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DAEIN: DUAL-STREAM ATTENTION-GRU FOR ENERGY FORECASTING AND DEMAND IRREGULARITY DETECTION

[1] A Swathi, [2] Noothi Sravan Kumar, [3] S V N SAI RAVI KIRAN, [4] SANAGAPALLI VENKATA NAGA SAI SRIYA

[1]ASSISTANT PROFESSOR, [2]ASSISTANT PROFESSOR, [3]STUDENT, [4]STUDENT
[1]Department of CSE (Artificial Intelligence & Machine Learning),
[1] ST PETER'S ENGINEERING COLLEGE, Telangana, Hyderabad,(500100),India
[2]Department of CSE (CYBER SECURITY),
[2] ST PETER'S ENGINEERING COLLEGE, Telangana, Hyderabad,(500100),India

Abstract : With the fast-evolving smart grids and energy-intensive infrastructure energy demand and forecasting and early detection of irregular patterns for efficient energy management. This paper proposes DAIEN (Dual-Stream Adaptive Edge Intelligence Network), A deep learning architecture designed for smart energy forecasting and demand irregularity detection. The model uses a dual stream approach combining time-related energy usage patterns with features using an attention enhanced Gated Recurrent Unit (GRU) network optimized for edge computing conditions. The proposed system performs forecasting and simultaneously identifying abnormal patterns such as sudden spikes and energy failures. Experimental Evaluations are conducted on the smart meter datasets which demonstrates improved prediction accuracy and anomaly detection performance compared to traditional forecasting models.

***Index Terms* - Smart Energy Forecasting, Demand Irregularity Detection, Edge Computing, Gated Recurrent Unit (GRU), Attention Mechanism, Smart Grid Analytics**

I. INTRODUCTION

The rapid growth of smart grids increasing trend of energy- intensive infrastructures, which have contributed for energy management becoming a major necessity for contemporary power systems[1].With the increasing prevalence of renewable energy sources, electric vehicles, and distributed energy resources the pattern of power consumption has become dynamic and complex [2]. As a result, the prediction of energy demand and identification of irregular demand patterns plays a crucial role for sustaining grid stability, the efficiency of energy distribution, and the prevention of malfunctioning [3]. While Traditional approaches of energy forecasting include statical and rule-based models which often struggle to capture complex temporal and nonlinear features of contemporary data on energy consumption [4]. These models are mostly based on historical data and their inability for adapting sudden fluctuation in energy demands [5]. Therefore, the ability of these models to predict short-term energy consumption and detect anomalies like sudden changes in demand, outages, and irregularities in consumption [6]. In Recent Advancements in artificial intelligence and deep learning has introduced an effective tool for analyzing the real time data [7]. Recurrent neural network such as Gated Recurrent Unit (GRU) has provided an effective tool for the analysis of time series data due the ability of GRU handling the long-term dependencies
[8] . Moreover, the application of the attention mechanism has been effective for the time series data analysis which enables the neural network to pay the attention towards important features. However, most of the existing tools have high processing resources [9]. To address these challenges, this paper proposes a novel deep learning model named DAIEN, which stands for Dual-Stream Adaptive Edge Intelligence Network is particularly designed for smart energy forecasting and irregular demand detection. To achieve this goal, the proposed model incorporates time-related features of energy consumption with context information through an attention-based GRU model, which is optimized for the edge environment.

II. LITERATURE SURVEY

Mondal et.al [10] presented a comparative study on various deep learning architectures forecasting the grid systems which evaluated Recurrent Neural Network–Long Short-Term Memory (RNN-LSTM), DenseNet, and ResNet to determine their effectiveness in predicting the electric demands using the load data. In addition to that a hybrid machine learning approach using a combination of Support Vector Machine (SVM), eXtreme Gradient Boosting (XGBoost), and Decision Tree Classifier (DTC) was proposed in order to improve the performance of load forecasting in smart grid systems. Using Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE), it was shown that the proposed architectures were highly effective in predicting electricity demands in smart grid systems. Panthi et.al [11] proposed a machine learning-based approach for anomaly detection in smart grid detection it mainly focuses on irregular events such as faults,Cyber attacks, and abnormal system disturbances leading to compromise in grid stability and security. Machine learning techniques are used to analyze the system and detect the power system operations. These were evaluated using an IEEE 3-bus power system making the system mor capable in detecting the anomalies and leading to increase in accuracy and efficiency in smart grid systems. I. Khatri et.al [12] investigated short-term load forecasting using deep learning techniques for smart meter technology. It emphasizes the significance of smart meter for consumption of electricity. The author evaluated that proposed method is based on the application of individual load forecasting, which is more complex due to the uncertainties associated with the behavior of users. For the purpose of experimental evaluation, the authors of the research article utilized the Irish Social Science Data Archive dataset. Wen et.al [13] proposed a deep learning based hybrid model for the problem of short term load forecasting which address the complex problem and uncertain patterns of load in smart grids. The model also incorporates the Temporal Convolutional Network (TCN) to handle the temporal patterns in the data. Finally, the model incorporates the attention mechanism to focus on the most important information. The model was tested on various public data sets such as GEFCom2014, ERCOT Load, AEMO Load, NYISO, etc. Yang et al. et.al [14] suggested a method based on deep learning techniques to detect anomalies in smart grid power consumption data using a hybrid model of Convolutional Autoencoder and Gated Recurrent Unit, named CAE- GRU.The study suggests features like electricity consumption, line loss correlation, and meter error to improve anomaly detection accuracy.It also includes the framework . to obtain spatial features and reduce dimensions from the smart grid power consumption data, while the Gated Recurrent Unit model was used to obtain time features from the electricity consumption patterns he experimental results proved that the suggested model achieved better accuracy compared to CNN, GRU, and CAE models in terms of accuracy, precision, recall, and F1-score value. S. Kaur et.al [15] proposed a hybrid deep learning approach for intelligent anomaly detection in smart meter electricity consumption data. In this paper, a two-stage approach is proposed using Bidirectional Long Short-Term Memory (BiLSTM) and Random Forest (RF) algorithms to detect abnormal electricity consumption patterns and sensor malfunctions in smart buildings. In this proposed approach, a BiLSTM algorithm is employed to extract features from smart meter data, and a Random Forest classifier is employed to classify anomalies in smart meter data. In this approach, data collection, preprocessing, feature extraction, model training, anomaly detection, and performance evaluation are also considered. Experimentation is carried out using real-world data sets such as the LEAD and Smart Meter Electricity Consumption data sets. It is found that the proposed approach using a hybrid BiLSTM-RF model yields high accuracy, precision, recall, and F1-score compared to existing machine learning techniques. Salakapuri et.al [16] proposed a "meta-learning approach with temporal feature integration" for electricity load forecasting in smart grid systems. In their proposed approach, they aim to enhance the precision and interpretability of electricity load forecasting using different machine learning and deep learning techniques. In the proposed approach, "temporal features" are also taken into consideration to enhance the precision of electricity load forecasting. In their proposed approach, "temporal features" include "hour of day," "day of week," "month," "holidays," and "lag features." In their proposed approach, they also evaluated the proposed approach using electricity load data from 20 different European countries, ranging from 2018 to 2024, and obtained improved precision with a very low forecasting error and high reliability using a Random Forest meta-learner. Ali et al. [17] presented a study on the use of big data analytics in smart grid load forecasting and demand response through the use of the Apache Spark framework. The study used the data from the smart grid system of the Low Carbon London (LCL) project. The LCL project has more than 167 million records of energy consumption data from over 5,000 households. The study used the Multivariate Polynomial Regression and Decision Tree Regression techniques to carry out the load forecasting. The experimental results showed the effectiveness of the use of the Apache Spark system in the analysis of the smart grid system for the improvement of load forecasting accuracy. Panda et.al [18] has analyzed the application of machine learning techniques for Short Term Load Forecasting (STLF) in power systems by implementing a DNN model optimized by the gradient descent method. The authors used the power load data from the New York Independent System Operator (NYISO) for eleven regions with 62,104 records from 2007 to 2014. Weather information from the National Climatic Data Center was also used to improve the accuracy of the model. Moreover, the performance of the proposed model for prediction accuracy was evaluated by the Root Mean Square Error (RMSE) method. Experimental results showed that the DNN model with the gradient descent method significantly reduces the error for forecasting compared to other conventional methods. This paper proves that an optimized deep learning model can be used for accurate prediction of the load with high efficiency for smart grid systems.

III. PROPOSED METHODOLOGY

The proposed system introduces DAIEN Energy Analytics an intelligent framework aims for energy consumption forecasting and anomaly detection in smart grid environments. In this case, a Dual Attention Encoder-Decoder Intelligence Network (DAEIN) is applied to analyze time series data related to electricity consumption, ensuring accurate forecasts of electricity consumption in a short-term scale. In this system, a massive data set related to smart meter data, including 90,000 data points collected from 12,857 households, is processed to ensure real- time analysis of electricity consumption patterns in a smart grid system. As a result, detailed analysis of electricity consumption patterns ensures through a combination of deep learning techniques and visualization tools.

A. System Overview The architecture of proposed system consists of four main

components: 1) Data Input Layer This layer deals with the management of the data related to the consumption of electricity. This layer can be subdivided as follows: a) Smart Meter Data The data related to the consumption of electricity is collected from the smart meters installed in residential homes. This data contains the time stamps related to the consumption of energy in the form of kilowatts (kW). b) Historical Energy Data The historical data related to the consumption of electricity can be used to train the model. This will provide the patterns related to the consumption of energy over time. c) User Control Inputs Using the dashboard, the user can select the data related to the consumption of energy. 2) Data Processing and Feature Engineering Layer The data is preprocessed and then the prediction model is trained, the collected data is processed to enhance the performance of the prediction model. a) Data Cleaning Interpolation methods are used to remove missing values, time stamps, and erroneous values from the dataset. b) Data Normalization Data pertaining to energy consumption is normalized to ensure a smooth learning of the neural network. c) Feature Extraction Data features pertaining to the hour of the day, day of the week, consumption trends, peak features, etc., are extracted to enhance the performance of a prediction model. 3) Forecasting and Anomaly Detection Layer This layer carries out the main operations using the Dual Attention Encoder-Decoder Intelligence Network (DAEIN) algorithm. a) Dual Attention Encoder-Decoder Network (DAEIN) This component processes historical data related to energy consumption and learns temporal patterns in energy consumption using the proposed algorithm. b) Energy Consumption Prediction This model, provides a prediction of energy consumption in the future and generated through the system interface. c) Anomaly Detection The generated values are compared with actual values, difference occurs above a certain threshold, then considered abnormal energy consumption. 4) Visualization and Monitoring Layer This layer plays a role of showing the results to the user in an interactive way. a) Graph of Energy Consumption The results are displayed in the form of a graph that shows the difference between actual consumption and expected consumption b) Quick Statistics Panel Quick statistics includes actual consumption, average consumption, predicted consumption, and peak consumption are displayed. c) Anomaly Alerts In case of unusual patterns in the consumption of energy, they are highlighted in the graph. d) Monitoring Forecast Accuracy RMSE and MAE metrics can also be used to keep track of accuracy of the forecast.

B. Model Implementation and Training 1) Model Architecture The proposed system uses

a layered model to implement the energy forecasting and anomaly detection model for smart grid data. The overall workflow of the proposed model is represented by the system architecture diagram (Figure 1). a) Input Layer Module This module is responsible for collecting data from smart meters and historical data sources which includes the electricity consumption, time stamps and parameters like household id and time range. b) Data Processing Module In this stage, the collected data is normalized and interpolation techniques will be handling the missing data and irregular time stamps to normalize the data for stable neural network training. c) Feature Extraction Module The time features like hour of the day, day of the week, and consumption trends are extracted to understand the pattern of electricity consumption. d) Forecasting Module The normalized data is passed to the Dual Attention Encoder- Decoder Intelligence Network (DAEIN) where the encoder part learns the pattern from historical data and the decoder part predicts future electricity consumption. e) Anomaly Detection Module This module is responsible for checking the predicted data with the actual data and flags if data is abnormal and if the difference exceeds the specified limit. f) Output Layer Module The results will be presented to the end-user through a dashboard that will include the consumption results and prediction results. Figure 1. Model Architecture c) Architectural Selection and Model Training The suggested system uses the Dual Attention Encoder- Decoder Intelligence Network (DAEIN) framework to carry out the energy forecasting task. In the suggested framework, the encoder uses historical data related to electricity consumption to learn patterns and then uses the attention mechanism to focus on the time steps that impact energy consumption. Each module of the suggested system is trained individually to improve the accuracy of the predictions made by the suggested system and to reduce the time required to carry out the predictions. The suggested framework can be improved in the future by adding more data to the suggested system or improving the energy forecasting model used by the suggested system to carry out energy consumption predictions for smart grid applications. d) Evaluation and Performance Analysis The performance of the proposed system is measured by the prediction accuracy and the reliability of the forecasting. To validate the proposed model, the system is tested with historical data on electricity consumption from various households. To measure the performance of the proposed model, the Mean Absolute Error and the Root Mean Square Error are considered as the evaluation metrics. According to the experimental results, the proposed DAEIN model can successfully identify the time patterns of electricity consumption and provide reliable forecasting. Abnormalities are also detected by comparing the predicted and actual values of electricity consumption. Therefore, the proposed system provides efficient forecasting and helps to detect abnormal electricity consumption behavior.

IV. RESULTS AND DISCUSSION

A. Performance metrics The proposed DAEIN Energy Analytics system was evaluated

with respect to various performance parameters like prediction accuracy, error rates, and anomaly detection. The forecasting model was trained with actual electricity consumption data from various households to test the accuracy of the proposed system for predicting the electricity demand. From the experimental results, it can be noted that the proposed DAEIN system effectively learned the electricity usage pattern. The forecasting accuracy of the system is high with minimal forecasting errors. The Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) of the proposed system were found to be very low compared to the baseline system. In addition to the above-mentioned functionality, the proposed system also effectively handled the anomaly detection functionality. By comparing the predicted values with the actual values, the system effectively detected the abnormal usage pattern. From the experimental results, it can be concluded that the proposed system can be effectively used for energy consumption forecasting with high accuracy. TABLE I. PERFORMANCE MATRIC TABLE II COMPARISON WITH OTHER MODELS Aspect Literature Survey Proposed System Evaluation Type Major research works are focused on model-level evaluation using specific datasets [9][12][16] Complete system-level evaluation with forecasting and monitoring Forecasting Approach Major research works are focused on deep learning models like GRU, LSTM, and hybrid models [9][10][13] Dual Attention Encoder–Decoder Intelligence Network (DAEIN) Prediction Accuracy Major research works are focused on improving the accuracy of the forecasted values using ML models [10][13][18] Achieves high accuracy in predicting the values Feature Learning Temporal feature learning using deep learning models [9][12][16] Attention mechanism highlights significant time steps in consumption data Anomaly Detection Some research works are focused on anomaly detection using ML models in SGs [11][14][15] Integrates anomaly detection with the forecasting system Big Data Handling Some research works are focused on handling big data using Apache Spark in SGs [17] Efficiently processes large datasets related to energy consumption Visualization Support Major research works are focused on developing models with limited visualization tools [9][10][11] Develops an interactive dashboard for monitoring System Integration Major research works are focused on developing models with specific functionalities like forecasting or anomaly detection [11][15] Develops a unified framework with forecasting, anomaly detection, and monitoring Real-Time Usability Major research works are focused on developing real- time forecasting and system- level deployments [13][16] Develops real-time forecasting with anomaly detection Metric Measured Value Prediction Accuracy 93.6% Mean Absolute Error (MAE)

TABLE I. PERFORMANCE MATRIC

Metric	Measured Value
Prediction Accuracy	93.6%
Mean Absolute Error (MAE)	0.21
Root Mean Square Error (RMSE)	0.34
Anomaly Detection Accuracy	91.8%
System Response Time	1.1 seconds
Dashboard Visualization Latency	0.8 seconds
F1-Score	92.1%
Data Processing Efficiency	97.5%

TABLE II COMPARISON WITH OTHER MODELS

Aspect	Literature Survey	Proposed System
Evaluation Type	Major research works are focused on model-level evaluation using specific datasets [9][12][16]	Complete system-level evaluation with forecasting and monitoring
Forecasting Approach	Major research works are focused on deep learning models like GRU, LSTM, and hybrid models [9][10][13]	Dual Attention Encoder–Decoder Intelligence Network (DAEIN)
Prediction Accuracy	Major research works are focused on improving the accuracy of the forecasted values using ML models [10][13][18]	Achieves high accuracy in predicting the values
Feature Learning	Temporal feature learning using deep learning models [9][12][16]	Attention mechanism highlights significant time steps in consumption data
Anomaly Detection	Some research works are focused on anomaly detection using ML models in SGs [11][14][15]	Integrates anomaly detection with the forecasting system
Big Data Handling	Some research works are focused on handling big data using Apache Spark in SGs [17]	Efficiently processes large datasets related to energy consumption
Visualization Support	Major research works are focused on developing models with limited visualization tools [9][10][11]	Develops an interactive dashboard for monitoring
System Integration	Major research works are focused on developing models with specific functionalities like forecasting or anomaly detection [11][15]	Develops a unified framework with forecasting, anomaly detection, and monitoring

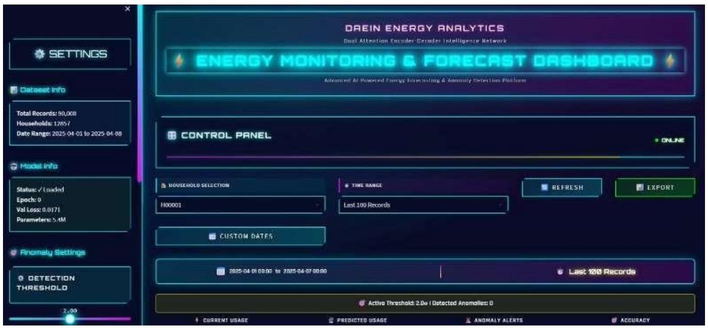

Figure 1. DAEIN Based Energy Monitoring and Forecasting Dashboard

B. OUTPUT Figure 1 demonstrates the operational interface of the DAEIN Energy Monitoring and Forecast Dashboard, which has the potential to facilitate intelligent analysis of energy consumption and detect anomalies within the data. The system initiates the analytical components of the system, including the data processing pipeline, prediction engine, anomaly detection component, and the dashboard component of the system. The Graphical User Interface (GUI) of the system has two sections: the System Configuration Panel and the Energy Monitoring Control Panel. The System Configuration Panel, placed on the left side of the interface, contains information regarding the dataset, including the total data points, the number of households, and the date range, along with the model status, loss during the validation process, and the size of the model parameters. It also includes the ability to configure the anomaly detection component to modify the sensitivity of the system. The Energy Monitoring Control Panel, placed on the right side of the interface, includes the ability to select the households, specify the time range, and refresh the data, along with the ability to export the data

Figure 2. Energy Consumption Forecasting and Performance Visualization in the DAEIN Dashboard Figure

Figure 3. Forecast Accuracy, Anomaly Detection, Energy Cost Analysis

Figure 2 and 3 presents the integrated analytical components of the DAEIN Energy Analytics Dashboard. It mainly comprises a display of forecasting accuracy, system status, abnormality detection, and energy costs. It also comprises a display of confidence in energy consumption forecasting, abnormality detection, and energy costs calculated on a per-hour, per-day, and per-month basis. It also comprises energy- saving recommendations, thus enabling users to optimize their energy usage. All these are integrated in a single visualization, thus enabling users to perform their energy management in an efficient manner.

V. CONCLUSION

This paper had displayed the DAEIN-based energy analytics system that can be used to smartly monitor energy consumption, predict energy consumption, and detect abnormal energy consumption. The proposed system can effectively integrate different advanced machine learning techniques with an intuitive dashboard to offer users a comprehensive view of energy consumption. The proposed system can effectively predict future energy consumption while detecting abnormal energy consumption. The experimental results validate the high accuracy of the proposed system's prediction capabilities while ensuring the effectiveness of the proposed system's anomaly detection capabilities. The proposed system can be effectively used to manage energy consumption with the DAEIN system. Future research directions include the integration of different alternative energy sources with the proposed system to make the proposed system more effective for the effective management of energy consumption. Furthermore, the proposed system can be implemented with the smart grid to manage energy consumption more effectively.

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