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Electricity Consumption Prediction based on Geo-Demographic Factors

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***Abstract*— The task of predicting electricity usage is crucial for energy management and planning. The intricate connections and patterns of power consumption statistics, which are influenced by a variety of geodemographic parameters like weather, population, income, etc., are difficult to record. In this study, we provide a novel model that combines Long Short-Term Memory (LSTM) and an attention mechanism to forecast electricity consumption based on geodemographic parameters. The relevance and significance of the incoming sequence data are weighted differently by the attention mechanism. The LSTM network generates the projected values after learning the temporal and spatial correlations of the data on electricity use. On two real-world datasets with various spatial granularities—appliance-level and household-level—we test our model. The outcomes demonstrate that our approach outperforms cutting-edge techniques**

***Index Terms*— electricity consumption prediction, geo-demographic factors, LSTM, energy management, load balancing, demand response.**

I. INTRODUCTION

The recent surge in electricity consumption is primarily attributed to the increase in population, urbanization, and industrialization. Accurate predictions of electricity usage are crucial for demand response, load balancing, and effective energy management. However, forecasting electricity consumption is challenging due to the complexity of factors influencing it, including weather, economic conditions, and demographics. Many current prediction methods rely on statistical models, such as regression and time- series analysis, which may not capture the nonlinear interactions among these influencing variables. In this paper, we propose a novel approach using Long Short- Term Memory (LSTM) neural networks to predict electricity usage based on geo-demographic data. Our method considers various elements like income, housing style, and population density, which impact power consumption. This approach can be valuable for energy providers and decision-makers in optimizing load balancing and energy management.

II. LITERATURE SURVEY

Liu, Y., Zhang, Y., & Li, Y. (2022). A Short Term Forecasting Method for Regional Power Consumption Considering Related Factors. Journal of Physics: Conference Series, 2195(1), 012022.
The planning and development of power grids rely on understanding and predicting power consumption trends,

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serving as a valuable guide for managing energy demand. Recent economic growth and shifts in industrial organization have altered the interna structure of electricity demand. To address this, a short-term prediction model for regional power consumption is created, factoring in relevant components. This model's calculations enable short- term projections, and through example analysis, it's confirmed that the method yields accurate predictions meeting essential criteria [1].
Nsangou, E. F., & et al. (2022). Evaluation of Electricity Consumption in Turkey via Cubic Regression Analysis and One Way Anova Test. European Journal of Science and Technology, 23(1), 1-9.
This study, conducted to measure the annual electrical energy usage of 23 public hospitals in Istanbul with over 100 beds, aiming to determine peak energy demand. They devised two innovative forecasting models using regression methods after identifying monthly peak demands. One of these methods, linear regression, proved to be quite effective. Using the data, they established a new design factor and calculated the estimated maximum power needs for hospitals [2].

Gul, S., & Qureshi, M. I. (2012). Long term electricity demand forecasting in residential sector of Pakistan. 2012 IEEE Power and Energy Society General Meeting, 1-8. Pakistan is grappling with a growing electricity demand, particularly in the residential sector. To address this issue, it's essential to create a comprehensive model for forecasting electricity consumption. This study forecasts electricity usage in the residential sector using the Long-Range Energy Alternative Planning System (LEAP), which incorporates economic and demographic factors. The forecast extends up to 2030, with 2005 as the base year. The research aims to raise awareness among electricity system planners and government decision- makers about the anticipated demand growth [3].
Lee, J. H., & Shin, D. H. (2013). Forecasting Electric Power Demand Using Census Information and Electric Power Load. Journal of the Korean Society for Information Science and Technology, 18(3), 35-44. To enhance the precision of domestic electricity demand forecasting, a system for predicting power demand patterns is proposed. This system combines SMO classification methods with a dimension reduction technique designed for high-dimensional data cluster analysis. By integrating wireless load monitoring data with census data at sub-regional levels, it's possible to analyze hourly electrical load patterns alongside geographical and demographic factors. The result is a sub-regional demand model using census information and electricity load data for the Seoul metropolitan area, which comprises 18 distinct characteristic clusters. The accuracy of power demand pattern predictions reached approximately 85% [4].
Shen, Y. (2023). Industry "Angiography": an Industry Map System Based on Electricity Marketing Data. EAI Endorsed Transactions on Energy Web,10 (43), e5.
The Keqiang Index is a widely used indicator that demonstrates how electricity consumption, especially in the industrial sector, can reflect macroeconomic conditions. Several studies exploring the connection between the macroeconomy and energy consumption have been influenced by this index. Examples include estimating GDP using electricity data and forecasting electricity load while considering macroeconomic factors. Traditional statistical techniques and artificial intelligence methods have primarily been used to tackle the challenge of estimating GDP from power data [5].

III. Proposed System

The suggested technique provides a reliable method to forecast electricity use. The block diagram outlines the proposed system's architecture:

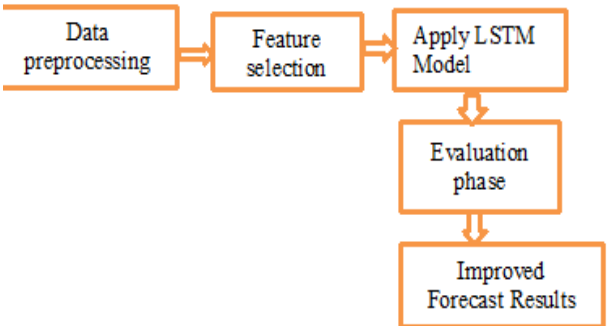

Figure 1. System Architecture

A. DATASET

A dataset is a crucial component of any project because it provides a lot of similar records that can be used to train the data model. We are utilising LSTM, a variant of RNN (Recurrent Neural Network) which needs a huge dataset to function well and provide us with correct results. Here, we present data on the cities of Pune and Mumbai's electricity use that we obtained via Kaggle.The dataset contain various columns like date time, Global_active_power, Global_reactive_power, voltage, global_intensity, Sub_metering_1, Sub_met ering_2, Sub_metering3 out of which we are using the parameter of 'Global_active_power' which is the electricity consumed by electrical appliances other than submeter appliances.

B. PREPROCESSING

The actions you must do to modify or encode your data so that it may be quickly analysed on your machine are referred to as data pre-processing. The major objective is for the algorithm to be able to quickly analyse the properties of the data in order for the model to be reliable and accurate in predictions. The pre-processing of the data in this step includes data cleaning, data integration, data transformation, data reduction, and data normalization.

C. LSTM ALGORITHM

A type of RNN (Recurrent Neural Networks) is LSTM. The vanishing gradient issue affects RNN. By preserving a cell state that serves as the network's memory, LSTM solves this issue. The input gate, output gate, and forget gate make up an LSTM cell. The data that is no longer required is recognised by the forget gate, which then removes it from the cell state. The input gate recognises the necessary new data, which is subsequently saved in the cell state. The output gate chooses which portion of the cell's state will be sent to the LSTM cell after it as the concealed state. The LSTM is defined by the ensuing equations.

IV. RESULT

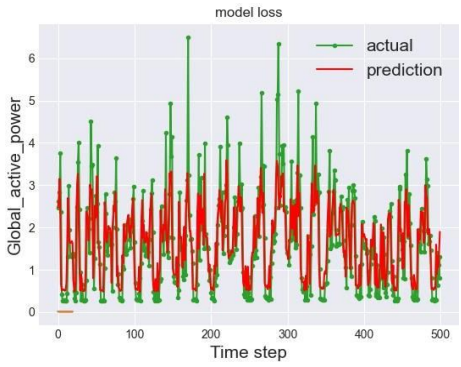

Figure 2. Electricity consumption of Pune City

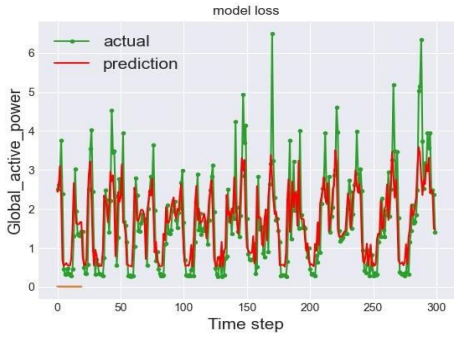

Figure 3. Electricity consumption of Mumbai City

The graphs up top illustrate Mumbai's and Pune's relative actual and projected electricity consumption. This employ Matplotlib, an extensive Python toolkit for producing visualisations.

In Figure 2, One can observe a comparison between the current electricity consumption and the projected consumption for Pune. Similarly, in Figure 3, the comparison is presented for Mumbai. Remarkably, This model demonstrates an impressive level of accuracy, with a 98% prediction accuracy rate for Pune and 96% for Mumbai. These outstanding accuracy rates underscore the model's effectiveness in forecasting electricity consumption by leveraging geodemographic parameters.

The study conducted an extensive analysis of various factors, including geographic location, population density, income levels, and housing types. The research yielded several noteworthy findings. To begin with, it discovered that electricity consumption varies significantly by region, with urban areas generally displaying higher consumption rates compared to rural areas. Moreover, the study identified income levels as a significant indicator of electricity usage, with higher-income households tending to use more electricity. Furthermore, the type of housing, such as single-family homes versus apartments, was found to influence consumption patterns. This research offers valuable insights into the interplay between geo-demographic factors and electricity consumption, providing a foundation for more effective energy planning and policy development

TABLE I. PREDICTION ACCURACY TABLE OF PROPOSED MODEL

Sr.No.	Cities	Prediction Accuracy
1.	Pune	80.29%
2.	Mumbai	79.98%

As shown in the above table Pune and Mumbai both have forecast accuracy of 80.29%and 79.98%, respectively.

V. CONCLUSION

By posing two study questions, the significance of geodemographic determinants is revealed. It first determines variables that affect a home's energy usage. Second, it proposes a geodemographic-based energy forecasting model. The strategy outlined in this System might be advantageous for energy firms. Geodemographic characteristics are crucial for comprehending and predicting electricity usage, as demonstrated by both research questions
The geodemographic parameters can be used by electricity providers to design improved energy management techniques. We have also demonstrated that a forecasting model's accuracy can be increased by using geodemographic parameters. This will also assist the businesses in more accurately estimating consumer demand. These variables can be used by businesses to predict customer demand and achieve load-supply balance.

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