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An IoT based Intelligent Smart Energy Management System with accurate forecasting and load strategy for renewable generation

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ABSTRACT

The challenge in demand side energy management lays focus on the efficient utilization of renewable sources without limiting the power consumption. To deal with the above issue, it seeks for design and development of an intelligent system with day-ahead planning and accurate forecasting of energy availability. In this work, an Intelligent Smart Energy Management Systems (ISEMS) is proposed to handle energy demand in a smart grid environment with deep penetration of renewables. The proposed scheme compares several prediction models for accurate forecasting of energy with hourly and day ahead planning. PSO based SVM regression model outperforms over several other prediction models in terms of performance accuracy. Finally, based on the predicted information, the demonstration of ISEMS experimental set-up is carried out and evaluated with different configurations considering user comfort and priority features. Also, integration of the IoT environment is developed for monitoring at the user end.

1. Introduction

Forthcoming years it is expected to witness rapid growth and challenges in power generation, delivery, and usage. There is a need for integrating Renewable and Distributed energy sources along with a demand side smart energy management system for efficient power utilization. Renewable energy sources play a vital role in the energy sector due to depletion of fossil fuel in the world, to fulfill ever increasing demand of consumers and need for more reliable and low-cost energy supply. Renewable Energy Sources such as photovoltaic (PV), Wind, Biomass, Micro-Turbines, etc. are in wide use [1]. Nowadays, among urban area domestic consumer, there is a significant interest to develop small roof-top photovoltaic (PV) system. The solar PV systems can be used either in standalone mode (off-grid connected) or in hybrid mode (grid-connected along with other renewable energy sources like wind energy or conventional supply).

Since the use of standalone PV needs large storage system, general grid-connected PV systems are more preferred over standalone PV system to get the uninterrupted supply for a maximum time. Hence, there is a growing demand for hybrid systems that contain elements of both off the grid and on grid systems. Most of the grid-connected systems do not have storage as unused power is exported to the grid. But in a developing country like India, there is an issue in exporting the power back to the grid as it is not stable and also grid outage occurs.

1.1. Motivation and contribution

There is a need for PV storage as part of the modern grid-connected system. On the other hand, the potential benefits of including renewable energy sources in a micro-grid are often difficult to realize due to their intermittent and highly unpredictable nature [2]. The grid-connected PV could lead to more mismatch between generation and consumption, causing fluctuation in the overall power system. To overcome this problem, an accurate prediction of renewable energy is very crucial. Furthermore, depending on the availability of the utility grid and PV energy, consumer loads have to be scheduled according to the assigned priorities and storage actions should be taken. For this, reliable prediction models should be developed to forecast PV output based on solar irradiation levels as well as local weather conditions or other extrinsic factors [3].

The research paper presented mainly covers the following important aspects of demand-side management.

1. Different machine learning methods-ANN, PSO based ANN, SVM, PSO based SVM, and Ensemble techniques are evaluated to find the accurate prediction models.
2. The developed prediction models are compared in terms of Mean Absolute Error(MAE) and Mean Absolute Percentage Error(MAPE) performance metrics.

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3. The simulation results show that the PSO based SVM model outperforms all other models used in the recent studies and also, in this case, hyperparameters are tuned automatically based on PSO optimization algorithm.
4. Hardware experimental setup exhibits power negotiation scenario considering the predicted power and further, dispatch the control action based on configurable priority choice.
5. Secure IoT environment is integrated for load monitoring and further data analysis.

In this work, an Intelligent Smart Energy Management Systems (ISEMS) architecture is proposed for demand-side energy management considering a Renewable source. The developed architecture has PV generated data collection for prediction models, smart energy management system for load scheduling and IoT environment for the user to access the energy details and management. The proposed architecture uses a machine learning approach to predict accurate energy for the day ahead and monthly basis. Based on the predicted information, ISEMS negotiates the available power and dispatch the control action depending on the consumer assigned priority of an appliance.

The rest of paper is organized as follows: Section 2 details about the literature survey and the need for the research work. Proposed methodologies are described in Section 3. Further, results and discussion are carried out in Section 4. Finally, conclusion and future scope are described in the last section.

2. Literature review

Renewable Solar PV power generation is an abundant and promising source of energy in the world. It depends on tropical region, environmental factor and meteorological parameters like irradiation, wind direction, wind speed, temperature, humidity, and also mainly on sun-rise and sun-set time. Hence, the main limitation remains that it is very unpredictable and intermittent [4]. Efficient usage and management of these resources are very crucial for fulfilling the ever-increasing energy demand of the consumer. In the digital world with an IoT environment, it has made so many advancements in the energy sector for reliable data acquisition, remote monitoring, and controlling [5,6].

In coming days standalone solar PV generation plays a significant role in the power industry due to growing concern over the usage of fossil fuel [7]. Hence it is essential to predict PV output data accurately and plan the load/appliance operation at the consumer end for efficient utilization. Different approaches can be considered for modeling of the solar irradiance depending on the availability of dataset length, parameters used, and usage details. There are many advantageous of accurate renewable forecasting for utilities as well as energy consumers such as low cost, dispatch-ability, and efficiency. Monitoring of the reliable and secure operation of power system mainly depends on day-ahead planning with renewable generation forecast and demand consumption information. Accurate forecasting information from renewable power generators helps energy sector to minimize power fluctuations and maintain overall reliability of the system. Further, continuous monitoring of the forecast information may also help the energy producers to preserve the health of the system [8].

In literature use of Seasonal Auto-Regressive Integrated Moving Average (SARIMA), Radial Basis Function Wavelet Decomposition (WD) network methods are employed. However, extensive use of these time series based model may not show high performance since they are efficient with small range prediction [9,10]. In literature, authors deployed of fuzzy logic technique to estimate insolation considering humidity and cloud parameters. Further, used a neural network technique to forecast solar energy with available data [11]. In a similar work, authors used historical data of solar irradiance along with weather condition for prediction of solar PV output using fuzzy logic method [12]. Aunedi et al. [13] have carried out an assessment of frequency regulated refrigerators with deep penetration of renewable and shown with the perspective of economic and environmental benefits. In a recent study feasibility of using extra trees, ensemble methods and support vector regression are evaluated to forecast PV output on hourly basis [14]. A weather-based hybrid model was developed combined with a different prediction model for accurate PV generation output [11,15]. It is evident from the recent literature, conventional ANN and SVR models have been widely used. However, the accuracy of this model depends mainly on parameter tuning.

On the other hand, there are several works carried out towards the deployment of the demand-side energy management system. The Demand Response(DR) event allows the consumer to change their power consumption pattern considering the time of usage and Utility tariff to avoid peak usage. An advanced smart energy management system for a smart grid enviornment considering DR event is presented in our previuous work [27]. In literature authors focus on scheduling and controlling in–home appliances to provide economic advantages for residential energy management [16,17]. In a recent work, the authors present an integrated environment to control appliance demand i.e., Heating Ventilation and Air Conditioning (HVAC) in a commercial building to maintain individual user satisfaction and appliance priority [18].

Based on the certain rule at a possible minimum cost with a predefined budget by the consumer, the authors suggested a demand-side load management technique that focuses on maximizing the user satisfaction level [19]. In a study, the authors suggest that the acquired data can be used for predictive analysis and further optimization in energy usage patterns [20]. In a similar work, to keep power usage under a pre-determined limit, authors have implemented event-driven scheduling algorithms by assigning priority class to home appliances [21]. However, authors considered constant power supply from the grid but not for the dynamic generation like a renewable source.

In our previous work the design of power meter for energy management application is presented [26]. The accuracy of the energy meter dramatically depends on the used current–voltage transducer in case of power measurement. It is also essential to calculate the overall power consumption of the unit, along with accuracy parameters for efficient use [22]. Authors et al. present an experimental work to investigate the metrological performance of CT's and PT's considering harmonic amplitude and relative phase angle. Also, new calibration steps are followed to achieve better accuracy [23]. The authors proposed a simple, flexible, and low-cost DAQ-based watt-meter for high precision electrical power measurement. The evaluation of metrological features is carried out. Besides the comparison with standard primary power module, a high accuracy digital meters are used to evaluate the performance [24]. The authors Cataliotti et al., work focuses on proposing a new method on characterizing and improvement in the metrological performance of current and voltage transducer in harmonic measurement. Further, the proposed work is verified with high accurate devices to test the performance of the proposed method [25].

In this work, solar irradiation data from NREL site is collected for Mangalore region; the solar irradiation output is usually available from 7 AM to 5 PM for a day. Dataset is used to train the different models and validate the results obtained to find the accuracy of the prediction techniques. In order to make proper load scheduling or pre-scheduling, accurate forecasting of source generation plays a key role in the energy management system. In the proposed method, Particle Swarm Optimization(PSO) technique is used to find the optimal parameters of ANN and SVR. The PSO based parameter tuning technique shows significant improvement in results in comparison with the state-of-the-art methods for the given database.

Based on the state-of-the-art lietratures, to manage demand-side appliance efficiently without limiting user comfort, there is a need for the more accurate renewable energy prediction models. In this context, developing an accurate prediction model is considered based on several advanced Machine Learning techniques. For an efficient energy management system, an user-configurable dynamic priority assignment feature is enabled associated with an IoT environment. The proposed architecture is evaluated at the laboratory level experimental set-up, which shows an advanced SEMS system with an accurate prediction model, along with an optimized load strategy and reliable communication. Further, on acquiring metering data extensively, it is possible to explore research on the management of energy systems. As of now several research groups are exploring research areas like real-time energy management solutions, big data analytics machine learning, and energy cost solutions.

3. Methodology description

The proposed Intelligent Smart Energy Management Systems (ISEMS) architecture is shown in Fig. 1 for demand-side energy management considering a Renewable source. It has three stages, which are PV generation and data collection module, smart energy management system based on prediction model and an IoT environment for the users to access the energy details and appliance management. The proposed architecture uses a machine learning approach to predict accurate energy for hourly and day ahead basis. Based on the predicted information, SEMS negotiates the available power and dispatch the control action depending on the consumer assigned priority for an appliance.

The machine learning methods are widely used as forecasting technique to predict the solar energy generation.

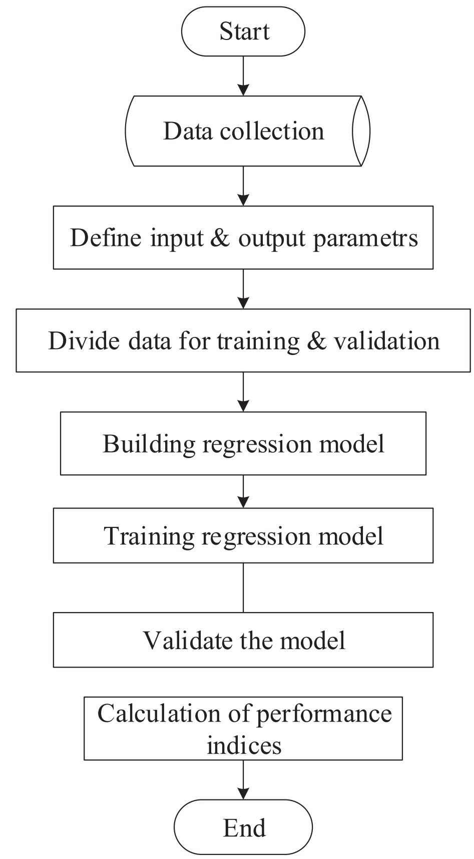


Fig. 2. Flowchart of a basic Prediction Model.

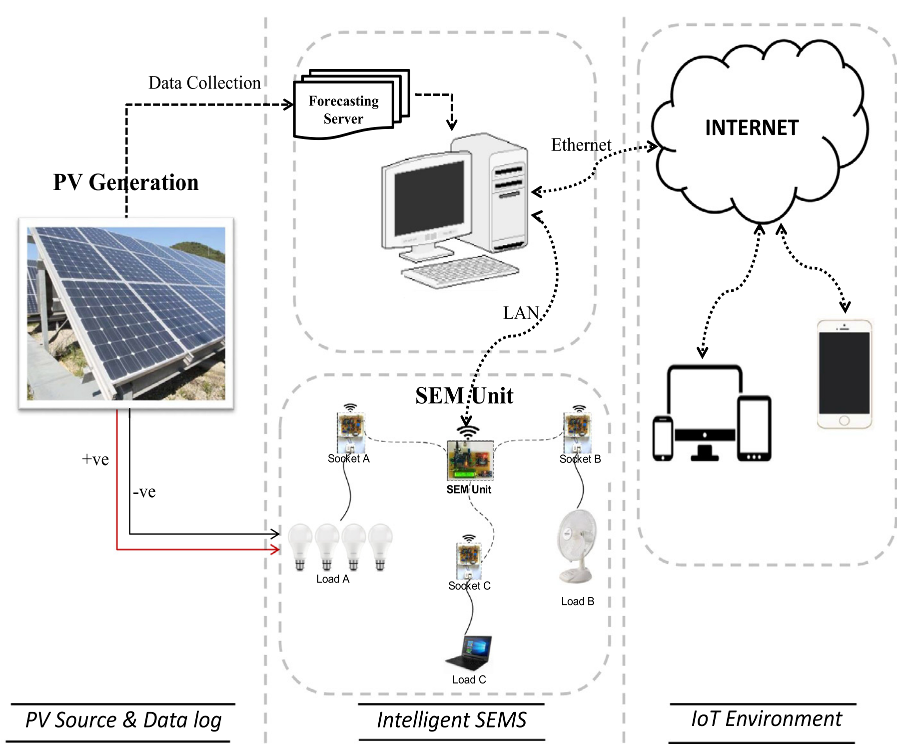


Fig. 1. Overview of Smart energy management system.

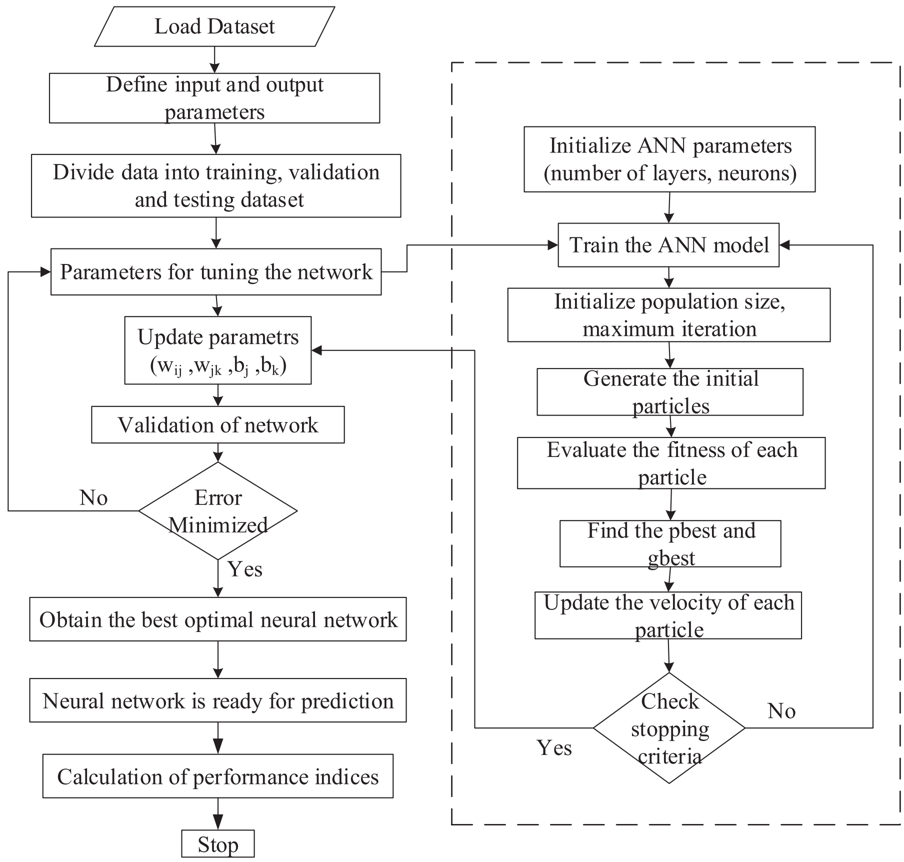


Fig. 3. PSO basd ANN Flowchart.

3.1. Design of machine learning framework

The basic idea of regression is to determine a function that approximates the target values accurately using a set of input values. In general, a regression model has three phases such as Data collection and Preprocessing, Building the model, Training and Testing Phase as shown in Fig. 2.

3.1.1. Data collection and preprocessing

Collecting a suitable dataset is the first stage of designing a prediction model. The research data of solar irradiation level is collected from National Solar Radiation Database (NSRDB) of NREL website for Mangalore region and data points used for feeding regression model are Temperature, Pressure, wind speed and Global horizontal irradiance(W/m^2). Further data preprocessing is done to solve the problem missing data by replacing it with an average data of the same day and normalization of the data is done.

3.1.2. Building the model

At this stage, the designer has to tune different parameters associated with the model such as initial variable, max-depth, and coefficients to build an accurate model. The above forecast models are evaluated to decide the best suitable model which gives better accuracy. Out of five models, PSO based SVM regressors outperforms other models in terms of accuracy, and hence it is used for ISEMS forecasting method.

3.1.3. Training and testing the model

During the training phase, the total dataset is made to split into training and testing section. In this work, for day-wise prediction, 2014 year dataset has been used to predict any day of the year. For Month-wise prediction 2013 year data is used to train and 2014 year same month data for the testing phase.

3.2. Evaluation of prediction model for energy management system

3.2.1. Artificial Neural Network (ANN)

The artificial neural network is a conventional prediction model used for solar irradiation forecasting. The working of the ANN model considers the historical data with different input parameters such as temperature, wind speed, time of the day, and month. Further, 75% Data is divided into a training set and 25% as testing data set. Several combinations of ANN parameters with number of neurons and hidden layers are tried to obtain the best optimal value. The best-trained model with minimum error is chosen for prediction after a number of trials.

3.2.2. ANN based Particle Swam Optimization (PSO)

The working of ANN model with PSO based parameter tuning is shown in Fig. 3. To find the best optimal parameter values, the various analysis are carried out with a different combination of input parameters. Initially, to find the optimal value of PSO particle size, a fixed value of acceleration factors (c1 and c2) and the number of hidden layers (n) are chosen with a different combination of variable particle size considering the minimum error. Further, the optimum value of acceleration factors (c1 and c2) are obtained using the acquired optimal particle size from the first analysis and keeping the same size of the hidden layer(n). Finally, the third analysis is carried out to find the optimal number of hidden layers considering the fixed optimum value of particle size and acceleration factor values (c1 and c2) obtained previously for a different combination.

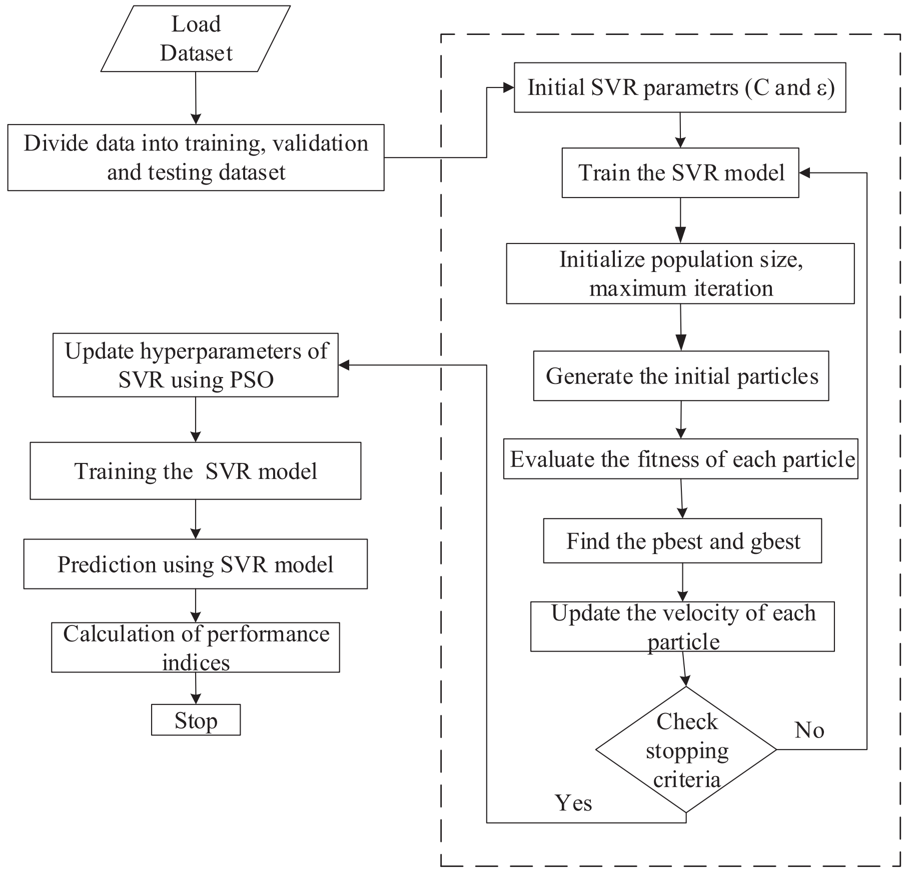


Fig. 4. PSO based SVR flowchart.

3.2.3. Support Vector Regression (SVR)

The SVR uses a different optimization technique compared to the ones used in logistic or linear regression such as neural networks. The meta–parameter 'Gama' defines Gaussian kernel function which determines how similar the different features are concerning each other and thus imparts weights to their corresponding optimization functions. The Regularization parameter C controls the tradeoff between hyperplane and minimizes the training error. The hyperparameters of the SVR model is derived from the pattern of data and a random initial setting. The value of these parameters decides the accuracy of the model and in SVR model: $\gamma = 1.25$ and $C = 1$ are used as the initial value. Further, tuning of these parameters using the optimization algorithm is discussed in the next section.

3.2.4. PSO based Support Vector Regression (PSO-SVR):

In the case of the SVR model, the optimal value of C and *Gamma* parameters decide the accuracy of prediction. PSO can be used to optimize these parameters of SVR. PSO obtains the prediction error of the SVR model in each of its iterations and finds the least prediction error possible from the whole solution space and uses that information to arrive at the optimal value of SVR parameters under investigation. In the PSO-SVR model, PSO obtains the prediction error of the SVR model in each of its iterations and finds the least prediction error possible from the whole solution space and further, uses that information to arrive at the optimal value of SVR parameters under investigation. The working of the PSO-SVR model is presented as a flowchart in Fig. 4. The hyperparameters of the SVR model are initialized with random values by the SVR function. The data is separated into training and testing sets using random indexing which is described in detail in the last section of this chapter. Further, the SVR algorithm is executed as instructed by the PSO, and the performance of the model is checked at each iteration. PSO decides the direction in which the iterations have to be performed. The value of hyperparameters at the minimum error value is selected as the optimal solution by the PSO. At the end, the model accepts the testing data and prediction is done by using the optimal set of hyper parameters.

3.2.5. Ensemble Methods (ENS):

The ensemble method of decision trees also known as weak or base learners. Feature selection is an essential criterion in data analytics; Decision Tree algorithms have the advantage as they perform feature selection implicitly choosing few top nodes when the dataset is fit. Decision tree needs little effort for data preparation, unlike some other regression model needs proportional scaling among the parameters used. Moreover, it gives better performance in the case of the non-linear relationship among the parameters without making any linear assumptions. In this work, 500 base learners are chosen by performing trial and error with a repeated number of experiments, learns with lower computational cost and achieves higher accuracy rate. It shows better performance compared to other conventional methods.

3.3. Prediction performance evaluation metrics

The performance evaluation of the trained model is a critical matter of concern. It defines the suitability of the model for a practical application. In this work, three major performance criteria that establish the accuracy of the model is investigated. Those three performance parameters are:

- Mean Absolute Error (MAE).
- Mean Absolute Percentage Error (MAPE).
- Root Mean Square Error (RMSE).

3.3.1. The mean absolute error (MAE)

The forecast error, which is the difference between actual and predicted data are calculated using MAEs. The mean absolute error is represented by the following expression.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|\hat{P}_i - P_i| \tag{1}$$

3.3.2. The mean absolute percentage error (MAPE)

The mean absolute percentage error (MAPE), also known as mean absolute percentage deviation (MAPD), is a measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation. It usually expresses accuracy as a percentage and is defined by the following expression.

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\frac{|\hat{P}_i - P_i|}{P_n}100 \tag{2}$$

where P_i is the actual value at the i_{th} hour, $\hat{P}_i$ is the predicted value and P_n is the nominal power, and N is the number of test points.

MAPE has two advantages. First, the absolute values keep the positive and negative errors from canceling out each other. Secondly, since relative errors do not depend on the scale of the dependent variable, this measure allows to compare forecast accuracy between the entirely scaled data.

3.3.3. Root Mean Square Error(RMSE)

The root means square deviation(RMSD) or root mean square error (RMSE) is a frequently used measure for the differences between values (sample and population values) predicted by a model or an estimator and the values actually observed. The root mean square mean error is represented by the following expression.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left|\frac{\hat{P}_i - P_i}{\hat{P}_i}\right|^2} \tag{3}$$

Furher, detailed analysis are carried out by combining several combinations of paramters and conducting number of trials for the developed models.

4. Evaluation of ISEMS experimental setup

This section describes the overview experimental set up of intelligent smart energy management system. Design of smart socket details are elaborated along with power negotiating decisive algorithms. Following, IoT framework is integrated with ISEMS for data remote monitoring.

4.1. The overall system set-up

The overall SEM system is shown in Fig. 5 it consist of a SEM unit(Gateway) and smart socket module at the other end. SEM Gateway acts as a brain of the system and smart socket controls the appliances. Bidirectional communication between SEM Gateway and smart socket module is established using XBee modules. The XBee modules are configured as coordinator at the Gateway end and router at the other end. The main SEM unit receives any external signal, runs power negotiating algorithm and sends the control signals to smart socket module. The appliance scheduled operation based on the predicted power information is discussed in the following section.

The experimental setup in the laboratory environment uses actual loads: a lighting load, a fan, and a charging laptop. Algorithms deployed in SEM unit are designed to run the appliances in the order of assigned priority during the Demand Response (DR) event considering the maximum demand limit. In addition, appliance scheduling considering the Time of Usage(TOU) is to accommodate it into the minimum slab rate.

Experimental work uses actual loads in the laboratory environment, an incandescent lighting load is used as Load-A, which has the provision for varying the power consumption by turning on/off the status of individual bulb within it. A fan is used as the Load-B in the setup, which has the provision for altering its speed and it is associated with humidity and a temperature sensor to demonstrate how the user comfort case is integrated with the algorithms deployed. A charging laptop is included as Load-C: this load is intentionally chosen to show the scheduling of chargeable loads considering the time of usage(TOU).

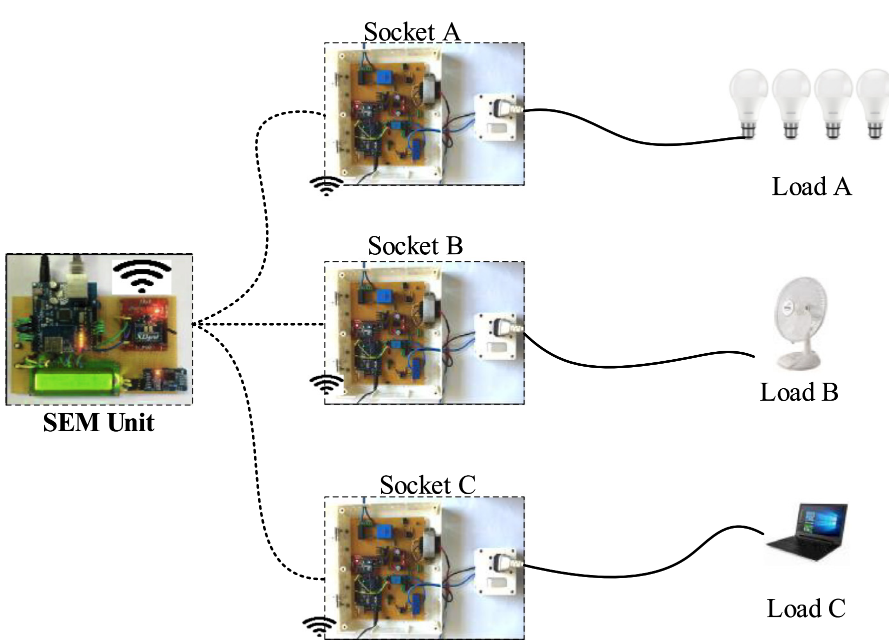


Fig. 5. Smart energy management system.

4.2. Design of smart socket for ISEMS

The schematic design of the smart socket is shown in Fig. 6. In this case, using the Hall Effect based voltage and current transducers, the single-phase power parameters (voltage and current) are stepped down to low-level voltage signals. The schematic of the voltage and current transducer included is shown in Fig. 6. The input resistance R_1 is chosen such that the measuring resistance R_M is selected in the range of $10 - 350\Omega$. The measuring resistance, R_M is selected in such a way that, the output voltage shouldn't exceed 4.5 V. Arduino ATMEGA-328 Microcontroller can read only positive voltages (0–5 V). Hence,the measured signals are further conditioned using a signal conditioning circuit to level shift the signal by 1.8 V DC offset voltage, which is generated by the power supply module using a voltage divider circuit. Further, if the input voltage to the microcontroller exceeds 5 V it may get damaged. Hence, in the signal conditioning circuit, a Zener diode with a cut-off voltage of 4.7 V is used at the output stage to prevent the overvoltage. The signal conditioning circuit is tested by applying the stepped down signals from voltage and current transducers and found to be within 0–4 V range. The conditioned output signals are fed to the analog pins of the Arduino microcontroller. The Relay module provides the capability to switch a selected appliance ON/OFF, depending on the command sent by the microcontroller unit. The phase wire from the load supply passes through the current transducer, and it is connected to the No Connection (NC) pin of the relay. Further, the COM pin of the relay module is connected to the one of the port of the socket, and the neutral wire is connected to the another port of the socket. The communication path is established using XBee series2 modules. The XBee module is attached to the SEMS unit (Coordinator) and enables it to send control commands to all Smart Sockets (Router). Further, in the coordinator module as discussed in the previsous section, Arduino Controller receives the commands from the different Routers/Smart Socket unit through Xbee modules. Thus, SEMS unit is responsible for collecting energy consumption data from all routers through XBee modules and providing an LCD interface for consumers to retrieve overall energy consumption data. In addition, the energy consumption data can be uploaded to the local server (WAMP) using the Arduino Ethernet shield.

4.3. Decisive algorithm operation based on predicted power data

An algorithm in SEM hardware is designed that allows a consumer to operate his/her relatively more important appliances even when the generated power is less than power demanded by considering consumer priorities of an appliance.

In the experimental demonstration, we assume the available power from solar PV output based on the predicted solar irradiation data.

4.3.1. Decisive algorithm operation during Demand Response

Stepwise explanation of the deployed algorithm is shown in Algorithm 1.

1. The SEM decisive algorithm starts by gathering power consumption data of all the appliances. The data collection is carried out in a predefined order. During this process, if any load controller does not respond when requested for data, SEM unit runs a self-diagnostic algorithm.
2. The collected data of power consumption is arranged in the order of consumer's priorities and then SEM unit checks for demand limit violations. In the case of demand limit violation, the decisive algorithm checks if apparent power consumed by appliances exceeds the specified maximum demand limit.
3. The SEM unit sends a command signals to switch ON a maximum number of high prioritized appliances such that demand limit is not violated and sends command signals to switch OFF remaining appliances.
4. The decisive algorithm also checks for peak load condition for any appliance whici is turned ON. In case of a peak load condition being satisfied, the SEM unit sends a command signal to the load controller to warn the consumer about the high power consumption during peak load hours to avoid high tariff charges. Load controller warns consumer by switching on the buzzer and LED for one second.
5. Finally, after sending respective command signals to all the appliances, SEM unit would wait for 30 s before the next data sampling and at the same time lets the consumer to update his/her priorities. Then repeat steps 1 to 5. Flow of the SEM decisive algorithm for 'n' number of loads in a household is shown in Algorithm 1. It is to be noted that before running this algorithm, priorities of appliances are initialized with predefined settings. Also, two variables 'i' and 'k' are used in the algorithm and variable 'i' increments in the order of priorities whereas 'k' increments in a predefined order to collect power consumption data of all appliances.

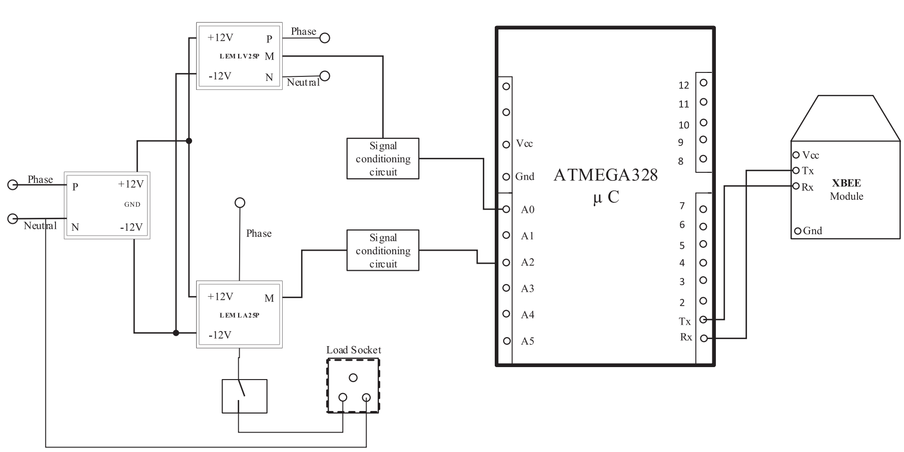


Fig. 6. Design of Smart Socket for ISEMS.

Algorithm 1: Decisive algorithm with self-diagnostic capability

```
Input: Total number of appliances (n)
Output: collect individual(id) appliance power consumption data
for k ← 1 to n do
    poll();                                ▷ Poll request signal to kth appliance
    if aplliance respond then
        readpower(k)                       ▷ collect its power consumption data
    end
    else
        wait(6);                           ▷ Wait for six seconds
        poll();                            ▷ poll request continuously for next five seconds
        readpower(k);
    end
end
PP=read_predicted_power();                 ▷ collect from prediction server
for k ← 1 to n do
    if Apparent Power demanded by k^th and other (K-1) high prioritized
    appliances less than available power(PP) limit? then
        switchon(k) ;                      ▷ switch on the k^th appliance
        if Is peak load condition satisfying then
            alarm();                       ▷ Warn consumer about peak load
        end
    end
    else
        Send command signal to switch off K^th appliance and other lowe
        prioritized appliances remaining (K-1) appliances
    end
    Wait(30);                              ▷ waiting time for consumer update priorities
end
```

4.4. IOT environment with energy monitoring system

A housing development of smart meters are used to monitor energy consumption in real time. The developed SEMS power data can be uploaded to the server by establishing a successful connection via an Ethernet shield. Further, uploaded data can be accessed and monitored using data monitoring systems. The graphical view of the overall system is depicted in Fig. 7.

The energy monitoring system consists of a server and a database management system for real-time monitoring and data acquisition. The server used is WAMP, and the overall application is accessed using localhost in intra-net. The hostname can be changed from localhost to specific domain name to access power parameters via Internet. Multiple databases are created in the server to store different power parameters. The firmware involved in establishing successful connection for data uploading is shown in the Fig. 8. Power data is uploaded to the server at the interval of 5 min. In the web portal only authorized person can access into the webpage using login credentials. Further, results and trend graphs are presented in the next section.

5. Results and discussion

This section describes the prediction results and validation of Intelligent Smart Energy Management System for demand side consumers. Different machine learning models are evaluated to find the accurate prediction scheme. Experimental set up is developed as discussed in the previous section-4, and different cases are demonstrated for optimal load scheduling with assigned priority considering predicted power. Finally, the IoT environment is integrated for data monitoring and analysis.

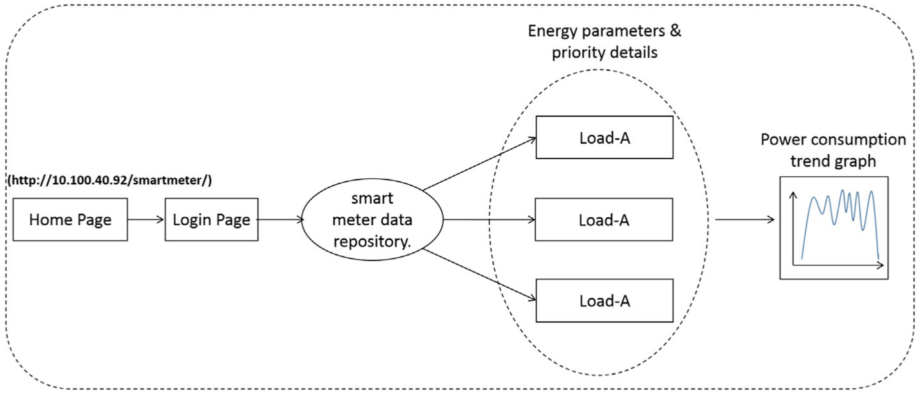


Fig. 7. Overview of IoT environment.

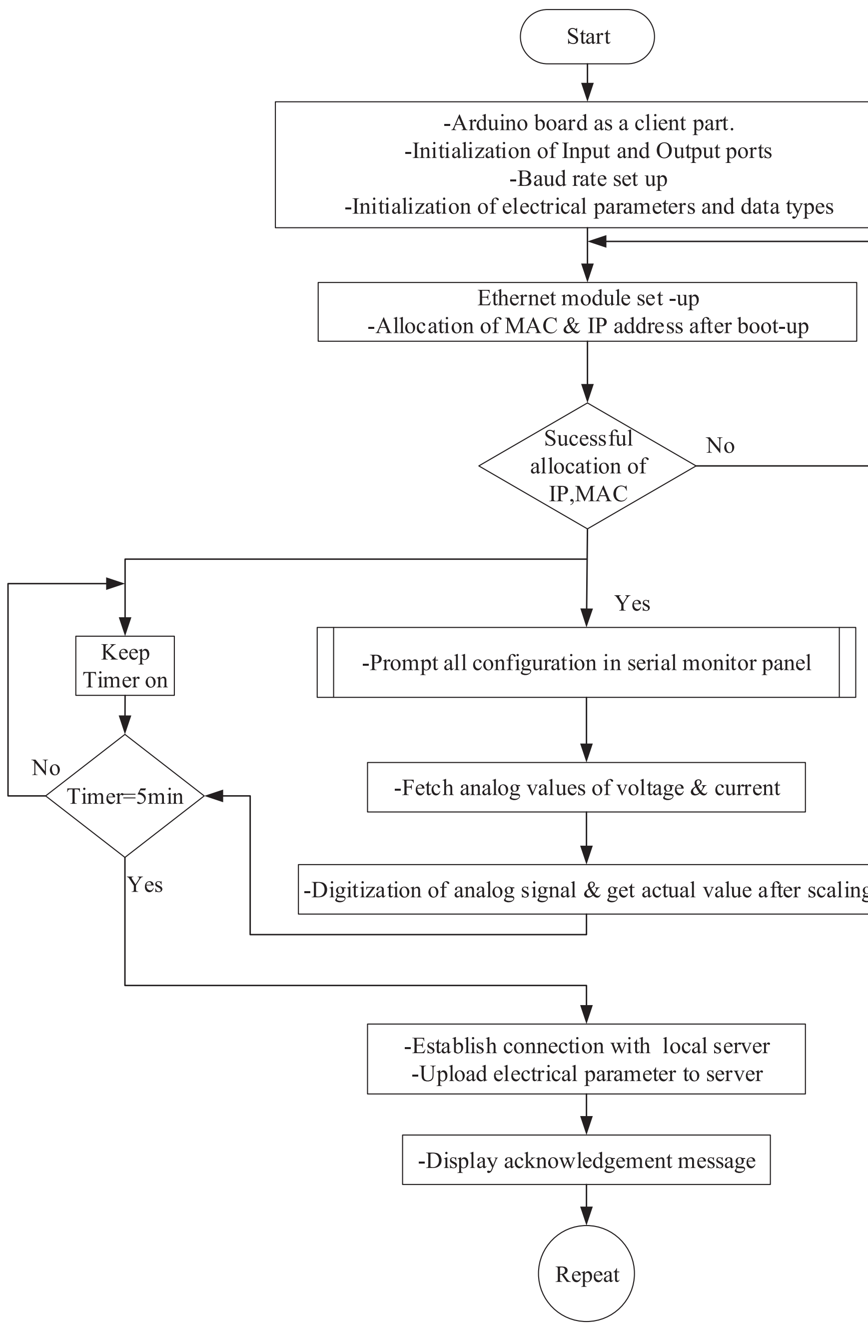


Fig. 8. Firmware flow of IoT environment for ISEMS.

5.1. Evaluation of prediction models

In this section, results are analyzed using different machine learning models to find an accurate prediction methodology. Parameter tuning process is discussed to find the optimal value. Foolwing, Month-wise and Day-wise prediction are carried out using different models developed. Further, error analysis is done to find the best accurate model.

5.1.1. Parameter tuning of optimization techniques

To find the best optimal value in the optimization technique, it needs parameter tuning with several different combinations of dependent variables. Following, the details of parameter tuning process for different algorithms are discussed in brief.

- Parameter tuning of SVR
  The hyperparameters of SVR are randomly selected in a typical SVR algorithm. However, PSO is a general optimization algorithm which is used in this context to find the optimal values of SVR parameters. As explained earlier, PSO searches for an optimal point in the whole solution space. Each point in the solution space is a candidate for the optimal value. The advantage of using PSO is that it reduces the time required for obtaining the optimal values by using an intelligent algorithm that doesn't have to check each and every point in the solution space.
- Parameter tuning of ANN
  The number of inputs are considered as independent and number of outputs as dependent parameters with variable number of neurons in the hidden layers. Different parameters of PSO

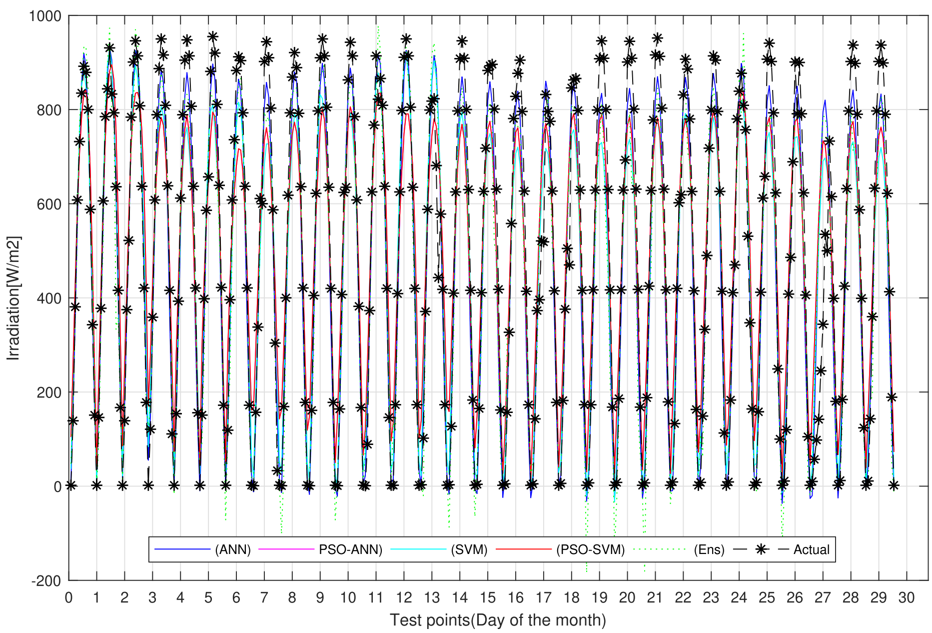


Fig. 9. Prediction for sunny days(April-month) using different models.

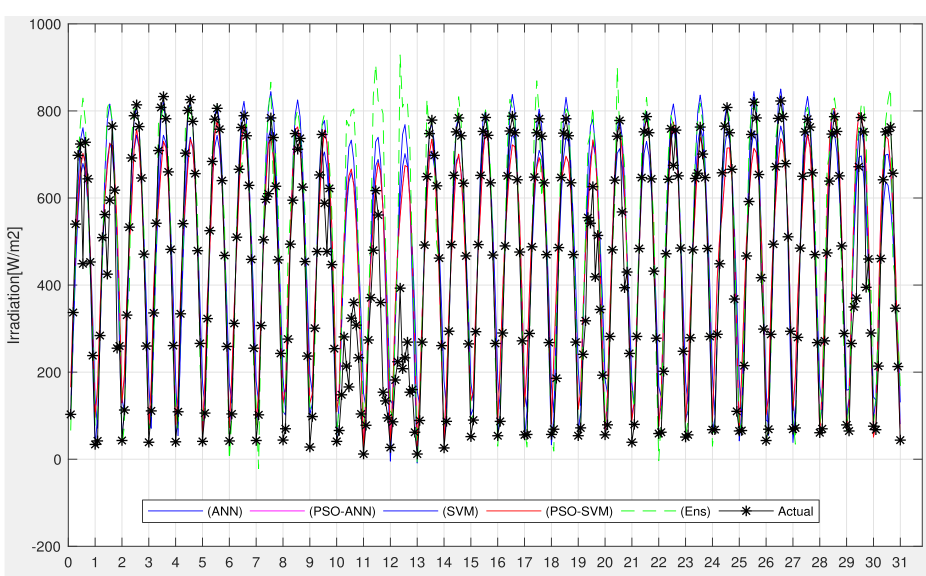


Fig. 10. Prediction for winter days(Dec-month) using different models.

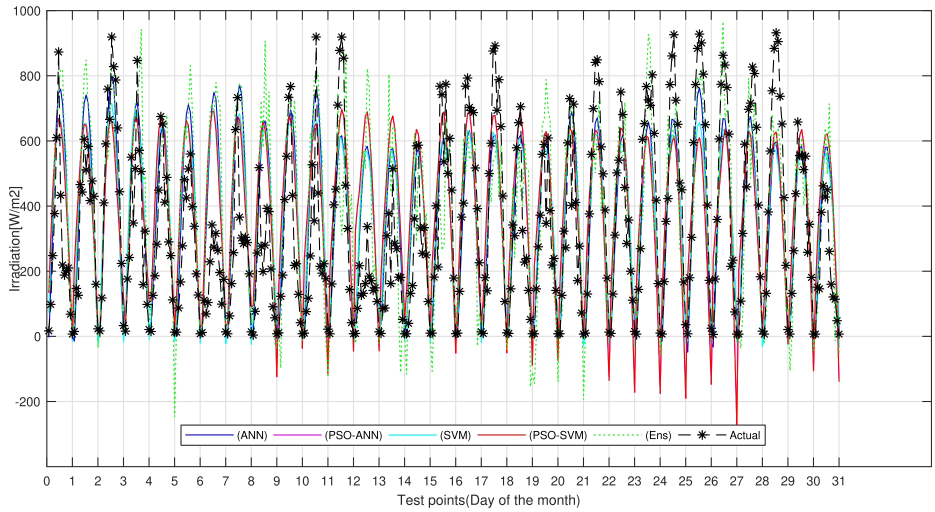


Fig. 11. Prediction for rainy days(July-month) using different models.

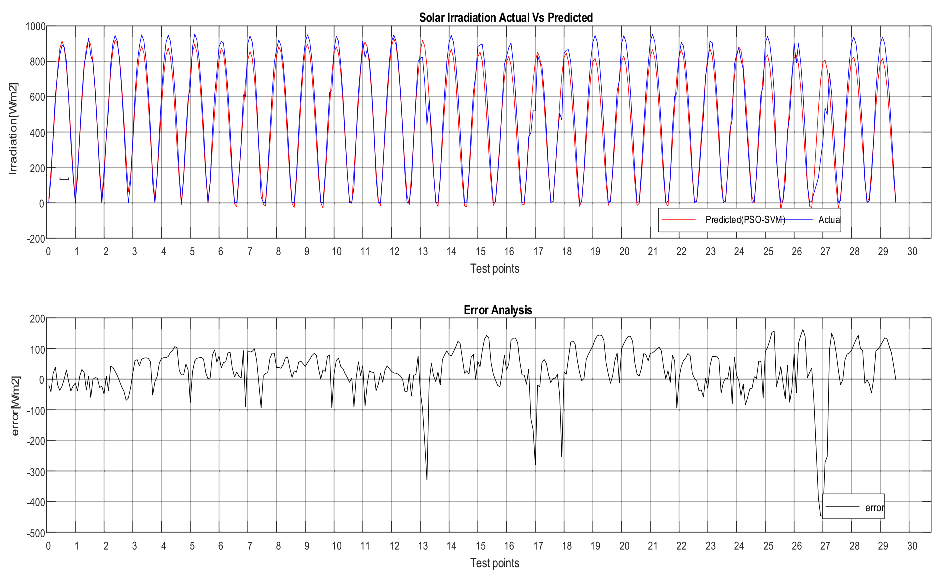


Fig. 12. Month-wise(April) prediction for sunny days based on PSO SVM model.

are swarm population size(N), acceleration factors (C_1 and C_2) and inertia weight(w). Whereas, the parameter of ANN is mainly dependenton the number of neurons in the hidden layer(n). The inertia weight is generally chosen randomly. Different combinational values of swarm population size, acceleration factor and number of hidden layers are chosen. In order to perform first analysis, constant value of acceleration factors (C_1 and C_2) and the number of hidden layer(n) are considers, and swarm size is varied to obtain optimum swarm size. Further, optimum acceleration factor values(C_1 and C_2) are obtained using optimum swarm size and same size of hidden layers(n). Finally, last analysis is carried out considering the optimum value of swarm size and optimum value of acceleration factor (C_1 and C_1). Different combinations of C_1, C_2 and swarm population size are used with different number of hidden layer to find the best optimal value.

5.1.2. Month-wise seasonal prediction using machine learning approach

In this section, for the month wise seasonal prediction of Mangalore region, the annual facts were referred from historical data to divide rainy, summer and winter season. It is found that heavy rain occurs in the month of June, July, August, September and October. However, the July month witness for the wettest month in a year. Further, May is considered to be warmest month and December is considered to be the coolest month of the year.

The simulation experiments are performed using five different prediction models such as ANN, PSO-ANN, SVM, PSO-SVM, and Ensemble techniques. Individual experiments are carried out using different models. Initially, models are trained using 2012 and 2013 year dataset, validated using 2014 dataset to check the accuracy of prediction models used. Different evaluation metrics such as MAPE and MAE are considered to check the performance of prediction models. From the prediction plots, it is observed that during sunny days as shown in Fig. 9, the solar irradiation is found to be periodic and also prediction error is minimum. Among the different models compared, the PSO based SVM outperforms all the other models in terms of accuracy.

Similarly, the simulation experiments are carried out for winter days by training the 2012 and 2013 year dataset and testing using the December month 2014 data as shown in Fig. 10. It is observed that solar irradiation level is less compared to sunny days.

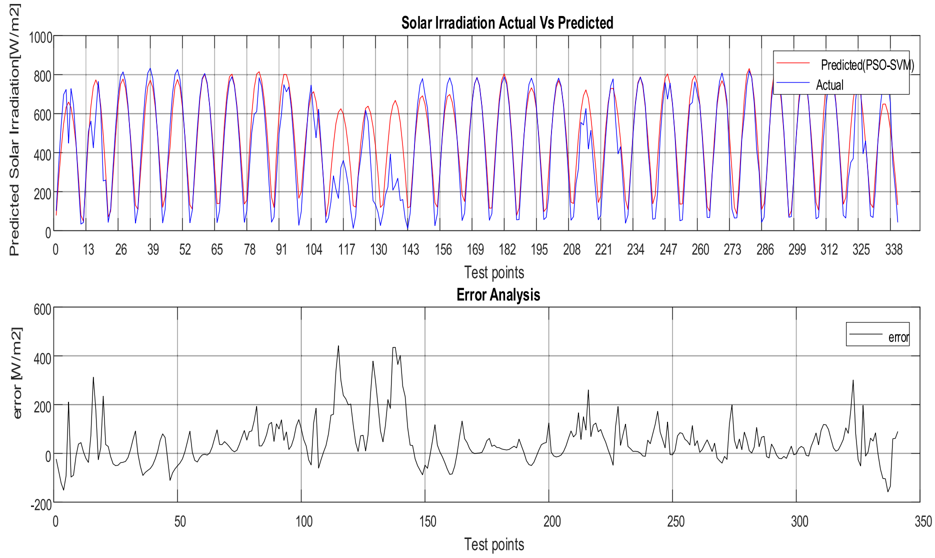


Fig. 13. Month-wise(Dec) prediction for winter days based on PSO SVM model.

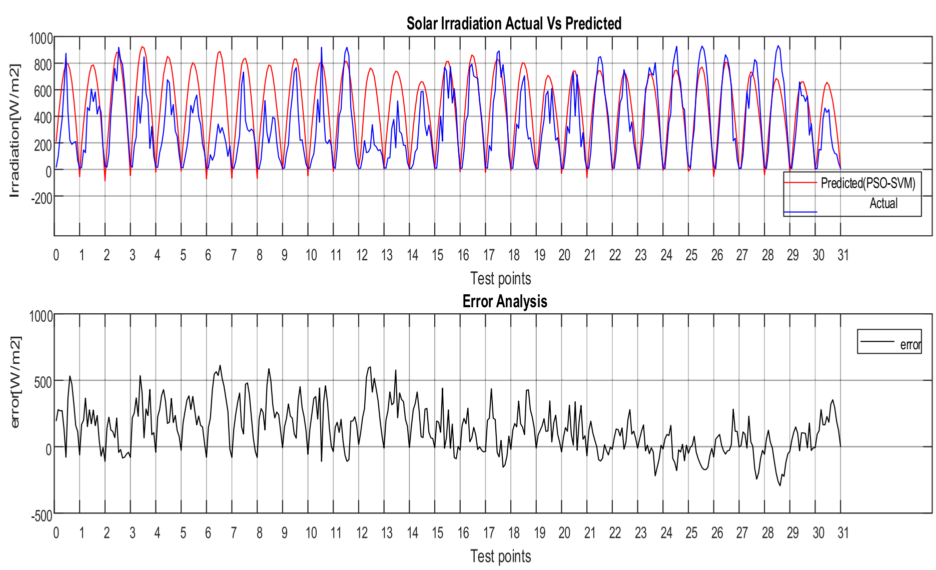


Fig. 14. Month-wise(July) prediction for rainy days based on PSO SVM model.

Table 1
Month-wise Error analysis.

	Error Index	ANN	SVM	ANN-PSO	SVM-PSO	Ensemble
December	MAE	67.1241	81.8647	65.5030	60.4142	80.6328
	MAPE	6.71241%	8.18647%	6.55030%	6.04142%	8.0633%
	RMSE	108.1940	115.3036	119.5684	109.6596	138.8190
April	MAE	70.2847	74.5081	68.9326	61.6458	75.5474
	MAPE	7.02847%	7.4508%	6.89326%	6.16458%	7.5547%
	RMSE	91.9098	114.3410	118.4938	83.7416	100.7348
July	MAE	126.8701	128.8019	126.199	115.6627	130.7009
	MAPE	12.68701%	12.8802	12.6199%	11.56627%	13.0709%
	RMSE	165.5247	162.9518	191.3242	157.9393	201.4113

However, the irradiation level is periodic, and hence prediction accuracy is better. PSO based SVM model shows better performance compared to all other models.

Finally, simulation experiments are carried out for rainy days by training the 2012 and 2013 year dataset and testing using the July month 2014 data as shown in Fig. 11. It is observed that solar irradiation level is less and very random compared to sunny and winter days. Hence, the error rate is also significant in the case of the rainy season.

In the following case, among the different methods compared, the error analysis for peak seasonal months are chosen. The summer season April month prediction for PSO based SVM model is

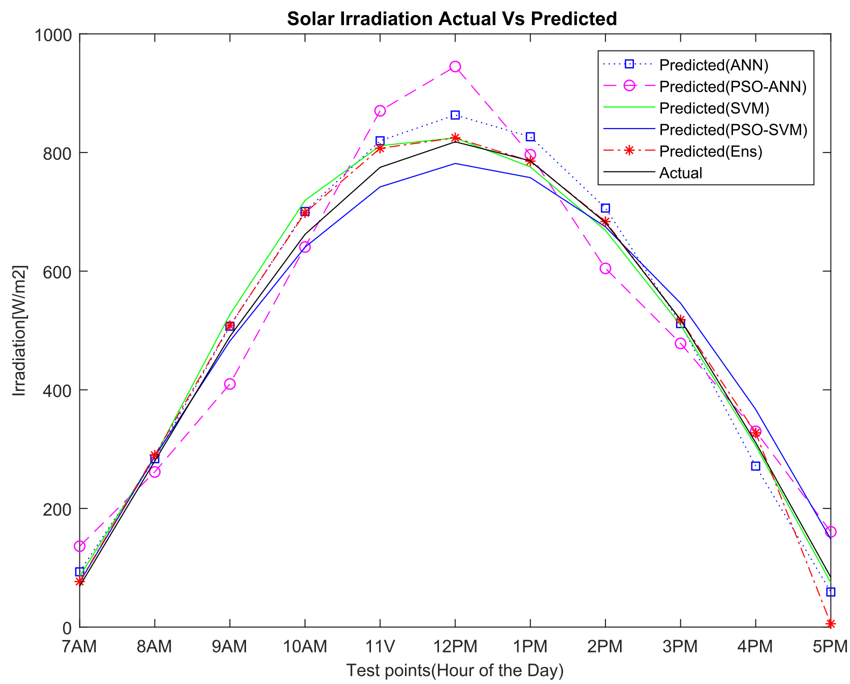


Fig. 15. Day-wise prediction of power level using different models.

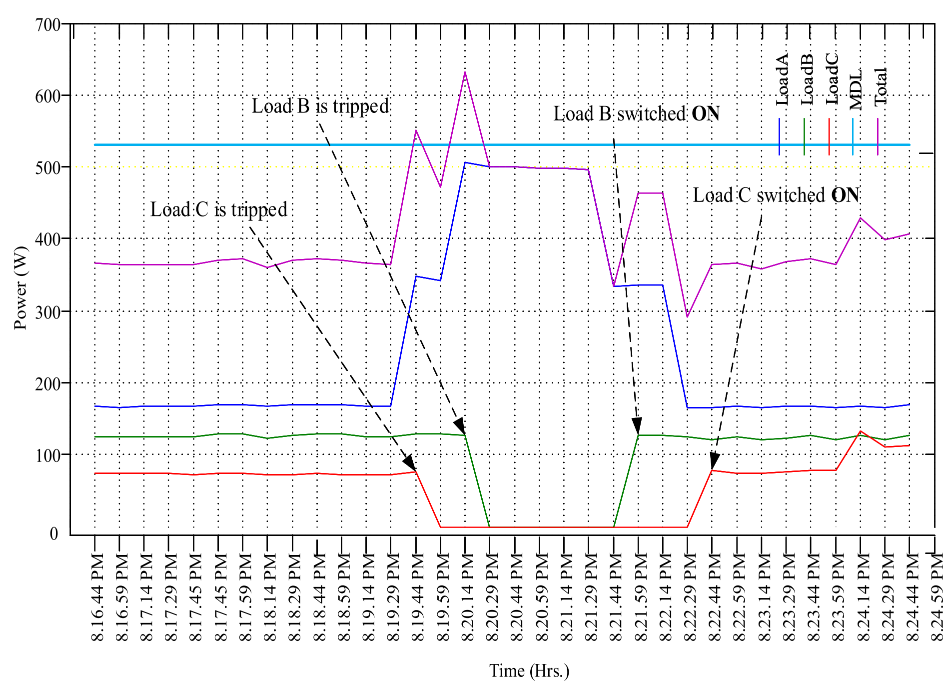


Fig. 16. Load scheduling based on assigned priority.

shown in Fig. 12. Further, for winter and rainy season, December and July month error analysis plot are presented in Fig. 13 and 14 respectively.

A more detailed month-wise comparison with the different evaluation metrics are tabulated in the Table 1. From the Table 1 it is observed that PSO based SVM model outperforms all other regressors in terms of mean absolute percentage error (MAPE). It is observed that ANN and Ensemble method also gives better accuracy during the month of December and April since the data is more periodic. Whereas, in the month July, as it is a rainy season the historical data is very random and it become difficult to predict accurately.

5.1.3. Day-wise Prediction using machine learning approach

The daywise short term prediction case is presented in Fig. 15, which compares the different machine learning based regressors for predicting solar irradiance for a day. The Figure shows a solar Irradiation (W/m^2) vs. Time (Hour) plot, the time slot is considered from 7 AM to 5 PM for a day. The models were trained with two-year dataset collected from NSRDB database and tested for a day basis to check the performance of the prediction model on the dataset. In this case, among all the forecasting regressor model implemented, PSO based SVM regressors shows significant performance over the other techniques as shown in Fig. 15.

5.2. Performance evaluation of ISEMS

In this section, results for different scenarios are demonstrated and analyzed. The experiments are conducted by assigning an order of priority to an Appliance with different configurations. Further, user comfort case and cost optimization technique are demonstrated to prove the effectiveness of the energy management system.

5.2.1. Operation strategy of loads for configured priority with available power

In this case, the incandescent bulb bank is considered as Load A, and it is assigned with the highest priority. A fan load is assigned with mid priority. Since the battery charging is a schedulable load, it is assigned with an low priority. The SEM load scheduling operation is depicted in Fig. 16.

In this case, as shown in Fig. 16, the maximum demand is set to be 530*W* (i.e., input from predicted PV output). During the period from 8.16.44 PM to 8.19.44 PM, all the three loads are turned 'ON' since the maximum power consumption is less than the available power or maximum demand limit (MDL). At the instant 8.19.44*PM*, extra incandescent bulbs in the bank are switched (i.e., two bulbs ON) so that the total power consumption exceeds the MDL. The proposed SEM controller immediately reacts to this scenario and turns off the battery charging load. Further, at the instant 08.20.29 PM, the power consumption of lighting load is increased by switching the extra bulb (i.e., three bulbs ON) and hence, the lighting load alone consumes 497 W of 530 W MDL. Therefore, the controller switches OFF the second load as well to balance the supply and demand. The Power consumption details and scheduling of appliances by SEMare listed in Table 2 as case (1). Similarly, case (2) is presented by changing the order of load priority as shown in Table 3 and the appliance status after load scheduling is listed for the same.

Table 2
Appliance status after load scheduling case(1).

Appliance	Appliance status	Priority	Apparent Power (kW)	Power Demanded (kW)	Maximum Demand Limit (kW)	Appliance status (After Power Negotiation)
Load a	On (2-bulb)	High	0.330	0.540	0.530	On
Load b	On	Medium	0.127			On
Load c	On	Low	0.083			Off

Table 3
Appliance status after load scheduling case(2).

Appliance	Appliance status	Priority	Apparent Power (kW)	Power Demanded (kW)	Maximum Demand Limit(kW)	Appliance status (After Power Negotiation)
Load a	On (2-bulb)	Low	0.330	0.540	0.530	Off
Load b	On	Medium	0.127			On
Load c	On	High	0.083			On

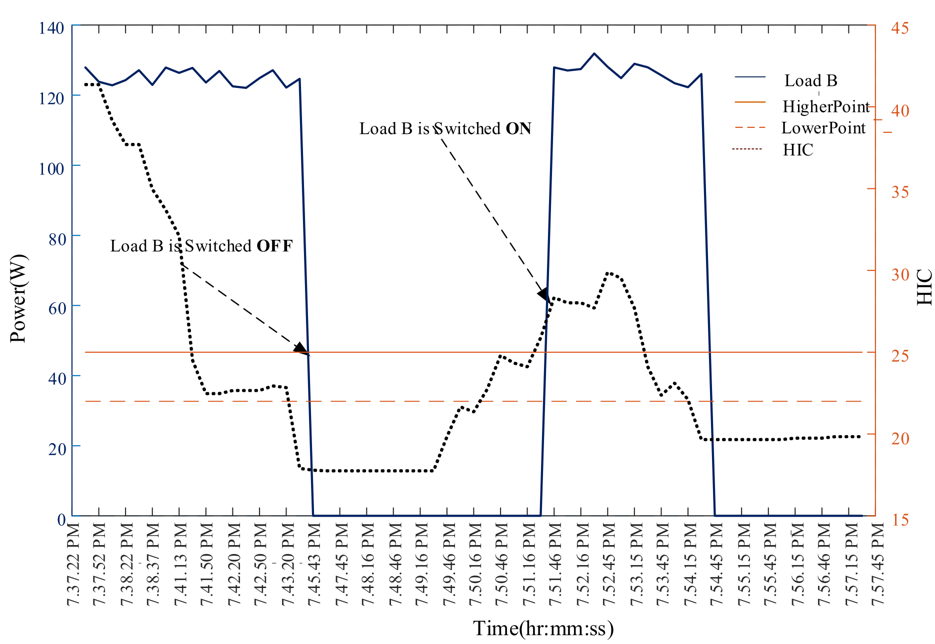


Fig. 17. Load scheduling with sensed parameter.

5.2.2. User preference setting with perceived data

This section presesents the experimental results to incorporate the user comforts case, the SEM system is equipped with a humidity and temperature sensor (i.e., *DTH*11 module). Load scheduling characteristics based on temperature and humidity conditions are shown in Fig. 17. In the proposed SEMS, the user can configure the lower and upper threshold limits for the temperature. When the room temperature crosses these limits, the proposed controller switches the fan load. In Fig. 17, at the instant $7:43:20PM$, room temperature is below 22 °C. Hence, the controller turned off the fan load. Similarly, after some time (i.e., at $07.51.16PM$) temperature has crossed the upper limit (i.e., 25 °C), the controller turned on the fan load.

5.2.3. Accuracy calculation and Power Consumption measurement of ISEMS Modules

The calibration method in our study is performed with a power meter considered as a reference model. The expressions are as follows:

$$(Measured\_value - offset\_factor) * k$$
$$= (Value\_observed\_in\_ref\_power\_meter)$$

where, k is a scaling factor. At more than two load conditions we have recorded power measured by our setup and that of reference meter. Thereby, we determine the offset factor and scaling factor. In our experimental module, to determine the accuracy, we to consider following error cases.

- Non-linearity of ADC module
- Tolerance of resistors components
- Accuracy of op-amps
- Accuracy of LEMs transducers

The ATMEGA 328 microcontroller is provided with successive approximation type analog to digital converter(ADC). The ADC module has a resolution of 10-bits. From the datasheet specification of ATMEGA328 controller it is found that there is a error of $\pm 1LSB$. Hence, the accuracy of the converter used is $\pm 0.125\%$. Further, assuming tolerance of resistors components used as 0.05%. The following calculations are made. Power(P) is calculated using the instantaneous product value of Voltage(V) and Current(I), which is expressed as follows.

$$P = V \times I \tag{4}$$

The designed power supply unit is supplied with $230V$ main supply, which outputs $\pm 12V$ to power up transducer. The power supply module has a possible measurement error of 2%. The resistor components used in the design of voltage divider circuit have a tolerance of 0.05%. Further, considering the internal reference voltage to be $0.9V$. Thus, the overall error might contribute to $2 + 0.05 \times 2 = 2.1\% = 0.0189v$.

To measure the instantaneous values of voltage and current from the transducer output multiplied by the suitable scaling factor, the equation can be written as,

$$V = \left((0.9 \pm 0.0189) \times \left(1 + \left(\frac{R_f}{R_1} \right) \right) - \left(\frac{R_f}{R_1} \right) \times V_{LEM(v)} \right) \times k_v \tag{5}$$

where, k_v is a Voltage scaling factor.

Similarly for the current measurement,

$$I = \left((0.9 \pm 0.0189) \times \left(1 + \left(\frac{R_f}{R_1} \right) \right) - \left(\frac{R_f}{R_1} \right) \times V_{LEM(i)} \right) \times k_i \tag{6}$$

where, k_i is a Current scaling factor.

The percentage of error in ADC is $\pm 0.125\%$.

Voltage accuracy measurement:

From the manufacturer data-sheet, it is observed that the percentage of error for LEM LV 25P transducers in secondary coil current I_S is found to be 0.9%. The RMS output of LEM transducer is measured to be $1.89V$ for input voltage supply of $230V$.

Table 4
Power Consumption Analysis of ISEMS.

SEM Component	Device	Approximate Power Consumption	Operating Duration	Annual Energy Consumption (kWh/Year)
SEM Unit (Coordinator)	- 16*2 LCD Display -Xbee module -Microcontroller with Ethernet shield. (data transmission at 1 min interval)	0.1945 Watts	Operates at 24/7 with energy display on LCD Screen	1.703 kWh/yr
Load Controller	(Router) -Sensor Module -Power supply module -Microcontroller -Zigbee Module -Relays	0.8492 Watts	Operates at 24/7 with energy display on LCD Screen	7.438 kWh/yr

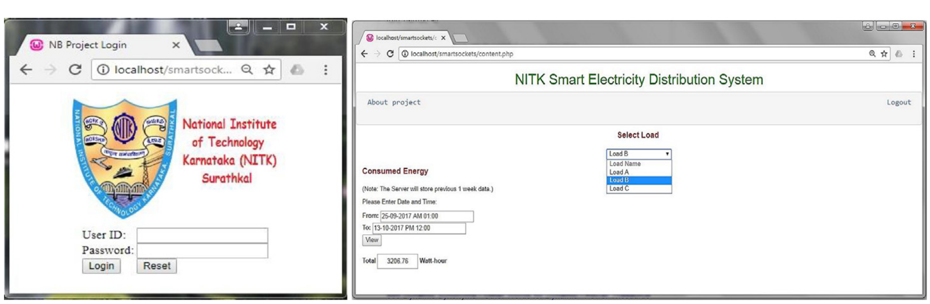
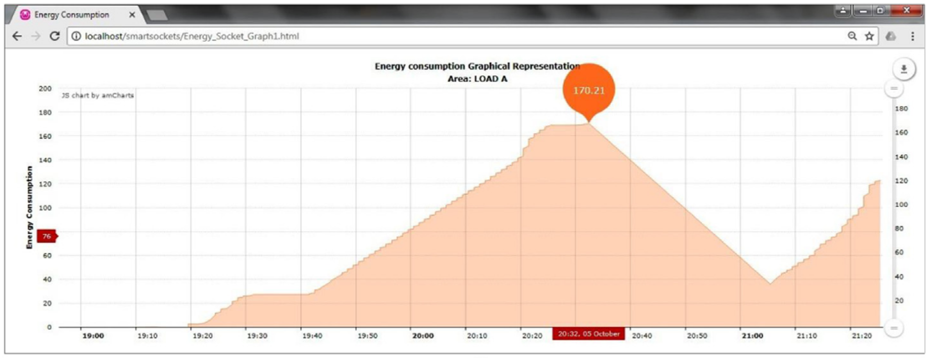


Fig. 18. Web access page.



(a)

SERIAL.NO	TIME	RMS VOLTAGE IN VOLTS	RMS CURRENT IN AMPS	APPARENT POWER DEMAND IN VA	POWER FACTOR	ENERGY IN WATT-HOUR	PRIORITY
107	2017-10-05 19:41:35	227.40	0.00	0.00	0.00	27.38	1
108	2017-10-05 19:41:50	226.22	0.77	174.32	1.00	27.98	1
109	2017-10-05 19:42:05	226.37	0.77	174.27	1.00	28.69	1
110	2017-10-05 19:42:20	225.80	0.77	172.98	1.00	29.44	1

(b)

Fig. 19. Power consumption data.

Considering the tolerance of all resistors used in circuit is 0.05%. The percentage of error for $V_{LEM(v)}$ is given by,

$$V_{LEM(v)} = LEM(error) + R_f(error) + R_1(error) + R_2(error) + R_3(error) \quad (7)$$

where, R_2=100 kΩ, R_3=100Ω.

$$\begin{aligned} V_{LEM(v)} &= 0.9\% + 0.05\% + 0.05\% + 0.05\% + 0.05\% \\ &= 1.1\% 0f 1.89v = 0.02079v \end{aligned} \quad (8)$$

Hence the above equation can be written as,

$$V = \left((0.9 \pm 0.0189) \times \left(1 + \left(\frac{R_f}{R_1}\right)\right) - \left(\frac{R_f}{R_1}\right) \times 0.02079\right) \times k_v \quad (9)$$

$$V = (1.8 \pm 0.0586) \times k_v \quad (10)$$

Thus, the percentage of error in voltage measurement is $\pm\frac{0.0586}{1.8} = \pm 3.25\%$.

Therefore, overall percentage of error in voltage measurement is calculated as: $3.25 + 0.125 = \pm 3.375\%$.

Current accuracy measurement: The supplied main current to the load is measured by passing through a current transducer LEM LA 25P. A nominal current of 2 A is considered to be passed through the transducer. In this case I_S = 2 mA which flows through a burden resistor of 100Ω leading to *RMS* output voltage of LEMs transducer proportional to 0.2 A.

Hence, the overall percentage error in current transducer can be calculated as:

$$V_{LEM(i)} = LEM(error) + R_f(error) + R_1(error) + R_2(error) + R_3(error) \quad (11)$$

where, $R_2 = 100$ kΩ, $R_3 = 100Ω$.

$V_{LEM(i)}$ = 1.05% of 0.2A = 0.02A

$$I = \left((0.9 \pm 0.0189) \times \left(1 + \left(\frac{R_f}{R_1}\right)\right) - \left(\frac{R_f}{R_1}\right) \times 0.02079\right) \times k_i \quad (12)$$

$$I = (1.8 \pm 0.0407) \times k_i \quad (13)$$

The percentage of error in the current measurement is $\pm\frac{0.0407}{1.8} = 2.26\%$.

The percentage of error in the current measurement including ADC error is $2.26 + 0.125 = \pm 2.385\%$.

Therefore, the cumulative percentage of error in power measurement is calculated as, $3.25\% + 2.385\% = \pm 5.635\%$.

Power consumption measurement: The deployment of SEM units which runs 24 h a day for 365 days a year will add to the annual electricity consumption due to the SEM's residual power needs. Therefore, we analyze the energy consumption of the demonstrated SEM unit and load controllers used in this experiment. Further, the estimated power consumption is shown in Table 4.

5.3. IOT environment with energy monitoring system

This section presents the details of remote monitoring and database of the energy management system. The user needs to enter the login credentials in the login page as shown in Fig. 18. Following, successful login into the webpage, the user can enter into the main page.

In the main page user can have all the privileges to select the different laboratories, check the real time energy consumption, power usage data and also, possible to view the trend graph of energy consumption. The load wise power data such as RMS current, power demand, power factor, energy consumption and assigned priority for a load of developed SEMS system is shown in Fig. 19.

At the end of the page, total energy consumption of the selected laboratory is displayed. In the main page, there is a provision for checking trend graph of power consumption of different loads as depicted in Fig. 19.

6. Conclusion

The ISEMS will be setting a platform in demand-side energy management system considering a renewable energy source. The ISEMS is designed and developed in the laboratory environment, and the experiments are conducted to demonstrate the working of the power negotiating algorithms deployed in the SEM unit.

The ISEMS ensures optimum utilization of renewable source when the available generation is limited, evaluated by accurate prediction of solar irradiation on the day ahead and month ahead basis, thus reducing the usage of non-critical (low priority) appliance. Following, the real time experimental tests are conducted to show the running of only higher priority appliance considering demand limit constraint. In this case, different machine learning methods-ANN, PSO based ANN, SVM, PSO based SVM and Ensemble techniques are evaluated to find the accurate prediction models. Comparison of different prediction models are carried out in terms of Mean Absolute Error (MAE), Mean Absolute Percentage Error(MAPE) and Root Mean Square Error(RMSE). Furthermore, the PSO based SVM model outperforms all other models used in the recent literature as per our understanding, where hyper parameters are tuned automatically based on the PSO based optimization algorithm. Thus, Intelligent Smart Energy Management System is developed which negotiates the available predicted power and dispatch the control action depending on the consumer assigned priority of an appliance. Finally, a secure IoT environment is integrated for remote load monitoring with a provision to use it for data analytics purpose such as load disaggregation.

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