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Integration of Deep Learning into Smart Distribution Panelboard at Household level with IoT Connectivity

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Abstract

Power management systems are becoming inevitable for enhancing efficiency, reliability, and sustainability in household electricity consumption. Unlike industry which has a robust intelligent power management system for effective control. The proposed system introduces an integration of IoT with cutting edge deep learning modality using the facilitation of microcontroller as entry-exit core point edge device to receive data from the sensor modules, conveying data to a visualization platform through Wi-Fi (MQTT protocol). In order to address the concern of power wastage due to unawareness of power consumption it needs to enable the visual portal which displays the power, current and voltage consumption of the household by deploying it as an application that could be scaled and installed into local mobile phones for real time monitoring. The sensor modules are embedded onto a distribution panel board prototype sensing the sample load in various distribution nodes and circuit interpreters to shut down during abnormality. In the second phase, these data are then transmitted to a central control unit for decision-making using advanced deep learning algorithms. The comparison of various deep learning algorithms like light gradient boosting machine (LGBM), neural network (NN) and long short-term memory (LSTM) tabulating their accuracy in a more deterministic aspect using the mean absolute percentage error (MAPE) as evaluation parameter attempting to be more data centric artificial intelligence. The prediction comes under the temporal categorization of load forecasting attempting to predict on a short term basis for effective system management.

Keywords: Smart Distribution Panelboard (SDP),Internet of Things (IOT), Deep Learning, Edge computing, Power management, Blynk Application

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1. Introduction

Global energy demand for 2024 is expected to rise significantly. The world's demand for electricity grew by 2.2% in 2023 [21].The demand originates from infrastructure development as buildings gets reconstructed and renovated from century to century. The MEP utility services continues to attain its zenith, accompanied by HVAC ventilation, aesthetic lighting systems [22]. The electricity demand in India is increasing due to various factors such as rapid industrialization, urbanization, and the increased consciousness as a result of which embracing renewable energy sources like solar and wind power perpetuates [23]-[24]. India's electricity demand is projected to grow by almost 5% per year by 2040. There are many key factors why the demand for electricity keeps on increasing every year. Most of the factors are however essential such as change of way production of electricity is crucial to reduce the dependency on Fossil and

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reduce emissions. However, a few factors could be avoided from the consumer's end. Additionally, the lack of comprehensive data on household consumption patterns and drivers poses challenges for accurate forecasting and strategic energy planning in the country [25]. There are various behavioral reasons that come into play in the rise of demand in households [26]. However, a study was undertaken involving the implementation of an Energy Monitoring system in certain households. A significant number of households displayed a gravitation in monitoring their energy consumption, with some successfully managing to reduce it. Noteworthy achievements included households effectively reducing their heating requirements by 20 to 45 %. This underscores the necessity for precise load forecasting at the individual household level. The industry has a well-established infrastructure to dynamically reduce electricity consumption. There are three phases of electricity generation, transmission, and distribution. At this juncture, the concept of a smart grid, a sophisticated electricity network leveraging digital technologies, sensors, and software to optimize the alignment of electricity supply and demand [30] the development of smart grids is of paramount importance for the transformation of the power industry into a secure, adaptable, sustainable, and digitally interconnected ecosystem in Indian level. This is achieved through advancements in communication and intelligence technologies. Smart grids enable real-time monitoring, measurement, and control of power flows, from the point of generation to the point of consumption, even down to the appliance level. The implementation of smart grid solutions can lead to a reduction in transmission and distribution (T&D) losses, peak load management, improved quality of service, increased reliability, better asset management, renewable energy integration, and self-healing grids [32]. It is an automated power network where there is bi-directional communication between utility and consumers [33]-[35]. Smart panels are essential for electrification projects that involve increased electricity usage or draw significant power, such as home EV charging stations or electric HVAC systems [34] electrical energy has been sent to the transformers to ESMBD/SMPD and finally to the basic circuitries in the household. Electric services are of the utility and prominent of any commercial or residential buildings. From the ESMPD the passage of electricity terminates to DB, it is furthermore branches into the basic sockets for all appliances of home [19] the sub-circuits are classified into lighting and power. The power is distributed to the sockets in a household. The panel board comprises a Protection device. In this work it aim to develop a Smart Distribution Panelboard that comprises Sensors to collect the data on electricity usage and a microcontroller for entry exit core point edge device. These Data constitute real and reactive power, Voltage and current. These could be visualized in an IoT platform for a purpose of consciousness about the timely consumption. The data has been further processed into a Load forecasting model for accurate small-scale household forecasting by giving a data centric approach.

2. Literature Survey

Time series forecasting earlier witnessed the prevalence of usage of statistical methodologies as a primary approach. Later there began a Transition towards more sophisticated and meticulous techniques. As any field experiences the inexorable march of evolution. Machine learning-based models have acquired a prominent eminence. Researchers have increasingly gravitated to machine learning theories for load forecasting, [1]leading to the development of more sophisticated and accurate models [2]. This paper brought out a unique aspect of Fuzzy LR for one category of load and after partitioning the load based on the consumption of us in weekly basis in early 2000s there were only quite of papers that were published on the 2000s focused on the temperature sensitivity's part overall giving a hybrid approach [3]. Most papers published in the 2000s focused on 24 ahead predictions where in this paper focused on one hour ahead using neural networks since learning of all similar day's data is very complex, and it is not very welcoming learning of neural networks. The classification of load forecasting could generally revolve around temporal, behavioural, demographic, and probabilistic/ deterministic factors [5]. In the aspect of temporal classification, there emerged a plethora of scholarly articles centred around the idea of short term focusing on one day ahead [4] centred on span of single hour [5]. The split of data relying on the linearity serving the usage with a usage of 2 algorithms. As the data is all about electricity consumption it revolves with a lot of uncertainty and sophistication [6] is more of a very in ground realistic study on interpreting the certain number of households and an attempt to forecast demand. As enumerated in the earlier part the categorization is also inclusive of behavioural factors. The intricate relationship with the use of an equipment with a personality ,habitual chores [7] focused on the study of behavioural contribution model tailored to prognosticate electricity load profiles of Swedish detached abodes, integrating modules for appliance utilization, (DHW) consumption, and space heating [8]-[9]. Within the development of IOT and its industrial applications the prospect of the integrating these cutting edge fields to cater the cause of reducing cost and overall consumption was brought up [10]highlights the utilization cloud computing capability and the author presents an algorithm for data collection, processing, and transmission in the panel board. The paper is a notable contribution on smart distribution panel boards, IoT, and ML-DL-AI utilization for power management [9] serves the significance of accurate load forecasting in the power utility sector to ensure uninterrupted power supply. It reviews the effectiveness of hybrid Machine Learning models that combine multiple algorithms for improved prediction accuracy. Furthermore, it utilized the MAPE error for the evaluation metrics [11]. Investigates the comparison of forecasting household electrical load in Jember, Indonesia, using a linear model and a hybrid of linear models with radial basis function neural network. In the 2010s, artificial intelligence (AI) based models, such as artificial neural networks (ANN), became more popular for short-term electricity forecasting. These models were primarily used for residential and commercial purposes, where electrical energy consumption patterns are more complex. The accuracy of these models was generally higher than traditional engineering methods, but there were still some challenges in identifying the relationship between household lifestyle factors and electricity consumption [12]-,[13]. In the 2020s, hybrid models of linear models and radial basis function neural networks have shown promising results in improving the accuracy of household electrical load forecasting. These models have been found to have higher forecasting accuracy than traditional short-term models (TSR) for 12 months based on RMSE and MAPE metrics. Additionally, there is a growing interest in exploring the use of deep learning [14]-[16] methods and multi-node load forecasting based on multi-task learning with modal feature extraction for improving the accuracy of load forecasting models [16] compares supervised deep learning models for a 24-hour ahead load forecast at a 1-hour resolution of 12 aggregated households [14]. The paper proposes a method based on CNN-LSTM for load forecasting at 96 time point.

3. Proposed Method

The proposed system of us introduces to an integration of AIOT with cutting edge deep learning modality using the facilitation of microcontroller as entry-exit core point edge device to receive data from the sensor modules, covey data to a visualization platform through Wi-Fi (MQTP protocol) for any time monitoring bringing up a continuous consciousness of consumption by deploying it as an application that could be scaled and installed into local mobile phones. The sensors modules are embedded onto a Distribution panel board prototype sensing the sample load in various distribution nodes, the usage of circuit interpreters as CBs, Relay to shut down on an abnormality occasion is also discussed, depicting the household panel board. The values are in their RMS form and processed, converted digitally and finally utilized for the purposes of analytics. It is validated by proper comparison of 3 deep learning algorithms Light GBM, Neural Network and LSTM tabulating their accuracy in a more deterministic aspect using the MAPE evaluation parameter attempting to be more Data Centric Al. The prediction comes under the temporal categorization of Load forecasting attempting to predict on a short term basis.

3.1. Circuit Breaker

The usage of MCCBs (Molded Case Circuit Breakers) that offer good protection against overcurrent and short circuits, the wiring in the fuse makes it a caveat and a need to opt for MCBs MCCBs. However, some studies state the use of SScb also for low-voltage DB [16]. The main driving reason for the employment of the CB is the detection of overcurrent or in general any abnormality in the parameters. In this experimental model, it is integrated with conventional 63A miniaturized circuit breakers (MCB) equipped with a 30 mA residual current device (RCD), alongside fitting sub-circuit breakers with current specifications of 32, 25, and 6A.

3.2. Current Transformer

The specific module employed in this prototype is DTCT03C.It has been chosen for a fact of its precise measurement of current. Mounted on the specific position it works for serving, the overall purpose of the DB. The detailed specifications of this are enumerated as. It can handle a maximum of 5A on input and 5mA on its output side. With a linearity of 0.2% and primary and second winding relation of 1000:1 and linear range of 100 ohm this implies it gives accurate measurement within the specified range. It has an insulation voltage of 4700 hence bestowing it as a safer option to be considered to install in DPB. It can receive a AC input the output current signal is transformed to a voltage and enters into the ADC of microcontroller The DTCT103C sensor module has four output pins - Ground (G), Signal Out, and VCC(+5V) and can be easily connected to a microcontroller or processor for data acquisition.

3.3. Voltage Sensor

The AC line-to-neutral voltage signal of the DPB was acquired by a Voltage sensor, a high precision acquisition module that combines mutual inductance acquisition and provides accuracy voltage transformation. The AC voltage signal can be acquired from 0 to 250 volts precisely with an operational amplifier or an op-amp onboard and other compensation capabilities.

3.4. Circuit Interpreters –Solid State Relay

By the implication of the word it has only stationary components unlike Electro Magnetic relay, it uses semiconductor switching elements, such as thyristors, triacs, diodes, and transistors, to transfer a signal without mechanical motion. It is basically a switching device it switches off whenever there applied a control signal in its terminals. SSRs are used in applications that requires high stability, high switching speeds for high load currents, and compact package size.

3.5. Microcontroller and IoT connectivity

A source has been set up to power the Microcontroller. Esp 32 has been very predominantly used in industrial IOT applications for various considerations it is medium in size favoring easy portability in wearable technologies and considered for portability. The intricate specifications are enumerated as The ESP32 comprises a Ten silica Xtensa LX6 microprocessor, with models like the ESP32-C and -S series incorporating Risc-V CPU models. (Harvard Architecture)

Processor: Dual core-one core for data processing and one core for communication.

Memory: 8 kB RTC, 448 kB ROM, and 520 kB SRAM memories and four 16 MB flash memory which could be used for external memory.

Protocol: MQTT is based on a publish/subscribe communication model, where clients can either publish messages (send data) or subscribe to topics (receive data) without needing to establish direct connections with each other. The protocol is designed to be lightweight and efficient, with a small code footprint and minimal overhead. MQTT provides three levels of Quality of Service (QoS) to ensure messaging reliability in different network environments. QoS 0 guarantees delivery at most once, QoS 1 guarantees delivery at least once, and QoS 2 guarantees delivery exactly once. These QoS levels allow for more reliable IoT applications, as they can adapt to different network conditions and requirements.

3.6. Blynk Application

A Blynk application is implemented as a user interface for remote monitoring and control of the smart distribution panel board. This mobile application provides real-time data visualization, allowing users to monitor power consumption, adjust relay settings, and receive notifications for critical events.

4. Deep learning Model

In the 2020s, there has been a drastic advancement in load forecasting techniques at the household level, mainly focusing on the integration of deep learning models. Many researchers have conducted comparative

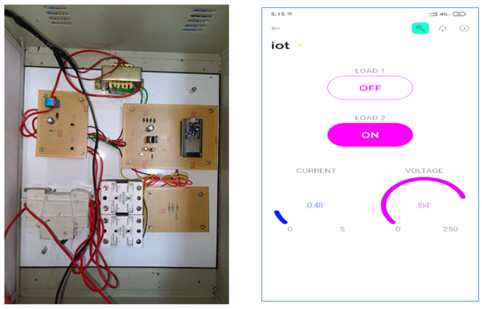

Figure 1. Hardware setup model and Output of Blynk App

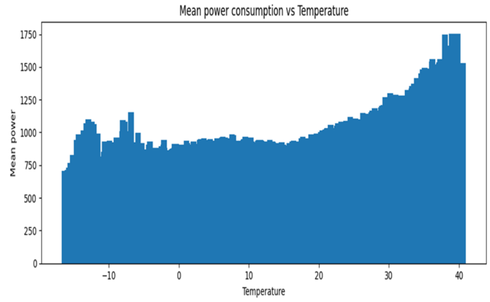

Figure 2. Mean Power consumption vs Temperature

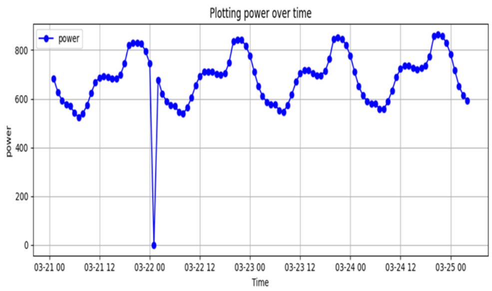

Figure 3. Plotting power over time

analyses to the accuracy metric and the performance of deep learning models for load forecasting using real-world datasets. These analyses have shown that the proposed models consistently outperform existing approaches, achieving superior predictive capability with lower Root Mean Square Error (RMSE). This gives a clear way of outperformance of Deep learning Compared to the traditional algorithm. In this paper it bestow the deployment of deep learning algorithms-based modality

Data Manipulation - preprocessing the dataset, which consists of 17 instances of load data along with corresponding date and temperature data in this phase a new data frame is created which has, time, power and temperature as its columns. It has two separate data frames, one is the values for each hour of the day and the other one is the hourly temperature. These two data frames will be concatenated into one.

4.1. LightGM-Bayesian Optimization for Hyperparameter Tuning

Data preprocessing: To train the GBM model, the data set has been prepared accordingly. Since it is needed to predict a future value based on a window size variable, first: it need to be normalized the "power" column to have mean and std =1, then: to create the function "create_historical_dataset" to create a historical dataset based on the window size variable.

Feature engineering:

- *Handling missing data:* Address missing values through imputation or interpolation.
- *Encoding categorical variables:* Convert categorical data into a numerical format using techniques like one-hot encoding or label encoding
- *Feature scaling:* Normalize numerical features to ensure uniform scales across the dataset.
- *Feature transformation:* Modify feature distributions using techniques like logarithmic or Box-Cox transformations.
- *Feature selection:* Identify and retain the most predictive features using statistical tests or machine learning models' feature importance scores.

Bayesian Optimization: For the search for the best parameter used Bayesian Optimization and eventually trained the model. Using the function best_pargms function. The predictions are merged and finally the actual vs prediction graph for the evaluation parameter.

4.2. Neural Networks with Grid Search Hyperparameter Optimization

The system made designed with a neural network model using TensorFlow or PyTorch and utilize grid search to identify the optimal architecture and hyperparameters. The experiment with different network architectures, activation functions, learning rates, and regularization techniques to maximize predictive accuracy.

4.3. LSTM Networks with Grid Search Hyperparameter Optimization

The proposed LSTM networks, a type of recurrent neural network designed to capture temporal dependencies in sequential data. LSTM networks are well-suited for time-series forecasting tasks such as load prediction. The training is started with the LSTM model using historical load data to learn long-term patterns and temporal dynamics.

Table 1. Model accuracy results

S.No	Model	Accuracy
1	LightGBM	99.95909187
2	Neural Network	99.95574588
3	LSTM	99.95634848

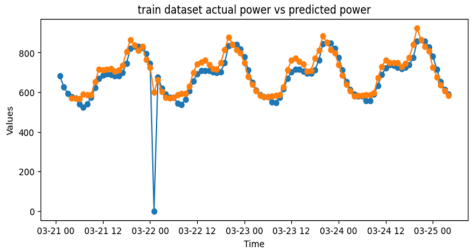

Figure 4. Training : LightGMB

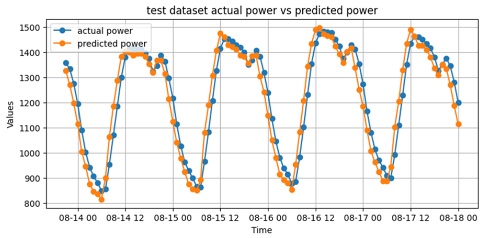

Figure 5. Testing : LighGMB

5. Results and Discussion

5.1. Model Evaluation

Mean Absolute Percentage Error (MAPE): This expresses the accuracy of a forecast as a ratio. It is most acceptably used in the Time series Analytics and Forecasting purposes. The concept of MAPE functions as the absolute difference between the predicted and actual value to the actual value and converted to percentage.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|actual - predicted|}{actual}\right) \times 100 \quad (1)$$

Root Mean Square Error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Predicted_i - Actual_i)^2}{N}} \quad (2)$$

6. Conclusion

In conclusion, the integration of IoT and machine learning techniques into the design of next-generation power management systems, particularly smart distribution panel boards, represents a significant leap forward in the quest for more efficient, reliable, and intelligent

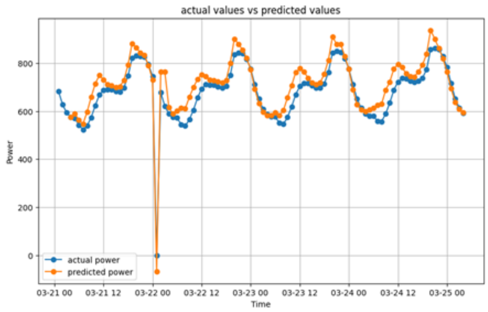

Figure 6. Testing : Neural Network

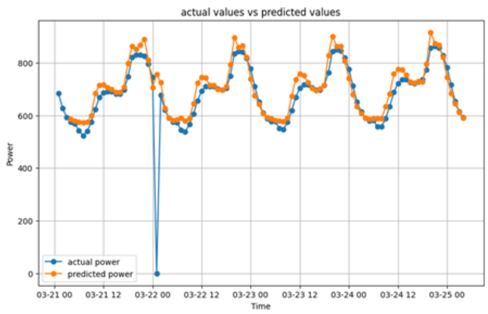

Figure 7. Testing : LSTM

energy infrastructure in the buildings . By incorporating a range of advanced components such as current sensors, relays, voltage sensors, and leveraging technologies like the Blynk application, ESP8266, and PLC load management, these systems offer a comprehensive solution for optimizing energy distribution and consumption. The cutting edge model offers an accurate prediction of load on 24 hour ahead basis. Future scope is to be deployed as product or application to integrating federated learning for the decentralization of the data ensuring data security and robustness.

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