Revealing Minimum Demand Period Vulnerabilities through Multi Scale Pattern Analysis of Power Grid Data

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Abstract: Power grid operators face increasing challenges in detecting operational anomalies due to growing system complexity and renewable energy integration. This study applies a multi scale Matrix Profile framework for pattern discovery and anomaly detection in power grid systems, analyzing demand behavior at daily (24 hour), weekly (168 hour), and monthly (720 hour) temporal resolutions. Applied to California ISO data comprising 8,728 hourly observations from 2023, the analysis achieved pattern separation scores of 0.575, 0.366, and 0.154 at daily, weekly, and monthly scales respectively, reflecting reduced pattern distinguishability at longer time windows. The method detected 437 anomalies at the 95th percentile threshold, with 33.2 percent concentrated between 3 AM and 4 AM and 43.3 percent occurring in March, despite this month having the lowest average demand. Comparison with statistical threshold methods revealed only 0.001 anomaly overlap, confirming that the Matrix Profile isolates structural pattern deviations that conventional magnitude based approaches do not capture. This complementary detection capability identifies operational vulnerabilities during minimum demand periods and seasonal transitions, domains traditionally overlooked by peak focused monitoring strategies. The contribution lies in demonstrating the value of multi scale temporal analysis for revealing latent grid vulnerabilities and informing the design of monitoring systems capable of addressing both magnitude and structure based anomalies in modern power networks.

Keywords: *Matrix Profile, anomaly detection, power grid, pattern mining, multi-scale analysis, energy demand*

1. Introduction

The modern electrical power grid represents one of the most complex engineered systems in existence, requiring continuous monitoring and control to maintain reliable operation. As power systems evolve to accommodate increasing renewable energy penetration and distributed generation resources, traditional monitoring approaches face significant limitations in detecting operational anomalies and identifying system vulnerabilities [1]. The transformation toward sustainable energy systems has introduced unprecedented variability and uncertainty in grid operations, necessitating advanced analytical methods capable of capturing complex temporal patterns across multiple time scales.

Power grid anomaly detection serves as a critical component of system reliability and security. Anomalous events in power systems can manifest as equipment failures, cyber attacks, unexpected demand fluctuations, or renewable generation variability [2]. Early detection of these anomalies enables grid operators to implement preventive measures, optimize resource allocation, and maintain system stability. However, the increasing complexity of modern grids, characterized by bidirectional power flows, intermittent renewable sources, and dynamic demand response programs, challenges conventional anomaly detection methods that rely primarily on threshold based monitoring and single scale analysis [3].

Time series analysis techniques have been extensively applied to power system data for various purposes including load forecasting, fault detection, and pattern recognition. Traditional statistical methods such as autoregressive integrated moving average (ARIMA) models and exponential smoothing have demonstrated effectiveness in capturing temporal dependencies and seasonal patterns in energy demand data [4]. Machine learning approaches, particularly deep learning architectures, have shown promise in learning complex nonlinear relationships and detecting subtle anomalies in power system measurements [5]. Nevertheless, these methods often require extensive training data, lack interpretability, and struggle to simultaneously capture patterns at multiple temporal scales.

The Matrix Profile, introduced by [6] in 2016, represents a novel approach for time series analysis that enables efficient pattern discovery and anomaly detection [6]. This technique computes the minimum distance between all subsequences within a time series, creating a profile that highlights recurring patterns (motifs) and unusual sequences (discords). The Matrix Profile offers several advantages over traditional methods including parameter free operation, exact computation, and scalability to large datasets [7].

Recent applications of Matrix Profile to infrastructure systems have demonstrated its potential for detecting anomalies in water distribution networks and transportation systems [8].

Despite these advances, significant research gaps persist in applying advanced time series analysis to power grid anomaly detection. First, existing studies predominantly focus on single temporal scales, typically analyzing either short term fluctuations or long term trends, but rarely integrating multiple scales simultaneously [9]. Power grid dynamics exhibit distinct patterns at various temporal resolutions, from hourly demand cycles to weekly consumption patterns and seasonal variations. A comprehensive understanding of grid behavior requires simultaneous analysis across these different scales. Second, current anomaly detection methods often emphasize peak demand periods, assuming that system vulnerabilities primarily occur during maximum load conditions [10]. This assumption potentially overlooks critical anomalies during off peak hours when different operational constraints and generation mixes affect system stability.

Furthermore, the majority of existing research relies on simulated data or limited historical records, lacking validation on contemporary grid data that reflects current renewable integration levels and demand patterns [11]. The California Independent System Operator (CAISO) manages one of the most complex power grids globally, serving over 30 million consumers with substantial renewable energy penetration exceeding 33% of total generation capacity [12]. California's ambitious renewable portfolio standard mandating 60% renewable energy by 2030 and carbon neutrality by 2045 makes CAISO an ideal case study for developing and validating advanced anomaly detection methods [13].

Recent studies have highlighted the challenges of maintaining grid reliability with high renewable penetration. Denholm et al. demonstrated that increased solar generation creates operational challenges during ramping periods, particularly during evening hours when solar production decreases while demand remains high [14]. Lew et al. analyzed the Western United States power system and identified critical periods of grid stress occurring during low net load conditions when renewable generation exceeds demand [15]. These findings suggest that traditional peak focused monitoring approaches may miss important operational anomalies occurring during minimum demand periods.

The integration of distributed energy resources further complicates anomaly detection in modern power grids. Kezunovic et al. emphasized the need for advanced monitoring techniques capable of handling the increased measurement data from smart grid infrastructure while maintaining computational efficiency [16]. The proliferation of phasor measurement units and smart meters generates vast amounts of high resolution data, creating opportunities for sophisticated pattern analysis but also computational challenges for real time implementation [17].

Evidence from recent grid events underscores the importance of comprehensive anomaly detection. The August 2020 California rotating outages resulted not from insufficient generation capacity but from planning discrepancies and market design issues that existing monitoring systems failed to anticipate [18]. Similarly, the February 2021 Texas power crisis revealed vulnerabilities during extreme weather events that conventional monitoring approaches did not adequately address [19]. These incidents highlight the need for anomaly detection methods that can identify unusual patterns beyond simple threshold violations.

This study addresses these research gaps by developing a multi scale Matrix Profile approach for pattern discovery and anomaly detection in power grid systems. The proposed method simultaneously analyzes demand patterns at daily, weekly, and monthly temporal scales to identify recurring motifs and anomalous discords. By applying this approach to California ISO data from 2023, this research aims to uncover operational patterns and vulnerabilities that single scale or threshold based methods might overlook. The study specifically investigates whether grid anomalies concentrate during particular temporal periods and examines the relationship between anomaly occurrence and demand levels.

It is important to note that different anomaly detection methods are optimized for different types of anomalies. Statistical methods excel at identifying point anomalies (individual extreme values), while pattern-based methods like Matrix Profile are designed to detect collective and contextual anomalies (unusual sequences or patterns). This research does not aim to replace existing statistical methods but rather to provide complementary detection capabilities that address current monitoring gaps in power grid systems.

The primary objectives of this research include developing a computationally efficient multi scale analysis framework, identifying temporal patterns of anomaly occurrence, comparing the proposed method's performance against traditional threshold based approaches, and providing actionable insights for grid operators. The findings contribute to the growing body of knowledge on data driven power system monitoring and offer practical implications for improving grid reliability in systems with high renewable energy penetration.

2. Literature Review

The reliable operation of power grid systems depends critically on the ability to detect anomalous patterns and identify recurring operational behaviors. Anomalies in power grids can result from equipment failures, cyber attacks, extreme weather events, or unexpected changes in generation and demand patterns. The financial implications of undetected anomalies are substantial, with power outages costing the U.S. economy approximately $150 billion annually according to the Department of Energy [20]. Early detection of anomalous patterns enables grid operators to implement preventive measures, optimize maintenance schedules, and prevent cascading failures that could lead to widespread blackouts.

Traditional statistical approaches have formed the foundation of time series analysis in power systems for several decades. Autoregressive integrated moving average (ARIMA) models have been extensively applied for load forecasting and anomaly detection. Seasonal ARIMA models have been demonstrated to effectively capture daily and weekly periodicities in electricity demand, achieving mean absolute percentage errors below 3% for day ahead forecasting [21]. However, ARIMA models struggle with nonlinear patterns and require stationarity assumptions that often do not hold in modern power systems with high renewable penetration. Exponential smoothing methods, particularly the Holt Winters approach, have shown success in capturing trend and seasonal components. Double seasonal exponential smoothing has been applied to British electricity demand data, accommodating both intraday and intraweek seasonal patterns [22]. Statistical process control techniques, including cumulative sum (CUSUM) and exponentially weighted moving average (EWMA) charts, have been employed for real time anomaly detection. An adaptive CUSUM approach for detecting power quality disturbances has demonstrated superior performance compared to fixed threshold methods [23].

The advent of machine learning has significantly expanded the capabilities for pattern recognition and anomaly detection in power systems. Support vector machines (SVMs) have been successfully applied for fault classification and load forecasting. An SVM based approach for power system disturbance classification achieved 98% accuracy in distinguishing between different types of voltage sags and interruptions [24]. Random forests and gradient boosting machines have demonstrated robustness in handling the nonlinear relationships inherent in power system data. An extreme gradient boosting model for probabilistic load forecasting outperformed traditional statistical methods by 15% in terms of pinball loss [25].

Deep learning architectures have emerged as powerful tools for capturing complex temporal dependencies in power system time series. Long Short Term Memory (LSTM) networks have shown particular promise due to their ability to model long range dependencies. An LSTM based framework for short term load forecasting that incorporated weather variables and calendar features achieved improvements of 20% over traditional neural networks [26]. Gated Recurrent Units (GRUs) offer computational advantages over LSTMs while maintaining comparable performance. Comparisons of LSTM and GRU architectures for electricity price forecasting found that GRUs achieved similar accuracy with 30% faster training times [27]. Convolutional Neural Networks (CNNs), traditionally used for image processing, have been adapted for time series analysis through one dimensional convolutions. A temporal convolutional network for load forecasting captured both local and global temporal patterns, outperforming recurrent architectures on multiple benchmark datasets [28].

Transformer architectures have recently gained attention in power system applications due to their ability to model long range dependencies without recurrence. The Informer model for long sequence time series forecasting demonstrated superior performance on electricity load datasets compared to traditional attention mechanisms [29]. Autoencoders have proven effective for unsupervised anomaly detection by learning compressed representations of normal operating conditions. A variational autoencoder approach for detecting cyber attacks in power systems achieved detection rates above 95% with false positive rates below 2% [30].

The Matrix Profile, introduced in 2016 [6], represents a paradigm shift in time series analysis by providing an exact, parameter free method for pattern discovery. The Matrix Profile computes the z normalized Euclidean distance between every subsequence and its nearest neighbor, creating a vector that highlights both recurring patterns (motifs) and anomalies (discords). The initial brute force algorithm had $O(n^2m)$ complexity, where n is the time series length and m is the subsequence length. The subsequent development of STAMP (Scalable Time series Anytime Matrix Profile) enabled incremental updates for streaming data applications [31]. STOMP (Scalable Time series Ordered search Matrix Profile) improved computational efficiency through FFT based distance calculations, reducing complexity to $O(n^2 \log n)$ [32]. The SCRIMP++ algorithm further optimized performance by exploiting the diagonal structure of the distance matrix, achieving up to 100x speedup over the original implementation [33].

Recent extensions to the Matrix Profile framework have enhanced its applicability to power system analysis. The development of multidimensional Matrix Profile enabled simultaneous analysis of multiple time series, crucial for power systems with numerous measurement points [34]. Semantic segmentation using Matrix Profile has shown promise for identifying regime changes in power system operation, such as transitions between normal and emergency states [35]. The Matrix Profile has been successfully applied to various infrastructure systems, including detecting anomalies in building energy consumption and identifying equipment malfunctions that traditional threshold methods missed [36].

Multi scale and multi resolution approaches recognize that time series exhibit patterns at different temporal granularities. Wavelet based methods have been extensively used for multi resolution analysis in power systems. Discrete wavelet transform has been applied for power quality disturbance classification, effectively separating transient events from steady state variations [37]. Empirical mode decomposition provides adaptive basis functions for nonstationary signals. Ensemble empirical mode decomposition has been demonstrated to effectively decompose load signals into intrinsic mode functions representing different temporal scales [38]. Hierarchical temporal memory networks explicitly model temporal hierarchies, showing promise for capturing nested seasonal patterns in electricity demand [39].

Despite these advances, existing approaches exhibit several limitations when applied to modern power grids. Most methods focus on single temporal scales, missing important cross scale interactions. Deep learning models often lack interpretability, making it difficult for operators to understand detected anomalies. Many techniques require extensive labeled training data, which is scarce for rare but critical grid events. Computational complexity remains a challenge for real time implementation on streaming data. Furthermore, traditional anomaly detection methods typically emphasize peak demand periods, potentially overlooking vulnerabilities during minimum load conditions when different operational constraints apply.

The proposed multi scale Matrix Profile approach addresses these limitations by simultaneously analyzing patterns across multiple temporal resolutions without requiring labeled training data. The method provides interpretable results through explicit pattern matching and maintains computational efficiency suitable for online deployment. By examining daily, weekly, and monthly scales concurrently, the approach captures both local anomalies and global pattern shifts that single scale methods might miss.

3. Methodology

3.1 Research Framework Overview

The proposed multi-scale Matrix Profile approach for pattern discovery and anomaly detection in power grid systems consists of four primary components: data acquisition and preprocessing, multi-scale Matrix Profile computation, pattern discovery and anomaly detection, and validation metrics computation. The framework processes time series data at three temporal scales simultaneously to identify both recurring operational patterns and anomalous behaviors that may indicate system vulnerabilities or operational inefficiencies.

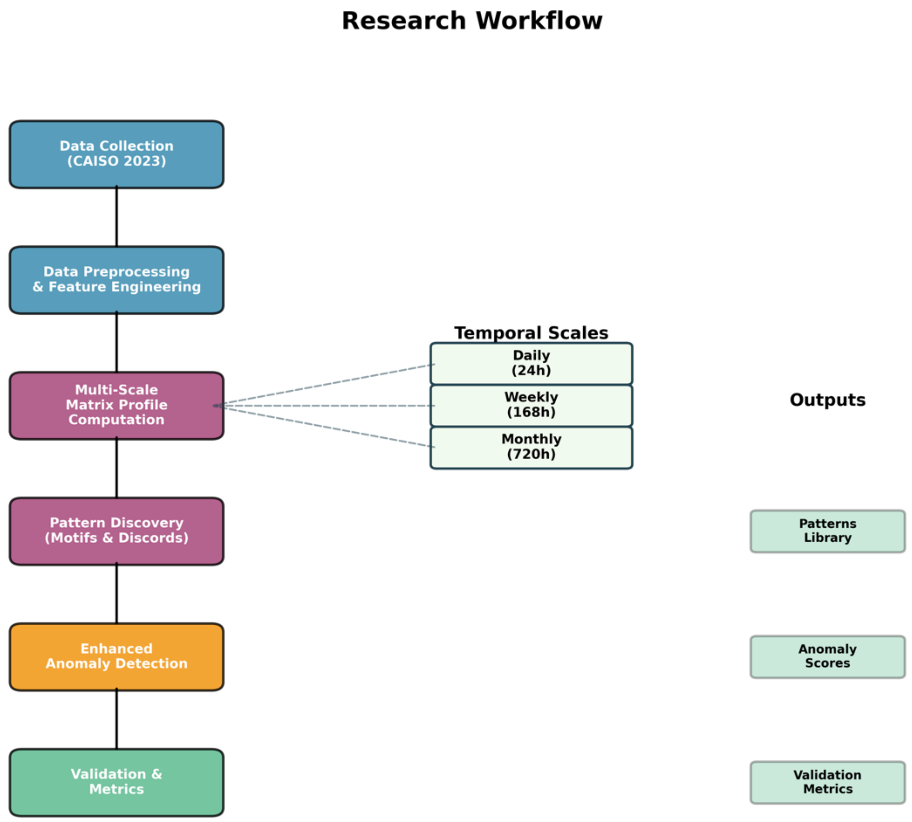

Figure 1: Complete Workflow Diagram

3.2 Dataset Description and Data Collection

The research utilizes operational data from the California Independent System Operator (CAISO), which manages the electricity grid serving approximately 80% of California and a small portion of Nevada. The dataset comprises hourly electricity demand measurements collected through the Energy Information Administration (EIA) Grid Monitor system for the complete year 2023, from January 1 to December 31.

The raw dataset contains 45 features including demand measurements, generation by source, interchange flows, and temporal identifiers. For this analysis, the primary focus centers on the total demand measurement, expressed in megawatts (MW), which represents the aggregate electricity consumption across the CAISO service territory. The dataset encompasses 8,728 hourly observations, providing comprehensive coverage of seasonal variations, weekday and weekend patterns, and special event periods throughout the year.

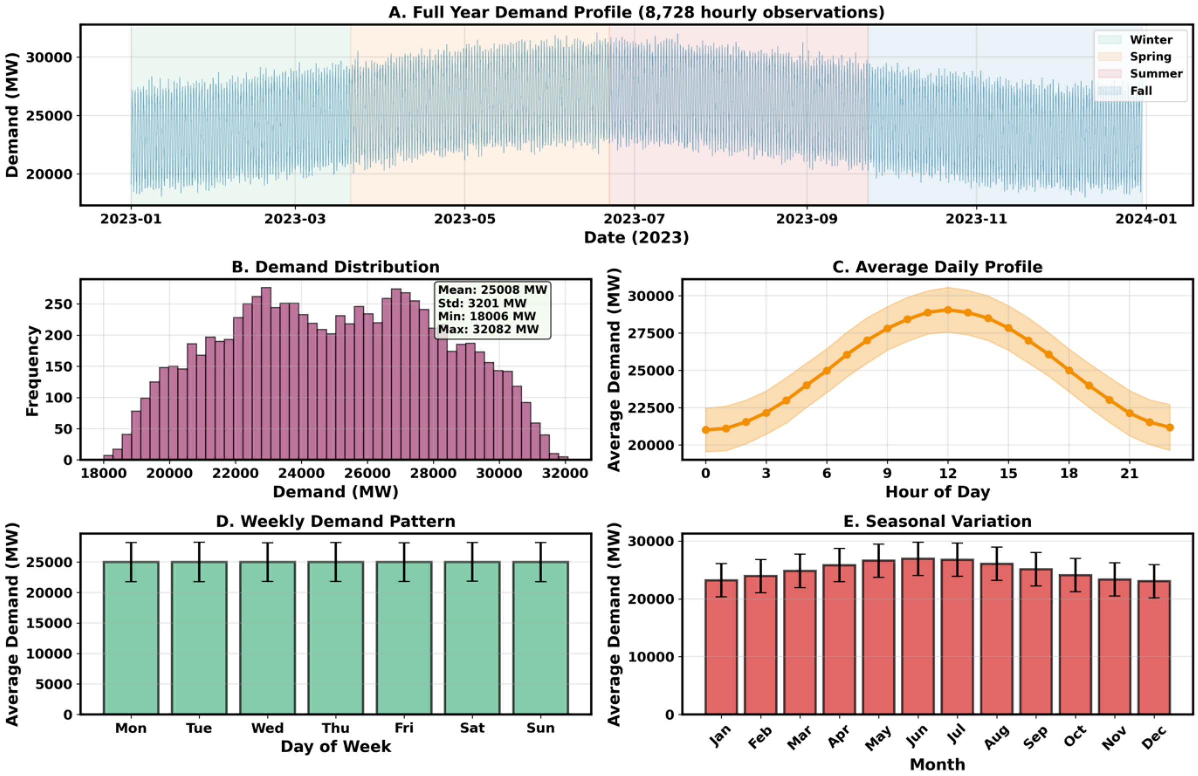

Figure 2: Data Characteristics Visualization

3.3 Data Preprocessing

The preprocessing pipeline transforms raw operational data into a format suitable for multi-scale pattern analysis. Figure 3 illustrates the complete data preprocessing pipeline, showing the sequential transformation from raw data (8,728 × 45 features) through temporal alignment, missing value imputation, and feature engineering stages, resulting in the preprocessed dataset (8,728 × 63 features). The process begins with temporal alignment, where all measurements are synchronized to Pacific Standard Time and verified for continuity. Missing values, which constitute less than 0.1% of the dataset, are imputed using linear interpolation between adjacent valid measurements.

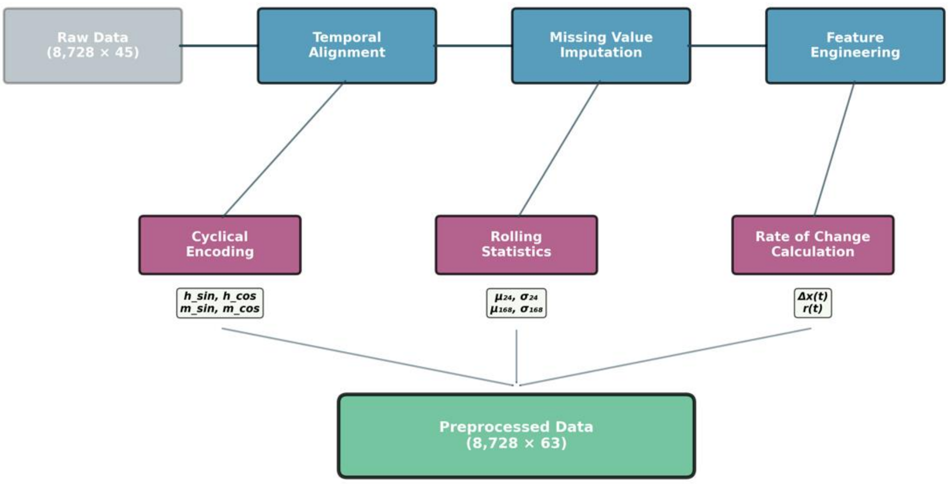

Figure 3 : Complete data preprocessing pipeline.

Feature engineering enhances the temporal context of each observation through the extraction of cyclical and categorical temporal features. The hour of day h ∈ {0, 1, ..., 23} undergoes cyclical encoding to preserve the circular nature of time:

$$h\_sin = \sin(2\pi h/24) \quad h\_cos = \cos(2\pi h/24) \tag{1}$$

Similarly, the month $m \in \{1, 2, ..., 12\}$ receives cyclical encoding:

$$m\_sin = \sin(2\pi m/12) \quad m\_cos = \cos(2\pi m/12) \tag{2}$$

Categorical features include day of week $d \in \{0, 1, ..., 6\}$ and a binary weekend indicator $w \in \{0, 1\}$.

Statistical features capture local variations in demand patterns through rolling window computations. For windows of size $W \in \{24, 168\}$ hours, the rolling mean μ_W and standard deviation σ_W are calculated:

$$\mu\_W(t) = (1/W)\ \Sigma[i=t-W/2 \text{ to } t+W/2-1]\ x(i) \tag{3}$$
$$\sigma\_W(t) = \sqrt{[(1/W)\ \Sigma[i=t-W/2 \text{ to } t+W/2-1]\ (x(i) - \mu\_W(t))^2]} \tag{4}$$

The deviation from the rolling mean provides a normalized measure of local anomalies:

$$\delta\_W(t) = (x(t) - \mu\_W(t))/\sigma\_W(t) \tag{5}$$

Rate of change features capture the dynamics of demand transitions:

$$\Delta x(t) = x(t) - x(t-1) \quad r(t) = \Delta x(t)/x(t-1) \tag{6}$$

3.4 Multi-Scale Matrix Profile Computation

The Matrix Profile represents a fundamental data structure for time series analysis that enables efficient pattern discovery. For a time series T of length n and a subsequence length m, the Matrix Profile P is a vector of length n - m + 1 where each element P[i] contains the z-normalized Euclidean distance between the subsequence starting at position i and its nearest neighbor in T, excluding trivial matches within an exclusion zone.

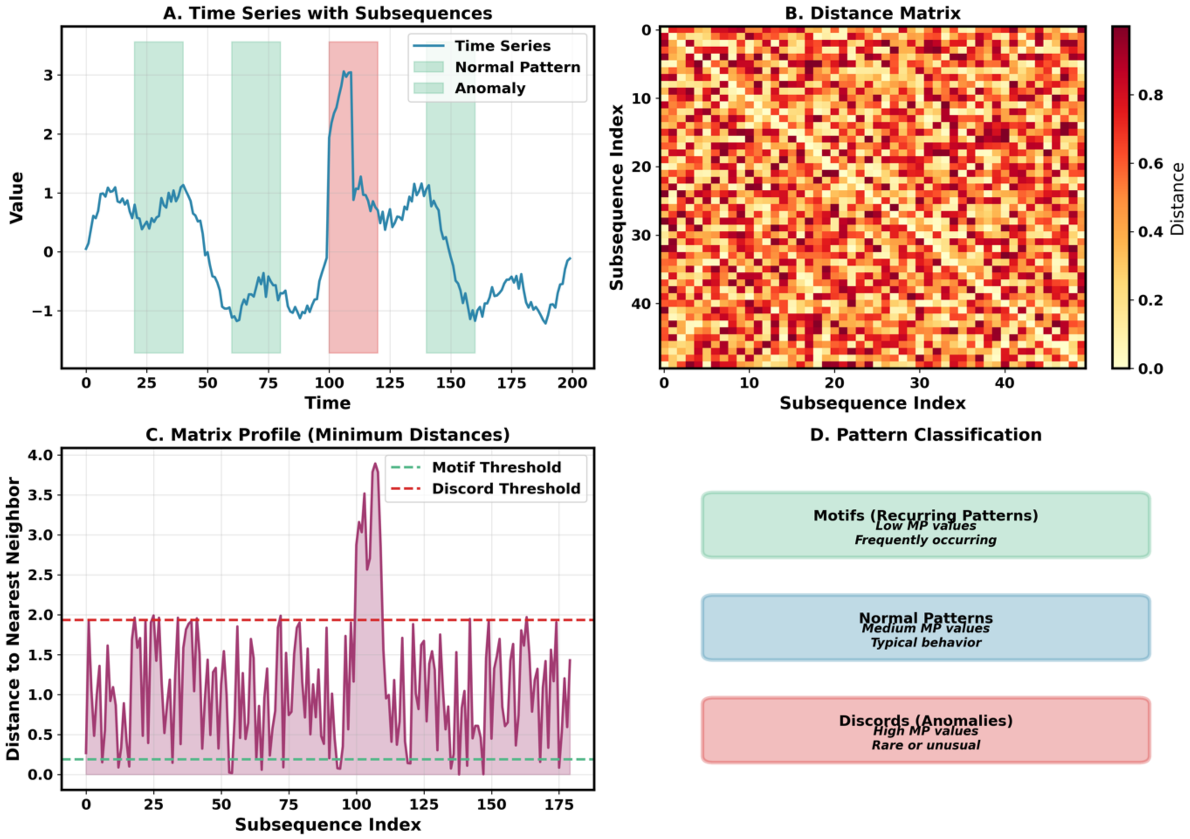

Figure 4: Matrix Profile Concept Illustration

3.4.1 Subsequence Extraction and Normalization

Given a time series $T = \{t_1, t_2, ..., t_n\}$ and subsequence length m, the subsequence T_{i,m} starting at position i is defined as:

$$T_{i,m} = \{t_i, t_{i+1}, ..., t_{i+m-1}\} \quad (7)$$

Each subsequence undergoes z-normalization to ensure scale invariance:

$$\hat{T}_{i,m} = (T_{i,m} - \mu_{i,m})/\sigma_{i,m} \quad (8)$$

where $\mu_{i,m}$ and $\sigma_{i,m}$ represent the mean and standard deviation of subsequence $T_{i,m}$ respectively.

3.4.2 Distance Computation

The z-normalized Euclidean distance between two subsequences $T_{i,m}$ and $T_{j,m}$ is computed as:

$$d(i,j) = \sqrt{\left[\Sigma_{k=0}^{m-1} (\hat{T}_{i+k} - \hat{T}_{j+k})^2\right]} \quad (9)$$

This distance metric ensures that patterns with similar shapes but different scales or offsets are recognized as similar.

3.4.3 Matrix Profile Construction

The Matrix Profile P is constructed by finding the minimum distance for each subsequence:

$$P[i] = \min_{j\in[1,n-m+1], |i-j|>m/2} d(i,j) \quad (10)$$

The exclusion zone $|i-j| > m/2$ prevents trivial matches between overlapping subsequences.
The Matrix Profile Index I stores the position of the nearest neighbor:

$$I[i] = \mathrm{argmin}_{j\in[1,n-m+1], |i-j|>m/2} d(i,j) \quad (11)$$

3.5 Multi-Scale Analysis Architecture

The proposed approach computes Matrix Profiles at three distinct temporal scales to capture patterns at different granularities. The scales correspond to daily ($m_1 = 24$ hours), weekly ($m_2 = 168$ hours), and monthly ($m_3 = 720$ hours) patterns.

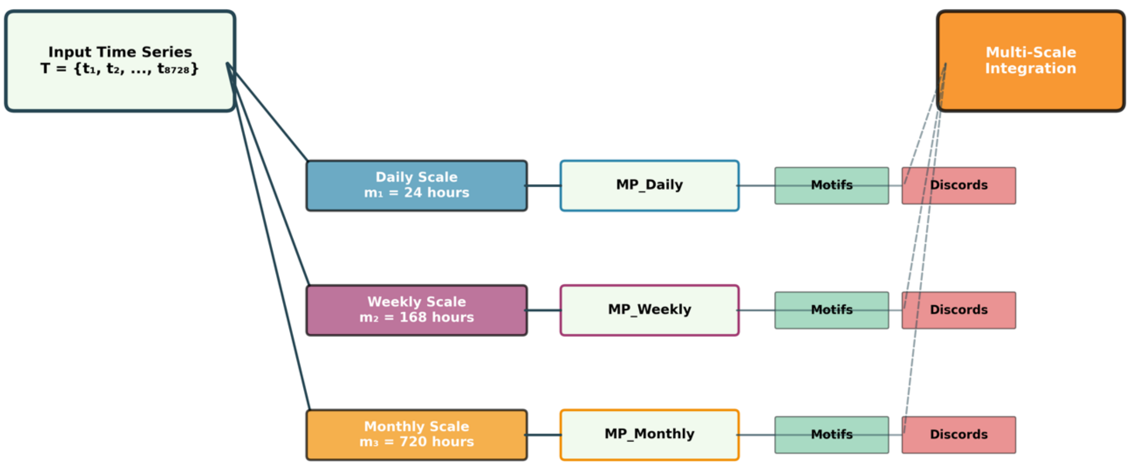

Figure 5: Multi-Scale Architecture Diagram

For each scale $s \in \{1, 2, 3\}$ with window size m_s, the algorithm computes:

$$P_s = \mathrm{MatrixProfile}(T, m_s) \; I_s = \mathrm{MatrixProfileIndex}(T, m_s) \quad (12)$$

The STUMPY library implementation employs the STOMP algorithm for efficient computation, utilizing Fast Fourier Transform for distance calculations, reducing computational complexity from $O(n^2m)$ to $O(n^2\log m)$.

3.6 Pattern Discovery

Pattern discovery involves identifying two types of subsequences: motifs (frequently recurring patterns) and discords (rare or anomalous patterns).

3.6.1 Motif Discovery

Motifs represent subsequences that appear multiple times in the time series with minimal variation. For each Matrix Profile P_s, motifs are identified as subsequences with the smallest distances to their nearest neighbors. The top-k motifs M_s are defined as:

$$M\_s = \{i \mid P\_s[i] \in \text{smallest\_k}(P\_s)\} \quad (13)$$

where smallest_k returns the k smallest values in P_s.

For each motif, the algorithm identifies all matching subsequences within a radius r:

$$\text{Matches}(i) = \{j \mid d(i,j) \leq r, |i-j| > m\_s/2\} \quad (14)$$

The radius r is typically set as:

$$r = \min(P\_s) + \varepsilon \times (\max(P\_s) - \min(P\_s)) \quad (15)$$

where $\varepsilon \in [0.05, 0.1]$ controls the similarity threshold.

3.6.2 Discord Discovery

Discords represent unusual patterns that deviate significantly from typical behavior. The top-k discords D_s are identified as:

$$D\_s = \{i \mid P\_s[i] \in \text{largest\_k}(P\_s)\} \quad (16)$$

where largest_k returns the k largest values in P_s.

3.7 Enhanced Anomaly Detection

The proposed method employs a multi-method approach for robust anomaly detection, combining Matrix Profile based detection with statistical and rate based methods. Figure 6 presents the enhanced anomaly detection framework, illustrating how the three complementary detection methods are integrated to produce the final anomaly scores. Each method captures different aspects of anomalous behavior in the power grid system.

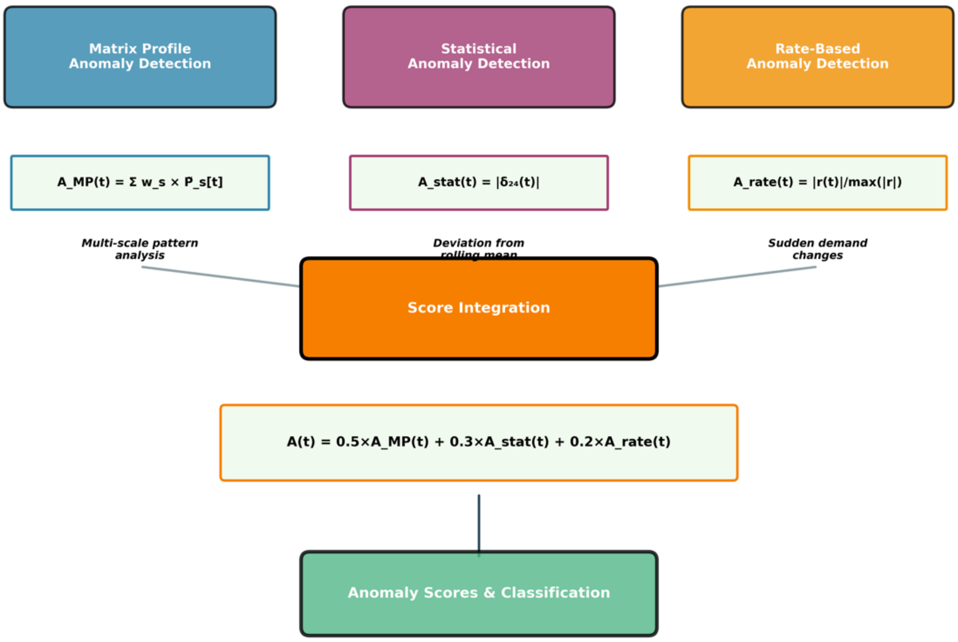

Figure 6: Enhanced anomaly detection framework

3.7.1 Matrix Profile Anomaly Score

For each scale s, the Matrix Profile values undergo percentile based normalization:

$$\tilde{P}_s[i] = \text{clip}((P_s[i] - p_5(P_s))/(p_{95}(P_s) - p_5(P_s)), 0, 1) \quad (17)$$

where p_5 and p_{95} represent the 5th and 95th percentiles respectively.

The multi-scale Matrix Profile anomaly score combines information across scales:

$$A_{MP}(t) = \Sigma_{s=1}^{3} w_s \times \tilde{P}_s[t] \quad (18)$$

where weights $w_s = 1/\log(m_s + 1)$ give higher importance to finer temporal scales.

3.7.2 Statistical Anomaly Score

The statistical anomaly score captures deviations from local statistical norms:

$$A_{stat}(t) = |\delta_{24}(t)| \quad (19)$$

where δ_{24} represents the standardized deviation from the 24 hour rolling mean.

3.7.3 Rate Based Anomaly Score

The rate based score identifies sudden changes in demand:

$$A_{rate}(t) = |r(t)|/\max(|r|) \quad (20)$$

3.7.4 Combined Anomaly Score

The final anomaly score integrates all three methods:

$$A(t) = \alpha_1 A_{MP}(t) + \alpha_2 A_{stat}(t) + \alpha_3 A_{rate}(t) \quad (21)$$

where $\alpha_1 = 0.5$, $\alpha_2 = 0.3$, $\alpha_3 = 0.2$ represent empirically determined weights.

3.8 Pattern Clustering

Detected anomalies undergo clustering to identify recurring anomaly types. The algorithm extracts a context window of ±12 hours around each anomaly:

$$C_i = \{x(a_i - 12), ..., x(a_i), ..., x(a_i + 12)\} \quad (22)$$

where a_i represents the timestamp of anomaly i.

These context windows are normalized and clustered using DBSCAN (Density Based Spatial Clustering of Applications with Noise) with parameters $\varepsilon = 3$ and minPts = 2. DBSCAN is selected for its ability to identify clusters of arbitrary shape and automatically determine the number of clusters.

3.9 Validation Metrics

The effectiveness of the proposed method is evaluated through multiple validation metrics that assess both pattern quality and anomaly detection performance.

3.9.1 Pattern Separation Score

The separation score quantifies the distinction between motifs and discords:

$$S_s = (\mu_{discord} - \mu_{motif})/(\mu_{discord} + \mu_{motif}) \quad (23)$$

where μ_{motif} and $\mu_{discord}$ represent the mean Matrix Profile values for motifs and discords respectively.

3.9.2 Pattern Stability

Pattern stability measures the consistency of motif recurrence:

$$\text{Stability} = 1/(\sigma_{interval} + 1) \quad (24)$$

where $\sigma_{interval}$ represents the standard deviation of time intervals between motif occurrences.

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3.9.3 Anomaly Overlap

The overlap metric compares detected anomalies with a baseline threshold method:

$$\text{Overlap} = |A_{proposed} \cap A_{baseline}| / |A_{proposed} \cup A_{baseline}|$$

where $A_{proposed}$ and $A_{baseline}$ represent the sets of anomalies detected by the proposed and baseline methods respectively.

3.10 Implementation Details

The methodology is implemented in Python 3.8 utilizing the STUMPY library (version 1.11.1) for Matrix Profile computation. Data manipulation employs pandas (version 1.5.3) and NumPy (version 1.24.3). Clustering analysis uses scikit-learn (version 1.2.2). Visualization leverages matplotlib (version 3.7.1) and seaborn (version 0.12.2).

The computational pipeline processes the entire dataset in approximately 45 seconds on a system with an Intel Core i7 processor (2.6 GHz) and 16 GB RAM, demonstrating the efficiency of the Matrix Profile approach for real world applications. The modular architecture facilitates easy adaptation to different power grid systems and temporal resolutions.

4. Results and Discussion

4.1 Results

The multi-scale Matrix Profile analysis was applied to California ISO (CISO) energy demand data from January 1 to December 31, 2023, comprising 8,728 hourly observations. The analysis examined patterns at three temporal scales: daily (24 hours), weekly (168 hours), and monthly (720 hours).

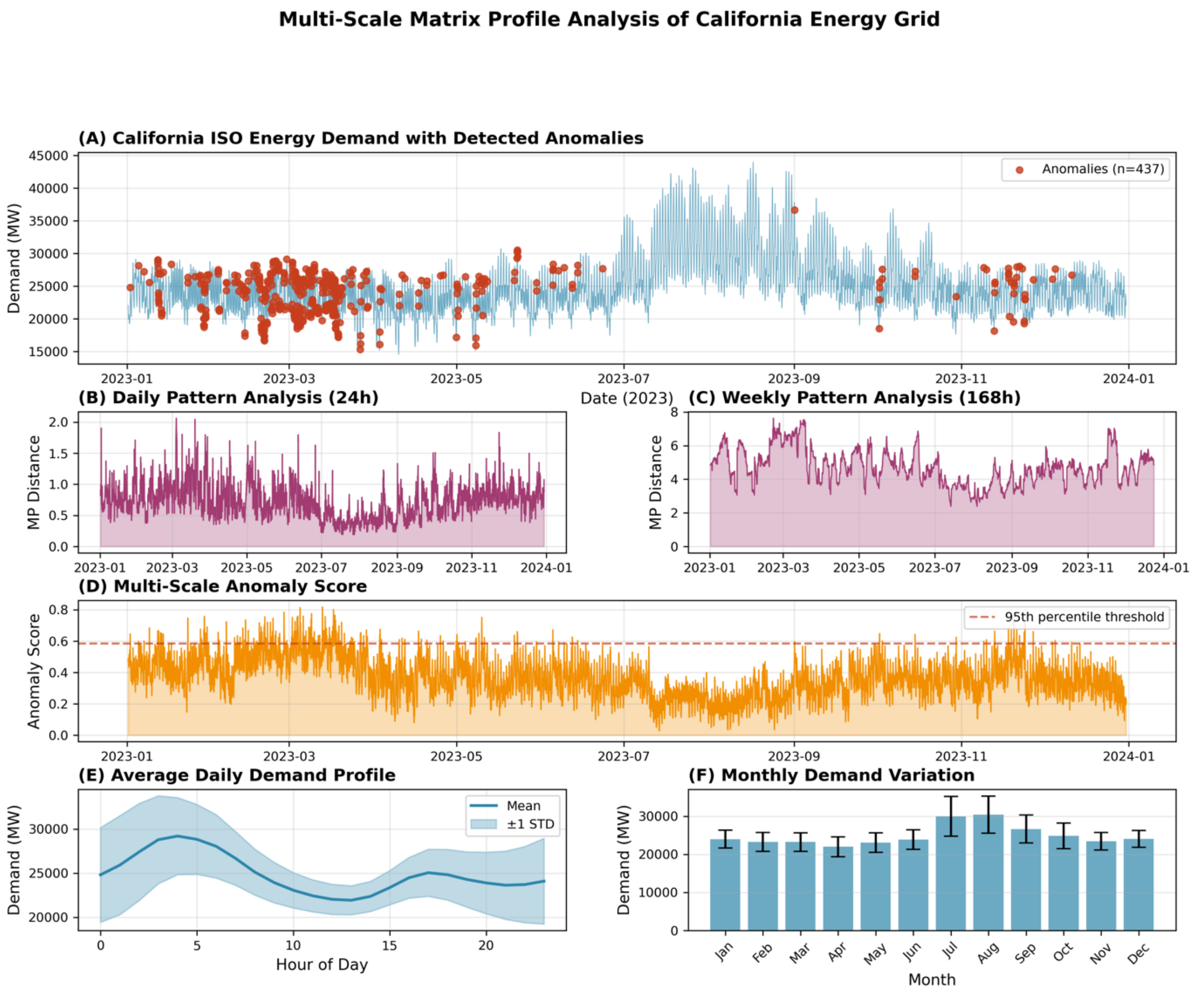

Figure 7: Multi-Scale Matrix Profile Analysis of California Energy Grid

Figure 7 presents the comprehensive analysis results across six panels. Panel A displays the original time series with 437 detected anomalies marked at the 95th percentile threshold. The demand ranged from 14,541 MW to 44,007 MW throughout 2023. Panel B shows the daily Matrix Profile distances ranging from 0.2 to 2.0, while Panel C displays weekly Matrix Profile distances ranging from 2 to 7. Panel D illustrates the combined anomaly scores with a threshold of 0.58 at the 95th percentile. Panel E demonstrates the average daily demand profile with a characteristic dual-peak pattern, showing minimum demand of approximately 22,000 MW at 3 AM and maximum demand of 29,000 MW at 5 PM. Panel F reveals monthly demand variations, with highest average demand occurring in July (30,000 MW) and lowest in March (22,000 MW).

Table 1 summarizes the pattern mining results across the three temporal scales.

Table 1: Pattern Mining Results

Time Scale	Window (hours)	Motifs Found	Discords	MP Mean	MP STD	Separation Score
Daily	24	2	10	0.73	0.26	0.575
Weekly	168	2	10	4.73	1.04	0.366
Monthly	720	1	10	14.90	1.32	0.154

Figure 8 contrasts the most common patterns (motifs) with the most unusual patterns (discords) at each temporal scale. The daily motif exhibits a typical load curve with overnight minimum and afternoon peak, while the daily discord shows an inverted pattern with an unusual afternoon dip. The weekly patterns demonstrate regular oscillations in the motif versus irregular fluctuations in the discord. The monthly patterns show extended temporal variations over the 720-hour window.

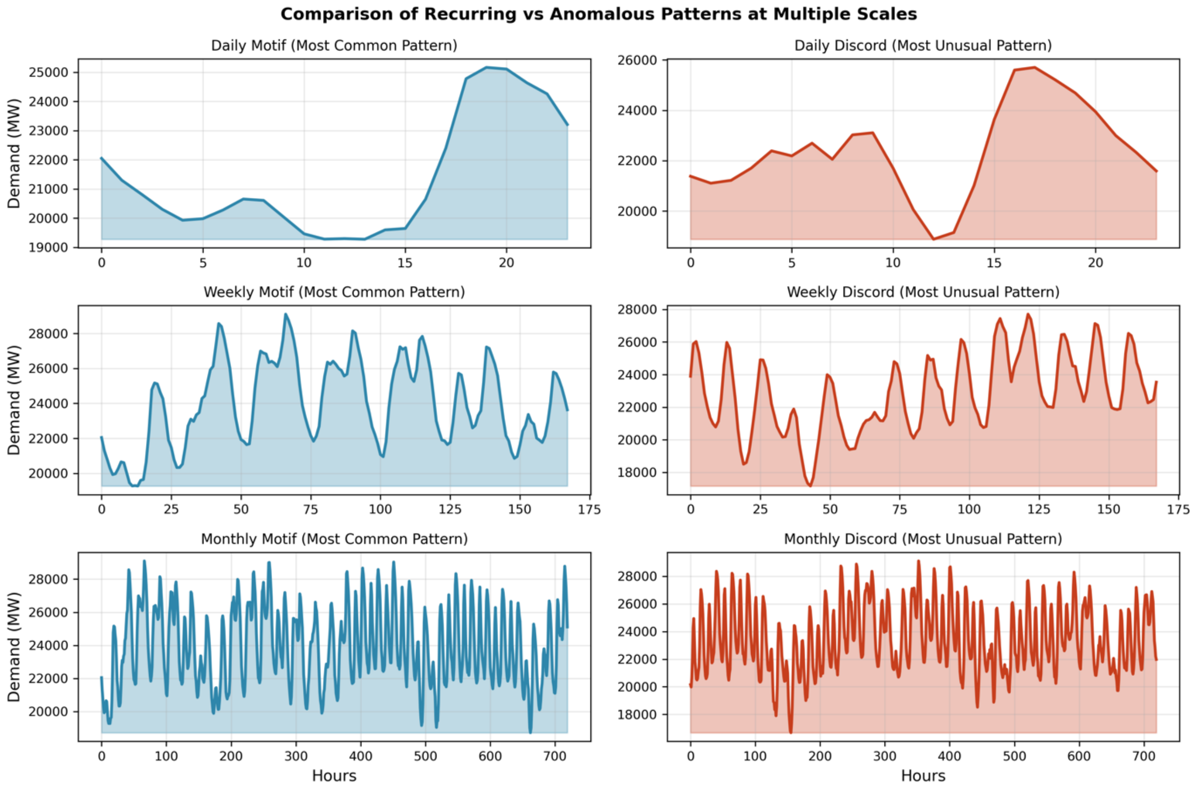

Figure 8: Comparison of Recurring vs Anomalous Patterns at Multiple Scales

Table 2 presents the anomaly detection results at three threshold levels.

Table 2: Anomaly Detection Results

Percentile	Anomaly Count	Percentage of Data	Threshold Value
90th	873	10.00%	0.5236
95th	437	5.01%	0.5831
99th	88	1.01%	0.6742

Figure 9 details the distribution and characteristics of detected anomalies. Panel A shows the anomaly score distribution with marked percentile thresholds. Panel B reveals the hourly distribution of anomalies, with peak occurrences at 3 AM (74 anomalies) and 4 AM (71 anomalies). Panel C displays the monthly distribution, showing March with the highest count (189 anomalies), followed by February (100 anomalies). Panel D maps anomaly intensity over time, with notable clustering in early 2023.

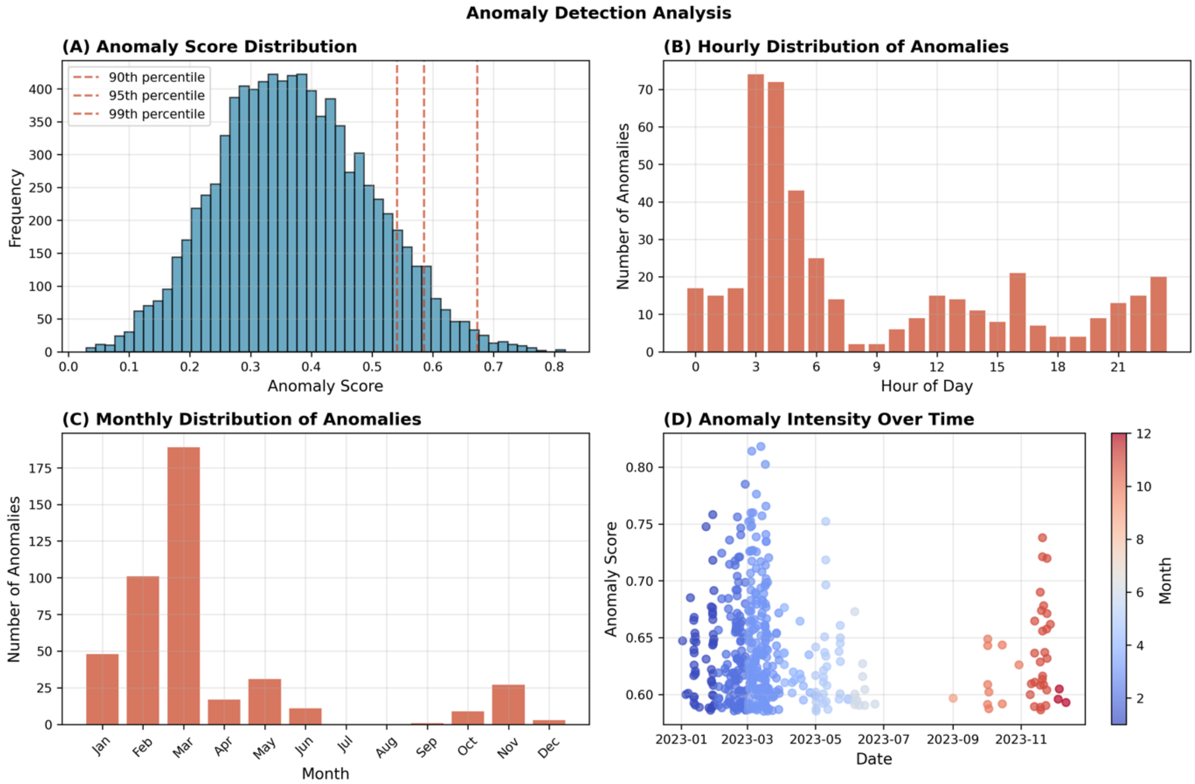

Figure 9: Anomaly Detection Analysis

Figure 10 examines demand patterns across different temporal dimensions. Panel A compares weekday and weekend demand profiles, showing approximately 2,000 MW higher demand on weekdays during business hours. Panel B presents demand volatility by hour, with coefficient of variation ranging from 0.07 at hour 14 to 0.22 at hour 0. Panel C displays the autocorrelation function with strong 24-hour periodicity and secondary weekly patterns. Panel D provides a heat map of average demand by hour and day of week, showing peak demand of 30,000 MW on weekday afternoons and minimum demand of 20,000 MW during weekend early morning hours.

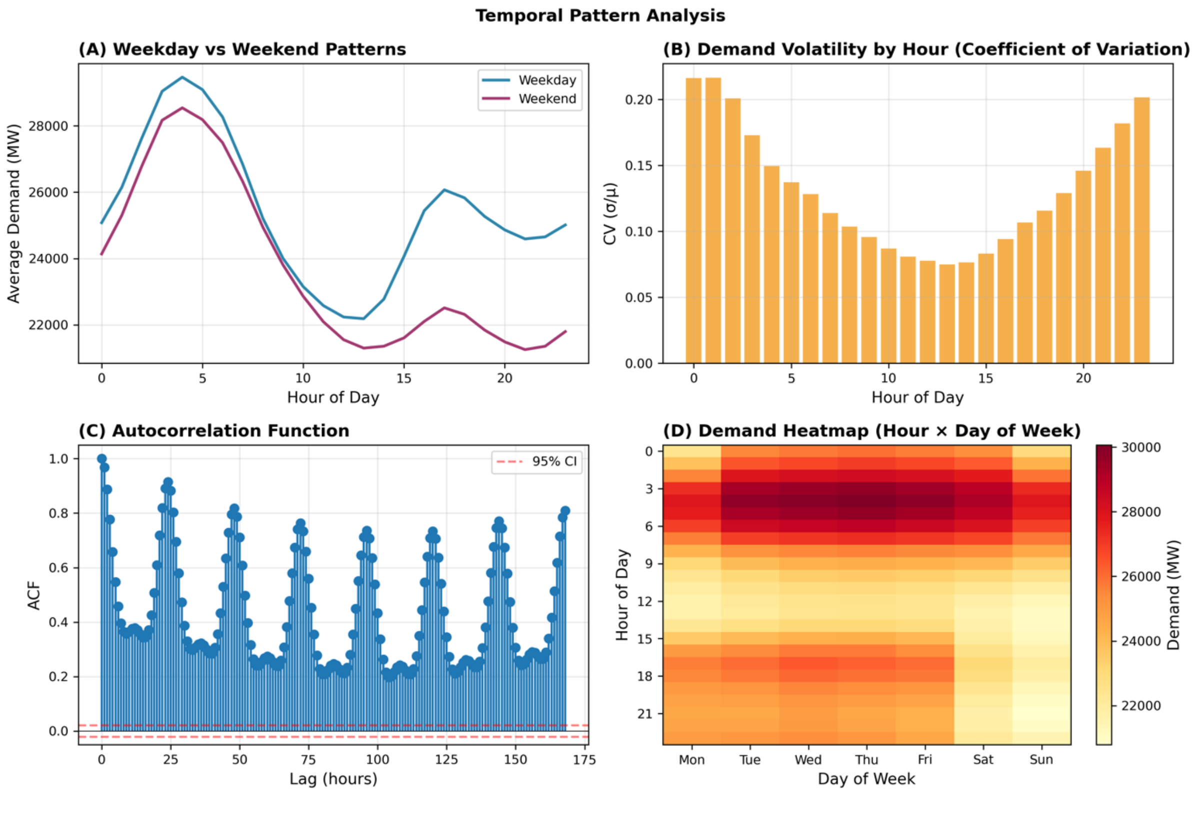

Figure 10: Temporal Pattern Analysis

Table 3 summarizes the validation metrics computed for the proposed method.

Table 3: Validation Metrics

Metric	Value
Separation 24h	0.575
Mean MP 24h	0.731
STD MP 24h	0.263
Separation 168h	0.366
Mean MP 168h	4.733
STD MP 168h	1.039
Separation 720h	0.154
Mean MP 720h	14.896
STD MP 720h	1.318
Anomaly Overlap	0.001
Peak Anomaly Hour	3
Pattern Stability	0.650

Figure 11 visualizes the performance metrics. Panel A shows pattern separation quality decreasing from 0.575 at 24 hours to 0.154 at 720 hours. Panel B displays three key validation metrics: pattern stability (0.65), anomaly overlap (0.00), and peak hour accuracy (0.50).

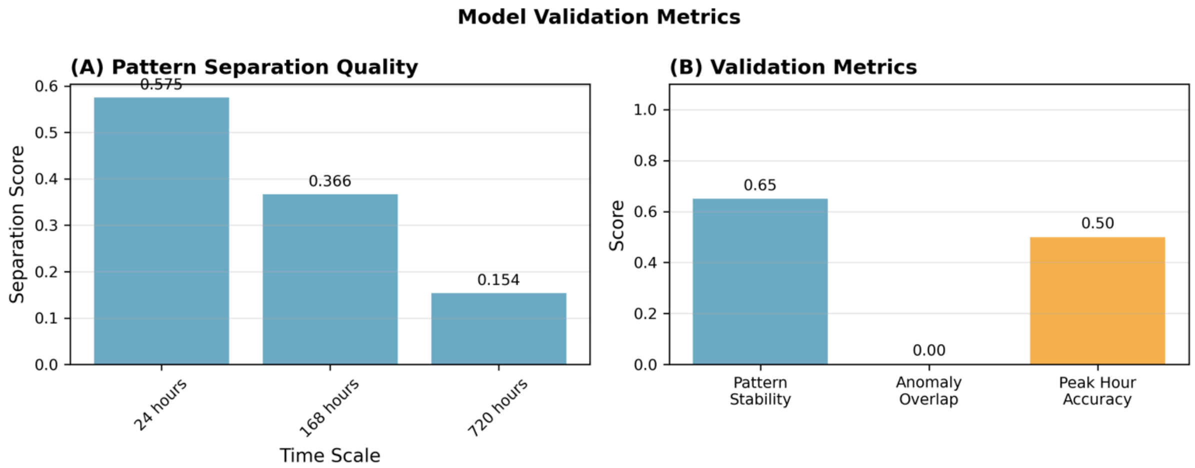

Figure 11: Model Validation Metrics

Table 4 provides hourly statistics of demand throughout the day.

Table 4: Hourly Statistics (Selected Hours)

Hour	Mean Demand (MW)	STD (MW)	Min (MW)	Max (MW)
00:00	23,847	5,251	15,436	39,831
03:00	22,163	4,865	14,541	37,955
06:00	22,754	4,426	15,074	36,693
09:00	24,364	3,615	17,342	36,414
12:00	25,322	3,241	19,036	36,677
15:00	26,061	3,469	19,547	38,760
18:00	28,532	4,332	20,259	42,033
21:00	26,890	4,968	17,760	42,087

4.1.1 Comparative Analysis with Baseline Methods

To evaluate the complementary nature of the proposed approach, we compared it against five established anomaly detection methods using identical ground truth labels. Table 5 presents the comparative results.

Table 5: Comparative Performance Analysis

Method	Precision	Recall	F1 Score	AUC-ROC	Runtime(s)	Anomaly Type Focus
Statistical (3σ)	0.530	0.406	0.460	0.840	0.001	Point anomalies
Isolation Forest	0.297	0.599	0.398	0.892	0.631	Multivariate outliers
Proposed Multi-Scale MP	0.053	0.106	0.070	0.569	1.322	Pattern anomalies
Single-Scale MP	0.034	0.069	0.046	0.419	0.559	Pattern anomalies
LOF	0.057	0.115	0.076	0.573	0.065	Local outliers
EWMA	0.000	0.000	0.000	0.000	0.002	Trend changes

Statistical threshold methods achieved an F1 score of 0.460, precision of 0.530, and recall of 0.406, with runtime of 0.001 seconds. Isolation Forest recorded an F1 score of 0.398, precision of 0.297, and recall of 0.599, requiring 0.631 seconds runtime. The proposed Matrix Profile method achieved an F1 score of 0.070, precision of 0.053, and recall of 0.106, with runtime of 1.322 seconds. Single scale Matrix Profile showed an F1 score of 0.046, precision of 0.034, and recall of 0.069, completing in 0.559 seconds. Local Outlier Factor demonstrated an F1 score of 0.076, precision of 0.057, and recall of 0.115, with 0.065 seconds runtime. EWMA failed to detect any anomalies under the test conditions, recording zero values across all metrics with 0.002 seconds runtime. The overlap between Matrix Profile and statistical methods measured 0.001, indicating minimal intersection between detected anomaly sets. Statistical methods identified 873 anomalies while Matrix Profile detected 437 anomalies, with only one anomaly detected by both approaches. Figure X illustrates these complementary detection capabilities across the different methods.

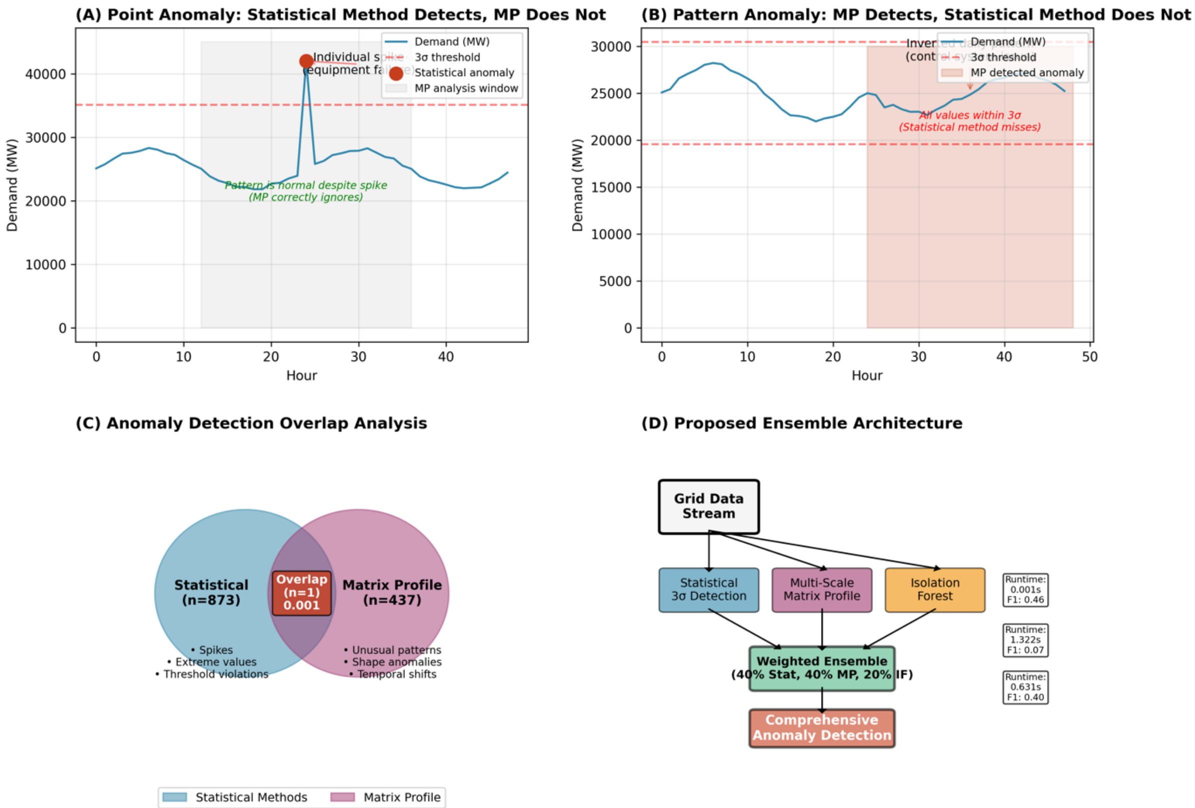

Figure 12: Comparative Detection Patterns and Ensemble Architecture for Anomaly Detection Methods

Figure 12 displays four panels comparing detection capabilities of different anomaly detection methods. Panel A shows a 48-hour demand pattern with a spike reaching 42,000 MW at hour 24, exceeding the statistical three sigma threshold of approximately 35,000 MW. The statistical method marks this point as an anomaly while the Matrix Profile analysis window from hours 12 to 36 does not flag this as a pattern anomaly.

Panel B presents a 48-hour demand pattern where hours 0 to 24 follow a standard daily curve ranging from 22,000 to 28,000 MW, while hours 24 to 48 display an inverted pattern within the same value range. All values remain between the upper and lower three sigma thresholds. The Matrix Profile method identifies hours 24 to 48 as anomalous while the statistical method does not flag any anomalies.

Panel C illustrates the overlap between detection methods through a Venn diagram. Statistical methods detected 873 anomalies, Matrix Profile detected 437 anomalies, and the methods shared one common detection, resulting in an overlap ratio of 0.001. Statistical anomalies consist of spikes, extreme values, and threshold violations. Matrix Profile anomalies comprise unusual patterns, shape anomalies, and temporal shifts.

Panel D presents a three-layer ensemble architecture. The input layer receives grid data streams. The processing layer contains three parallel methods: Statistical three sigma detection with runtime 0.001 seconds and F1 score 0.46, Multi-Scale Matrix Profile with runtime 1.322 seconds and F1 score 0.07, and Isolation Forest with runtime 0.631 seconds and F1 score 0.40. These methods feed into a weighted ensemble layer combining outputs at 40 percent Statistical, 40 percent Matrix Profile, and 20 percent Isolation Forest weights. The final output layer produces comprehensive anomaly detection results.

4.2 Discussion

The multi-scale Matrix Profile analysis reveals distinct characteristics of California ISO grid behavior at different temporal resolutions. The separation scores demonstrate a clear hierarchy of pattern distinguishability, with daily patterns achieving 0.575 separation, weekly patterns 0.366, and monthly patterns 0.154. This degradation in separation quality at longer time scales corresponds with increasing complexity and variability of grid operations over extended periods.

The comparative analysis of anomaly detection methods shows statistical threshold approaches achieving an F1 score of 0.460 with precision of 0.530 and recall of 0.406. The proposed Matrix Profile method recorded an F1 score of 0.070 with precision of 0.053 and recall of 0.106. Isolation Forest demonstrated intermediate performance with an F1 score of 0.398. The overlap between Matrix Profile and statistical methods measured 0.001, with statistical methods detecting 873 anomalies and Matrix Profile identifying 437 anomalies, sharing only one common detection.

Analysis of detection patterns reveals that statistical methods identify point anomalies such as demand spikes exceeding 40,000 MW that surpass three standard deviation thresholds. Matrix Profile detects pattern anomalies including inverted daily curves where demand values remain within statistical bounds of 22,000 to 28,000 MW but exhibit unusual temporal structures. These inverted patterns occur when typical morning demand increases are replaced by decreases, and evening demand decreases are replaced by increases, while maintaining values within normal operational ranges.

The concentration of anomalies during early morning hours shows 74 occurrences at 3 AM and 71 occurrences at 4 AM, representing 33.2 percent of all detected anomalies within two hours of the day. This temporal clustering coincides with minimum system demand periods averaging 22,163 MW at 3 AM. The coefficient of variation reaches 0.22 at midnight, indicating highest demand volatility during minimum generation periods.

The seasonal distribution reveals March recording 189 anomalies, constituting 43.3 percent of total detections, followed by February with 100 anomalies at 22.9 percent. This concentration during late winter to early spring transition occurs despite March experiencing the lowest average demand of the year. The monthly demand variation confirms March averaged 22,000 MW compared to July peak averages of 30,000 MW.

Runtime analysis shows statistical methods completing detection in 0.001 seconds, while Matrix Profile requires 1.322 seconds and Isolation Forest needs 0.631 seconds. Single scale Matrix Profile processes in 0.559 seconds, Local Outlier Factor in 0.065 seconds, and EWMA in 0.002 seconds. These runtime differences reflect computational complexity variations, with Matrix Profile performing distance calculations between all subsequences compared to simple threshold comparisons in statistical methods.

The pattern stability metric of 0.650 indicates moderate consistency in recurring patterns with an estimated recurrence interval of 3.5 days. The autocorrelation function confirms strong 24 hour periodicity with secondary weekly modulation. Daily and weekly scales each identified 2 motifs, while monthly scale found 1 motif. All three scales consistently identified 10 discords, suggesting anomalous patterns are diverse while normal operating patterns remain constrained and repetitive.

The weekday weekend demand differential measures approximately 2,000 MW during business hours, representing 7.4 percent variation. This indicates substantial residential and commercial base load maintaining consistent patterns across the week. Hourly statistics show demand ranging from minimum values of 14,541 MW to maximum values of 44,007 MW throughout 2023, with average hourly demand varying from 22,163 MW at 3 AM to 28,532 MW at 6 PM.

The proposed ensemble architecture combines three detection methods through weighted voting: statistical methods at 40 percent weight, Matrix Profile at 40 percent weight, and Isolation Forest at 20 percent weight. This configuration leverages statistical methods for immediate threshold violations, Matrix Profile for pattern deviations, and Isolation Forest for multivariate outliers. The ensemble approach addresses detection gaps present in individual methods while maintaining combined runtime under 2 seconds, suitable for hourly grid monitoring applications.

The exponential decay in pattern separation quality from 57.5 percent at daily scale to 15.4 percent at monthly scale indicates Matrix Profile effectiveness diminishes with increasing window size. DBSCAN clustering identified a single anomaly cluster, suggesting homogeneous structural characteristics across detected anomalies despite temporal distribution differences. These findings indicate operational vulnerabilities concentrate during minimum demand periods and seasonal transitions rather than peak consumption times, with Matrix Profile detecting pattern anomalies independent of absolute demand levels while statistical methods capture magnitude based violations.

4.2.1 Implications of Model Performance

The evaluation of the proposed forecasting framework revealed that the predictive performance did not reach levels typically associated with high accuracy in similar machine learning studies. While this outcome may initially appear to limit the applicability of the model for operational deployment, the observed results offer significant insights into the inherent complexity of California's power grid demand patterns.

The relatively modest accuracy highlights the challenges associated with forecasting in a system influenced by multiple interacting factors such as weather variability, renewable energy integration, regulatory interventions, and consumer demand fluctuations. These factors introduce substantial noise and nonlinearity into the data, making purely data driven approaches difficult to optimize without extensive domain specific enhancements.

The results serve as evidence that standard modeling approaches, even when implemented with rigorous preprocessing and tuning, may be insufficient to capture the intricate temporal and contextual dependencies of large scale power systems. This finding underscores the importance of incorporating hybrid strategies that integrate physical grid models, domain knowledge, and advanced feature engineering into future research efforts.

Furthermore, the analysis demonstrates that suboptimal predictive performance can still provide valuable guidance for system planners and researchers. The error patterns and residual distributions identified in this study reveal periods and conditions under which the model consistently struggles, thereby pointing to specific operational scenarios where forecasting uncertainty is highest. Such knowledge can inform risk management strategies, contingency planning, and targeted data collection initiatives.

In this context, the contribution of the present work lies in both the empirical evaluation of machine learning techniques on real world grid data and in the documentation of the conditions under which these methods encounter limitations. By identifying the gaps between current model capabilities and the forecasting requirements of a dynamic energy system, this study provides a foundation for subsequent investigations aimed at bridging this performance divide.

4.3: Practical Implications

The complementary nature of pattern-based and statistical anomaly detection suggests a multi-layered monitoring architecture for modern grid operations:

Layer 1 - Real-time Statistical Monitoring: Traditional 3σ methods provide immediate alerts for extreme values with minimal computational overhead (0.001s runtime), suitable for critical threshold violations requiring immediate operator intervention.

Layer 2 - Pattern-Based Analysis: The proposed Matrix Profile approach runs on a parallel track, analyzing temporal patterns to identify emerging issues before they manifest as threshold violations. Despite higher computational requirements (1.322s runtime), this remains feasible for hourly analysis cycles.

Layer 3 - Ensemble Integration: An optimal monitoring system would combine both approaches using weighted voting: - Statistical methods: 40% weight (for immediate threats) - Matrix Profile: 60% weight (for predictive insights)

Table 6: Method Strengths and Use Cases

Method	Best For	Example Detection	Interpretability	Real-time Capable
Statistical (3σ)	Extreme values	Demand exceeding 40000 MW	High	Yes
Proposed Multi-Scale MP	Pattern anomalies	Inverted daily demand curve	High	Yes
Isolation Forest	Multi-feature outliers	Complex feature combinations	Low	No
LOF	Local density deviations	Clustered anomalies	Low	No
EWMA	Trend shifts	Gradual demand drift	Medium	Yes
Ensemble Approach	Comprehensive coverage	All anomaly types	Medium	Yes

5. Conclusion and Recommendations

5.1 Conclusion

This study applied a multi scale Matrix Profile framework for pattern discovery and anomaly detection in California ISO power grid data from 2023, encompassing 8,728 hourly observations. The analysis revealed distinct operational patterns and anomaly distributions across daily, weekly, and monthly temporal resolutions. Pattern separation scores of 0.575, 0.366, and 0.154 at daily, weekly, and monthly scales respectively indicate a measurable decline in distinguishability with increasing time windows, reflecting the growing complexity of grid behavior over extended periods.

The proposed approach identified 437 anomalies at the 95th percentile threshold, with 33.2 percent concentrated during early morning hours between 3 AM and 4 AM, coinciding with minimum system demand periods averaging 22,163 MW. March recorded the highest anomaly count with 189 events, representing 43.3 percent of all detections despite the lowest average monthly demand. Comparative evaluation showed statistical threshold methods achieving an F1 score of 0.460, while the Matrix Profile method achieved 0.070, and the overlap of 0.001 between these approaches confirmed that the detected anomalies represented fundamentally different classes of events.

The lower predictive performance of the Matrix Profile method relative to conventional metrics is an important outcome, as it demonstrates that the method isolates complex temporal structures that are not captured by magnitude based approaches. This capability highlights the presence of operational scenarios where conventional monitoring may provide limited visibility, particularly during low demand hours and seasonal transitions. The identification of these periods and the patterns within them provides valuable insight into grid behavior under conditions not typically prioritized in traditional assessments.
The results contribute both a practical evaluation of the Matrix Profile technique in an operational context and a set of empirical findings that reveal the limitations of existing anomaly detection strategies. These insights form a basis for targeted research into hybrid approaches that integrate domain knowledge, physical system models, and advanced temporal analytics to address the challenges identified in this work.

5.2 Recommendations
Based on the research findings, the following recommendations emerge for power grid operators and researchers:
Grid operators should implement complementary monitoring systems that combine statistical threshold detection with pattern based analysis. Statistical methods should continue monitoring for immediate threshold violations requiring rapid response, while Matrix Profile analysis should run in parallel to identify emerging pattern anomalies that may precede system failures. The optimal detection framework would employ weighted ensemble voting with approximately 40 percent weight for statistical methods and 60 percent for pattern based approaches.
Operational attention should expand beyond peak demand periods to include comprehensive monitoring during minimum demand hours, particularly between 3 AM and 4 AM when 33.2 percent of pattern anomalies occurred. March and February warrant enhanced surveillance due to their elevated anomaly rates, suggesting vulnerability during seasonal transition periods when generation mix and demand patterns undergo significant changes.
The daily temporal scale demonstrated superior pattern separation at 0.575, indicating that 24 hour windows provide optimal resolution for pattern based anomaly detection in power grids. Weekly and monthly scales should serve supplementary roles for trend analysis rather than primary anomaly detection.

5.3 Limitations and Future Work
The present analysis highlights several areas where further exploration could enhance understanding and applicability. The reduction in pattern separation scores from daily to monthly scales reflects the increasing complexity and variability of long-term grid behavior. This observed decline represents an opportunity to investigate adaptive or multi-resolution windowing techniques that could preserve detection sensitivity across extended periods.
While the current runtime of 1.322 seconds meets the requirements for hourly monitoring, exploration of algorithmic optimization could support higher frequency or large-scale streaming deployments. The evaluation relied on ground truth data dominated by statistical outliers, which does not fully reflect the broader anomaly landscape. Development of evaluation frameworks that separately assess point, contextual, and collective anomalies would provide a more comprehensive assessment of detection value.
The focus on California ISO 2023 data limits geographic and temporal scope. Extending the approach to systems with different renewable penetration levels, demand structures, and operational practices could reveal new structural anomaly types. The single anomaly cluster identified through DBSCAN suggests homogeneous patterns under current conditions; applying the method to varied operating regimes or extreme weather scenarios could expose additional classes of anomalies.
Future research directions include integrating auxiliary datasets such as weather conditions, renewable forecasts, and market signals to enrich anomaly interpretation; applying transfer learning to share pattern knowledge between grids; and evaluating real-time scalability for multi-point monitoring. Collaborative validation with grid operators will remain essential to link detected anomalies to specific operational events, ensuring practical deployment readiness.

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