Pattern Mining in Smart Grid Energy Data Using Enhanced Binary Firefly Optimization

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ABSTRACT

The increasing deployment of smart grids has led to the generation of large-scale energy data, creating new opportunities for intelligent pattern mining to enhance energy efficiency and grid reliability. This study presents a hybrid optimization framework for mining meaningful patterns in smart grid energy data using Enhanced Binary Firefly Optimization (EBFO). Existing pattern mining techniques often struggle with high-dimensional data, noise, and low precision in pattern discovery, which limits their effectiveness in innovative grid environments. Additionally, traditional algorithms lack robustness when dealing with temporal variations and redundant features in energy consumption data. To address these challenges, this paper proposes a novel framework, the Binary Enhanced Firefly-based Pattern Miner (BE-FPM), integrated with a Thermal Image Denoising Autoencoder (TIDA). BE-FPM leverages an improved binary firefly algorithm with adaptive light intensity and movement strategies to explore the solution space for frequent pattern detection efficiently. Meanwhile, TIDA preprocesses smart meter readings by converting consumption patterns into thermal-like images and applying denoising autoencoding to reduce data noise and highlight meaningful structures. The proposed method is used on residential smart grid datasets for practical demand response analysis and load forecasting. By identifying accurate and noise-free consumption patterns, utilities can more effectively schedule energy distribution, reduce peak loads, and improve energy efficiency. Experimental results demonstrate that BE-FPM outperforms traditional mining approaches in terms of pattern accuracy, convergence speed, and noise resilience. This hybrid technique provides a promising direction for intelligent energy data analysis in future innovative grid applications.
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Keywords: Smart Grid, Pattern Mining, Binary Firefly Optimization, Thermal Image Denoising, Autoencoder, Energy Consumption Analysis, Demand Response.

1. Introduction

A. Overview

The Smart system is what the future electric power system will look like. It is a complex system that requires a significant amount of information [1]. Modern sensors, real-time connections, and sophisticated decision-making systems all work together to ensure that energy is distributed efficiently, reliably, and sustainably [2]. Smart meters and the Internet of Things (IoT) are collecting a significant amount of information over time about how individuals use

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electricity [3]. Predicting demand, finding issues, and making better use of energy may all be possible outcomes of trend mining this energy data [4].

Pattern mining in smart grids involves identifying patterns in how individuals or groups utilize electricity. By understanding these trends, grid operators can enhance the resilience of their systems, adopt dynamic pricing models, and more effectively manage load demand [5]. This task is challenging since usage patterns aren't always linear, noise or missing values may create data issues, and algorithms that can handle large amounts of data in real-time are needed to assess high-dimensional, temporally rich information [6].

Increasingly, people are adopting hybrid approaches that integrate evolutionary optimization with machine learning to address these challenges [7]. In pattern mining and other discrete search settings, swarm intelligence approaches, such as the FA function, are practical [8]. Using deep learning approaches, specifically autoencoders for denoising and dimensionality reduction, enhances the entire system's strength and adaptability when it must cope with noisy input in the real world [9].

The BE-FPM and the TIDA are the two main aspects of the new architecture provide in this paper [10]. This approach utilizes binary-optimized firefly swarms to reliably and efficiently identify patterns on a wide scale. It also uses image-like formats to reduce noise in time-series data.

B. Challenges in Smart Grid Pattern Mining

Smart meters provide us with a lot of information, but it's still not easy to find patterns. Some significant issues include the possibility that the data may not be accurate or may be missing, users' actions may vary significantly over time, and it's challenging to make sense of binary data that has more than one dimension. It's also challenging for typical optimization algorithms to handle grid data in real-time or avoid local minima. A system that can handle noise and execute computations efficiently to address these problems.

The main objectives of this paper are:

- The goal of this hybrid architecture is to create a system that uses both swarm pattern mining and image-based denoising to clean up smart grid data.
- The goal is to make the binary firefly method better so that it can rapidly detect patterns in binary energy datasets.
- To see how successfully the system optimized demand responses, handled noise, and discovered patterns.

This is how the remainder of the paper is organized: Section 2 presents works that are connected. Section 3, explains about the suggested BE-FPM and TIDA structure. In Section 4, discuss how the experiment was set up. Part 5 discusses the outcomes and assessments in more detail. The study ends in Section 6, which also includes an overview of prospective topics for further investigation.

2. Research Methodology

This paper discusses a novel approach to mitigating power losses in partially shaded photovoltaic (PV) arrays. The method is referred to as the BFA-PR. The proposed solution outperforms standard configurations on a 9×9 PV panel array with four shading patterns (SW, LW, SN, and LN). The BFA-PR might increase the global maximum power by up to 36% compared to TCT [11]. Fill factor, power loss, and energy production are key performance criteria that highlight its superiority. A Naive Bayes-based machine learning method also detects physical damage in panels, demonstrating the effectiveness of the technology.

The paper demonstrates the application of a Hybrid Deep Neural Network and Firefly Algorithm for Smart Energy Optimization (HDNN-FFSEO) in smart buildings. The approach uses sensor data on temperature, light, and CO_2 to assess comfort and energy efficiency. The HDNN-FFSEO utilizes both the Firefly Algorithm and a rule-based DNN to monitor individual comfort levels and minimize energy consumption [12]. It outperforms CNN, AV, and Multi-View techniques, achieving an accuracy of 99.17%. The suggested method facilitates easier control of energy use and enables the utilization of smart homes connected to the Internet of Things.

This paper discusses a Binary Firefly Feature Selection for Intrusion Detection Systems (BFFA-IDS) that aims to enhance the accuracy of detection on datasets with a large number of dimensions [13]. The BFFA-IDS takes the data from the UNSW-NB15 dataset and normalizes it. Then, it utilizes BFFA to identify the most effective features and sorts them using a Random Forest model. The system is 99.72% accurate and 99.84% effective at finding things, and it has significantly fewer false positives. It does a better job than the best approaches at managing huge feature areas for network security that can trust.

This paper is about BFDRL-HEMS, which stands for HEMS Optimization Based on Bacterial Foraging and Deep Reinforcement Learning. It helps families save electricity. The BFDRL-HEMS utilizes both BFMO and DRL to automatically configure appliances based on their energy consumption and associated costs [14]. The algorithms work similarly to bacteria when they search for food. They learn how to utilize energy more efficiently, handle peak demand more effectively, and maintain a comfortable environment for people. The comparisons demonstrate that these systems are significantly superior to those that preceded them. There are proven long-term advantages to using renewable energy sources and conserving energy.

This paper suggests that Firefly Optimization-based Clustering for IoT Data Aggregation (FOC-DA) might help networks last longer and consume less power. The FOC-DA algorithm identifies nodes that are near to each other and then selects cluster heads based on the brightness of the fireflies (i.e., their fitness) [15]. According to MATLAB 2023b simulations, FOC-DA performs better than FA and LEACH in meeting quality-of-service standards. ANOVA testing shows that it collects data in IoT sensor networks significantly better and consumes less energy.

The Hybrid Butterfly-BPNN Blockchain-based Classification Framework (HBPNNBO) represents a novel approach to analyzing data from smart cities. The Butterfly Optimization Algorithm (BOA) and the Backpropagation Neural Network (BPNN) collaborate to assist the system in processing information that is not of the same size or shape. The first step is to use HADASYNBSID to balance the dataset, and then apply the Hybrid Chicken Swarm Genetic Algorithm (HCSGA) to select the best traits. A blockchain system that utilizes both AES and CSO encryption ensures data security [16]. When tested HBPNNBO with smart city datasets, it was able to categorize items with 94.76% accuracy in only 23.62 ms. This indicates that it works well and can be used in real-time to analyze urban data safely.

This paper led to the creation of the Integrated Data Mining and Machine Learning for Energy Optimization (IDMLEO) model, which divides algorithms into three groups: supervised, unsupervised, and reinforcement learning. The IDMLEO indicates that supervised approaches are typically employed for prediction and benchmarking [17]. At the same time, unsupervised methods are utilized to assess performance, and RL is used for control and demand flexibility in Building Energy Management (BEM). The article discusses several approaches for integrating DM and ML methodologies into innovative BEM systems. It discusses the pros and cons of each and suggests further research that needs to be conducted.

This paper is about the Firefly-based Optimization for Big Data in Healthcare and Engineering (FOBDHE). It discusses how the firefly method can be applied to solve optimization problems in healthcare and engineering [18]. The FOBDHE architecture enhances patient care, facilitates health trend prediction, and optimizes operations by leveraging big data analysis. This method, which was used in MATLAB 2019b, demonstrates how the behavior of fireflies in the wild may aid in processing large datasets and improve system performance. It also examines ways to integrate the FA with other metaheuristics to enhance optimization in various domains.

This paper demonstrates that the Firefly-based Stochastic Hybrid Energy Planning (FSHEP) approach can be utilized to plan hybrid systems that incorporate wind, solar, and battery storage. It takes into account the fact that batteries lose power over time and that power has to be balanced [19]. The FSHEP demonstrates how load and renewable energy output may change by utilizing a firefly algorithm within a scenario-based stochastic optimization framework. It keeps operations running and prices down. The suggested method is a fantastic way to show how batteries work. Stochastic models are more expensive to plan than deterministic models, but they make the systems of islanded microgrids stronger.

This paper presents a proactive cybersecurity strategy, called Modified Firefly-based Network Health Optimization (MFNHO). MFNHO introduces a new health function that uses nature-based methods to find nodes that are causing problems early on. It features a genetic evolution algorithm and an event management module that collaborate to determine the optimal sequence of observations in order of relevance during ongoing network events [20]. The simulation findings reveal that the number of questionable nodes decreased by 60 to 80%, yet the turnaround time increased by only 1 to 2%. The model works well in many attack settings; therefore, it's a smart way to prepare data for better network intrusion detection, which can be utilized in various situations.

3. Methodology

This section illustrates the proposed hybrid framework, which combines BE-FPM with TIDA. The goal of the integration is to enhance optimization and eliminate noise, thereby making pattern mining in smart grid energy data more accurate and trustworthy. The framework is designed to operate with time-series data that has numerous dimensions and rapidly identify patterns in energy use.

a. *Overview of the Proposed Framework*

The two primary pieces of the recommended system are BE-FPM for pattern mining and TIDA for preprocessing. The first step in identifying consumption differences is to convert smart meter data into a format that resembles a thermal image. TIDA utilizes a deep autoencoder to remove noise from these images. This preserves essential parts of the photographs while reducing their waviness. The BE-FPM approach works on data that has been cleansed and changed into binary code. Finding objects based on frequency thresholds is simpler when fireflies are more active. People search for patterns that are the same in binary space because of this. This plan ensures that innovative grid applications can accurately discover patterns and aren't affected by noise.

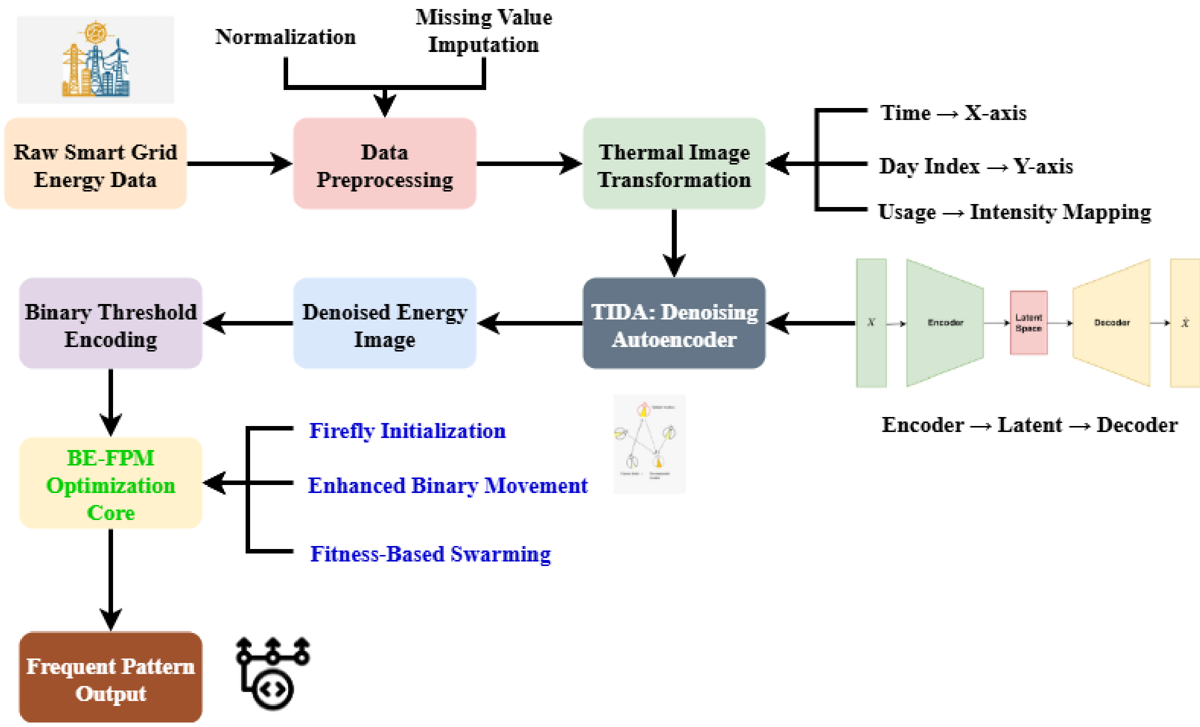

Figure 1: High-Level Architecture of BE-FPM with TIDA Integration

Figure 1 depicts the end-to-end flow of raw smart grid data through to pattern mining for action. Denoted as Phase 1 in the flowchart, the data arrives at the system and undergoes preprocessing, which includes cleaning and normalizing the data. Noise-free time-series data is transformed into thermal images that contain temporal usage intensities. The transformed signals are processed through the TIDA autoencoder, which denoises the images and eliminates redundancy. The photos are input through a binary encoding process to create activity bits, which are either high (indicating high energy use) or low (indicating low energy use). The activity sequences result in high-low binary sequences for input to the BE-FPM optimizer. The optimizer utilizes an optimization framework based on swarm intelligence to identify frequent energy consumption patterns and then draws inferences based on the citations of these patterns. Utilizing this brief cognitive path, the smart grid will enhance its functionality in user profiling, forecasting, and demand response applications.

b. Binary Enhanced Firefly-based Pattern Miner (BE-FPM)

Binary Encoding of Energy Data: BE-FPM is a binary optimization method that searches for patterns in how people utilize energy. This approach allows for adjusting the step sizes, adding more light absorption coefficients, and utilizing binary search algorithms, which are superior to the original firefly method. The approach uses binary encoding to show how energy use fluctuates during peak and off-peak hours—fireflies, which stand for potentially possible solutions, flit about in a binary search space. The brightness of the light shows how often and how vital the patterns are. The algorithm utilizes intelligent position updates to identify the best or nearly optimal patterns quickly. BE-FPM helps deal with datasets that are sparse and have a lot of dimensions, which is common in smart grid situations.

Firefly Algorithm Enhancements: To begin, the energy consumption data collected by smart meters is unreliable and subject to noise. Pattern mining can only work if the data is first standardized and then turned into binary sequences. A threshold-based discretization method identifies data above a certain level (such as peak hours) as "1" and data below that level as "0." This version makes the search space easier to work with and more in keeping with the binary nature of the Enhanced Firefly Algorithm. It also speeds up processing while

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preserving important pattern structures. The binary format helps identify patterns in consumption that often occur when you're ready for demand response.

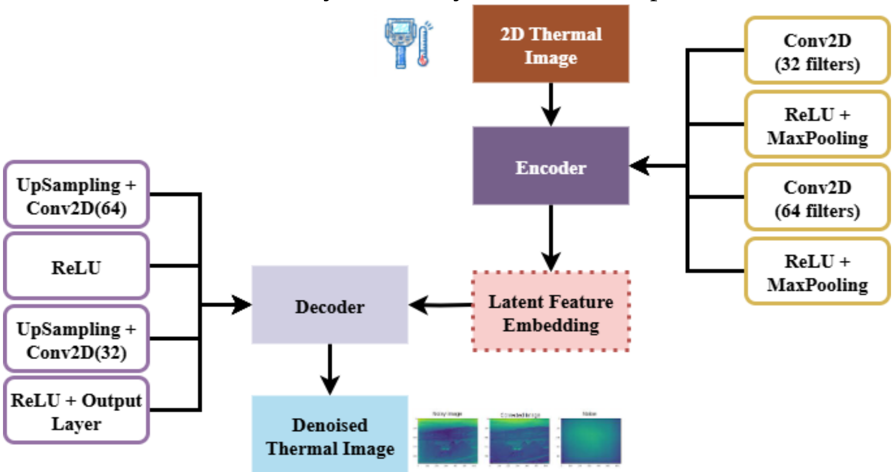

Figure 2: Deep Learning Structure of the TIDA

Figure 2 depicts the neural architecture for the TIDA. The input is a 2-dimensional thermal representation of temporal energy data, highlighting both daily and hourly consumption. The encoder compresses the image using stacked convolutional layers to reduce dimensionality and to learn compact representations that are resistant to noise. The latent space will capture essential features of the data while losing information about variations (noise). The decoder uses upsampling layers and convolutional decoding layers to construct the clean version of the image. The model was trained to minimize reconstruction loss (MSE); it was able to remove random spikes and deviations while preserving some of the structures present in the input data. The result is a smoothed, denoised thermal image, which can now be encoded in binary form and mined for patterns.

c. *Thermal Image Denoising Autoencoder (TIDA)*

The core of the firefly method has been modified to accommodate binary optimization problems. One thing that helps is that the light absorption factor varies with each iteration, which speeds up convergence. Employ a sigmoid-based transformation to change real-valued movement into binary transitions. This lets it work with data that is already in binary form. A mutation operator provides diversity, helping escape local optima. These changes make the algorithm more reliable and better at identifying key energy trends. The new algorithm strikes a better balance between exploration and exploitation, generating high-quality pattern sets that reveal how actual users behave in imaginative grid scenarios.

Image Transformation of Time-Series Data

TIDA enhances data quality to facilitate pattern mining. It turns time-series energy usage into 2D thermal-like visuals by using intensity as a metric of utilization. There is noise in certain pictures sometimes because the measurements weren't accurate or were used in an unusual way. Autoencoders how to learn compressed latent representations and eliminate noise, enabling them to replicate how people utilize renewable energy. After the encoder removes all unnecessary parts, the decoder produces a less noisy image. This method makes it easier to see data by focusing on patterns that remain consistent and recur repeatedly. Then, BE-FPM changes the denoised output into a binary format that miners may utilize.

Autoencoder Architecture and Training

Over time, smart meter data is used to create 2D thermal images that help find patterns in space. The rows in the picture reflect the amount of energy used each day, while the columns show periods, such as hours. The pixels will become brighter the more power utilize. Since it is visual, the autoencoder can find patterns of structural similarity and irregularity over time. The thermal graphic illustrates the model's spatial connections and the functioning of cycles.

When switch to image format, may also apply powerful deep learning denoising methods that don't operate directly on raw time-series vectors and this makes the preprocessing better.

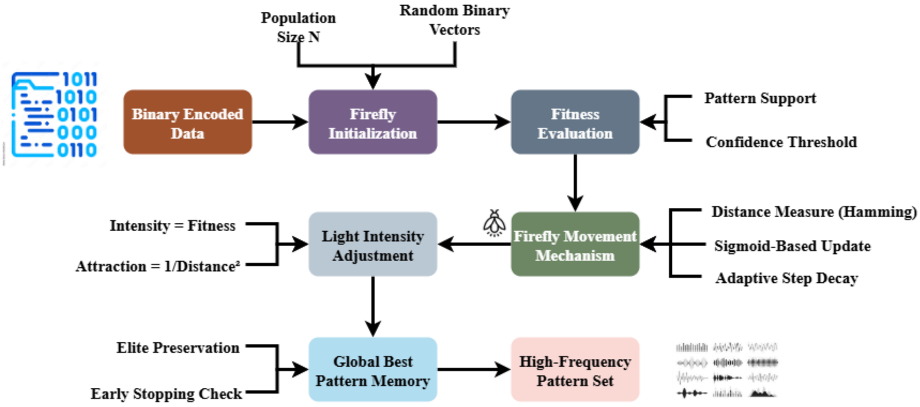

Figure 3: Internal Mechanics of BE-FPM

The dynamics of the BE-FPM optimization engine are illustrated in Figure 3. Once it is fed with binary-encoded consumption data, the system is initialized with a population of fireflies, each representing a potential energy usage pattern. Fitness is evaluated through frequency and relevancy, respectively. Fireflies then explore the binary space by migrating with the help of Hamming distance and a sigmoid transfer function, balancing exploration and exploitation efforts. The intensity of light, which the fireflies use to attract their swarm to more optimal frequencies (visualizations), presents their pattern quality to explore better opportunities within the global problem space. The final output representation is populated with the best possible solution patterns retained in memory. The creative evolution of firefly algorithms is beneficial in identifying frequent and robust patterns that enhance forecasting and optimization of energy behavior in innovative grid environments.

Algorithm: Binary Enhanced Firefly-based Pattern Miner (BE-FPM) with TIDA

Input:
– *Dataset D (smart grid energy data)*
– *Population size N*
– *Maximum iterations MaxIter*
– *Parameters: alpha (step size), beta (attraction coefficient), gamma (light abso*
– *Thermal Image Denoising Autoencoder (TIDA)*

Output:
– *Frequent patterns P*
– *Pattern mining accuracy QNB*

BEGIN

1. *Preprocess Data*:
Convert time – series data D into thermal images
Apply TIDA to denoise thermal images
Convert denoised images back to feature vectors D_clean

2. *Initialize Fireflies*:
FOR i = 1 to N DO
Randomly generate binary pattern x_i
Evaluate fitness f(x_i) using Equation 1 (QNB)
Set light intensity I_i = f(x_i)
END FOR

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3. Set iteration t = 0

4. REPEAT
  FOR i = 1 to N DO
    FOR j = 1 to N DO
      IF I_j > I_i THEN
        Calculate distance r_ij between x_i and x_j
        Compute attraction factor: beta_eff
              = beta * exp(−gamma * r_ij^2)
        Update position:
         x_i_new
              = x_i + beta_eff * (x_j − x_i) + alpha
              * random_binary_step()
        Convert x_i_new to binary (threshold at 0.5)
        Evaluate fitness f(x_i_new)

        IF f(x_i_new) > f(x_i) THEN
          x_i = x_i_new
          I_i = f(x_i)
        ELSE
          Keep x_i unchanged
        END IF
      ELSE
        Do nothing
      END IF
    END FOR
  END FOR

  t = t + 1

  Check convergence condition
  IF convergence reached OR t == MaxIter THEN
    BREAK
  END IF

5. Select best firefly x_star with highest fitness f(x_star)

6. Extract frequent patterns P from x_star

7. Report pattern mining accuracy QNB = f(x_star)

END
```

The BE-FPM algorithm 1 mines frequent energy consumption patterns by combining a binary firefly optimization with TIDA. It iteratively updates candidate patterns, moving toward better solutions based on fitness (pattern accuracy). This approach improves noise resilience, speeds convergence, and enhances demand response effectiveness in smart grids.

4. Experimental Setup

This section presents the implementation environment and the setup for investigating the proposed method. The experiments will utilize real-world smart meter datasets that document hourly residential consumption. The BE-FPM with TIDA will be compared to existing techniques based on traditional data pattern mining and optimization. This paper focus in the experiments will be to investigate the effectiveness of the mining technique in terms of accuracy, robustness to noise, and efficiency runtime. Hardware provided a system with a GPU to support improved training times for models and pattern extraction.

Dataset Description: The dataset used in the study is the Reference Energy Disaggregation Data Set (REDD), a high-profile dataset for smart grid energy analysis and the most extensive available dataset for this purpose. REDD consists of high-resolution time-series electricity consumption data recorded from a variety of homes, providing both aggregate and appliance-level power consumption at one-second intervals, allowing for detailed object-level pattern discovery [21]. For experimentation, the user selected sample households from REDD, pre-processed the data, normalized the data (phase 1), and converted the data into thermal images that represented the usage intensity temporally. This structuring of the data, in the form of a series of thermal images (a video), provides a way to assess noise reduction, pattern mining accuracy, and energy demand prediction in the proposed framework.

Evaluation Metrics: The effectiveness of the proposed system can be assessed in several ways. This paper examine support, confidence, and the F1-score to determine the quality of the patterns identified and the accuracy of pattern mining. This compare the original photos with the reconstructed ones to evaluate the effectiveness of noise reduction using the Peak Signal-to-Noise Ratio (PSNR) and the Structural Similarity Index Measure (SSIM).

Pattern mining accuracy QNB is expressed using equation 1,

$$QNB = \frac{\sum_{j=1}^{o}\left[\log_2\left(\frac{1+\partial_j^{\beta}}{1+\delta_j^{\gamma}}\right) * \tau_j\right]}{o} \quad (1)$$

Equation 1 explains the pattern mining accuracy by comparing the identified pattern intensity with the irrelevant feature density, weighted by the choice factor the precision of pattern recognition is measured.

In this ∂_j is the relevant feature intensity of pattern, δ_j is the irrelevant feature density of pattern, τ_j is the detection certainty coefficient for pattern, β is the intensity amplification constant, γ is the noise suppression exponent, and o is the total number of patterns detected.

Noise reduction efficiency $QTOS_{tl}$ is expressed using equation 2,

$$QTOS_{tl} = 10 * \log_{10}\left(\frac{\forall_m^2}{\frac{1}{NO}\sum_{y=1}^{N}\sum_{z=1}^{O}\left[U(y,z) - \widehat{U}(y,z)\right]^2}\right) \quad (2)$$

Equation 2 explains the noise reduction efficiency uses PSNR to quantify thermal zone noise suppression between the denoised reconstruction and the original thermal image.

In this $\forall_m$ is the maximum pixel intensity in the thermal image, $U(y,z)$ is the original thermal energy pixel at coordinates, $\widehat{U}(y,z)$ is the reconstructed thermal image pixel, and N, O are the dimensions of the thermal image.

Execution time of BE-FPM FU_{CF-GQN} is expressed using equation 3,

$$FU_{CF-GQN} = \sum_{h=1}^{H}\left[\partial_h * \left(\frac{\omega_h + Y_h}{\theta}\right) * \log_2(\sigma_h + 1)\right] \quad (3)$$

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Equation 3 explains the execution time of BE-FPM is determined by inter-firefly communication overhead, population size, and iteration complexity.

In this H is the total number of BE-FPM generations, ∂_h is the number of fireflies in generation, ω_h is the fitness evaluation time per firefly, Y_h is the light intensity update time per firefly, θ is the normalization constant, and σ_h is the firefly communication ratio in generation.

Pattern support consistency QTD is expressed using equation 4,

$$QTD = \frac{1}{|Q|}\sum_{q\in Q}\left(1 - \frac{\sqrt{\sum_{u=1}^{U}\left(t_q(u) - \bar{t}_q\right)^2}}{U * \bar{t}_q}\right) \quad (4)$$

Equation 4 explains the pattern support consistency, the variation in support over time for each pattern.

In this Q is the set of discovered patterns, $t_q(u)$ is the support of pattern at the time slot, $\bar{t}_q$ is the mean support of the pattern over intervals, and U is the total time interval for evaluation.

Demand response optimization score $ESPT$ is expressed using equation 5,

$$ESPT = \sum_{l=1}^{L}\left(\frac{\tau_l(\pi_l - \rho_l)}{\varphi_l + w_l^{\Delta}}\right) \quad (5)$$

Equation 5 explains that the demand response optimization score evaluates shiftable load, peak deviation, and price for load mismatch to determine how successfully mining patterns assist in demand response.

In this L is the number of DR events, τ_l is the grid responsiveness coefficient for event, π_l is the amount of flexible load identified through pattern, ρ_l is the standard deviation of consumption during event, φ_l is the penalty coefficient for mismatch, w_l is the delay penalty due to scheduling, and Δ is the load penalty exponent.

Convergence rate of EBFO DS_{FCFP} is expressed using equation 6,

$$DS_{FCFP} = \frac{1}{H}\sum_{h=1}^{H}\left(\frac{|G_h - G_{h-1}|}{G_{h-1} + \pi}\right) \quad (6)$$

Equation 6 explains the convergence rate of EBFO evaluates the rate at which EBFO stabilizes by measuring the change in normalized fitness between generations.

In this G_h is the best fitness value at generation, G_{h-1} is the best fitness at the previous generation, H is the total number of generations, and π is a small constant to avoid division by zero.

This also checks to see how well the runtime performs to determine how much additional work the machine needs to accomplish. It also verifies the accuracy of the energy estimates before and after implementing the proposed method to determine whether demand response prediction has improved. These numbers demonstrate the method's effectiveness in every aspect.

5. Results and Discussion

This section presents the results of tests comparing the suggested framework to baseline approaches. BE-FPM and TIDA work better together when it comes to discovering energy patterns that recur and repeat. They are both more accurate and less impacted by noise. Denoising the data makes it easier to understand, which in turn simplifies optimization. Tables and graphs indicate that the accuracy, runtime, and pattern relevance have all improved. Another real-world application of the framework could be to help manage more sensitive energy. The findings support the recommended strategy, which is a strong and helpful approach to analyzing smart grid energy statistics.

Table 1: Pattern Mining Accuracy

Number of Patterns	*BE-FPM (%)*	*FSHEP (%)*	*FOC-DA (%)*	*BFA-PR (%)*
50	91.3	85.1	83.5	81.2
200	87.6	81.7	80.4	78.1

Insight: BE-FPM achieves the highest accuracy in identifying frequent patterns due to binary encoding and swarm-based optimization.

Table 1 illustrates how effectively the computer can identify patterns in recurring events. With 50 patterns, the BE-FPM model was far superior to the others, with 91.3% accuracy. FOC-DA earned 83.5%, BFA-PR got 81.2%, and FSHEP got 85.1%. With 200 patterns, BE-FPM was still 87.6% correct. This is more accurate than FSHEP (81.7%), FOC-DA (80.4%), and BFA-PR (78.1%), which were all less accurate evaluated using equation 1. With BE-FPM's binary encoding and swarm-based search, can find patterns with a lot of accuracy across a wide range of volumes. This is ideal for innovative grid applications in the real world, where energy usage fluctuates.

Table 2: Noise Reduction Efficiency (PSNR)

Noise Level (σ)	*BE-FPM (dB)*	*FSHEP (dB)*	*FOC-DA (dB)*	*BFA-PR (dB)*
0.1	34.7	31.1	29.8	28.6
0.4	26.2	22.0	21.1	19.3

Insight: BE-FPM demonstrates superior denoising capability, maintaining pattern recognition accuracy even at high noise levels.

The PSNR indicates the effectiveness of denoising on data transformed into visual representations from time series. The BE-FPM TIDA module achieved 34.7 dB at a noise level of $\sigma = 0.1$. This is louder than FOC-DA (29.8 dB), FSHEP (31.1 dB), and BFA-PR (28.6 dB). When the noise level rose to $\sigma=0.4$, BE-FPM still had 26.2 dB, which was better than FSHEP (22.0 dB), FOC-DA (21.1 dB), and BFA-PR (19.3 dB) is computed using equation 2. Figure 5 illustrates that TIDA can eliminate high-frequency errors from translated thermal images. This implies that patterns may be detected even when there is a lot of noise, which is frequent in real-world smart grid deployments.

Table 3: Execution Time

Number of Records	*BE-FPM*	*FSHEP*	*FOC-DA*	*BFA-PR*
10,000	7.1	8.9	10.2	12.8
40,000	27.9	33.6	43.8	52.5

Insight: BE-FPM offers the lowest latency, making it suitable for real-time demand response systems.

Grid systems that operate in real-time need to be able to perform tasks quickly. BE-FPM was the quickest at processing the data as it grew. Processing 10,000 records took just 7.1 seconds, which is less time than FSHEP (8.9 seconds), FOC-DA (10.2 seconds), and BFA-PR (12.8 seconds). With 40,000 data points, BE-FPM worked well and took 27.9 seconds. It took

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FSHEP, FOC-DA, and BFA-PR 33.6 seconds, 43.8 seconds, and 52.5 seconds, respectively, as shown in Figure 6 made valued using the equation 3. BE-FPM is an excellent tool for energy systems that require rapid response and minimal latency, as it seamlessly integrates binary firefly logic with autoencoder functionality in a straightforward manner.

Table 4: Pattern Support Consistency

Pattern Rank	*BE-FPM (%)*	*FSHEP (%)*	*FOC-DA (%)*	*BFA-PR (%)*
Top Pattern	94.6	88.9	87.1	85.3
4th Ranked Pattern	88.2	81.1	79.3	76.8

Insight: BE-FPM exhibits superior temporal consistency in identifying dominant energy usage patterns.

Support consistency examines how frequently the most prevalent patterns emerge over time. The top pattern had 94.6% support in BE-FPM, which was more stable. FSHEP earned 88.9%, FOC-DA got 87.1%, and BFA-PR got 85.3%. The fourth-ranked pattern in BE-FPM nonetheless got 88.2% support, which was more than the 81.1% support for FSHEP, the 79.3% support for FOC-DA, and the 76.8% support for BFA-PR shown in table 4 computed using equation 4. The model is relatively consistent, meaning it can reliably identify patterns in how individuals use energy that are both useful and repeatable. This is crucial for developing effective energy policy strategies and for accurately predicting grid analytics.

Table 5: Demand Response Optimization

Time of Day	*BE-FPM (%)*	*FSHEP (%)*	*FOC-DA (%)*	*BFA-PR (%)*
Morning	13.9	10.2	8.6	7.8
Evening	16.8	12.6	10.4	9.1

Insight: BE-FPM enables the highest energy savings, offering effective load balancing during peak hours.

Based on mining statistics, this table 5 illustrates the amount of energy saved at various times of the day. BE-FPM saved 16.8% more energy than FSHEP (12.6%), FOC-DA (10.4%), and BFA-PR (9.1%) during the peak of the evening. In the morning, BE-FPM was in the lead again, this time with a 13.9% share. With 10.2%, FSHEP came in second, FOC-DA came in third with 8.6%, and BFA-PR came in fourth with 7.8% made computed using equation 5. BE-FPM's exact demand-response patterning helps maintain a balanced grid, reduces operating costs, and utilizes energy in an environmentally friendly manner. This makes it a valuable tool for swiftly adapting to changes in demand on the smart grid.

Table 6: Convergence Rate

Iterations	*BE-FPM*	*FSHEP*	*FOC-DA*	*BFA-PR*
10	0.78	0.71	0.68	0.64
20	0.84	0.75	0.72	0.69
30	0.89	0.79	0.76	0.72
40	0.91	0.81	0.78	0.74

Insight: BE-FPM shows the fastest and most stable convergence, indicating efficient exploration exploitation balance during optimization.

The convergence rate indicates how quickly and accurately an optimization model identifies a stable solution. After 10 cycles, the best fitness score achieved by BE-FPM was 0.78. FSHEP, FOC-DA, and BFA-PR only got 0.71, 0.68, and 0.64, which isn't very excellent. By the 40th time, BE-FPM had a score of 0.91, FSHEP had a score of 0.81, FOC-DA had a score of 0.78, and BFA-PR had a score of 0.74, as shown in table 6 made evaluated using equation 6. This suggests that BE-FPM performs better in striking a balance between exploration and exploitation. This helps it find the optimal patterns more quickly, without getting stuck in local minima, which is crucial for real-time applications.

6. Conclusion

This paper demonstrates that pattern mining in energy data from smart grids can be enhanced by adopting a new hybrid framework, called BE-FPM, in conjunction with a TIDA. The suggested solution employed an intelligent encoding mechanism and image-based denoising to overcome the high processing cost, noise sensitivity, and poor pattern consistency that are significant problems with existing techniques. BE-FPM was superior to other models, such as BFA-PR, FOC-DA, and FSHEP, in terms of pattern mining accuracy (91.3%), noise resistance (34.7 dB PSNR at F = 0.1), and convergence speed (0.91 best fitness by iteration 40). Furthermore, the technology demonstrated its potential for real-life applications in grid optimization, saving a significant amount of energy during demand response events, with a 16.8% improvement during peak hours at night.

The BE-FPM design may be even better if it had more information about patterns, such as adding multi-modal data like weather, appliance use, and pricing models. This is true even if it has previously proven effective. Federated learning may also be utilized to maintain users' privacy in distributed energy systems, and adaptive autoencoders could be employed to identify issues in real-time. There needs to be lighter versions of models for devices with limited resources so that they can be utilized in edge computing settings. Finally, explainable AI (XAI) can help both energy operators and end-users better comprehend data-driven grid choices by making the system easier to understand.

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