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Household Energy Consumption Forecasting Using Historical Load Time-Series Modeling

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Abstract: Energy consumption forecasting is necessary for the planning process and predicting electric consumption. It plays a key role in building an efficient energy system for power generation, distribution, and sustainable consumption. An accurate forecast of electric load is essential for a power system to be planned properly, generation to be scheduled, and electricity to be delivered economically. The complexity and non-stationary of the electricity load caused by industrial growth, urbanization, and changes in lifestyle in households make applying the classical statistical and rule-based forecasting methods difficult. Customary methods are not able to capture the nonlinear fluctuation in the load, long-range dependencies in time and the specific patterns in the various sectors, leading to wastage and uncertainty in operations. To this end, the present work proposes a time- series based energy consumption forecasting system that utilizes historical load data to forecast the future electricity demand for industry and household sectors. The system follows time- series modeling techniques to analyze historical consumption data and seasonal trends of load variations. The model can also be used to forecast consumption for each sector because the consumption of industrial and residential sectors varies both in demand and in terms of frequency. Long Short-Term Memory (LSTM), a deep learning model, can be implemented to capture the time series dependencies. From the experimental results, the proposed model has been proven to perform customary statistical forecasting approaches in terms of prediction accuracy and stability. The proposed model is able to recognize peak demand periods and provide reliable demand forecasts for load management on time. The optimal prediction of demand plays an essential role in effective power generation and consumption management for power utilities and policymakers to ensure sustainable operation.

Index Terms: Energy Forecasting, Time-Series Analysis, ARIMA, LSTM, Load Prediction, Power Systems.

I. INTRODUCTION

Electricity has become an essential resource in our daily life and also for the industrial activities and development of the economy. Industries heavily depend on a continuous power supply for maintaining production and to run machines, while households use electricity for lighting, communication, cooling, and domestic appliances. Because of population growth, urbanization and increase in industry expansion, consumption of electricity is increasing rapidly and becoming predictable. Also, this growing electricity consumption pressure on power generating systems and energy management authorities. Accurate energy demand forecasting is important for maintaining balance between generation and consumption of electricity. Proper forecasting of demand is helpful for power utilities to plan power generation, reduce energy wastage, lower opera- tional costs, and also avoid blackouts or power shortages. If demand is not predicted correctly, it leads to overproduction of electricity. So, it is very important to forecast accurate energy demand. Traditional energy forecasting mainly are rule-based systems, linear regression and statistical time-series models. These methods are simple but have some limitations like struggling to handle changes in demand and difficult usage patterns. Moreover, such methods deals with all the consumers equally, ignoring the distinct characteristics of industries and households.

Data-driven forecasting systems have attention with more availability of large amounts of historical energy data and advancements in machine learning, deep learning. Time-series modeling methods are useful for studying the past energy consumption trends. Deep learning models, especially Long Short-Term Memory (LSTM) network is very useful for analyzing time-series data and also in learning complex patterns related to power consumption [6], [7]. This project mainly focuses on developing a time-series based forecasting system which predicts electricity consumption for both household and industries using historical data. By performing this proposed approach, we can find different electricity consumption behaviors. Finally, this proposed system helps to improve energy planning, handles peak load, and operates the power system more efficiently.

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II. LITERATURE SURVEY

Due to increasing electricity usage in both industrial and household sectors energy consumption forecasting has become an important research topic. Accurate expectation of energy demand helps in proper planning, reducing energy waste and maintaining electricity supply. From many years different statistical, deep learning and machine learning approaches are used to find the electricity consumption using past data. In olden, traditional statistical learning methods are mostly used. Vapnik (2000) [1] From this research paper, we should learn only theoretical explanation behind the machine learning. Here they introduces statistical learning concepts like risk manage- ment, SVM (Support Vector Machines) are used. It is used as a base reference for learning algorithms. Hippert et al. (2001) [2] from this reference we learn about traditional neural network methods for load forecasting. This paper focuses on short- term electricity demand prediction. Taylor (2003) [3] In this reference they showed that if we include time based patterns it will improve the short term electricity demand forecasting. But this focuses on seasonality and demand variations are explained in it. Fan, S., & Hyndman, R. J. (2012) [4] In this reference they proposed semi-parametric additive models to improve the accuracy of the energy consumption forecasting. The models perform well but these models require advanced feature engineering. Box, Jenkins & Reinsel (2015) [5] In this they introduced ARIMA and SARIMA models. This explains time series models for electricity demand forecasting. When the demand patterns are not changing the model works well, but when there are sudden changes in the electricity consumption they failed to handle that situations. Marino et al. (2016) [6] In this reference they uses deep neural networks for energy forecasting. It takes multiple input features that are used to improve accuracy. The results are show deep learning performs better than traditional models. The study supports using DNNs in energy systems. Makridakis et al. (2018)

[9] compared statistical and machine learning forecasting ap- proaches and highlighted the effectiveness of hybrid methods, while also noting challenges related to interpretability and real-world deployment. Kong et al. (2019) [7]. This paper give information about LSTM network for load forecasting. LSTM is used for time dependency. This model is better than standard neural networks. Ahmad et al. (2021) [8] investigated AI-based energy management systems for sustainable power operation. Although their approach improved decision-making, it primarily relied on aggregated consumption data rather than sector-wise analysis. It shows how AI supports sustainable and intelligent energy solutions. Bedi & Toshniwal (2023) [13] it gives the details about a real time load forecasting. Here we use deep learning models for prediction. The results are having high accuracy and it is suitable for power management sys- tems. At last the recent paper Oyinlola & Oluseyi (2025) [15] This paper mainly focuses on campus energy management. Here they uses clustering and time series models like ARIMA, SARIMA, LSTM, GRU to forecast the electricity demand. It improves energy and system reliability. It is used for predict the energy management on a university campus.

According to the literature reviewed the research gaps are as follows:
Most of the existing studies rely on the single models such as LSTM or ARIMA. There is a limited exploration of hybrid approaches that combines various deep learning models like LSTM, GRU, CNN, transformer to improve accuracy and energy optimization. There is no unified framework for clustering and forecasting. The another disadvantage is limited use of attention mechanisms and transformers.

III. METHODOLOGY

A. **Proposed System**

The proposed system is designed using historical load data from industrial and household sectors to forecast energy consumption. The model consists of various steps like data collection, preprocessing, time-series modeling, forecasting, and performance evaluation stages. The proposed model uses the past energy usage patterns to identify trends, seasonal- ity, and demand fluctuations. Different forecasting models are developed for industrial and household data to improve prediction accuracy. The final output provides future energy that is required, estimates and assist in energy planning and peak load management.

B. **Data Acquisition**

Data Acquisition is collecting the raw data from different sources to process the data. Here in our project historical electricity consumption data which is the past data that is collected from power utility records or publicly available energy datasets. The dataset contains time-stamped energy usage values measured at regular intervals (hourly or daily). Separate datasets are maintained for industrial and household consumers to capture sector-specific consumption behavior.

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C. Data Preprocessing

Data preprocessing is a critical step to ensure model accu- racy and reliability. The following preprocessing techniques are applied: Missing Value Handling: Missing entries are filled using machine learning techniques. Noise Removal: Outliers caused by measurement errors are filtered and re- moved. Normalization: Data is scaled to a uniform range for efficient model training. Time-Series Decomposition: Trend and seasonal components are extracted.

D. Forecasting Models

Here we use two models which are ARIMA along with LSTM which are used to capture the trends and patterns. Linear patterns and non-linear patterns are the patterns that can be achieved respectively and a brief description is as followed: The ARIMA model is used to capture linear trends and seasonal patterns in stable consumption data. It is effective for short-term forecasting where demand behavior is consistent. LSTM is a deep learning model designed to handle sequen- tial data and long-term dependencies. It effectively captures nonlinear patterns and sudden demand fluctuations in energy consumption data [5], [7].

IV. RESULTS

A. Experimental Setup

The experimental evaluation of the proposed energy con- sumption forecasting framework was conducted using histori- cal load time series data collected for industrial and household sectors. The dataset was divided in to training and test sets using 80:20 split to ensure unbiased evaluation. Where 80% of data is used to train the model which is used to predict the output. The 20% of the data is used to test the model. Here the data sets which are collected from the past historical data is used for Data preprocessing techniques such as missing value handling, normalization, and time series decomposition were applied before model training. The forecasting models were implemented using Python-based machine learning and deep learning models were trained under the same experimental conditions to allow fair comparison of performance

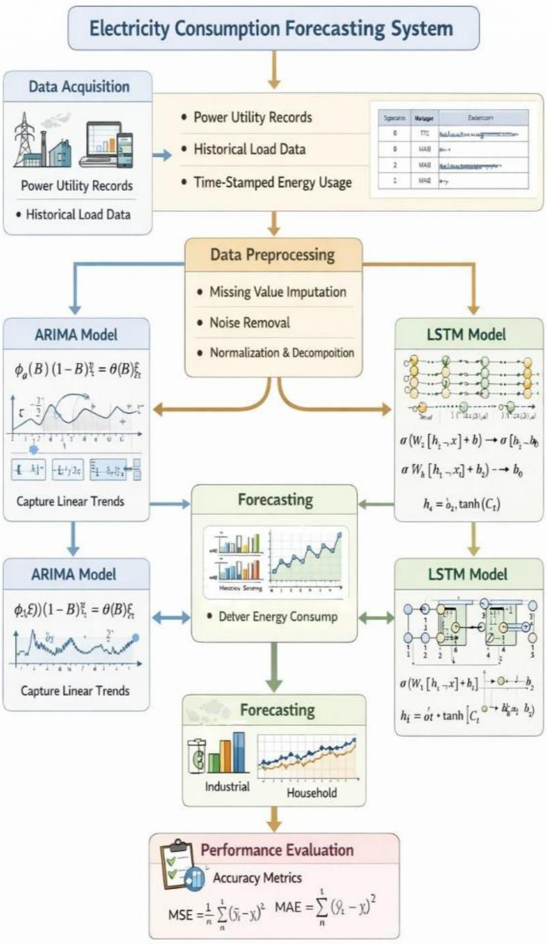

Fig. 1: Data preprocessing workflow for energy consumption time-series

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B. Evaluation Metrics

To evaluate the forecasting accuracy of the proposed system, standard regression-based performance metrics were used. The most frequently used metrics are followed. Mean Absolute Error (MAE) which Measures the average absolute difference between actual and predicted values. Root Mean Square Error (RMSE) which reduces larger prediction errors and reflects overall prediction stability. Mean Absolute Percentage Er- ror (MAPE) which Indicates relative prediction accuracy in percentage terms. Lower values of these metrics represent better forecasting performance

Root mean squared error	$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$
Mean absolute error	$\text{MAE} = \frac{1}{n}\sum_{t=1}^{n} \lvert e_t \rvert$
Mean absolute percentage error	$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n} \left\lvert \frac{e_t}{y_t} \right\rvert$

and higher reliability of the model. Each metric is calculated with the formula which are mentioned below.

C. Performance Analysis

The performance comparison shows that traditional statis- tical models perform reasonably well for stable consump- tion patterns but feel difficult with nonlinear variations and peak demand periods. In contrast, deep learning-based models demonstrate improved accuracy by learning long-term tem- poral dependencies in the data using the ARIMA, LSTM models which are forecasting models [5], [7]. The proposed forecasting model achieves lower MAE and RMSE values which are evaluation metrics that are used to get the accu- rate values. Compared to conventional methods, particularly during high-demand and seasonal fluctuation periods Sector- wise forecasting further enhances performance by considering different industrial and household consumption behaviors. These results are provided based on or by using time-series models for accurate energy demand prediction. Time series can be referred to the sequence of data points that are collected at a regular interval of time, used to analyze the patterns, trends and any other required factors that will be useful for the prediction of energy consumption.

V. DISCUSSIONS

The proposed system analyses the electricity usage patterns in both industrial and household sectors. Due to the model's capability to learn long-range temporal relationships and complex demand variations higher prediction accuracy is achieved. Industrial and residential consumers improves reliability by reflecting their different energy usage characteristics as this is independent modelling. Generally industrial demand follows the structured operational trends whereas household consumption varies in seasonal fluctuations Whereas the conventional statistical techniques shows the difficulties or failures when exposed to accidental load changes and non- linear behavior. While comparing with the deep learning based forecasting models demonstrate stronger adaptability to evolving demand patterns [6], [7]. This model appropriately predicts or expect high-load intervals, enabling for more better accuracy for peak demand conditions. Appropriate prediction provide power utilities in optimizing generation planning and reducing unnecessary or unwanted which is not useful operational expenditure. Improved demand prediction also contributes to minimize the energy wastage and using the resources efficiently. Overall, the results validate the intelligent time-series models for contemporary energy planning and management.

VI. CONCLUSION

By using historical load data we can provide the time series based framework for forecasting industrial and house- hold energy consumption. The proposed model considers the factors like temperature, seasonal variations, and fluctuations in electricity usage based on demand. By performing sector- wise forecasting in which the system accurately provides the different consumption behaviors of industrial and residential users, which results in improved prediction accuracy when compared to traditional statistical methods [5]. The experimental output demonstrates the forecasting models that provide definitive or good reliable and stable demand predictions, particularly during peak load period of time. Power generation planning, optimal resource utilization, and load management will be done by energy forecasting. The proposed model serves as a valuable decision-support tool for power utilities and energy planners who

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plan the power generation and all other management works. Finally, the developed energy consumption forecasting system contributes to sustainable power system operation by reducing energy wastage, minimizing operational risks, and supporting informed decision-making. This model can be further developed or can be expanded by integrating real-time data sources, weather information, and renewable energy forecasting to improve scalability and real- world applicability.

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