Smart Energy Management System for Cities

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I. Introduction

This study delves into the intricate dynamics of electricity consumption within two prominent Indian urban centers, Mathura and Bareilly. Recognizing the pivotal role of data-driven insights in informing effective urban planning and energy management strategies, we embark on a rigorous analysis of smart meter data to unravel the underlying factors shaping energy demand in these cities.

The utilization of smart meter data offers a granular perspective into electricity consumption patterns, providing a unique opportunity to explore the interplay of various socio-economic, demographic, and environmental factors. By employing advanced statistical techniques and exploratory data analysis (EDA), we aim to uncover meaningful insights into the drivers of energy usage, facilitating a deeper understanding of consumption behaviors within urban contexts. [1]

Furthermore, we recognize the importance of effective data visualization in communicating our findings succinctly and comprehensively. Leveraging the capabilities of Tableau, a leading visualization platform, we endeavor to transform our analysis into intuitive visual representations, enabling stakeholders to grasp complex trends and patterns with ease.

Through this research endeavor, we aspire to contribute valuable insights to the discourse on sustainable urban development and energy management practices. By shedding light on the factors influencing electricity consumption in Mathura and Bareilly, we aim to inform evidence-based decision-making processes, ultimately paving the way towards a more resilient and energy-efficient urban future. [2]

II. Dataset Description

The dataset utilized in this study encompasses a comprehensive array of parameters crucial for the analysis of electricity consumption patterns in the cities of Mathura and Bareilly. It includes the following key variables: [3]

Timestamps: Recorded at minute-level granularity, comprising year, month, day, hour, and minute information, facilitating temporal analysis of electricity usage trends over time.

kWh Used: A numerical measure representing the amount of electricity consumed by users during the recorded time interval, serving as the primary indicator of energy consumption.

Average Voltage: A numerical metric denoting the average voltage levels observed within the electricity distribution network during the recorded time period, indicative of electrical stability and performance.

Average Current: A numerical measure representing the average electrical current flowing through the distribution network during the recorded time interval, providing insights into load demand and system utilization.

Average Frequency: A numerical indicator of the frequency of electrical oscillations within the distribution network, measured in hertz (Hz), aiding in the assessment of power quality and system reliability.

Meter Names: Unique identifiers assigned to individual smart meters, facilitating the aggregation and analysis of electricity consumption data at the meter level.

By encompassing these diverse parameters, the dataset enables a multifaceted analysis of electricity consumption dynamics, encompassing temporal trends, load characteristics, and system performance metrics. Such comprehensive data granularity empowers researchers to discern meaningful insights into the factors influencing energy usage and inform evidence-based decision-making processes in urban energy management and planning initiatives.

III. Novelty

This study introduces a novel approach to analyze and forecast electricity consumption patterns by merging and aggregating smart meter data from two distinct Indian cities, Mathura and Bareilly. The integration of datasets from multiple urban centers offers a unique opportunity to uncover insights into energy usage dynamics and address region-specific challenges in energy management.

TABLE I
PREVIEW OF DATASET - MATHURA (RAW)

x_Timestamp	t_KWh	z_Avg Voltages (volts)	t_Avg current (Amp)	t_Avg freq (Hz)	Meter
02-01-2021 00:57	0.004	269.73	1.28	50.04	MH01
02-01-2021 01:00	0.005	269.82	1.28	50.06	MH01
02-01-2021 01:03	0.006	270.05	1.28	50.06	MH01

TABLE II
PREVIEW OF DATASET - BARRIELLY (RAW)

x_Timestamp	t_KWh	z_Avg Voltages (volts)	t_Avg current (Amp)	t_Avg freq (Hz)	Meter
02-01-2021 00:00	0.002	253.36	0.25	50.09	BR02
02-01-2021 01:03	0.002	253.87	0.25	50.11	BR02
02-01-2021 01:06	0.02	253.25	1.67	50.14	BR02

Key innovations of this study include:

Data Fusion and Aggregation: By merging smart meter data from Mathura and Bareilly, this study consolidates information from diverse sources, enabling a comprehensive analysis of electricity consumption patterns across both cities. This approach facilitates a holistic understanding of regional energy demand trends and variations. [4]

Temporal Analysis and Resampling: The study employs resampling techniques to aggregate minute-level smart meter data into daily consumption trends. This temporal aggregation enhances the granularity of the analysis, allowing for the identification of seasonal variations, long-term trends, and anomalous consumption patterns.

Machine Learning-based Forecasting: Leveraging recurrent neural network (RNN) models, the study conducts predictive modeling of electricity consumption, enabling the forecast of future energy demand trends. This machine learning approach provides actionable insights for energy planners and policymakers to optimize resource allocation and infrastructure planning. [5]

Interpretation and Visualization: The study utilizes data visualization techniques to communicate findings effectively, enabling stakeholders to grasp complex consumption patterns intuitively. Visual representations of consumption trends, such as line plots and predictive forecasts, facilitate decision-making processes and support evidence-based policy formulation.

By integrating advanced analytical techniques with real-world smart meter data, this study contributes to the advancement of energy analytics and informs sustainable urban development strategies. The findings provide valuable insights for policymakers, utility providers, and urban planners to optimize energy infrastructure, enhance grid reliability, and promote energy efficiency initiatives in urban environments. [6]

This novel approach underscores the importance of data-driven decision-making in addressing the challenges of urban energy management and underscores the potential for interdisciplinary collaboration in advancing the field of energy analytics.

IV. PROPOSED ALGORITHM

- Data Integration and Preprocessing:
  - Merge smart meter data from multiple cities (e.g., Mathura and Bareilly) into a unified dataset.
  - Aggregate minute-level data into higher temporal resolutions (e.g., daily) using resampling techniques.
  - Perform data cleaning and preprocessing steps, including handling missing values, outlier detection, and feature engineering.
- Exploratory Data Analysis (EDA)
  - Conduct exploratory data analysis to understand the distribution, trends, and patterns in electricity consumption data. [7]
  - Identify seasonality, temporal trends, and anomalous consumption patterns through visualizations and statistical analysis.

	Column	Data Type
1	Electricity_Consumption (Wh)	float32
2	Month	int32
3	Year	int32
4	Date	object
5	Time	object
6	Week	UInt32
7	Day	int32
8	Hour	int32

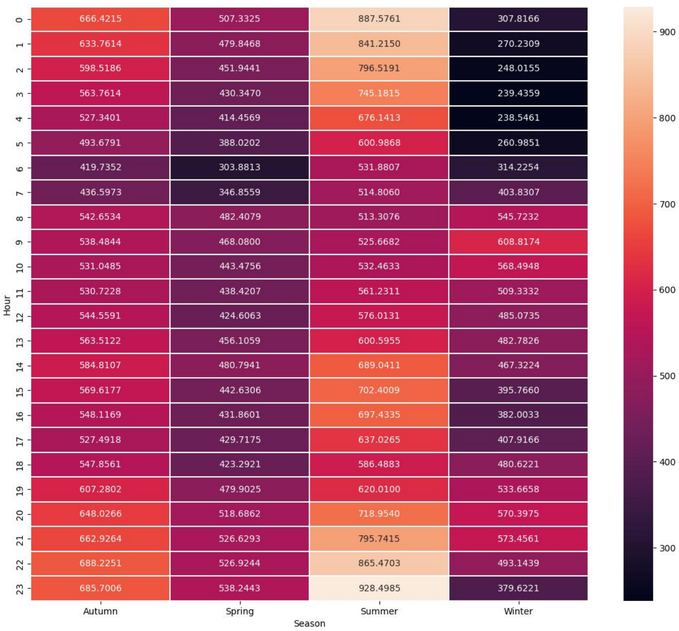

Fig. 1. Barriely's Correlation Plot

- Temporal Analysis and Feature Engineering
  - Extract temporal features from the timestamp data, such as month, year, day, week, and time of day.
  - Compute aggregate statistics (e.g., mean, median, max, min) for electricity consumption and other relevant variables across different temporal resolutions. [8]
- Machine Learning Model Training
  - Split the preprocessed dataset into training and testing sets.
  - Apply recurrent neural network (RNN) [9] models, such as Long Short-Term Memory (LSTM), for electricity consumption forecasting.
  - Configure RNN architecture with multiple LSTM layers and dropout regularization to capture complex temporal dependencies. [10]
  - Train the RNN model on the training dataset using historical electricity consumption data and corresponding temporal features.
- Model Evaluation and Validation

Fig. 2. Mathura's Correlation Plot

  - Evaluate the trained RNN model's performance on the testing dataset using appropriate evaluation metrics, such as mean squared error (MSE) or root mean squared error (RMSE). [11]
  - Validate the model's predictive accuracy and generalization ability by comparing predicted electricity consumption values with actual observed values.
  - Conduct sensitivity analysis and robustness testing to assess the model's stability under different scenarios and conditions.
- Forecasting and Visualization
  - Utilize the trained RNN model to forecast future electricity consumption trends for Mathura and Bareilly. [12]
  - Visualize the predicted electricity consumption values alongside historical data using line plots or interactive dashboards.
  - Communicate the forecasted results and insights to stakeholders, policymakers, and urban planners to inform decision-making processes and facilitate proactive energy management strategies.

By following the proposed algorithm, this study aims to advance the state-of-the-art in urban energy analytics and contribute actionable insights to enhance energy efficiency, sustainability, and resilience in urban environments.

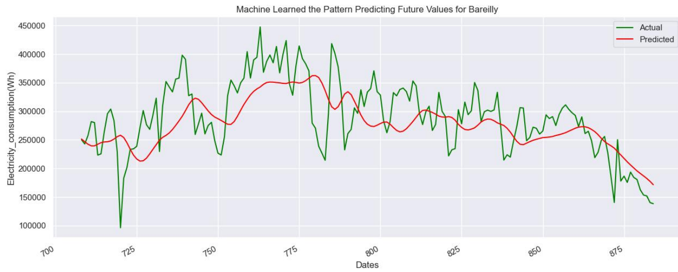

Fig. 3. Visualization of Actual vs Predicted graph of Barreily

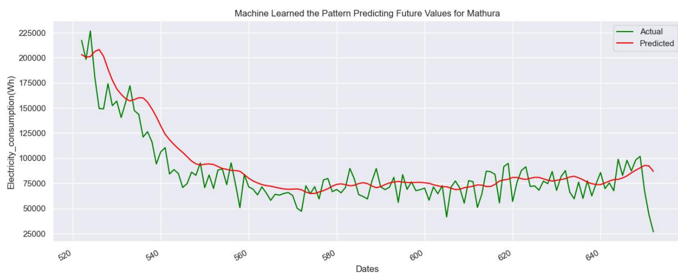

Fig. 4. Visualization of Actual vs Predicted graph of Mathura

References

[1] Sagar V Belavadi, Sreenidhi Rajagopal, R Ranjani, and Rajasekar Mohan. Air quality forecasting using lstm rnn and wireless sensor networks. *Procedia Computer Science*, 170:241–248, 2020.

[2] Liu Yunpeng, Hou Di, Bao Junpeng, and Qi Yong. Multi-step ahead time series forecasting for different data patterns based on lstm recurrent neural network. In *2017 14th web information systems and applications conference (WISA)*, pages 305–310. IEEE, 2017.

[3] Salah Bouktif, Ali Fiaz, Ali Ouni, and Mohamed Adel Serhani. Multi-sequence lstm-rnn deep learning and metaheuristics for electric load forecasting. *Energies*, 13(2):391, 2020.

[4] Matthias Vodel and Wolfram Hardt. Data aggregation and data fusion techniques in wsn/sanet topologies-a critical discussion. In *TENCON 2012 IEEE Region 10 Conference*, pages 1–6. IEEE, 2012.

[5] Salah Bouktif, Ali Fiaz, Ali Ouni, and Mohamed Adel Serhani. Multi-sequence lstm-rnn deep learning and metaheuristics for electric load forecasting. *Energies*, 13(2):391, 2020.

[6] Mohamed Abdel-Nasser and Karar Mahmoud. Accurate photovoltaic power forecasting models using deep lstm-rnn. *Neural computing and applications*, 31:2727–2740, 2019.

[7] Estelle Camizuli and Emmanuel John Carranza. Exploratory data analysis (eda). *The encyclopedia of archaeological sciences*, pages 1–7, 2018.

[8] Jason Y Cain, Jacob I Evarts, Jessica S Yu, and Neda Bagheri. Incorporating temporal information during feature engineering bolsters emulation of spatio-temporal emergence. *Bioinformatics*, 40(3):btae131, 2024.

[9] Shuai Li, Wanqing Li, Chris Cook, Ce Zhu, and Yanbo Gao. Independently recurrent neural network (indrnn): Building a longer and deeper rnn. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 5457–5466, 2018.

[10] Alex Sherstinsky. Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network. *Physica D: Nonlinear Phenomena*, 404:132306, 2020.

[11] Richard Sproat and Navdeep Jaitly. Rnn approaches to text normalization: A challenge. *arXiv preprint arXiv:1611.00068*, 2016.

[12] Alex Sherstinsky. Fundamentals of recurrent neural network (rnn) and long short-term memory (lstm) network. *Physica D: Nonlinear Phenomena*, 404:132306, 2020.