Analyzing Peak Electricity Usage Periods with Eigenvalue Analysis in Residential Areas

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***Abstract*—Electrical energy consumption is the main problem in residential sections. Difficulties in energy balance (supply and demand) often arise during peak periods of electricity use, which is by far the most significant point that need to be analyzed. The objective of this study is to investigate the peak period of electricity usage in residential areas using the eigenvalue analysis method, which is a method that is able to extract patterns in the electricity usage data. The data used are records containing some electricity usage of different households throughout the residential area over a time period. Using eigenvalue analysis, the study was able to identify the peak period for electricity usage as well as where consumption varies with time and weather. These results offer valuable information for designing more efficient and sustainable energy supply at the domestic scale.**

***Keywords*—Eigenvalue analysis, electricity usage, peak period, residential areas.**

I. Introduction

One of the great factors affecting the planning and management of efficient electrical system is utilizing electrical energy at home. As the population is growing along with the technology developed for social activities daily, the demand for electricity is also on the rise. Peak electricity usage periods or in other words, periods of high electricity usage are one of the most significant challenges when it comes to managing electricity supply.

In most cases, peak consumption times are observed in the early morning hours when residents start up their routines and in the night hours when many electronics are utilized. The growing need for electricity during peak hours can lead to disruptions in energy demand and supply, which could lead to significant breakdowns including power cuts or excess pressure on the distribution network. Hence, peak load analysis is an essential exercise for improving the efficiency and sustainability of energy management, in particular in residential environments where electricity consumption patterns are dynamic.

Eigenvalue analysis is one approach that can be applied to the analysis of peak electricity consumption. This technique is used for discovering interesting patterns or structure in large and complex datasets. In the context of getting electricity use, eigenvalue investigation can help in getting deep connections between electricity consuming related measurements like temperature, time, number of occupants in the house, and the devices used.

The aim of this study is to use the eigenvalue analysis approach to analyze peak periods of electricity usage in residential areas. It hopes to find better electricity usage patterns to be used for insight for better energy management planning, and solutions for mitigating peak loads that stress out the electricity system. This study will focus on peak value detection rather than a general approach to avoid overconsumption based on climatic conditions, such as averaging temperatures throughout the entire season and thus deriving an understanding of how much should be consumed, but rather, a very structured and data-oriented approach to acknowledge the way households consume electricity and what factors tend to influence more on peaks of usage.

II. Theoretical Foundation

A. Electricity Consumption in Residential Areas

Electricity consumption at home depends on many interrelated factors, such as time of use, weather conditions, and the habits of its occupants. Usually, every day, electricity consumption at home varies according to the routine activities of its occupants. For example, in the morning between 06.00 and 09.00 when the occupants are active, and in the afternoon between 18.00 and 21.00, many electronic devices are used (lights, televisions, and other electronic devices).

Air temperature is also another major statistic after time in electricity consumption. Air conditioners (AC) are used more in hot temperatures, while in cold temperatures, we use more space heaters. In addition, this consumption pattern is also influenced by the behavior and habits of its occupants: Number of occupants, Number of electrical devices used, daily habits in using electrical energy, and so on. This includes the design and type of building, number of services, functions, climate, and behavior of occupants, which work together to shape the overall electricity demand in a housing complex (Surya & Sriwijaya, 2018; Wang et al., 2020).

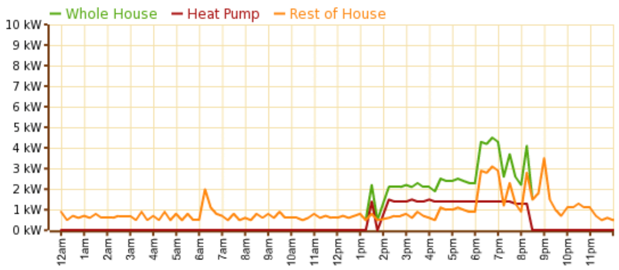


Fig. 2.1 Power Consumption of a household Over a 24-Hour Period
Source: ResearchGate

B. Peak Electricity Usage

Peak electricity usage is the time period when households have the highest electricity consumption, typically in the morning and evening. Peak hours are the hottest hours of the day, where the ambient heat affects households throughout the day, typically starting around 6:00 a.m. and ending around 9:00 p.m. This high power consumption is caused by increased use of electrical appliances such as lights, heaters, air conditioners, and other electronics.

In addition to time, weather also plays a significant role in determining peak electricity usage. For instance, extreme temperatures, whether hot or cold, lead to increased reliance on climate control systems such as air conditioners during summer or heaters during winter. Humidity levels, wind conditions, and sudden weather changes can further influence the demand for electricity.

Peak loads during these critical time frames and under extreme weather conditions can put undue stress on the electricity distribution network, leading to blackouts or worse. As a result, understanding both the time-based and weather-related factors contributing to peak periods is an important element in planning energy distribution so that a stable electricity supply can be maintained during peak periods. A study by Ghahramani and Mahdavi (2017) found that congestion management during peak hours is necessary to avoid major energy supply disruptions.

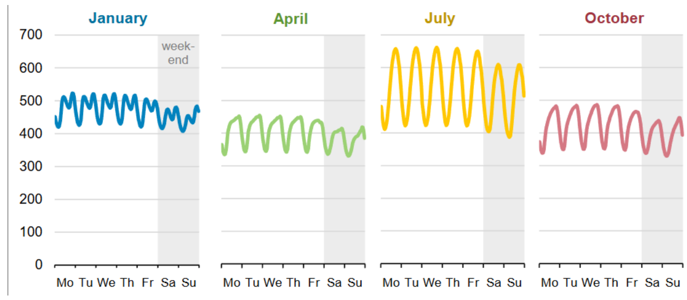


Fig. 2.2 Average hourly U.S. Electricity Load During Typical Week, Selected Months
Source:
https://www.eia.gov/todayinenergy/detail.php?id=42915

C. Electricity Demand and Supply Management

This need is potentially being met through electricity demand management, a form of strategy like this that allows customers to more efficiently manage their electricity consumption, particularly in times of peak demand. One well-known approach to achieving this is the use of time based electricity tariffs, which incentivizes consumers to cut back on consumption during peak times and move consumption to cheaper hours.

Smart grids and smart home devices are also being increasingly utilized to allow automatic management of consumer electricity use. These technologies facilitate the consumers to monitor their electricity usage, preventing overconsumption during peak time. Research by Zhao et al. (2020), highlights that effective demand management strategies can mitigate electricity transmission network pressure and promote sustainable energy consumption.

So, the right technologies and policies for demand management must be implemented to support a balance of electricity supply to meet demand.

D. Eigenvalue Analysis

Eigenvalue analysis is one of the most significant methods that emerged in linear algebra, which is used to analyze large and multivariable data including electricity consumption data. In this case, we can use the concept of eigenspace, where we look for patterns or structures in a matrix to find data with better dimensionality by identifying the eigenvalues and eigenvectors of the matrix that describe the relationship between different variables.

The eigenvalue approach can help in understanding the major factors that influence the electricity consumption behavior of users such as time, temperature, number of devices, etc. Common data preprocessing techniques as mentioned above can be very helpful in identifying cyclical, seasonal, or periodic data behavior, as is common practice in analyzing time series data such as electricity consumption (Jolliffe, 2002).

PCA is one of the common applications of eigenvalue analysis that helps in reducing the dimensionality of large data sets which helps in identifying the major factors behind the consumption patterns (Fukunaga, 1990).

1. Calculation of Eigenvalue and Eigenvector
   1.1. Determine the Characteristic Polynomial: The equation linking the eigenvalue to the matrix is:

$$\det(A-\lambda I) = 0$$

   - I is the identity matrix of the same dimension as *A*
   - λ is the eigenvalue that is being solved for

   1.2. First step will be to find out the characteristic polynomial, solving it will give us values of λ. These values represent the eigenvalues of the matrix A

   1.3. After we find the eigenvalues λ, the eigenvectors can be found. You can do that by plugging in the eigenvalue λ into the equation. 2. Eigenvalue and Eigenvector Based PCA (Principal Component Analysis) Using PCA to look at Electricity Usage

2. PCA (Principal Component Analysis) Using Eigenvalue and Eigenvector
   2.1. The first step is to organize the data in the form of a matrix *X* where each row is an instance, each column,

a feature (e.g., consumption at different points in the day).

2.2. The data is often normalized or standardized so that each feature has the same scale

2.3. The covariance matrix shows how the different features in the data relate to each other. For instance, this matrix is computed by the equation:

$$C = \frac{1}{n-1} X^T X$$

Where n is the number of samples, and C is the covariance matrix.

2.4. After obtaining the covariance matrix C we compute the eigenvalues and eigenvectors of C Larger eigenvalues indicate greater variance along the corresponding eigenvectors.

2.5. The eigenvectors corresponding to the highest eigenvalues are the principal components of the data. These components are the directions in which the data has most variance.

2.6. The dimensionality of the data is drastically reduced by choosing a fixed number of most important principal components. We may represent the data in two dimensions (for example, we can take the two first eigenvectors) preserving most information in the data.

3. PCA Application in Electricity Consumption

In the context of electricity consumption data, PCA can help identify the main factors that influence consumption patterns. For example, large eigenvalues might indicate factors such as specific times of day, temperature, or the number of devices used, which have a significant influence on energy consumption.

Furthermore, PCA can uncover hidden patterns in the data that may not be immediately obvious through direct observation. This is useful in building more accurate prediction models or detecting anomalies in electricity consumption patterns.

E. Related Studies on Peak Electricity Usage and Eigenvalue Analysis

Several previous studies have explored the use of eigenvalue analysis to analyze electricity consumption patterns and detect peak periods. Zhang et al. (2018) used Principal Component Analysis (PCA) to analyze household electricity consumption data and found hidden patterns related to factors such as time and temperature. The results of this analysis are very useful for planning electricity demand management in a more effective way. In addition, Kim & Lee (2016) also used eigenvalue analysis to detect peak periods in household electricity consumption data, considering factors such as the number of occupants and the use of high-power electrical devices. These studies demonstrate the great potential of the eigenvalue analysis method in providing deeper insights into electricity consumption patterns that can help design more efficient energy management strategies.

F. Challenges and Limitations

While eigenvalue analysis has numerous advantages, it also comes with challenges and limitations that should be understood. The reasons for this are, among others, the complexity of large and interdependent electricity consumption data that may degrade the accuracy of results if the data is not duly treated. Such as, the incompleteness or noise in the data will weaken the effectiveness of the results of eigenvalue analysis. Also, the analysis results can be difficult to interpret, particularly when the analyzed data is very large and complex. Thus, even though this approach is very helpful in recognizing patterns from data, the ends still need further exploration in order to improve understanding and application in effective energy management policies (Zhou et al., 2019; Duda et al., 2001).

III. IMPLEMENTATION

A. Dataset Description

This dataset consists of a continuous record of household power consumption in Europe, over a specified time duration. It provides various degree metrics made out of electricity usage, which can be tracked over time to identify consumption tendencies. There are very few features in the dataset:

```
Date;Time;Global_active_power;Global_reactive_power;Voltage;Global_intensity;Sub_metering_1
16/12/2006;17:24:00;4.216;0.418;234.840;18.400;0.000;1.000;17.000
16/12/2006;17:25:00;5.360;0.436;233.630;23.000;0.000;1.000;16.000
16/12/2006;17:26:00;5.374;0.498;233.290;23.000;0.000;2.000;17.000
16/12/2006;17:27:00;5.388;0.502;233.740;23.000;0.000;1.000;17.000
16/12/2006;17:28:00;3.666;0.528;235.680;15.800;0.000;1.000;17.000
16/12/2006;17:29:00;3.520;0.522;235.020;15.000;0.000;2.000;17.000
16/12/2006;17:30:00;3.702;0.520;235.090;15.800;0.000;1.000;17.000
16/12/2006;17:31:00;3.700;0.520;235.220;15.800;0.000;1.000;17.000
16/12/2006;17:32:00;3.668;0.510;233.990;15.800;0.000;1.000;17.000
16/12/2006;17:33:00;3.662;0.510;233.860;15.800;0.000;2.000;16.000
```

Fig. 3.1 Some Example of The Dataset
Source:
https://archive.ics.uci.edu/dataset/235/individual+household+electric+power+consumption

- Global_active_power (in kilowatts, kW), which is usable by households. This metric is an important sign of actual power consumption that runs devices and other household needs.
- Global_reactive_power: Reactive power (in kVAR). This power does not perform useful work but is solely needed to ensure balance in the electric power system.
- Voltage, voltage of household electricity (volts). Stable voltage shows good quality in good electricity distribution.
- Intensite, that is the intensity of the current, measured in Ampere, the amount of current flowing through the system.
- Sub_metering_1, Sub_metering_2, Sub_metering_3 which give a measurement of Electricity consumption for individual sub-areas within house, a kitchen, water-heating or lighting etc.

This dataset is integrated, in the sense that each row of the dataset will represent the measurement of the consumption of electricity at a specific time. In particular, these features enable daily, weekly, and even seasonal consumption pattern analysis while the dataset identifies variables influencing electricity usage.

B. Data Preprocessing

Cleaning the raw data as well as preparing it for more preparation is the goal of the preprocessing stage. Data cleaning is the process of preparing raw data for analysis. The preprocessing steps such as time format change, missing value filling and numeric value standardization, etc.

The first step was to convert the time column to the DateTime format so that we could make time based analysis. Numerical data (e. g. active and reactive power) often has a heterogeneous format (e. g. comma (,) instead of a decimal). The commas are then replaced by periods to cast these columns in a numerical format.

Forward-fill and backward-fill methods are then employed to impute any missing values that may be present in the data, preventing unnecessary loss of data and a lack of a smooth trend. The new data is also broken down into time periods (hourly averages) to examine consumption patterns.

```python
def load_and_preprocess_data(file_path):
    print("Reading data...")
    # Read data
    df = pd.read_csv(file_path, sep=';',
                     dtype={
                         'Global_active_power': str,
                         'Global_reactive_power': str,
                         'Voltage': str,
                         'Global_intensity': str,
                         'Sub_metering_1': str,
                         'Sub_metering_2': str,
                         'Sub_metering_3': str
                     })

    print("Processing datetime...")
    # Convert datetime
    df['DateTime'] = pd.to_datetime(df['Date'] + ' ' + df['Time'],
                                    format='%d/%m/%Y %H:%M:%S',
                                    dayfirst=True)
    print("Converting numeric columns...")
    # Convert numeric columns
    numeric_columns = ['Global_active_power',
                       'Global_reactive_power', 'Voltage',
                      'Global_intensity', 'Sub_metering_1',
                      'Sub_metering_2', 'Sub_metering_3']

    for col in numeric_columns:
        df[col] = pd.to_numeric(df[col].str.replace(',', '.'),
                                errors='coerce')
    print("Adding hour column...")
    # Add hour column
    df['Hour'] = df['DateTime'].dt.hour  # Extract hour only
    print("Handling missing values...")
    # Handle missing values
    df = df.fillna(method='ffill').fillna(method='bfill')
    return df
```

Fig. 3.2 Preprocessing code
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

C. Implementation of Eigenvalue Analysis

Dominant patterns in the electricity consumption data are obtained through eigenvalue analysis. This is done by using Principal Component Analysis (PCA), a technique which reduces the dimensionality of data to keep only the most significant information.

It starts with the construction of the hourly consumption matrix The data is aggregated per hour for each day, creating a matrix where days are columns, and hours represent rows. Next, we fit this matrix using StandardScaler to ensure all features are scaled the same. Principal component analysis (PCA) is performed to obtain significant principal components indicative of predominant consumption modes.

```python
def perform_pca_analysis(consumption_matrix):
    """
    Perform PCA analysis on hourly consumption patterns
    """
    print("Performing PCA...")
    # Standardize the data
    scaler = StandardScaler()
    data_scaled = scaler.fit_transform(consumption_matrix)

    # Apply PCA
    pca = PCA()
    pca_result = pca.fit_transform(data_scaled)

    return pca, pca.explained_variance_ratio_, data_scaled
```

Fig. 3.3 PCA code
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

The PCA results show the variance explained by each principal component. The first principal component reveals the most significant consumption patterns, such as peak periods and low-usage hours.

D. Consumption Pattern Analysis

This stage inteants to know how household watts consumption looks like in hours. Daily patterns are found by averaging electricity consumption by hour of the day. The maxima, minima, & peaks are detected using these averages.

```python
def analyze_daily_patterns(df):
    """
    Analyze daily consumption patterns by hour
    """
    print("Analyzing daily patterns...")
    # Calculate average consumption by hour
    hourly_avg = df.groupby('Hour')['Global_active_power'].mean()

    # Calculate peak, minimum, and maximum consumption
    max_consumption = hourly_avg.max()
    min_consumption = hourly_avg.min()

    # Calculate threshold for peak detection
    threshold = hourly_avg.mean() + hourly_avg.std()
    peak_hours = hourly_avg[hourly_avg > threshold].index.tolist()

    return hourly_avg, peak_hours, threshold, max_consumption, min_consumption
```

Fig. 3.4 Consumption Pattern Analysis code
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

E. Visualization and Interpretation

Multiple visualizations were produced to understand PCA results and consumption patterns The first graph presents the averagenbsp;daily consumption per hour for each time of the day. In this graph, the peak period threshold is represented by the red line, while consumption maximum and minimum by green and blue lines respectively.

The next graph shows the cumulative variance that is explained by the PCA components. This graph illustrates how much of the information in the data is captured using how many principal components. The third graph shows the pattern of the first principal component, which captures important trends in electricity usage.

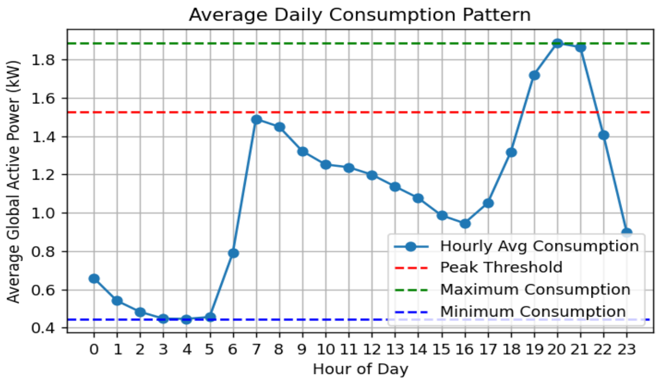


Fig. 3.5 Average Daily Consumption Pattern (with threshold, maximum, and minimum lines).
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

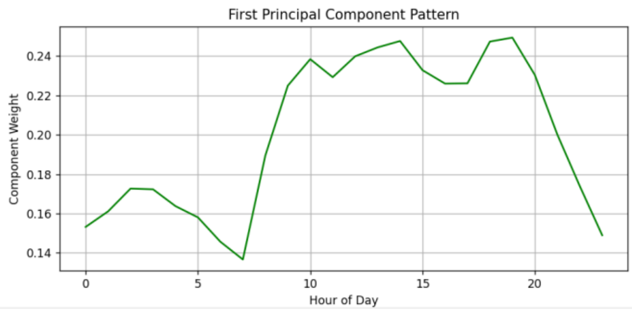


Fig. 3.6 PCA Cumulative Explained Variance.
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

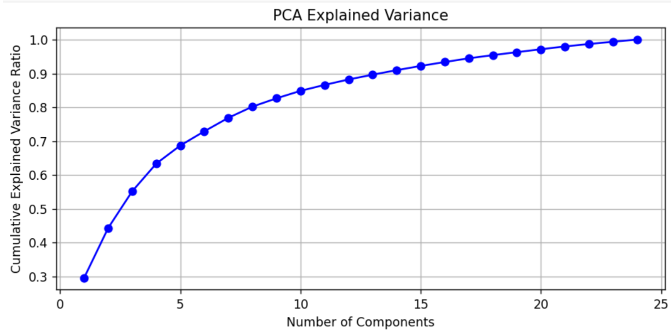
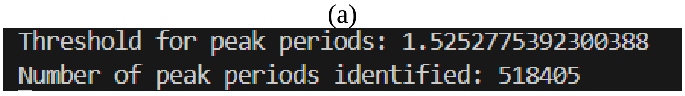


Fig. 3.7 First Principal Component Pattern.
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

F. Supply and Demand Analysis

The eigenvalue method analysis determined meaningful patterns of how electricity is consumed. By national smart grid data, the peak periods can be set based on the threshold that 1.525 times the average usage can be considered peak, when electricity consumption reaches 152.5% of normal usage, that period is peak period. With this threshold, there are 518.405 peak periods in the data, indicating that peak load periods appeared very frequently in household electricity consumption. The eigenvalue analysis method efficiently analyzes data and showcases the excellently low processing time of 13.43 seconds when the dataset is immense.

(a)



(b)

Fig. 3.8 Program Execution Results showing (a) Peak Period Threshold and Count (b) Data Processing Time
Source:
https://github.com/Abrar-Abhirama/MakalahAlgeo/blob/main/main.py

For a more detailed analysis of these results, here are some key takeaways:

1. Characteristics of Peak Periods

   The 1.525 threshold indicates household electricity consumption regularly exceeds normal usage by 52.5%. This trend is in line with high electricity consumption in the morning (6:00 AM - 9:00 AM) and in the evening (6:00 PM - 9:00 PM) when several electronic appliances are used at a time. The determined threshold is vital for electricity utilities to consider, and can help them with the planning and optimization of the distribution network capacity.

2. Frequency of Peak Periods

   The analysis demonstrates that electricity usage does not contain anomalies but instead finds a peak usage for each of the 518,405 periods in the dataset. Average household experiences multiple peak periods in a day this data also indicates that the household consumption remains constant over a period of time. The fact that peak periods occur at a high frequency indicates the necessity of working on sustainable load management strategies.

3. Efficiency of the Analysis

Our use of eigenvalue method to process PCA determined that the processing time for processing the full dataset was only 13.43 second which demonstrates effectiveness of eigenvalue method in processing electricity consumption data. This is supported by the real-time analysis in load monitoring which provides faster adaptation to fluctuations in consumption and the creation of early warning systems to predict peak load periods.

4. Implications for Energy Management

In addition, the electricity supply providers must be prepared to prepare an additional capacity of no less than 52.5% more than the normal load peak period. It is essential to develop demand response strategies for all identified peak periods that amount to the 518405 shown above. Real-time monitoring systems can provide intervals as low as 15 seconds (with process times of efficient system), enabling optimal load monitoring and management capabilities.

5. Recommendations Based on the Results

Based on the analysis results, some recommendations can be introduced. First, the establishment of dynamic tariff systems that refer to the 1.525 threshold to promote more efficient electricity use. Second, setting demand response programs on the predicted peak periods. Third, the use of energy storage systems for load balancing at peak times. Lastly, it would be beneficial to inform consumers on the patterns of electricity uses derived from data analysis to give them awareness and better choice to participate in load management.

Eigenvalue Analysis performed using PCA yielded a few notable patterns on the supply & demand for electricity. As shown in Figure 3.5, data consists of two peak periods: (i) morning peak period between 06:00-09:00 and (ii) evening peak period between 18:00-21:00. In contrast, the early hours of the morning, especially between 01:00-04:00, is when electricity usage is low and provides the perfect time for maintenance to occur on the grid. Such results are consistent with the theory presented in Section II. B, which describes patterns of peak electricity use.

In terms of principal component analysis, Figure 3.6 demonstrates that the first three principal components account for approximately 85% of the variance in the dataset. The first principal component, illustrated in Figure 3.7, represents the basic daily consumption pattern, highlighting regular peaks and troughs. These insights are invaluable for electricity utilities, as they provide a foundation for more accurate and efficient supply planning.

From a supply management point of view, the grid needs to have a capacity of 1.5-2 times the baseline consumption to cover the demand peaks. At the same time, the shift from off-peak to peak periods requires a rapid ramp of generation capacity to keep the system stable. The consistent daily consumption patterns that the PCA analysis enabled provide better electricity generation scheduling, reducing the level of inefficiency.

Nonetheless, several hurdles still exist to match supply and demand. However, the morning peak period happens during the early hours of the day when solar energy generation is relatively low. The evening peak is also at a time of day when solar generation dips dramatically. To overcome these challenges, we need both baseload plants and more peaker plants to meet the variability in electricity demand effectively.

To make grids more efficient some recommendations can be made. Utilizing demand response programs to shift or curtail consumption during peak periods. Energy storage systems can also be installed to collect excess energy during off-peak times and save it for future use. Moreover, the use of smart grid management systems, which rely on the trends identified via PCA to optimize supply-demand dynamics, can contribute to a smooth operational and delivery of a stable and efficient electricity grid.

IV. Conclusion

Methodologically, this study validated the efficacy of PCA based eigenvalue analysis for identifying and analyzing the peak household electricity consumption profiles. Consumption was found to have two time slots in a the daily profile, with a morning (06:00-09:00) and an evening (18:00-21:00) peak, where consumption could reach two times the baseline levels. PCA revealed that three principal components explained 85% of the variance in electricity consumption profiles, and that the first component distinctly captured the underlying daily usage cycle.

For example, the results reveal significant issues with electricity supply management, especially for periods of peak demand, when solar generation might not be available. In order to tackle these problems, a few strategies such as demand response programs, energy storage systems and smart grid management systems based on insights derived by PCA, could also be integrated. These solutions could better balance supply and demand while keeping the grid stable.

The study adds to the existing literature on residential electricity use and can inform utilities and policymakers about the implementation of more effective energy management strategies. Future work could build on the current study by including additional features including seasonal variation and socio-economic variables to generate better models for predicting and managing electricity demand.

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STATEMENT

I declare that the paper I wrote is my own writing, not an adaptation or translation of someone else's paper, and is not plagiarized.

Bandung, 31 Desember 2024

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