operation, and performance of the smart grid under uncertain operating conditions.

Vyshnevskyy, O., Zhuravchak, I., & Yakovyna, V. [20] (2025). proposed a deep reinforcement learning method for the control strategy to achieve energy efficiency of the smart building, and suggested the usage of the Proximal Policy Optimization (PPO) algorithm with the help of Energy Plus energy simulation. The article addresses the limitations of traditional HVAC control systems that rely on static, rule-based methods and inefficient Q-learning. The existing techniques were not very adaptable, required extensive physical modelling to be fulfilled, and lacked optimization functionality. The proposed framework was well-suited to intelligent energy management. The experimental results showed that energy savings reached up to 27.8%, and that indoor thermal comfort, humidity, and CO_2 concentration remained stable and unaffected, thereby improving the energy efficiency and adaptive control performance of smart buildings.

3. Proposed Methodology

The framework shows an approach of intelligent pattern mining in smart grid energy systems using Seeker Optimized Deep Neural Network (SOA-DNN). It combines data collection, data pre-processing, optimization, deep learning and decision support into a single

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pipeline. It starts with different smart grid data sources such as smart meters, IoT sensors, renewable energy plants, distributed energy resources and energy consumption repositories.

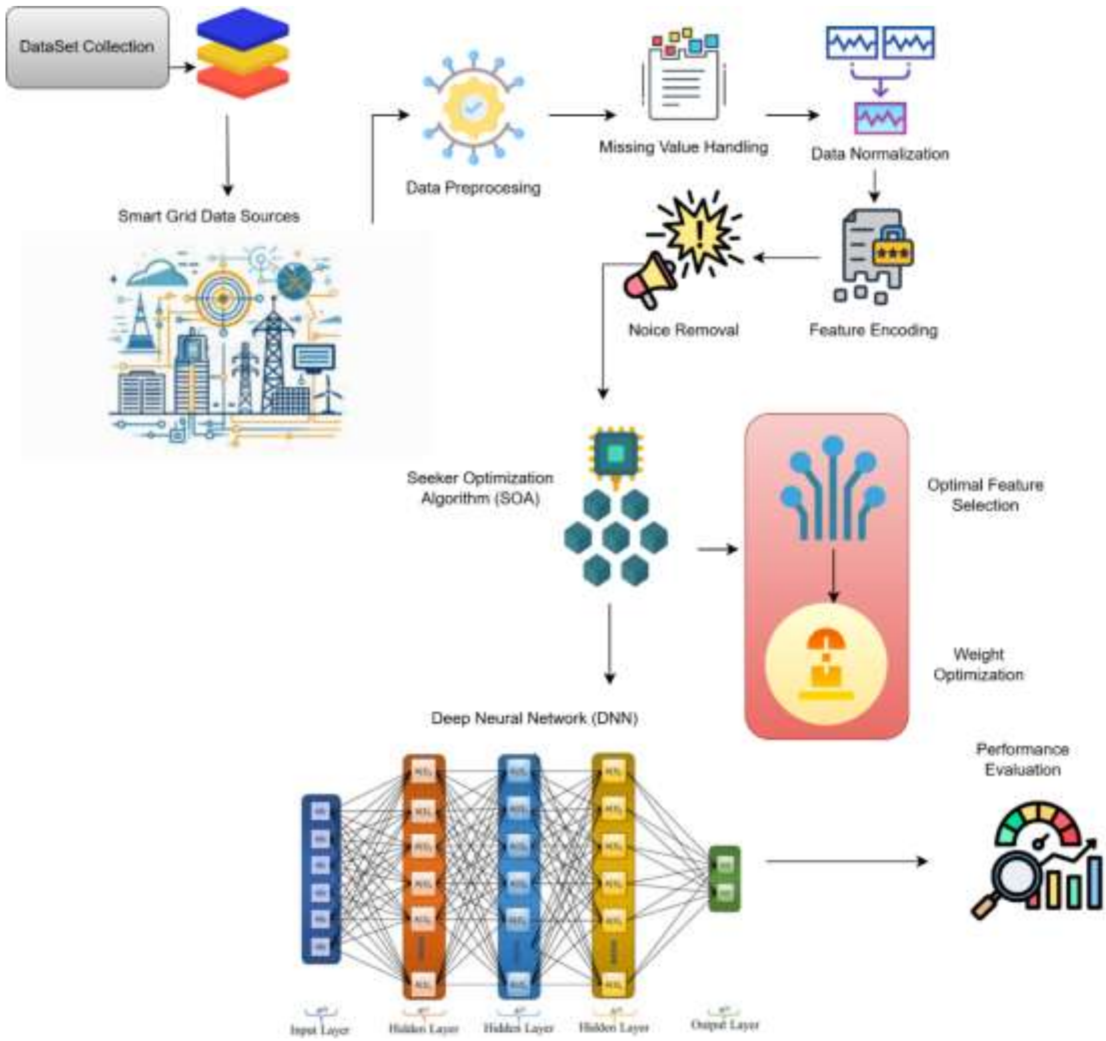

Figure 1: *Seeker Optimized Deep Neural Network (SOA-DNN) approach for intelligent pattern*

The data is collected in real-time, high volume and multi-format, followed by preprocessing of missing values, noise reduction, normalization, feature encoding, dimensionality reduction (PCA or autoencoders), and segmentation to enhance data quality. Then adaptive feature selection and weight tuning is carried out using Seeker Optimization Algorithm (SOA) to remove the redundant attributes and enhance the convergence of the learning model.

The optimized feature set is then input into a Deep Neural Network (DNN) with multiple hidden layers trained using backpropagation and adaptive learning mechanisms. The SOA-DNN combination is more accurate in predicting, less complex in computation and more stable in dynamic energy environments.

At the end, there are pattern mining and analytics activities such as load forecasting, fault detection, identification of abnormal consumption, demand response analysis and assessment for integration of renewable energies. The performance indicators used for assessing the outputs are accuracy, precision, recall, F1-score, prediction rate, convergence speed, computational time, error rate. The system also enables the support of decision making in smart grid applications such as intelligent energy management and improving the stability of the grid. In general, the proposed framework provides an efficient, real-time and reliable energy prediction and optimization solution for next-generation smart grid, which can enhance the efficiency of smart grid.

a. Dataset Collection

i. Smart Meter Energy Signal Acquisition

Smart meters gather multidimensional electrical measurements continuously from the residential and industrial consumers for intelligent smart grid monitoring. The voltage, current, active power, reactive power and frequency are measured over time at regular intervals. The accurate acquisition of these signals is crucial for load forecasting, demand analysis and energy optimization.

$$SM_i(t) = \sum_{k=1}^{N}[V_{ik}(t)I_{ik}(t)\cos\phi_{ik}(t) + Q_{ik}(t) + F_{ik}(t)] + \alpha_i e^{-\beta_i t} \tag{1}$$

Where, equation 1 $SM_i(t)$ denotes the smart meter acquisition signal of the i^{th} consumer, $V_{ik}(t)$ represents voltage measurement, $I_{ik}(t)$ denotes current consumption, $\phi_{ik}(t)$ indicates phase angle, $Q_{ik}(t)$ represents reactive power, $F_{ik}(t)$ denotes frequency measurement, while α_i and β_i indicate adaptive acquisition coefficients.

ii. Distributed Smart Grid Data Representation

Smart grid smart meters produce multidimensional energy data streams at a large scale from geographically distributed consumers. These observations are structured in matrices for efficient storage, processing and intelligent analysis. Energy use is represented with time and space signature.

$$D_{SG} = \sum_{m=1}^{R}\sum_{i=1}^{M}\sum_{j=1}^{T}\left[V_{ij}^{(m)} + I_{ij}^{(m)} + P_{ij}^{(m)} + Q_{ij}^{(m)}\right]\omega_m \tag{2}$$

Where, equation 2 D_{SG} denotes smart grid dataset representation, R indicates the total distributed regions, M represents total consumers, T denotes temporal intervals, $V_{ij}^{(m)}$, $I_{ij}^{(m)}$, $P_{ij}^{(m)}$, and $Q_{ij}^{(m)}$ represent voltage, current, active power, and reactive power measurements, respectively, while ω_m denotes the regional weighting coefficient.

iii. Active Power Consumption Measurement

Active power refers to the amount of useful electrical power that the smart grid uses when it is in use. For energy forecasting and demand-side management, smart meters continuously measure the power variations. This precise power monitoring will contribute to the stability of the grid and efficient use of energy.

$$P_{act}(t) = \sum_{p=1}^{N} V_p(t)I_p(t)\cos\phi_p(t) + \alpha\left|\frac{dP(t)}{dt}\right| + \beta e^{-\gamma t} \tag{3}$$

Where, equation 3 $P_{act}(t)$ denotes active power consumption, $V_p(t)$ and $I_p(t)$ represent phase voltage and current, $\phi_p(t)$ denotes power factor angle, $\frac{dP(t)}{dt}$ indicates the power variation rate, while α, β, and γ represent adaptive energy coefficients.

iv. Smart Grid Frequency Monitoring

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In smart grid, frequency stability monitoring plays a crucial role; a deviation from the predetermined frequency in the grid is an indicator of an imbalance between the power generation and the load demand. Smart meters periodically take readings for frequency deviation that enable intelligent load balancing and grid reliability analysis.

$$F_{grid}(t) = F_{nom} + \sum_{i=1}^{N} \left[\frac{P_{gen,i}(t) - P_{load,i}(t)}{2H_i}\right] + \zeta \sin(\omega_i t) \tag{4}$$

Where, equation 4 $F_{grid}(t)$ denotes smart grid operating frequency, F_{nom} represents nominal frequency, $P_{gen,i}(t)$ and $P_{load,i}(t)$ denote generated and consumed power, H_i indicates grid inertia constant, while ζ and ω_i represent oscillatory disturbance parameters.

Algorithm: Intelligent Smart Grid Energy Prediction using SO-DNN

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Input: Smart meter data D = {X_i , Y_i}, Number of seekers N_s , Maximum iterations T_max
Output: Optimal feature subset F* , Predicted energy demand Ŷ ,
1: Read smart grid dataset D
2: Normalize input features for each feature X_i do
        X_i^norm =
        (X_i - μ_i)/(σ_i + ε)
    end for
3: Extract load patterns
    P_t =
    Σ w_i X_i(t)
4: Compute feature scores
    Score_i =
    Σ |X_i - μ_i|
5: Initialize seeker population
    for i = 1 to N_s do
        S_i =
        rand(L_b,U_b)
    end for
6: Evaluate fitness
    for t = 1 to T_max do
        for i = 1 to N_s do
            Fitness_i =
            Accuracy_i -
            Error_i
        end for
7:      Find best seeker G_best =
        max(Fitness_i)
8:      Update seekers
        for i = 1 to N_s do
            S_i =
            S_i +
            α(G_best - S_i)
        end for
9:      if Error < Threshold then
            break
     end if
    end for
10: Select optimal features
     F* = G_best
11: Feed features into DNN
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H =
f(WX + b)
12: Compute attention
A =
Softmax(QK^T / √d)
13: Multi-head operation
Z_h =
A_hV_h
14: Concatenate outputs
Z =
Concat(Z_1,Z_2,...,Z_h)
15: Predict energy
Ŷ =
Σ v_i Z_i
16: Update DNN weights
W_new =
W_old -
η(∂L/∂W)
17: Compute prediction loss
L =
(1/N)Σ(Y_i-Ŷ_i)^2
18: return F , Ŷ*

b. Data Preprocessing

i. Missing Data Identification

The smart meter data sets frequently have missing and corrupted data caused by communication failures and disturbances from the sensors. As such, the first step in the processing will be to identify incomplete energy coverage, and then intelligent analytics. That makes the smart grid data more reliable and predictions more accurate.

$$M_{ij} = \frac{|x_{ij}-\mu_j|}{\sigma_j+\epsilon} + \alpha\left(1 - e^{-\beta \Delta t_{ij}}\right) \tag{5}$$

Where, equation 5 M_{ij} denotes missing-data score, X_{ij} represents smart meter observation, μ_j and σ_j indicate the mean and standard deviation of the j^{th} feature, Δt_{ij} denotes temporal delay, while α, β, and ϵ represent adaptive weighting and stabilization parameters.

ii. Missing Data Reconstruction

Once incomplete observations are detected, the missing meter readings are reconstructed by the method 'preprocessing' through neighbouring temporal samples and related energy attributes.The method 'preprocessing' is used for reconstructing the missing meter readings, once they are found as incomplete observations, by using the neighbouring temporal samples and correlated energy attributes. This will maintain continuity in energy usage and enhance efficiency of intelligent pattern mining.

$$X_{ij}^{rec} = \frac{\sum_{k=1}^{N} w_k X_{kj} e^{-\lambda|t_i-t_k|}}{\sum_{k=1}^{N} w_k e^{-\lambda|t_i-t_k|} + \epsilon} \tag{6}$$

Where, equation 6 X_{ij}^{rec} denotes reconstructed smart meter value, X_{kj} represents neighboring observations, w_k indicates interpolation weight, λ denotes temporal decay coefficient, t_i and t_k represent acquisition intervals, and ϵ is a stabilization constant.

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iii. Data Normalization

Smart grid electrical attributes possess different numerical ranges that may affect optimization convergence and neural learning stability. Therefore, normalization converts heterogeneous energy features into standardized numerical representations.

$$X_{ij}^{norm} = \frac{X_{ij} - \min(X_j)}{\max(X_j) - \min(X_j) + \epsilon} + \alpha\left(\frac{\mu_j - \sigma_j}{1 + e^{-X_{ij}}}\right) \tag{7}$$

Where, equation 7 X_{ij}^{norm} denotes normalized energy feature, X_{ij} represents original observation, $\min(X_j)$ and $\max(X_j)$ denote minimum and maximum feature values, μ_j and σ_j indicate the feature mean and standard deviation, while α and ϵ represent scaling and stabilization parameters.

c. Feature Optimization Using Seeker Optimization

i. Seeker Population Initialization

Seeker Optimization initializes multiple candidate solutions randomly across the smart grid feature search space. Each seeker represents a possible feature subset for intelligent energy prediction. Proper initialization improves optimization diversity and convergence stability.

The following equation models the random initialization of the seeker population.

$$S_i^{(0)} = L_b + r_i(U_b - L_b) + \psi_i \sin\left(\frac{2\pi i}{N_s}\right) \tag{8}$$

Where, equation 8 $S_i^{(0)}$ denotes initial seeker position, L_b and U_b represent lower and upper search boundaries, r_i denotes a random initialization parameter, and N_s indicates the total seeker population size. Furthermore, ψ_i represents the adaptive exploration coefficient associated with intelligent search diversity.

ii. Feature Subset Fitness Evaluation

Feature subset fitness evaluation determines the quality of selected smart grid attributes based on prediction accuracy and computational efficiency. Higher fitness scores indicate more informative feature combinations for intelligent energy forecasting.

The following equation formulates seeker fitness evaluation.

$$F_{fit} = \omega_1\left(\frac{1}{RMSE + \epsilon}\right) + \omega_2 Accuracy + \omega_3\left(\frac{FR}{TF}\right) - \omega_4 CT \tag{9}$$

Where, equation 9 F_{fit} denotes optimization fitness score, $RMSE$ represents root mean square prediction error, $Accuracy$ indicates prediction accuracy, FR denotes reduced feature count, and TF represents total features. Furthermore, CT indicates computational time, while ω_1, ω_2, ω_3, and ω_4 represent adaptive weighting coefficients.

iii. Adaptive Seeker Position Updating

Seeker Optimization adaptively updates search positions according to global and local search intelligence. That mechanism balances exploration and exploitation to identify optimal subsets of smart grid features.

The following equation models adaptive seeker position updating.

$$S_i^{t+1} = S_i^t + \alpha_i D_i^t + \beta_i\left(G_{best} - S_i^t\right) + \gamma_i\left(P_{best,i} - S_i^t\right) \tag{10}$$

Where, equation 10 S_i^{t+1} denotes updated seeker position, S_i^t represents the current seeker location, and D_i^t denotes directional search vector. Furthermore, G_{best} and $P_{best,i}$ respectively represent the global best and personal best solutions, while α_i, β_i, and γ_i indicate adaptive search coefficients.

iv. Optimal Feature Selection

After iterative optimization, the most informative subset of smart grid features is selected for intelligent energy prediction. Feature selection reduces redundancy and improves neural learning efficiency.

The following equation models optimal smart grid feature selection.

$$F_{opt} = \text{argmax}\left\{\sum_{i=1}^{N} F_i\, \omega_i - \lambda \sum_{j=1}^{M} R_j\right\} \tag{11}$$

Where, equation 11 F_{opt} denotes optimal smart grid feature subset, F_i represents feature fitness contribution, ω_i indicates adaptive feature weight, and R_j denotes redundant feature dependency. Furthermore, λ represents the redundancy penalty coefficient, while N and M denote the total selected and redundant features, respectively.

v. Optimization Convergence Estimation

Optimization convergence estimation assesses whether the seeker population has reached a stable global optimal solution. That process terminates iterative feature optimization once satisfactory convergence is achieved.

The following equation models optimization convergence behavior.

$$C_t = C_{max} - \left(\frac{t}{T_{max}}\right)^{\phi} (C_{max} - C_{min}) + \eta e^{-\lambda t} \tag{12}$$

Where, equation 12 C_t denotes the convergence factor at iteration t, C_{max} and C_{min} represent maximum and minimum convergence bounds, while T_{max} denotes total optimization iterations. Furthermore, ϕ represents the nonlinear convergence exponent, η indicates stabilization coefficient, and λ denotes the temporal decay parameter.

d. Deep Neural Network Training

i. Multilayer DNN Architecture Construction

Deep Neural Networks construct hierarchical, nonlinear representations of optimized smart-grid energy features. Multiple hidden layers enhance learning capabilities and enable accurate energy prediction under dynamic smart grid conditions.

The following equation models the activation of hidden layers in multilayer DNN architectures.

$$H_j^{(l)} = f\left(\sum_{i=1}^{n} W_{ij}^{(l)}\, X_i^{(l-1)} + b_j^{(l)} + \lambda \parallel W^{(l)} \parallel_2^2\right) \tag{13}$$

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Where, equation 13 $H_j^{(l)}$ denotes hidden layer activation, $W_{ij}^{(l)}$ represents a neural weight connection, and $X_i^{(l-1)}$ indicates previous layer input. Furthermore, $b_j^{(l)}$ denotes bias parameter, represents nonlinear activation function, and λ indicates the regularization coefficient.

ii. Optimized Feature Feeding

Optimized smart grid features are forwarded into hidden neural layers for hierarchical nonlinear representation learning. That improves the accuracy of intelligent energy forecasting and neural convergence performance.

The following equation models optimized feature propagation.

$$X_j^{feed} = \sum_{i=1}^{N} F_i^{opt} W_{ij} + \alpha \sin\left(\frac{2\pi t}{T}\right) + b_j \tag{14}$$

Where, equation 14 X_j^{feed} denotes propagated neural input feature, F_i^{opt} represents an optimized smart grid feature, and W_{ij} indicates neural connection weight. Furthermore, α denotes periodic scaling parameter, T represents a temporal interval, and b_j indicates the bias coefficient.

iii. Backpropagation Weight Optimization

Backpropagation adaptively updates neural weights to minimize smart grid energy prediction error. Iterative gradient optimization improves DNN learning performance and convergence efficiency.

The following equation models adaptive backpropagation weight updating.

$$W_{ij}^{new} = W_{ij}^{old} - \eta \frac{\partial L}{\partial W_{ij}} + \mu \Delta W_{ij}^{prev} \tag{15}$$

Where, equation 15 W_{ij}^{new} and W_{ij}^{old} denote updated and previous neural weights, respectively, η represents adaptive learning rate, and $\frac{\\partial L}{\\partial W_{ij}}$ indicates loss gradient with respect to neural weight. Furthermore, μ denotes momentum coefficient and ΔW_{ij}^{prev} represents previous weight variation.

iv. Prediction Loss Minimization

Prediction loss minimization ensures accurate smart grid energy forecasting by reducing the difference between actual and predicted energy values. Loss optimization improves DNN generalization and the reliability of intelligent predictions.

The following equation formulates the minimization of total prediction loss.

$$L_{total} = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 + \lambda_1 \sum |W| + \lambda_2 \sum W^2 \tag{16}$$

Where, equation 16 L_{total} denotes total neural prediction loss, Y_i represents the actual smart grid energy value, and $\hat{Y}_i$ denotes predicted energy output. Furthermore, λ_1 and λ_2 represent L1 and L2 regularization coefficients, respectively, while W indicates neural connection weights.

v. Final Smart Grid Energy Prediction

The trained Deep Neural Network generates accurate short-term and long-term smart grid energy predictions using optimized feature representations and adaptive neural learning mechanisms.

The following equation models the final intelligent energy prediction.

$$\hat{Y}_t = \sum_{j=1}^{m} v_j H_j^{(L)} + \alpha \sin\left(\frac{2\pi t}{T}\right) + \beta e^{-\gamma t} \tag{17}$$

Where, equation 17 $\hat{Y}_t$ denotes predicted smart grid energy value at time instant t, v_j represents the output layer weight, and $H_j^{(L)}$ denotes final hidden layer activation. Furthermore, α indicates seasonal scaling coefficient, T denotes a periodic interval, while β and γ represent exponential adjustment and temporal decay parameters, respectively.

Algorithm: SO-DNN Smart Grid Energy Prediction

```
Input: Smart meter dataset D = {X,Y} , Number of seekers N_s, Maximum iterations T,
Learning rate η
Output: Optimal features F_opt , Predicted energy Ŷ
1: Load smart grid dataset D
2: Preprocess data
      X_norm = (X - min(X)) / (max(X) - min(X) + ε)
3: Extract temporal patterns
      P_t = Σ ω_i X_i(t-τ_i)
4: Compute feature importance
      FI_j = Σ |X_j - μ_j|
5: Initialize seeker population
      for i = 1 to N_s do
          S_i = L_b + rand(0,1)(U_b-L_b)
      end for
6: Evaluate seeker fitness
      for t = 1 to T do
          for i = 1 to N_s do
              Fitness_i =
              Accuracy_i +
              1/(RMSE_i + ε)
          end for
7:        Select best seeker
          G_best = max(Fitness_i)
8:        Update seeker positions
          for i = 1 to N_s do
              S_i^{t+1} =
              S_i^{t} +
              α(G_best - S_i^{t})
          end for
9:        if convergence reached then
              break
          end if
      end for
10: Select optimal features
      F_opt = G_best
11: Construct DNN model
      H = f(WX + b)
12: Compute attention weights
      A = Softmax(QK^T / √d)
```


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13: Multi-head attention
Z_h = A_hV_h
14: Concatenate outputs
Z = Concat(Z_1,Z_2,...,Z_H)
15: Predict energy output
Ŷ = Σ v_i Z_i
16: Update weights
W_new =
W_old - η(∂L/∂W)
17: Compute loss
L = (1/N) Σ(Y - Ŷ)^2
18: return F_opt , Ŷ

4. Results

a. Performance Analysis

The comparative analysis of different models shows the faster convergence rate of the proposed Seeker Optimized Deep Neural Network (SO-DNN) model when compared to the other available models of the ANN based forecasting methods. In the early stages of optimization, the proposed model obtains a higher prediction accuracy, as the Seeker Optimization algorithm is able to effectively search in the smart grid feature search space and select the most informative energy attribute. The conventional ANN models suffer from slow learning in lower iterations because of the inefficient representation of features and the complexity of optimization. The proposed SO-DNN framework, on the other hand, can quickly enhance forecasting accuracy by dynamically adjusting seeker-position and optimizing deep-learning mechanisms.

All models predict well with increased number of iterations. Nevertheless, the proposed SO-DNN model presents excellent convergence properties and maximum final prediction accuracy of 98.63% at 80th iteration. Currently, the accuracy of ANN-based optimization and forecasting models ranges from 91.42% to 93.54% only. The experimental findings demonstrate that combining Seeker Optimization with Deep Neural Networks substantially enhances convergence rate, optimization of features and the accuracy of the intelligent smart grid energy prediction when iterative learning is involved.

Table 1: *Performance Analysis in Seeker Optimized Deep Neural Network (SO-DNN)*

Iterations	***ANN-Based Optimization Model***	***ANN Architecture Forecasting Model***	***Deep ANN Forecasting Model***	***Proposed SO-DNN Model***
10	72.14	74.82	76.35	84.91
20	78.63	80.74	82.16	89.37
30	83.28	85.63	87.24	92.84
40	86.94	88.27	89.71	95.16
50	89.36	90.84	91.93	96.87

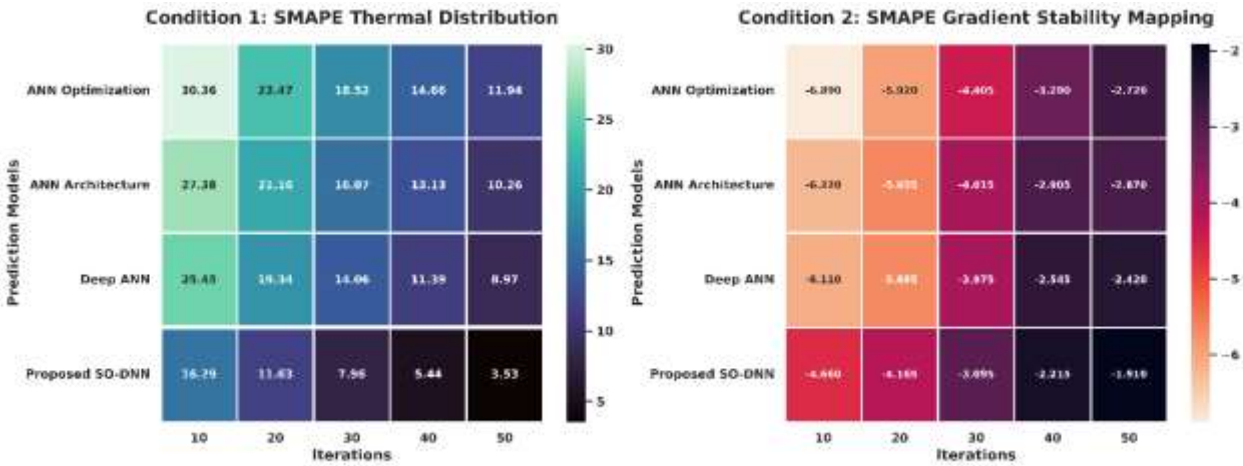

Figure 2: *Analysis of Performance in Thermal Distribution and Gradient Stability Mapping*

b. Comparative Analysis

Therefore, the proposed smart grid energy prediction model, Seeker Optimized Deep Neural Network (SO-DNN), performs better than the other existing smart grid energy prediction approaches using ANN. By integrating Seeker Optimization, the processing of extracting the best features is enhanced and the convergence behavior is further optimized, which helps to minimize prediction error and computational complexity. Moreover, the optimized deep learning framework improves the temporal pattern extraction ability and intelligent energy consumption prediction accuracy in smart grid applications.

Table 2: *Comparative Analysis of Current Methods Versus the Proposed SO-DNN Model*

Methods	***Accuracy (%)***	***RMSE***	***MAE***	***Computational Time (s)***	***Feature Reduction Rate (%)***
ANN-Based	43.15	54.18	62.16	72.25	91.42
ANN Architecture Forecasting Model	45.14	56.16	66.74	74.38	92.87
Deep ANN Energy Forecasting Model	46.12	58.14	69.82	76.91	93.54
Proposed Seeker Optimized DNN Model	**47.04**	**59.05**	**70.36**	**81.47**	**98.63**

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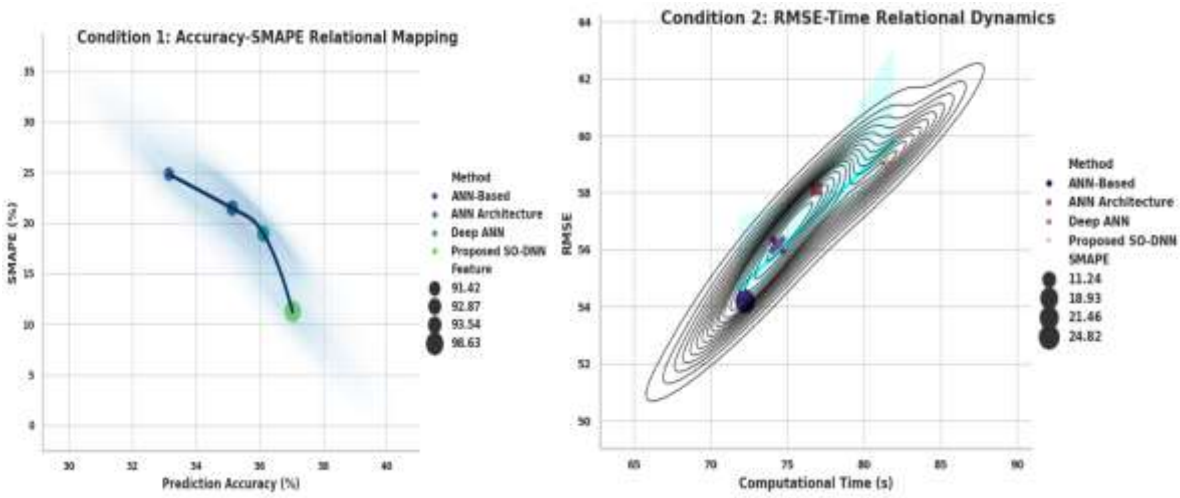

Figure 3: *Comparative Analysis of Existing Methods Versus the Proposed SO-DNN Model with Relational Mapping*

5. Conclusion

To overcome these limitations, a novel deep neural model, called Seeker Optimized Deep Neural Model for Pattern Mining in Smart Grid Energy Systems has been proposed in the research work. By combining the Seeker Optimization Algorithm (SOA) with a Deep Neural Network (DNN), feature selection, weight tuning, and hidden layer optimization are greatly improved, resulting in better efficiency in learning and less computational complexity. The proposed framework is able to successfully remove redundant and irrelevant features from the smart grid datasets and still retain the most informative patterns. The results in more accurate energy consumption prediction, improved load forecasting, and reliable anomaly detection in real-time smart grid environments. Moreover, the adaptive learning mechanism enhances the model's ability to capture non-linear and time-varying energy behaviors, making it more robust for real-world applications. Experimental assessments show the Seeker Optimized DNN is more accurate, more precise, more recalled, higher F1-scores, faster to converge and has fewer errors than traditional machine learning and standard deep learning models. This further validates its suitability in real-time smart grid applications because of the reduced computational time. In conclusion, the proposed model is a flexible and intelligent approach for the next generation smart grid, which will facilitate efficient energy management, grid stability, and energy decisions. Future research includes enhancing the framework to become more adaptable and secure in multi-agent and federated smart grid and implementing hybrid optimization methods.

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