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IOT based Online Load Forecasting using Machine Learning Algorithms

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Abstract

This paper presents a novel online load forecasting using supervised Machine Learning (ML) algorithms in Internet of Things (IOT) environment. Short Term Load Forecasting (STLF) is an essential aspect for smart grid operations such as power dispatch and load management. IOT is an emerging Technology breaching into every segment of science and engineering. This work presents the possibility of STLF online with accurate prediction models by using ML algorithms. Electrical load consumption data and weather data at a research Lab, JNTUH, Hyderabad is used to train ML algorithms in order to implement STLF. ML algorithms based forecasting models are developed using MATLAB code through cloud computing. Online forecasting is more sophisticated and effective because of its ability to use recent data logs for training and forecasting online. Online forecasting is useful in Online Home Energy Management Systems (OHEMS) for effective energy management. ML algorithms such as Linear Regression (LR), Support Vector Machines (SVM) for regression, Ensemble Bagged (EB) regression, Ensemble Boosted (EBo) regression, Gaussian Process Regression (GPR) and Fine Tree (FT) regression are implemented on the cloud to forecast the power consumption. Performance parameters such as RMSE, MSE and MAE are derived to evaluate the effectiveness of the ML algorithms implemented. Cost effective Arduino Uno, Node MCU/ESP8266, PZEM 004T and DHT 11 sensors are used to fabricate the hardware model in order to acquire the load data for the proposed load forecasting approach. Best suited ML algorithm is suggested for the proposed online forecasting with supporting results.

Keywords: Machine Learning (ML), Internet of Things (IOT), Short Term Load Forecast (STLF), Linear Regression (LR), Support Vector Machine (SVM), Fine Tree (FT), Ensemble Boosted (EBo), Ensemble Bagged (EB), Gaussian Process (GP) algorithms;

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1. Introduction

The chronicle of electricity had begun long before in ancient Egyptian time and underwent many changes and developments to what we see now. Today, major part of power generation is being done by Rankine cycles which are the causes of pollution due to their low efficiency nature. But in recent years, advancements in areas of renewable energy, Information and Communication Technology (ICT) enabled more efficient green power, effective tracking of power usage and generation at every node. The coordination between central grid and renewable energy grid by using ICT could achieve effective use of main grid, produce lesser bills both for service provider and consumer. Also the global carbon output can be reduced significantly. Almost all sectors need electrical power to meet their work requirements in one or the other form. Comparing the statistical data increase of power demand annually, one can see that the graph is exponential. Considering the fact that fossil fuels (which are major source of power production) are going to run out in near future, research on alternative energy sources has begun. Although the solar, wind and nuclear energies seem to be promising, they are currently unable to meet the present and predicted power demand. To meet the required electrical demand across the load, a lot of research is being done, to mention one of it; Load forecasting - it is the significant method for understanding the demand before the day with satisfied accuracy. There are three different types of load forecasts: firstly, short-term forecast - which is about predicting the demand from few hours to days. Secondly, medium forecast - which is about predicting the demand from few weeks to months, and long-term forecasts - which is about predicting the demand from few months to years [1]. Different possible load forecasting methods are reviewed and presented in [1], such as Similar Day Approach, Regression, Time series Analysis, Artificial Neural Networks, Expert system (rule based), Fuzzy logic and SVM. This paper addresses the core idea of load forecasting using ML algorithms in IOT environment to use these predictions online for effective energy management.

2. Literature survey on load forecasting

The STLF was not started until the late 90's. One of the early approaches considered for forecasting was Time Series approach [1] which included the effect of temperature on loads. The non-linear nature of the system is compromised by updating the parameters regularly by external means as there was no online system in those days. Later the development of Artificial Intelligence led to the use of Artificial Neural Networks (ANN) in STLF, which unlike Regression models, do not assume the relationships between the parameters but they build their own relationships based on inputs and outputs. Hence the ANN is first trained and then the operator gives the real input values for estimated outputs. The first neural network based STLF models were proposed with three-layer neural network to forecast the next hour, peak and total daily load by Park et al. [2]. In the later years there was increased interest in this method because these models learn by themselves without human intervention. Many researchers had improved this method like in [3] S.J. Kiartzis proposed a model to reduce the forecast errors. Since the ANN was beginning in that era, to remove the hesitancy among the contemporary researchers Henrique Steinherz Hippert has given a review and evaluation on Neural Networks in STLF [4].

All the models discussed above are of offline type, where data has to be put explicitly and regularly. Also the system may not be modified once the model is trained. With the advent of digital sensors and improved communications system, the online STLF is made possible. Here the continuous data is sent to the master station where the storage, analysis and prediction takes place. Online models use autoregressive models, for instance Peder Bacher proposed an autoregressive model where weather predictions were given as inputs achieving Root Mean Square Error of 35% [5]. Although there has been great improvement from past decades there still were certain limitations such as robustness and unavailability of appropriate sensors. Advancements of ICT through IOT made the systems more reliable and accurate. June tae kim in his thesis proposed Multi Linear Regression (MLR) towards STLF where he also mentioned that MLR is best suited with higher accuracy [6], which is investigated and proved again as the best regression model for STLF in this paper. Ahmed Yousuf Saber [7] explored all together a new approach that is IOT based online forecasting, which is the present area of interest for many researchers. In this paper we propose Online forecasting using IOT and MATLAB abilities and implement six different ML algorithms and conclude with a suggestion of best online forecasting exclusively for the circumstances considered.

As discussed earlier, we can see a paradigm shift of the power systems from offline methods to online methods. In online methods as said, the system uses advanced and robust sensors to sence real time data. But to store, analyse and to respond we need a platform that works all around the clock. The cloud computing technology is used for the proposed online forecasting system. Cloud computing platform is a virtual platform where it can be available anytime and anywhere if the internet is available. There are three types of cloud computing services [8] named as follows:

1. SaaS (Software as a Service)
2. PaaS (Platform as a Service)
3. IaaS (Infrastructure as a Service)

The SaaS (software-as-a-service) acts as software which is hosted on a remote server and customers can access it anytime and anywhere from a Web browser or API. The SaaS providers are responsible for backups, maintenance, and updates. The SaaS service comes as a customized application which is valid for all users who pay for licenses. The application cannot be changed on the platform level by customers so this application is easy to use but is not robust. In this paper we have used ThingSpeak cloud platform [9] for our data storage, analyzing and deploying the results. ThingSpeak is application development cloud platform and comes under SaaS and as said SaaS provides customized tools, apps and security. ThingSpeak cloud has the provision to run MATLAB code, the developed code on cloud receives and analyses the data as soon as the fresh data logs are updated. Apart from the storage and analysis it can also alert the customer through Twitter Tweets or alert messages [10]. It also has a responsive app known as REACT [11], in which, if the data satisfies certain conditions the protective or control signal can be sent back to the load point. This control signal can alter the existing environment for better protection of the system. Out of the different types of the Load Forecasting techniques STLF is the effective method used for Online monitoring systems. As discussed earlier there are several ways of STLF which are discussed as follows [12]. Similar day approach is a method where the load is predicted based on the previous day, month or year. This method is the most common method of practice, and it does not give any direct relationship in terms of systematic way between parameters. Linear Regression method is the method in which a relationship is formulated between the independent and dependent variable. Time Series method predicts by modelling patterns in time series plots. Then it extrapolates them for future use. Since we cannot get a smooth curve with limited number of data points, this method needs large number of data points and is a composite structure.

In this paper, load forecasting of a research lab facility at a university campus, Hyderabad by implementing different ML algorithms such as Regression, SVM, Ensemble, FT, GPR online on ThingSpeak cloud platform is presented. Performance parameters are also presented to compare the effectiveness of the ML algorithms implemented on the cloud. At the outset the proposed online forecasting system is an extension of the work presented in [7].

3. Different Machine learning algorithms implemented

3.1. Linear regression algorithm

Regression is a method of modelling a target value based on independent predictors. It is mostly used for forecasting and finding out cause and effect relationship between different variables. Regression techniques mostly differ based on the number of independent variables and the type of relationship between the independent and dependent variables. Simple LR and Multiple LR implements a regression analysis between the independent variables (x_1, x_2.. x_n) and dependent variable (y). Moghram et al. have explored about MLR to forecast 24 hours load consumption based on temperature and wind speed for winter and summer [13].

3.2. Support vector machines algorithm

SVM is one of the most effective supervised ML algorithms, it can be used for either classification or regression challenges. However, it is mostly used in classification problems. In this algorithm, each data item is plotted as a point in n-dimensional space (where n is number of features you have) with the value of each feature being the value of a particular coordinate. Then, classification by finding the hyper-plane that differentiates the two classes very well is performed. SVM for regression problem is first presented by Chen et al. in 2001, which is first developed to win a competition, later it has become very popular and named as Support Vector for Regression (SVR) [14]. Later in 2004, Smola et al. have presented a complete tutorial on SVR [15]. Survey provided by Sapankevych et al. on time series prediction using SVM in 2009 widens the scope of SVR [16]. In this paper, supervised learning of SVM for regression problem is implemented.

3.3. Ensemble algorithm

Ensemble algorithms refers to multiple models that are mixed to address both classification and regression problems. Classification aims to identify the discrete set of a new observation by perusing a training set of data. Ensemble forecasting can be categorized into competitive and cooperative ensemble forecasting. A survey presented by Soares et al. reveals the possibilities of the effective ensemble ML algorithms in solving regression problems [17]. State of the art ensemble methods is presented in 2015 by Ren et al. in which they have focused on forecasting wind and solar power [18]. In ensemble methods, data manipulation is done in three different ways: subsampling from the training set, manipulating the input features, and manipulating the output variable. In subsampling there exists two different methods where one is Bagging and the other is Boosting. Bagging and Boosting based subsampling is successfully applied to regression algorithms. Bagging is one of the popular methods to address regression problems [19]. It considers randomly generated training sets to achieve an ensemble of predictors. If the original training set K has J examples, Bagging generates a model by uniformly sampling J examples with replacement. Both Breiman [19] and Domingos [20] gave clear description on why and how bagging works.

Subsequent important subsampling-based ensemble method is boosting. As per Schapire [21], Freund and Schapire [22] boosting algorithm is quite effective and popular. The fundamental idea is that it is possible to convert a weak learning algorithm into one that arbitrarily achieves high accuracy. A weak learning algorithm performs little superior than random prediction. The said conversion is performed by overlapping the assessment of several predictors. Like in Bagging [19], the examples are arbitrarily selected with replacement but, in AdaBoost which is one of the methods of boosting, each example takes different probability to get selected. In this work both Bagging and boosting subsampling data based algorithms are considered to forecast the load demand.

3.4. Fine tree Algorithm

Regression trees are presented by Brieman et al. in 1984 along with classification trees. The decision tree allows to extract rules and clarify the relationship between predictor and response variables. Regression tree is a sub type under the concept of decision tree, along with classification trees. The classification tree deals with a qualitative output variable. On the other hand, the regression tree handles a quantitative one. This paper considers the regression tree because STLF handled is a quantitative problem. The regression tree consists of the split and terminal nodes. The input data is compared with the split conditions and it proceeds to the left or the right-side node. This process is repeated until the input data reaches a terminal node. Split conditions guides the tree to form clear relationship between input and outputs [23].

3.5. Gaussian Process Regression Algorithm

GPR is a form of supervised learning in which the training data is harnessed in a subtler way. GPR is employed to generate probabilistic forecasts. GPR is a principled and practical probabilistic approach, which is advantageous in the interpretation of model predictions. It possesses very good adaptability and strong generality to deal with high dimensions and small samples in complex nonlinear problems. Compared with ANN and SVM, GPR is easy to implement, self-adaptive to enable superior parameter estimation, and flexible enough to make nonparametric inferences [24]. GPR is explained with a simple example: If we expect the underlying function f(x) to be linear, and can make some assumptions about the input data, we might use a least-squares method to fit a straight line (LR). Moreover, if we suspect f(x) may also be quadratic, cubic, or even non polynomial, we can use the principles of model selection to choose among the various possibilities. GPR is an even finer approach than this. Rather than claiming f(x) relates to some specific models (e.g. f(x) = mx+ c), a Gaussian process can represent f(x) obliquely, but rigorously, by letting the data "speak" more clearly for themselves.

4. Proposed Architecture of the Online Forecasting System

This paper presents a hardware set up comprising of sensors and microcontrollers which first gathers the data from domestic load center and subsequently logs in the data to the ThingSpeak cloud to run the forecasts needed. Fig.1 presents the detailed architecture of the hardware setup for the said purpose. The hardware is built with components such as PZEM 004T, Single channel relay, Node MCU and Arduino UNO. PZEM004T used in the proposed architecture is also called as multi meter, which has the ability to sense current, voltage, power and energy simultaneously.

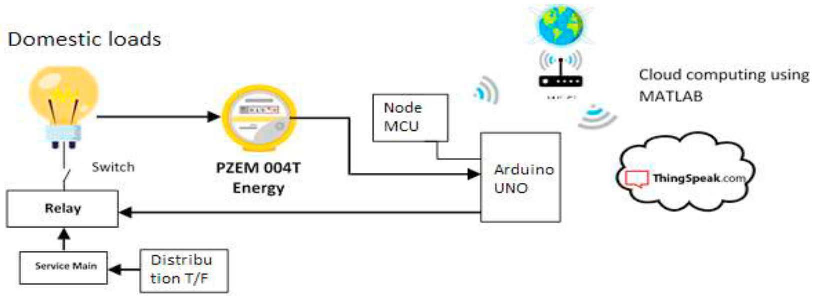

Fig. 1. Architecture of the system used for the proposed online load forecasting in IOT environment.

Power sensed by PZEM004T is accessed with Arduino Uno with ESP 8266 /Node MCU and fed on to cloud with a specific time stamp. Data analytics is performed and STLF is carried out by implementing multiple ML algorithms on the cloud itself, using MATLAB code developed in ThingSpeak cloud application.

5. Different stages of the online forecasting

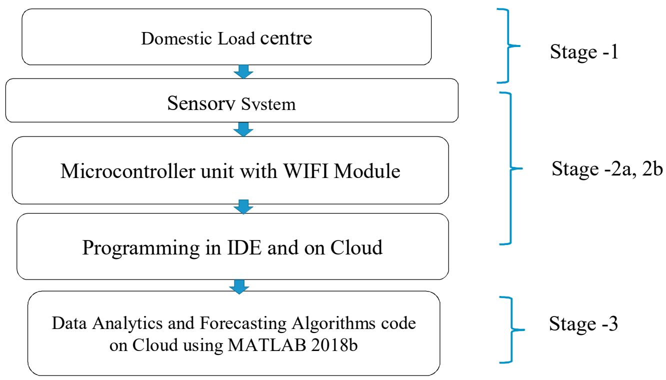

Fig. 2. Different stages of online load forecasting.

Fig. 2 presents different stages involved in the online load forecasting approach, as per the flow chart the forecasting triggers from the load data collection at the load centre. These stages are emphasized in the subsequent sections.

5.1. Stage-1: Load data selection and collection for prediction

Review on forecasting of power consumption published in [1], indicating research findings of 22 papers out of which 13 papers considered only historical data of temperature as input variable for prediction, 3 considered historical temperature and humidity data, 3 used additional weather parameters such as wind etc., and 3 papers used only load parameters. Hence, this paper implements load forecasting with weather and load parameters with time stamp as predictors to train ML algorithms.

$$L(t) = F(d(t), h(t)).\, f(w(t)) + R(t) \qquad (1)$$

Equation (1) speaks about the actual load at time 't' denoted with L (t), where F (d, h) is the daily and hourly component, d (t) is the day of the week, h (t) is the hour of the day, w (t) is the weather data that includes temperature and humidity, and R (t) is a random error. This expression is approximated with only day of the week, hour of the day, daily hour component, temperature and humidity. These are the essential inputs considered to forecast the power consumption at the load center and the same is presented in equation (2).

$$\mathrm{L(t)} = F(d(t), h(t).)\ .\ f\big(w(t)\big) \qquad (2)$$

As per the equations 1 and 2, load prediction depends on various parameters such as individual load parameters, temperature and humidity [1]. In this paper, individual power consumption load data, temperature and humidity over the past few months with same time stamp are used for the proposed online forecasting. To implement the proposed load forecasting, a research lab facility named Disaster Management Lab at Electrical and Electronics Engineering Department, JNTUH, Hyderabad is considered. Historical load and weather data is collected and exported to the cloud through the hardware setup installed at the lab facility. The size of the room is of 100 square feet, having 4 loads which are 2 lights and 2 fans. The power rating of Fan 1, Fan 2 is of 80W each and Lamp 1, Lamp 2 is of 40W each. A total of 64197 data samples of 6 variables are collected and used to train the ML algorithms. Though the data collected is not sufficient in developing the prediction model, we have made an attempt to forecast the power consumption using ML algorithms online using most recent data logs on the cloud.

5.2. *Stage-2a: Domestic load sensing and accessing the load data using Micro controller-IOT devices*

Different hardware components used in the hardware setup is detailed below:

Sensory systems: The sensors used in this system are PZEM004T and DHT11 where PZEM004T can measure the voltage, current and power using Node MCU/ Arduino with ESP8266. Testing Ranges of PZEM004T are as follows Power measurement range: 0 ~ 22kW, Power measurement range: 0 ~ 9999kWh, Voltage Test Range: 80 ~ 260VAC, Current measurement range: 0 ~ 100A. The DHT11 is a basic, ultralow-cost digital temperature and humidity sensor. It uses a capacitive humidity sensor and a thermistor to sense the surrounding air and spits out a digital signal on the data pin.

Arduino controller: The Arduino Uno is designed with multiple I/O lines with extended sketch memory and increased size of RAM. Due to larger space for sketch it is widely used in 3D printers and robotics at student level experimentations. It is much preferred because of the ease of the programming in Arduino IDE environment [25].

ESP 8266: It is an explicit WIFI module used to interact with cloud platforms and operate the devices wirelessly when connected to Arduino.

Node MCU: Node MCU is an open source LUA based firmware developed for ESP8266 WIFI chip. Node MCU firmware comes with ESP8266 Development board. Since Node MCU is open source platform their hardware design is open for edit/modify/build. Node MCU board consist of ESP8266 WIFI enabled chip which is a low-cost Wi-Fi chip developed with TCP/IP protocol. Node MCU board has one analog input and 9 digital output pins, supporting serial communication protocols i.e. UART, SPI, I2C etc. The circuit connections between PZEM004T sensor and IOT device Node MCU is presented in Fig. 3.

The starting node of this system is at PZEM004T sensor. It has 4 inputs on power side incorporating two wirings, one is inductive coil through which the power line goes and other is voltage wiring. Former senses currents and latter voltage. The data side has 4 pins as well. They are for voltage input, RX, TX and ground. The PZEM004T transmits the data in TTL serial communication. Hence the microcontroller should communicate in the desired language for retrieving data from this sensor. Other important sensor for this system is DHT11 which provides temperature and humidity. This sensor has 3 pins namely source input, data and ground. The data from this sensor can be received conveniently by simple Arduino code. The core hardware element is Arduino Uno whose 4 serial communication ports are used for retrieving the data from the PZEM004T. One of the analog pins is used for taking the data from DHT11. Thus hardware setup is designed and installed at the load centre to packetize and export the load and weather data to the cloud via local WIFI module through Node MCU/ ESP8266 [26].

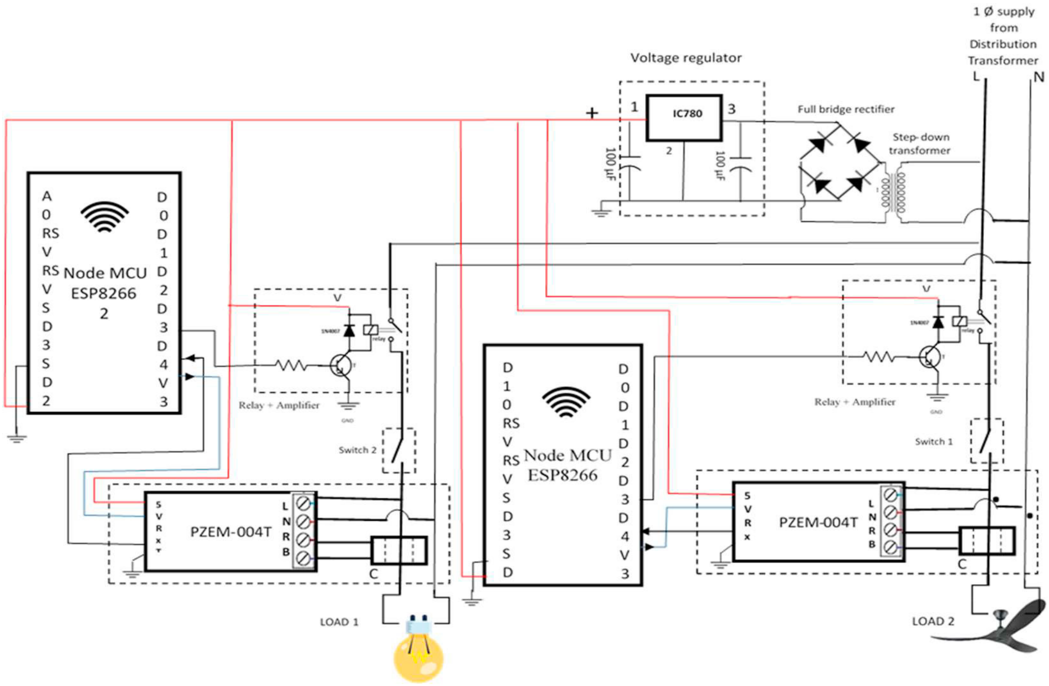

Fig. 3. Basic circuitry of load sensing and data logging on to cloud

ThingSpeak cloud accepts data for every 15 seconds hence the Node MCU is programmed such that it sends the data for every 15 seconds. The sending string has a maximum length of 64 bytes, which when translated to available information, in each string we can send about 4 fields' data in one hand shake protocol. After some cycles of running the program by Node MCU its memory can be overloaded, so we have to reset the Node MCU in regular intervals. This can be done in two ways, by hardware and software. For human free system, the reset should be done automatically, hence software reset is done here.

5.3. Stage-2b: Programing for load data collection and load forecasting

Novelty of the work presented in this paper is very significant in terms of software code developed for data collection, analysis and forecasting the power consumption. Two different codes in two separate environments are developed to execute the proposed online load forecasting. The two stages of programming is presented in Fig. 4. Firstly, Arduino IDE based code is developed to customize Arduino Uno, ESP 8266/Node MCU and sensors connected to them, in order to observe the load, temperature and humidity profiles. This code exports the data to ThingSpeak cloud and updates the data in every 15 seconds too. A MATLAB code is developed on the cloud to process, analyse the data logged on the cloud and ML algorithms are also developed using MATLAB code to prepare a forecasting model which predicts the future load behaviour.

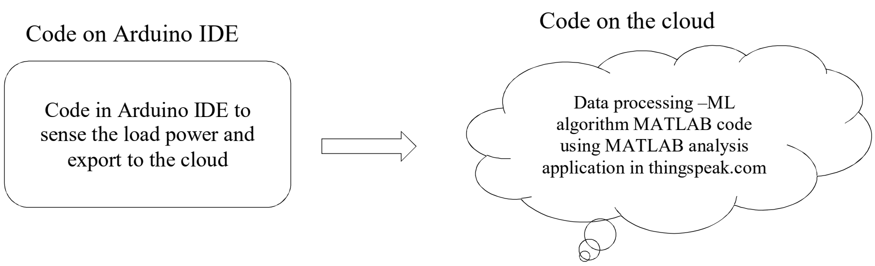

Fig. 4. Stages of programming

Fig. 5. Fan1, Fan2, Light1, Light 2, Humidity and Temperature data logs on ThingSpeak cloud

The sensory system and Arduino-Node MCU setup are wired as per the circuit mentioned in the earlier section, and the whole experimental setup is presented in Fig. 6. This setup senses the load data and exports it to the customized fields of the channel on ThingSpeak cloud. Fig. 5 presents ThingSpeak channel fields tracking all six different variables, which includes four loads, temperature and humidity variables. To implement forecasting using ML algorithms the data in all fields should be at same timestamp and equal intervals so for this purpose the data logged on to the cloud is first regularized in each field by using "RETIME" function in ThingSpeak analysis app. MATLAB analysis code with said function is activated for every 5 minutes by time control application on the ThingSpeak cloud. Thus, all the data logs can be stream-lined with same time stamp.

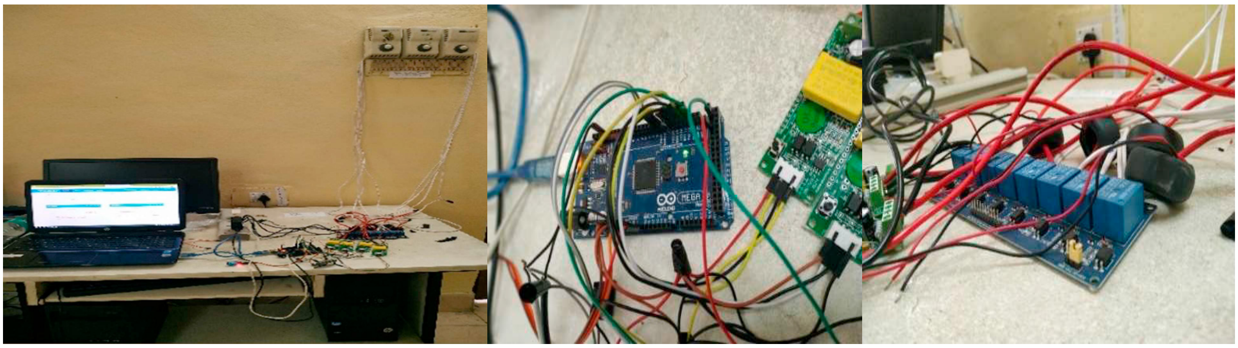

Fig. 6. Hardware setup at the lab facility: power sensory circuits and regularized temperature on the cloud

5.4. Stage 3: Implementing ML algorithms on the cloud using MATLAB application.

Total of six algorithms are implemented for the task of STLF based on the real time load data logged on ThingSpeak cloud. ML algorithms are trained with most recent data to predict the day ahead behavior of the load from 1 to 24 hours. Logged data of 64197 data samples are used to train the ML algorithms on the cloud. Two important findings of STLF are presented in this paper, one is forecasting using individual load power consumption data along with weather parameters and the other is forecasting using only weather parameters. Primarily, STLF is carried out by training ML algorithms with 64197 data samples of 7 predictors, which consists of 4 load variables, 2 weather parameters and the concerned time stamp (predictor matrix of size 64197x7). Secondly, the same ML algorithms are trained with 64197 data samples of 3 predictors, which consists of 2 weather parameters and the concerned time stamp (predictor matrix size of 64197x3). Both the results with 7 and 3 predictors are presented in Table 1. It is observed that ML algorithms with 7 predictors perform quite accurate than 3 predictors. Among six ML algorithms implemented, LR based ML algorithm with multi variables out performed all other ML algorithms in terms of RMSE, MSE and MAE. Plots between predicted response (total power forecasted) and true response (total power fed to ML algorithm during training) for all the ML algorithms built using 7 predictors are presented in Fig. 7. It is observed in Fig. 7a, 7c and 8c that LR, SVM and GPR algorithms results a similar fit between the predicted response and true response because of their low RMSE. Implementation of ML algorithms presented is carried out using MATLAB 2018b with Dell G3 laptop machine, Intel(R) Core (TM), i7-8750H CPU @ 2.20GHz, installed RAM of 16GB.

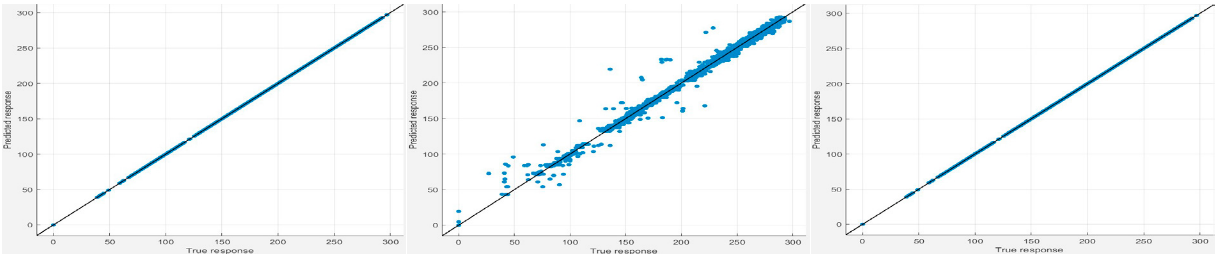

Fig. 7 (a). True response and predicted response of Linear regression ML; (b) True response and predicted response of Fine tree regression ML;(c) True response and predicted response of SVM ML

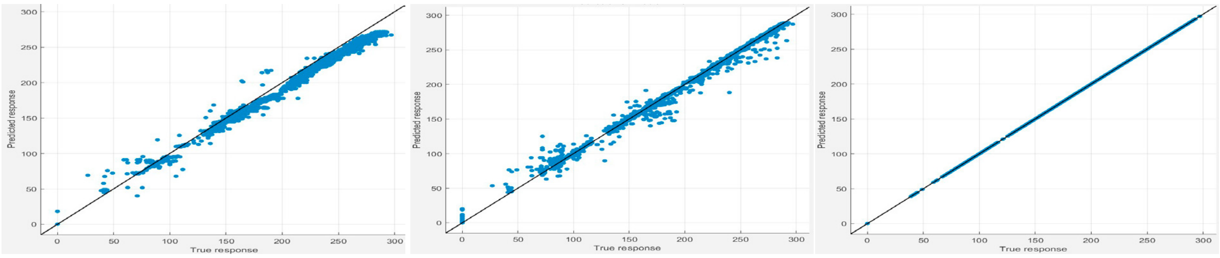

Fig. 8. (a) True response and predicted response of Ensemble Boosted tree ML; (b) True response and predicted response of Ensemble bagged tree ML; (c) True response and predicted response of Gaussian Process Regression ML;

Table 1. Performance parameters of the Machine learning algorithm used to predict the load behavior

Name of the ML Algorithm	RMSE		MSE		MAE	
	7 predictors	3 predictors	7 predictors	3 predictors	7 predictors	3 predictors
Linear Regression	4.44E-13	6.07E+01	1.97E-25	3.69E+03	2.11E-13	3.43E+01
SVM Regression	7.13E-02	6.41E+01	5.08E-03	4.11E+03	7.05E-02	1.93E+01
Ensemble Bagged	2.43E+00	3.56E+01	5.91E+00	1.27E+03	3.90E-01	1.58E+01
Ensemble Boosted	3.69E+00	4.85E+01	1.36E+01	2.35E+03	1.08E+00	2.38E+01
Fine Tree Regression	2.45E+00	3.12E+01	6.02E+00	9.76E+02	4.17E-01	7.39E+00
GPR	1.02E-04	2.84E+01	1.04E-08	8.05E+02	3.97E-05	9.39E+00

6. Conclusion

The work presented in this paper focuses on implementing ML algorithms on the cloud to carry out STLF for load centre. All the necessary sensory units, micro controller units and essential IOT devices are installed in a research lab at the university to carry out the experimentation. Thus, a Cost effective hardware setup is fabricated by which the load data is packetized and exported to the cloud to implement online load forecasting. Over 64197 samples of load data samples are stacked on the cloud and used to train ML algorithms, in order to predict the total power consumption at the research lab. MATLAB code is developed on the cloud to train and test ML algorithms with both 7 predictors and 3 predictors. As per the response vs load plots presented in Fig. 7(a), (b), (c), LR with multi variables and GPR ML algorithms are the best fitting forecasting algorithms for the load data considered in this paper. As per the performance parameters such as RMSE, MSE and MAE presented in table 1, it is evident that LR ML algorithm is superior over other ML algorithms presented in this paper. Using the online forecasting presented in this paper, immediate hour's power consumption data can be predicted using the live data stamps, which is very essential towards effective energy management. The methodology presented is much preferred in IOT based Online Home Energy Management System (OHEMS) to manage energy at domestic load centre in smart grid environment.

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