Distributed Renewable Energy Sources for Load Balancing in Smart Grid

Thesis Report

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Submitted By

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Certificate

I hereby certify that the matter which is being presented in the thesis report entitled, *"Distributed Renewable Energy Sources for Load Balancing in Smart Grid"*, in partial fulfillment of the requirements for the award of degree of Masters of Engineering submitted in Computer Science and Engineering Department of Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of *Dr. Neeraj Kumar*.

The work presented in this thesis has not been submitted for award of any degree of this or any other university.

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This is to certify that the above statement made by the candidate is correct and true to the best of my knowledge.

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Abstract

Existing electric grid is facing one of the major concerns, to decarbonize the electricity generation and consumption at various levels in power sector. However, with an inclusion of information and communication technology (ICT)-based infrastructure in the existing electric grid, it can act as smart grid (SG) by making a balance between demand and supply which in turn decarbonize the environment. Various strategies for efficient energy consumption with reduced dependency on fossil fuels to control carbon emissions are under development across the globe. However, in extreme load conditions, these strategies may not work well due to inefficient usage of renewable energy sources (RES). To achieve the aforementioned goals, an adaptive approach towards distributed generation by incorporating RES in the existing electric grid is required. Moreover, there is a requirement to shift the conventional users from passive consumers to active *"Prosumers"* to meet the ever-increasing growth of energy demand during peak hours. Prosumers can feed locally generated energy back to the grid to make a balance between demand and supply in the peak hours. In this paper, a novel scheme to address the aforementioned issues is proposed in which many prosumers are combined into a single unit to incorporate RES in SG. In the proposed scheme, an intelligent Artificial Neural Network (ANN)-based controller is designed for day-ahead load prediction to manage the mismatch between load demand and renewable generation supply in real-time. Also, to ensure energy availability at all times to the end users, a greedy heuristic scheduling algorithm is designed. The proposed scheduling algorithm allows the controller to select between various power options to meet the energy demands. The proposed scheme is evaluated with respect to various evaluation metrics such as-Mean Square Error (MSE), Mean Absolute Error (MAE), and Root Mean Square Error (RMSE). Also, simulation of the proposed scheme for a set of twenty-five prosumers illustrates that the amount of energy drawn from grid is reduced by 46.90% in comparison to the case when RES are not used. The results obtained clearly show the efficacy of the proposed scheme in real-time scenario.

Keywords: Artificial neural network, Load forecasting, Machine learning, Renewable energy sources, Smart grid.

Contents

List of Figures

List of Tables

List of Symbols

Symbols	Definitions
α	Constant of yield power.
Δw_{ij}	Connection weight change between two consecutive layers of ANN model.
η	Learning rate of ANN model.
γ_s	Error in solar panel production calculations.
γ_w	Error in wind generator production calculations.
λ	Error in day-ahead load forecasting.
μ	Scalar for levenberg-marquardt algorithm.
Ω	Momentum factor of ANN model.
π	Activation function used in ANN model.
ρ	Air density.
σ	Performance ratio for solar panel which gives the quality of PV installation irrespective of orientation of the panel with values from 0.5 to 0.9.
θ	Dimensionless energy coefficient with values from 0.25 to 0.45.
A	Rotor swept area.
$B_{n,t}$	Mismatch between the total load demand and total RES generation for a set of N prosumers.
C_t	Energy received from grid during interval t (kW).
d_i	Target of Artificial Neural Network model.
e_i	Error of i^{th} node in the proposed ANN model.
e_j	Error of the output node in the proposed ANN model.
E_s	Solar energy generated (kW).
E_t	Energy stored in battery at beginning of interval t (kW).
E_w	Wind energy generated (kW).
E_{max}	Battery capacity.
G_{max}	RES generation capacity of a set of N prosumers (kW).
$G_{n,t}$	Total RES generation for the set of N prosumers (kW).
$g_{n,t}$	Cumulative RES generation in prosumer n during t (kW).

$L_{n,t}$	Total day-ahead predicted load for the set of N prosumers (kW).
$l_{n,t}$	Day ahead load requirements of prosumer n during t (kW).
M	Total number of input output patterns in the ANN network.
m	Input-Output pattern used for learning; $m \in M$.
N	Total number of prosumers in the proposed system.
n	Number of prosumers in the proposed system; $n \in N$.
o_i	Output of Artificial Neural Network model.
P	Solar panel area (m^2).
S	Average solar radiation on solar panels (kWh/m^2).
$s_{n,t}$	Energy generated by solar panel in prosumer n during t (kW).
T	Total number of time intervals per day; here $T = 24$.
t	Number of intervals per day for which scheduling is to be performed; $t \in T$.
V	Wind speed (miles per hour).
$w_{\iota,j}$	Connection weight between two consecutive layers of ANN model.
$w_{n,t}$	Energy generated by wind generator in prosumer n during t (kW).
Y	Solar panel yield which gives the ratio between electrical power generation and area of a single solar panel.
ι	Inputs to the ANN nodes.
ψ	Objective function.

List of Abbreviations

AMI	Advanced metering infrastructure
ANN	Artificial neural network
DC	Demand center
EMS	Energy Management Systems
GC	Generation center
GHG	Green house gas
GLS	Greedy load scheduling
ICT	Information and communication technologies
MAE	Mean absolute error
MAPE	Mean absolue percentage error
MSE	Mean square error
RES	Renewable energy sources
RMSE	Root mean square error
SG	Smart grid

Chapter 1

Introduction

1.1 Electric Grid

The existing electric grid can be viewed as an interconnected network for supplying energy from generation centers (GC) to demand centers (DC). In this context, the GC refers to the center where energy is generated, traditionally using fossil-fuel sources of energy. Furthermore, the DC refers to the consumers of energy. Moreover, transmission lines are made use of to carry energy from distant GCs to various DCs, which are interconnected using distribution lines. Fig. 1.1 shows the basic block diagram of the existing electric grid. The major operations of an electric grid can be outlined as follows:

- Energy Generation
- Energy Transmission
- Energy Distribution
- Energy Control

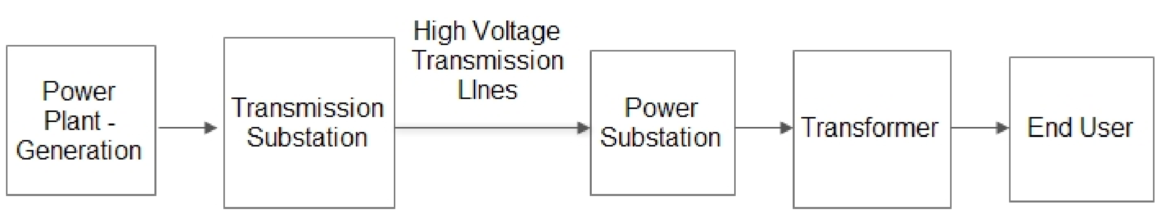

Figure 1.1: Basic layout of the existing electric grid.

In other words, the existing electric grid is simply a hierarchical network of GC, DC, transmission and distribution lines. It employs a one way communication between its components as shown in Fig. 1.1. Thus, there are limited control options because GC has no real-time information about the energy requirements at the DC. Furthermore, the metering technology, i.e., automatic meter reading (AMR) enables the smooth operation of the existing electric grid by automatically collecting the usage and control data of users. It also transfers this data to the central database for analysis and bill generation. Thus, AMR assists in metering the energy consumption. However, there are various drawbacks in the existing electric grid. Firstly, its infrastructure is outdated and there is a lack of communication among its components. Secondly, the AMR technology does not accommodate corrective actions by users based on the information received from the meters. Hence, this technology fails to address the issue of demand side management. Thirdly, the existing electric grid is not flexible with respect to the user's demands and doesn't support distributed generation. Furthermore, it operates on a centralized model of generation and distribution. Consequently, the existing electric grid faces numerous challenges, such as - blackouts, unbalanced load, energy conservation, and environmental preservation. In addition to this, the existing electric grid relies heavily on fossil-fuel sources of energy, which are depleting day-by-day. This results in a rise in fossil fuel prices, thus increasing the energy prices. Hence, the aforementioned problems need to be addressed to ensure reliability, security, and sustainability. For this purpose, an adaptive approach towards distributed generation by incorporating renewable energy sources (RES) in the existing electric grid is required. However, the existing electric grid is not prepared to easily accommodate RES. This is where smart grid (SG) comes into play.

1.2 Smart Grid

SG is a modern grid which incorporates advanced sensing and control technologies to regulate the power flow between GC and DC. With the inclusion of information and communication infrastructure in the existing electric grid, it can act as an intelligent controller to take adaptive decisions with respect to demand response, data analytics, and load management [1]. For this purpose, it enables bidirectional communication between its components, i.e., GC, DC, monitoring substations, smart meters, and smart devices. Hence, it can be viewed as a convergence of computational intelligence with power system engineering which dynamically optimizes the existing electric grid operations. Moreover, it incorporates intelligent distribution topologies which change in real-time to meet the goals of efficient power delivery and cooperative generation from various conventional and non-conventional energy sources. This helps in tackling power outages by re-routing power across the grid. Fig 1.2 shows the basic architecture of SG over and above the existing layout of electric grid.

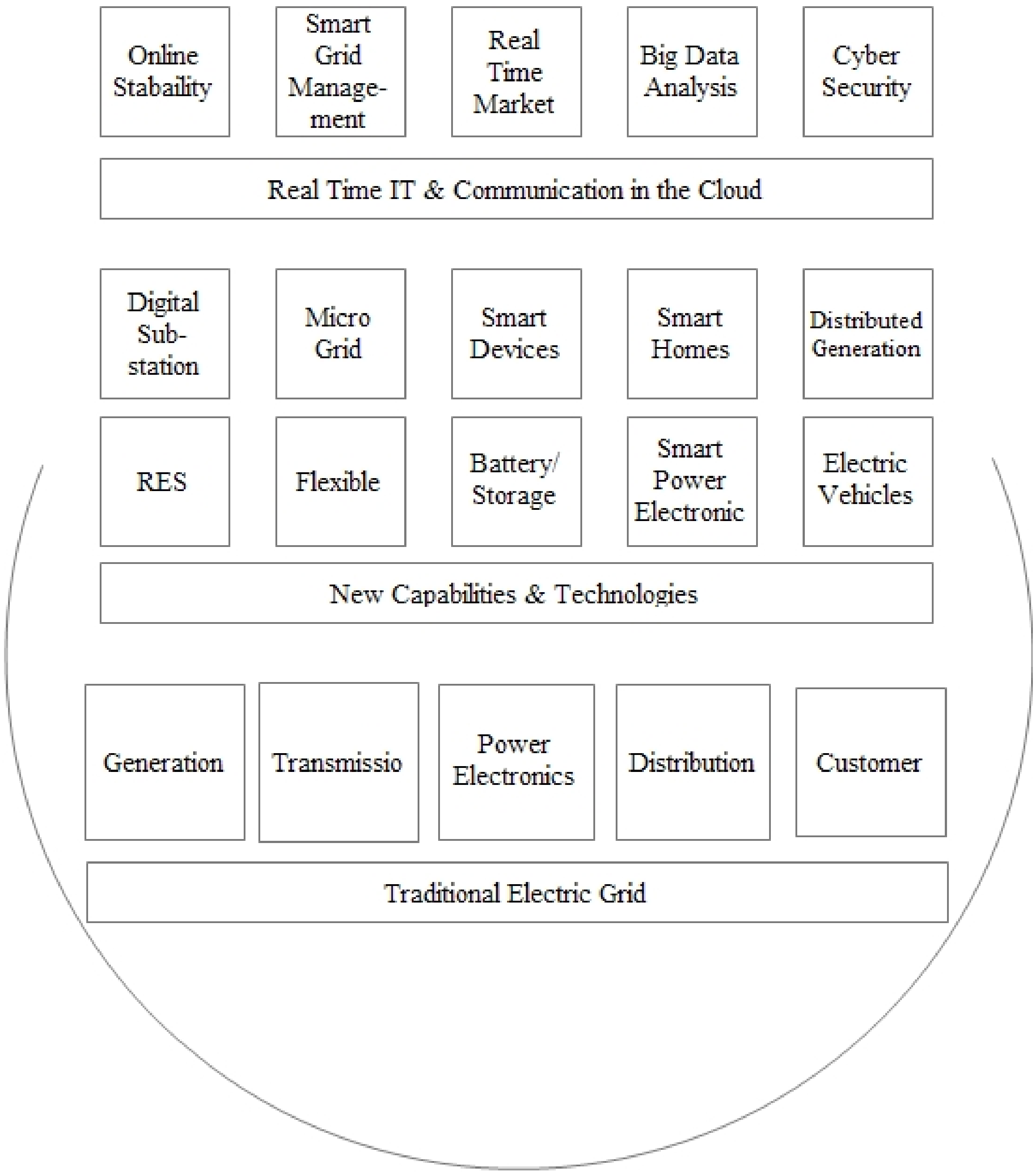

Figure 1.2: Architecture of smart grid.

In view of the aforementioned features of SG, it has its usage in many applications such as home automation, grid asset planning, and efficient power management for plug-in hybrid vehicles (PHEVs) by providing low carbon transportation [2]. Also, to enable a smooth transition into SG, a new metering technology, i.e., advanced metering infrastructure (AMI) was introduced. It can not only obtain real-time information of the individual and total demand but can also impose certain restrictions on consumption,as well as enact numerous revenue models to control expenses. Furthermore, SG also accommodates decentralized generation, sensing, and storage units. This paves the way for an effective utilization of RES, thus reducing the environmental impact of the existing electric grid. Hence, by making an efficient ICT-based infrastructure, SG can deliver an uninterrupted power supply to the consumers while reducing carbon emissions. Fig 1.3 shows the basic applications of SG.

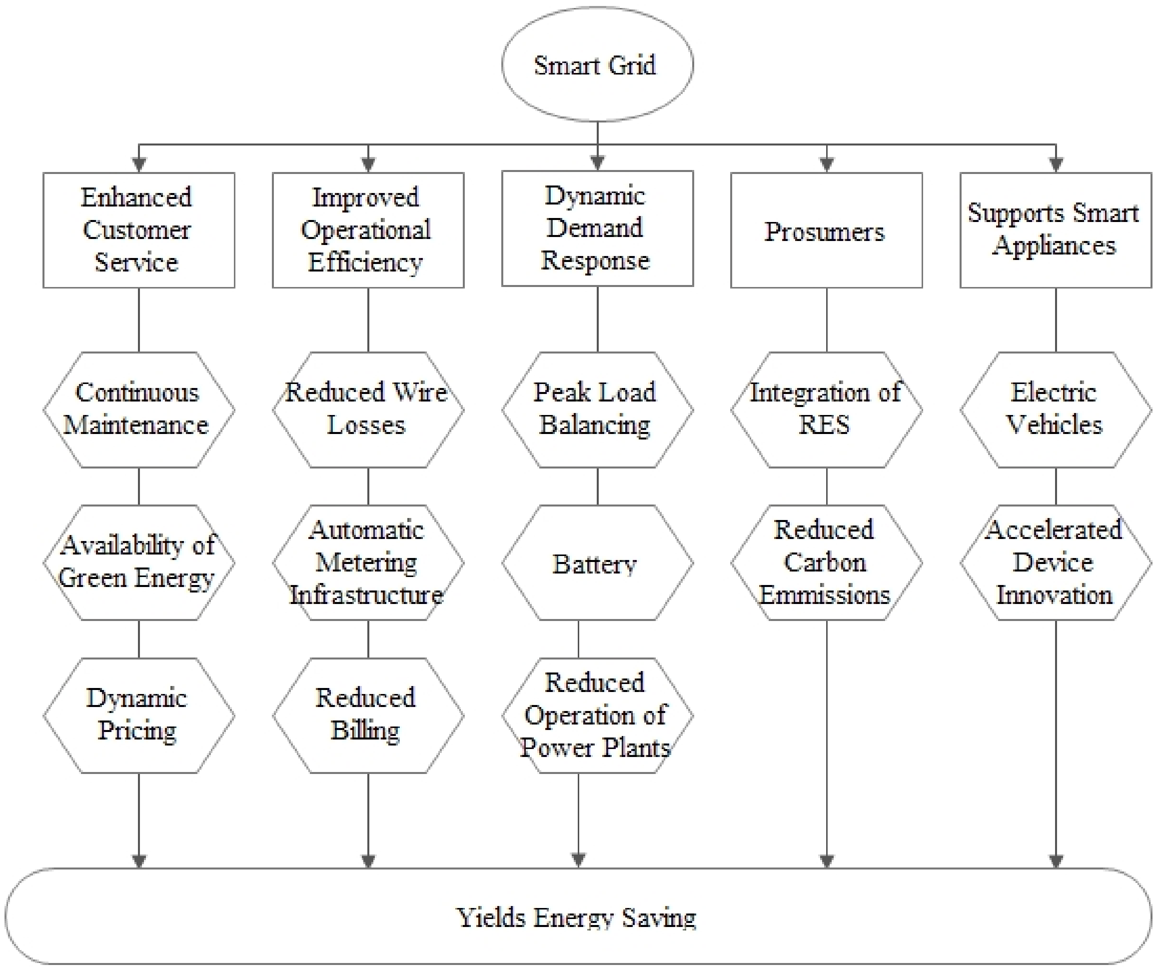

Figure 1.3: Applications of smart grid.

1.3 Basic Differences between Existing Electric Grid and Smart Grid.

The comparison between the existing electric grid and a smart grid is outlined in table 1.1.

Table 1.1: Comparison between the existing electric grid and a smart grid.

Existing Electric Grid	**Smart Grid**
Electromechanical	Digital
One-way communication between various components	Bi-directional communication between various components
Centralized generation model	Distributed generation model
Manual monitoring and restoration	Self monitoring and self healing
Limited control	Adaptive and pervasive control
Does not offer any flexibility to consumers	Consumers can keep a track of their energy consumption in real time and optimize the usage cost based on dynamic pricing
Unsuitable for implementation of smart appliances	Smart appliances can monitor load in real-time, anticipate demand and automatically adjust energy flows
Prone to blackouts	Peak Load Balancing is performed by interacting with customers
Does not support incorporation of RES	Enable incorporation of RES to pump energy back into the grid
Limited sensors and control units	Speedy isolation of network faults and recovery using advanced sensors

1.4 Key Features of the Smart Grid

The key features of the SG technology are listed below.

1. **Reliability** : SG ensures efficient fault detection without manual intervention, thus providing reliable energy supply to the users round the clock.

2. **Flexibility in Network Topology** : Network topology allows bidirectional flow of energy. As a result energy produced from RES can be fed back to the grid. SG offers overall improvement in energy usage efficiency.

3. **Efficiency** : It allows users to optimize their energy usage and cost dynamically. For instance, turning off high energy demand devices during peak hours.

4. **Load Balancing** : To manage peak load hours, SG makes use of mathematical prediction algorithms to predict the load requirements and therefore, managing it in a timely fashion. Alternatively, the users in a SG environment can also participate in peak load management using RES and energy efficiency mechanisms. Furthermore, AMI and communication technologies track energy demands of smart devices, thus preventing sudden overloads.

5. **Sustainability** : SG is flexible, hence permitting higher penetration of volatile RES in the network infrastructure. It allows inclusion of multiple feed-in points, i.e., distributed generation, in contrast to the traditional centralized generation model of existing electric grid. This idea of using SG for effective incorporation of RES in the energy grid infrastructure allows users to actively participate in the energy generation process. Consequently, the concept of ”Prosumers” was introduced, as discussed in the next section.

1.5 Prosumers

In the existing electric grid environment, there are two active participants, i.e., producers and consumers. Alternatively, in a SG environment, distributed RES and battery storage allows the consumer to generate as well as store energy. Therefore, the consumers can also feed locally generated energy back to the grid. Such consumers who produce, store and consume energy are referred as Prosumers [2]. The components of prosumer primarily consists of energy generation sources, energy consuming devices, battery storage and connection to the electric grid. A prosumer makes use of RES and battery storage and is controlled by smart energy management systems (EMS). A prosumer can also draw economic benefits by economically optimizing its energy use.

1.6 Renewable Energy Sources

RES refers to organic energy sources since these are replenished continuously by nature. Examples include solar energy, wind energy, geo-thermal energy etc. Solar cells or photovoltaic cells are used to convert light into electrical energy. Similarly, wind generators are used to convert wind energy into electrical energy. Therefore, RES offers an environmental friendly approach to tackle ever increasing load requirements. RES can be used for power generation as a standalone system or they can be integrated into the existing electric grid as well [1]. But, integration of RES in power distribution systems is a difficult task due to its intermittent nature and variable power generation [2]. To tackle this, various authors have proposed techniques for an effective incorporation of RES in SG, as discussed in the chapter 2.

1.7 Artificial Neural Network

1.7.1 Machine Learning

Machine learning is the study of computational learning using artificial intelligence. Artificial intelligence is the study of computer's ability to learn without being explicitly programmed. Hence, machine learning explores various algorithms that can learn from available data and use this knowledge to make predictions on data. Machine learning finds its application in many fields, such as pattern recognition, forecasting, clustering etc. Hence, machine learning can be associated with the task of learning from historical data. In this respect, there are three paradigms of learning.

- Supervised learning
- Unsupervised learning
- Reinforcement learning

In Supervised Learning, a mathematical function is used which tries to reduce the average error between the target output and the obtained output over the input data. Learning is performed from datasets consisting of input data with labeled responses. In order to minimize this function, an error back propagation algorithm is used for training neural networks, as discussed in the sections ahead. Alternatively, in unsupervised learning, inferences are drawn from datasets consisting of input data without labeled responses. In contrast, reinforcement learning is inspired by behavior analysis. It learns the actions of certain software agents in an environment such that the cumulative reward is maximized. It finds its applications in game theory, simulation-based optimization, and genetic algorithms.

In the work presented here, load forecasting needs to be performed. For this purpose, a machine leaning technique, i.e., artificial neural network (ANN) is explored. ANN is a form of supervised learning. The approach applied in this work uses feed forward ANNs with Levenberg-Marquardt backpropagation (LMB) technique.

1.7.2 Concept of Artificial Neural Network

An Artificial neural network (ANN) is an adaptive system which can be viewed as a collection of neurons, i.e., processing elements connected together to solve specific problems. It is a form of artificial intelligence which uses statistical analysis to learns patterns and relationships in training data. Furthermore, it uses predictive analysis to make predictions that are useful within an acceptable limit of errors. The learning rules in the network allows it to gather knowledge from available data and apply it to make future predictions. The property of ANN to analyze as well as learn from the information that flows through the network makes it appropriate for forecasting. The structure of ANN mimics the human brain's ability to adapt to evolving environment.

1.7.3 Analogy with Human Brain

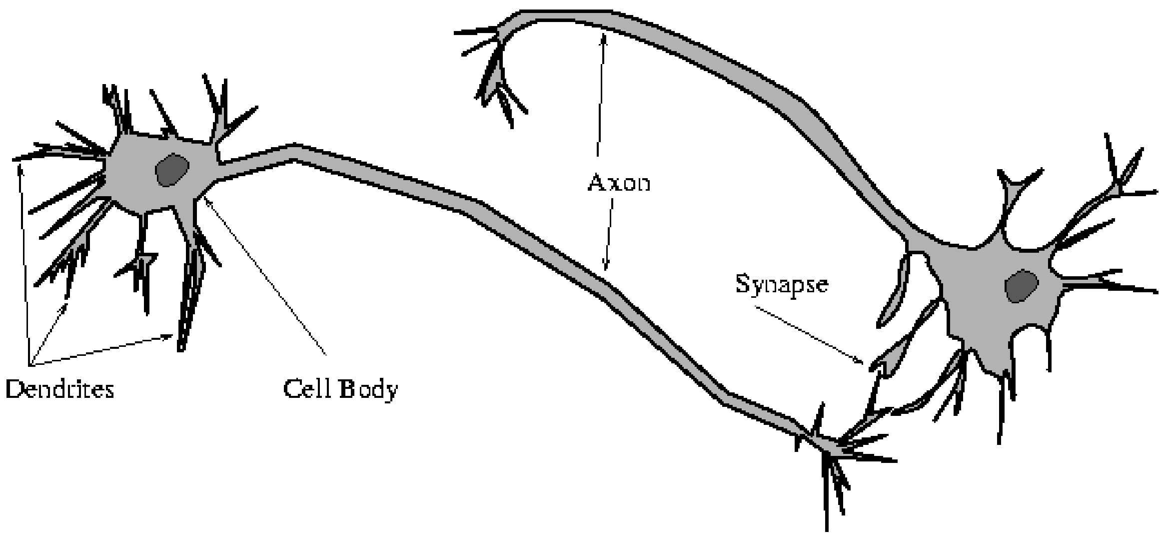

Figure 1.4: Structure of a neuron.

The brain consists of a mass of interconnected "neurons", such that each neuron is connected to many other neurons. Neurons transmit signals to each other. This signal transmission is an atomic event, i.e., all or nothing. The structure of a neuron is shown in Fig. 1.4. Inter-neuron connection strengths known as synaptic weights are used as a storehouse of knowledge. To simulate the functioning of a neuron, a digital computer would require hundreds of CPU cycles.

1.7.4 Structure of Artificial Neural Network

A typical feed-forward ANN with back propagation network consists at least three layers, as shown in Fig. 1.5.

- Input layer
- Hidden layer
- Output layer

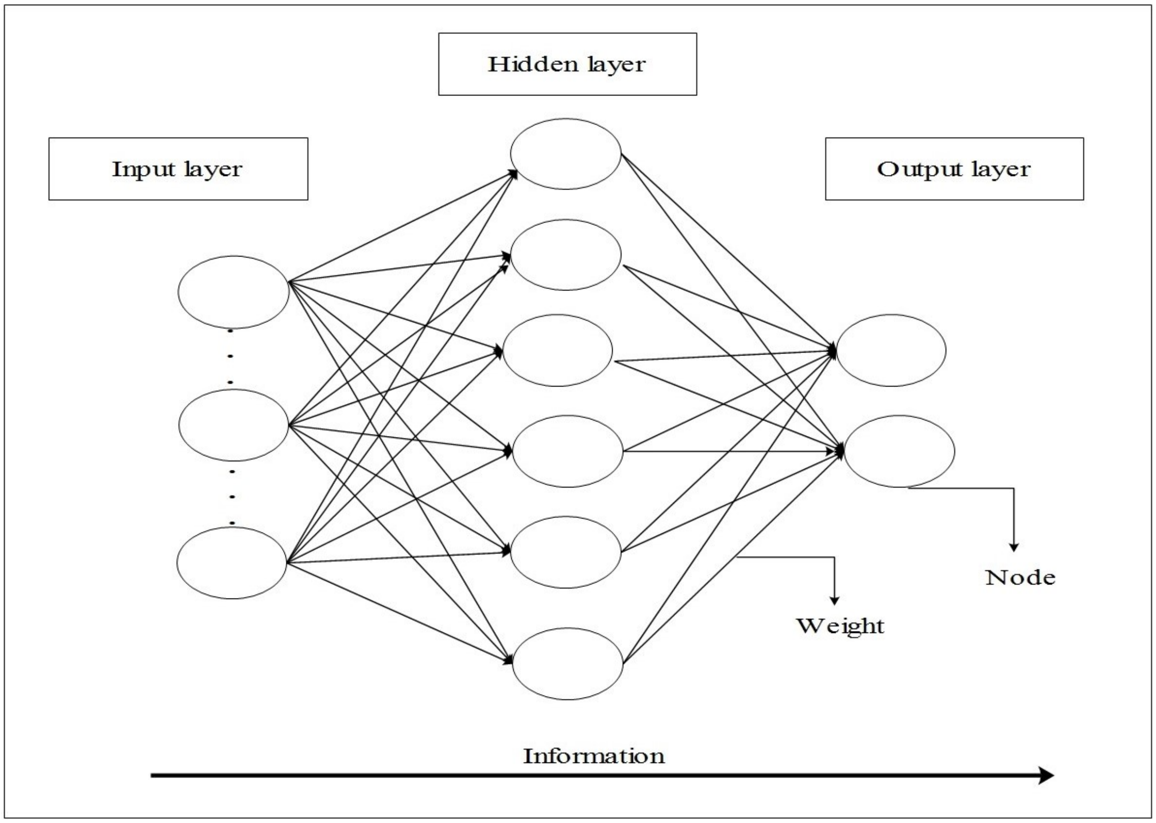

Figure 1.5: Basic layout of the existing electric grid

Each of the above layers consists of one or more processing nodes. Also, an ANN can have many various layers, and any number of nodes per layer. The interconnecting lines between them show the information flow from one node to the next. During the learning phase, the network changes its structure based on the information that flows through it. The information flow is unidirectional, i.e., from the input to the output nodes. Initially, data is presented to the input layer. The input layer nodes are passive in nature, and does not modify the data. In comparison, the nodes of the hidden and output layer are active. Each value from the input layer is duplicated and sent to all of the hidden nodes, thus forming a fully interconnected structure. Furthermore, network weights are multiplied to the values entering hidden nodes. These are a set of predetermined numbers stored in the network. The weighted inputs are then passed through a nonlinear mathematical function called the activation function. Hence, in an ANN, information is distributed and processing work is done in a parallel fashion. Furthermore, the training algorithm used for forecasting is the error back propagation algorithm.

Next, a brief overview of multi-layer perceptron (MLP) is presented here. A MLP network is a feed forward ANN that maps sets of input data onto a set of appropriate output. An MLP consists of multiple layers of nodes in a directed graph, with each layer fully connected to the next layer. A supervised learning technique known as error back propogation is used by MLP to train the network. It acts as training method for multilayer ANN and has a strong mathematical foundation. It is a multi-layer feed-forward network which uses an extended gradient descent based delta learning rule, commonly known as Error-Back propagation rule. Gradient descent method minimizes the total squared error of the output computed by the network. A supervised learning algorithm trains the network. The aim of training this network is to attain a balance between the capability of responding to input patterns used for training purposes and also giving better responses to similar inputs. Furthermore, in a typical feed forward network, the performance function is mean square error (MSE). It tries to minimize the average squared error between target (d_i) and output (o_i).

In the work presented in this thesis, day-ahead load demand forecasting is performed using ANN.

1.8 Greedy Algorithms

Greedy paradigm is basically used to solve optimization problems, where certain constraints need to be satisfied. Optimizations generally require an objective function to be maximized or minimized, as per constraints. Hence, greedy technique incorporates a heuristic problem solving approach. Therefore, it finds best-possible local solutions at each step, which is extended progressively to get an optimum global solution. In the thesis work presented here, the heuristic is to maximize RES usage per time slot, as discussed in the sections ahead.

1.9 Structure of the Thesis

The remaining thesis is structured based upon chapters as shown below:

- **Chapter 2 - Literature Review:** This chapter introduces the related work that has been done in the field of incorporation of RES in SG, their challenges and limitations.
- **Chapter 3 - Proposed Work:** In this chapter, the gaps in the field of incorporation of RES in SG and objectives of proposed research work has been described. Furthermore, this chapter describes the proposed methodology. It includes the techniques, input variables, RES generation calculations and algorithms designed in this

work. Moreover, it investigates the heuristic scheduling algorithm based on greedy technique, to manage the mismatch between demand and supply.

- **Chapter 4 - Results & Discussions:** This chapter contains the description of the results achieved against experiments conducted in MATLAB and observations of the experimental analysis of proposed system.

- **Chapter 5 - Conclusion and Future Scope:** The whole work presented in thesis is summarized in this chapter and it also contains the scope for future research work in same or different problem domain.

Chapter 2

Literature Review

2.1 Incorporation of RES in the SG : Opportunities and Challenges

One of the major challenges faced by the existing electric grid is to meet the ever increasing energy requirements. To meet these requirements, it relies heavily on fossil fuel sources of energy, which are depleting day-by-day. Moreover, energy generation using fossil fuel sources contribute towards environmental degradation due to excessive emission of green house gases (GHG). Consequently, it is required to de-carbonize the electricity generation and consumption at various levels in the power sector. Therefore, to control carbon emissions, various strategies for efficient energy generation/consumption with reduced dependency on fossil fuels are under development across the globe, as discussed ahead. /par Existing work in this area has revealed that, the existing electric grid needs to incorporate non-conventional energy sources, such-as RES into its infrastructure. RES offers an environmental friendly approach to tackle ever increasing load requirements. It can be used for power generation as a standalone system or it can be integrated into the existing electric grid as well [1]. However, the existing electric grid is not prepared to easily accommodate RES. This is where smart grid (SG) comes into play. The SG is a modern grid which incorporates advanced sensing and control technologies to ensure uninterrupted power supply to consumers. As described in chapter 1, SG is flexible, such that it allows a higher penetration of RES in the network infrastructure. Furthermore, to manage peak load hours, SG makes use of mathematical prediction algorithms to predict the load requirements and therefore, managing it in a timely fashion. Hence, with an inclusion of information and communication technology (ICT)-based infrastructure in the existing electric grid, it can act as smart grid (SG) by making a balance between demand and supply.

Furthermore, the users in a SG environment can also participate in peak load management using RES and energy efficiency mechanisms. Therefore, this idea of using SG for effective incorporation of RES in the energy grid infrastructure allows users to actively participate in the energy generation process. Consequently, the concept of ”Prosumers” was introduced. Such consumers who produce, store and consume energy are referred as ”prosumers” [1]. Prosumers can feed locally generated energy back to the grid to make a balance between demand and supply in the peak hours. Furthermore, a prosumer makes use of RES and battery storage and is controlled by smart energy management systems (EMS). To tackle the aforementioned issues, an adaptive approach towards distributed generation by incorporating RES in the existing electric grid is required. But, incorporation of RES in power distribution systems is a tedious task due to its intermittent nature and variable power generation. To eliminate the aforementioned issues, various authors have proposed innovative EMS for integration, monitoring, scheduling, and control of intermittent RES generation and transmission as discussed ahead.

Cecati *et al.* [3] proposed an EMS which acts like an aggregator of distributed RES and optimizes the generation capacity at DC. The proposed EMS acts as a centrally controlled load limiting device. Consequently, it can limit the load to the total generation capacity of the subscribed users. Furthermore, it evaluates a schedule of distributed generators for one trade day, i.e., 48 hours. It then provides the day-ahead cost and capacity information for the distributed generators. Next, based on the cost and the support offered by distributed generators, the schedule is modified such that cost optimization is performed in real-time. This cost optimization of the RES energy generation is accounted by a bidding system for the energy producers and consumers. For the consumers, the EMS aims to maximize the benefit function, thus minimizing the cost. Alternatively, for the producers, the EMS aims to maximize the revenue obtained by supplying energy to the grid. Hence, the authors explored the benefits of RES to mitigate high demand levels, keeping in vie of the economic aspects. Authors verified the efficiency of the proposed solution on a 23-bus 11-kV distribution network.

Byun *et al.* [4] proposed an EMS which monitors user consumption via load demand forecasting. For this purpose, the authors proposed a smart energy distribution and management system. This system is assumed to be connected to the existing grid as well as the RES energy systems. Now, the information from each local domain is converged and stored in a knowledge repository. This repository is updated at regular intervals. Hence, it is ensured that EMS uses the information generated in all the domains. Then, the EMS sends this information to the domain management agent, which is responsible for similarity calculations using a similarity function. Now, similarity calculations are performed based on a user consumption, location characteristics, temperature, and humidity. Based on these similarities, domain grouping is performed. Using this information, rules are learned by the EMS. Next, domain grouping is performed effectively based on rules and clustering techniques such that power consumption pattern is similar for all users in each domain. Furthermore, load forecasting is performed for each domain. The authors conducted a simulation for eight rooms spread over 198 m^2. Experimental results reveal that the proposed system reduced the service response time by 45.6% and power consumption by 9-17%. Hence, authors proposed a system architecture for integration of RES in a home EMS, thus ensuring smart energy distribution and control.

Winkler *et al.* [5] described an EMS that allows optimal scheduling of power systems by incorporating distributed RES feeding points. Authors have illustrated the role of intelligent management for renewable energy sources to achieve economical benefits. Furthermore, to optimize the energy delivery, the EMS processes the probability density distributions of the forecasted loads. Authors have illustrated the use of evolutionary algorithms and ANN to forecast and schedule energy usage. Input parameters used for load forecasting are previous load values, temperature, and special days.

Zhang *et al.* [6] proposed a power scheduling approach which incorporates RES in to the grid to maintain demand supply balance while minimizing the cost. The authors assumed a microgrid which consisted of fossil fuel generators, RES, and battery storage. Furthermore, the microgrid operates in a grid connected mode. Moreover, load is classified into two categories, i.e., elastic and inelastic loads. Elastic loads can be scheduled, whereas inelastic loads need immediate energy supply. Next, for each time slot, upper and lower bound of renewable energy generation is determined based on historical data using inference schemes. Now, the microgrid can buy/sell energy from/to grid using a transaction mechanism. In each time slot, an auxiliary variable is assumed. This variable denotes the net energy supplied from RES to microgrid to maintain demand-supply balance. The shortage energy is bought by the grid, while the surplus energy is sold to grid. The designed EMS targets to lower the net cost of the microgrid.

Lakshminarayana *et al.* [7] proposed a technique to mitigate the intermittent issues of harvesting RES using two approaches-one was based on usage of battery and another was based on distributed generation. The authors assumed a set of interconnected microgrids, which are capable of harvesting energy from RES. Furthermore, it is equipped with battery to store the harvested energy. Now, each microgrid contribute to RES generation per time slot. Furthermore, load requirements of the users are served per time slot. Now, certain restrictions are imposed on the aforementioned system. Firstly, from the set of microgrids, a microgrid can serve excess load of another microgrid. Secondly, the same does not apply for battery charging, i.e., a microgrid cannot charge the battery of another microgrid. Now, the objective of the system is to optimize the system parameters such that the cost of energy transfers across the grid is minimized subject to battery storage and RES generation capacity per time slot.

Now, RES is uncertain. Therefore, it leads to some variations in load balancing at prosumer level. To tackle this, Gast *et al.* [8] proposed an algorithm for optimal scheduling between energy loss and use of storage. The authors explored the applicability of battery storage to deal with load forecast uncertainties, consequently maximizing revenue. Furthermore, the authors have outlined the optimized battery size for large, moderate and small units for integration of wind energy in grid. The authors assumed time-slotted model, such that during each time slot, the wind generation is scheduled based on demand forecast. However, in case of shortage, the mismatch energy is consumed from fast ramping storage, wherein the objective is to minimize the cost using secondary reserves. Hence, the authors assume that demand is completely predictable.

Hakimi and Tafreshi *et al.* [9] explored the integration of heating/cooling systems into SG with high penetration of RES using a controller. The authors tried to reduce the overall cost and size of SG units, while reducing the energy imported from the conventional sources of energy. The proposed scheme also aims at maximizing reliability of the proposed controller in a SG environment. The aforementioned studies attempt to scale the existing electric grid by using wind turbines and photo-voltaic modules [10]. Voorden *et al.* [11] have investigated the changes in load curve due to installation of wind turbines and solar panels. The authors concluded that load variation increases due to uncertain output of the RES.

RES are inconsistent due to their intermittent nature. Hence, their generation fluctuates with time, which results in undesirable variation in power delivery. Various authors have attempted to minimize power fluctuations using energy storage and distributed controllable loads. Dan Wang *et al.* [12] modeled a set of distributed heat-pumps in a microgrid. Furthermore, the authors presented an algorithm to smoothen the connection between the grid and the microgrid, taking into account battery storage and demand response. Now, to counter for power fluctuations due to intermittent power generation a hierarchical control configuration is proposed. It limits and manages the distributed RES and grid resources. The network configuration and communication channels are discussed to improve the overall performance of the system.

Tanaka *et al.* [13] attempted to minimize power flow fluctuations due to uncertain power from RES, This objective function is achieved using distributed controllable loads such as battery, and heat pumps. Now, the charging/discharging power of battery and heat pumps is determined using an extended local search algorithm, i.e., tabu search such that it avails the high search efficiency of local searching. Also, it can escape from the current local optimum and move to neighborhood solution using global search ability of intelligent algorithms. First of all, the default state exists, and tabu list is formatted. Then, neighboring solutions are determined and evaluated against the current best solution. The best solution is updated if evaluated solution turns out to be better as compared to the best solution previously recorded. Therefore, it helps in smoothing power flow fluctuations in battery and heat pumps in each smart house.

2.2 Socio-Economic Impacts

Various economic aspects are associated with incorporation of RES in existing electric grid. These include fuel generation costs, hardware set-up costs, battery storage costs, and forecast error costs. These economic aspects have also been analyzed to maximize the profit at prosumer level. Lakshminarayana *et al.* [7] proposed an analytical model to minimize the time average price of energy exchanges within the grid. The authors concluded that in case of limited availability of battery storage, the grid can benefit from cooperative generation. While, in case of large storage capacity, cooperation does not yield much benefits.

Several authors have attempted to optimize the cost of energy driven from grid using various optimization techniques. Rahbar *et al.* [14] proposed an EMS attempting to optimize the cost of energy drawn from the grid using a sliding window based online algorithm which schedules renewable energy storage in real time for a microgrid. Atzeni *et al.* [15] have proposed a model to minimize the expenses of users to buy or produce their energy needs. The authors have simulated the model using proximal decomposition and day ahead optimizations. Kim *et al.* [16] proposed an EMS based on photo voltaic cells, and battery storage in real-time. The proposed EMS considers power generation from PV, load demand variations, and cost. The authors also simulated the proposed EMS on a 4kW photo voltaic hybrid power conditioning system with lithium-ion battery. Lee *et al.* [17] have proposed a business model to motivate prosumers such that they can achieve profits by trading energy back to the electric grid.

Lampropoulos *et al.* [18] have modeled the architecture mapping SG, decentralized generation, and role of prosumers. Furthermore the authors modeled the behavior of prosumers within SG by classifying the users into various categories and analyzing load requirements of different user groups. Various studies have been conducted around the world for integration of RES in SG. Mukhopadhyay *et al.* [19] have discussed the progress of renewable energy integration into SG in India. Sarker and Nagasaka [20] have analyzed the effectiveness of a smart micro grid model integrating RES, smart sensors and data management in Bangladesh power system for dynamic demand response. Khalil and Abas [21] have discussed the renewable energy potential and its integration in the existing power system of Pakistan. Liu *et al.* [22] have discussed the effects of various distributed renewable energy generations on dispatch modes of power systems in Guangdong region of China. Das and Balakrishnan [23] illustrated the applicability of RES into existing electric grid for sustainable development. The authors proposed the concept of a mobile SG city to ensure sustainability. Furthermore, the authors proposed the cost model for integration of distributed RES to existing electric grid. The cost factors are divided broadly into installation cost, transmission cost, and system cost. Hence, in recent years, a significant number of projects have been implemented in various parts of the world to study the technical and economic feasibility of incorporating RES in the SG technologies [1]. Therefore, the existing work in this field have evaluated the techno-socio-economic impacts of integration of RES in SG technology.

2.3 Role of Load Forecasting

The analysis of technical, social and economic factors for integration of distributed RES into existing grid have revealed that penetration of RES in the existing grid is feasible. It is achievable by the design of online algorithms that use artificial intelligence, and ICT to perform dynamic demand response in real-time. Furthermore, for efficient encapsulation of demand response and demand-side resources, it is required to forecast load requirements at DC. Forecasting load demand allows the demand side resources to balance the variability of renewable generation. This can be performed using ANN. Previous work in this area demonstrated that ANN performs efficiently for short term load forecasting. Hsu and Yang [24] proposed a multilayer feed forward neural network which is uses day-type and weather as an input factor along with historical data. The output is hourly load prediction. The authors simulated the network on Taiwan power system data, and achieved an average error of 0.536%., thus depicting the effectiveness of using ANN for short-term load forecasting. Peng and Hubele [25] explored week-ahead load forecasting using ANN using an auto regressive moving average model, such that continuous updates are performed for network parameters. The authors achieved MAE of 3.4%. Senjyu *et al.* [26] attempted to reduce the network size by incorporating a correction of similar day data. The authors used a euclidean norm with weighted factors to determine the similarity between the given day and a previously searched day. Simulation show MAE of 1.63%. Taylor and Buizza [27] investigated the role of weather for day-ahead load forecasting to reduce uncertainty and errors. However, it complicated the process and increases network size. Chow and Leung [28] proposed neural network model to accurately predict the changes in electric load consumption with a 0.9% reduction in forecast error. Therefore, various studies have been conducted in this area which illustrated the applicability of ANN for load forecasting.

Chapter 3

Proposed Work

3.1 Motivation

The rapid depletion of the fossil fuel sources has made a revolution towards the modernization of the existing electric grid [1], [11]. This generates the need of usage of RES resources to ensure sustainable demand side management. It results in the growth of prosumers [2]. In order to maximize their participation, various studies have been conducted around the world for incorporation of intermittent RES in the existing grid [9]- [12], [14], [17]- [23]. The literature survey suggest that most of the researchers have proposed hierarchical solutions to ensure scalability [3], [6], [13], [16]. But, these proposed solutions fail to deal with the possibility of decentralization of energy sources, so that prosumers can regulate the power flow. Also, in all these existing techniques, there is a single decision making agent for global optimization [5], [7]- [8], [10], [15] which does not explore the aspect of a distributed set of prosumers controlled by a local decision making agent. Moreover, most of the existing proposals have focused on the traditional aspects of distribution systems [4], [7], [11], [15]. They do not consider the incorporation of machine learning techniques for obtaining the self-sustainability. In the field of load forecasting, most of the existing works deal with day ahead peak load forecast using a wide range of information [24]- [28]. This complicates the process of estimation and adjustment of network parameters. Furthermore, it also expands the neural network structure and learning time. This wide range of information can be limited using efficient learning techniques. The aforementioned limitations are mitigated in the proposed solution, as discussed in the sections ahead.

3.2 Problem Statement

The work presented in this thesis work is concentrated on decentralized generation to meet the ever increasing energy demand by promoting active prosumer participation. This replaces the existing centralized generation model with a prosumer based distributed generation model incorporating distributed RES, battery energy storage and a controlling agent. The main research contributions of the work presented here are described as follows:

- An efficient prosumer based scheme is designed for incorporation of RES in SG using a self learning ANN-based controller.
- The proposed system is coordinated by an intelligent controller which uses ANN to perform day-ahead load forecasting and an optimized scheduling at *prosumer* level.
- Real-time day-ahead load requirement prediction is performed using two input parameters, i.e., historical demand over the past week and time slot of the day (24 slots per day).
- To ensure the demand supply balance at all times in the proposed solution, a heuristic scheduling algorithm based on greedy technique is proposed.

3.3 System Model

Over the last few decades, there has been a steep increase in the availability of RES such as-solar panels and wind generators. As a result, RES can be adapted in the existing electric grid to promote decentralized energy generation. This can be achieved by using the concept of prosumers [2]. But, due to its intermittent nature, energy generated from RES is variable. It introduces uncertainties in terms of its usage, and performance analysis. Therefore, it adds complexity to the normal grid operations. Hence, to incorporate RES in the existing electric grid, an adaptive approach towards distributed generation is required. To achieve this, a novel scheme is proposed in this paper which combines many prosumers into one unit. The proposed system is shown in Fig. 3.1. It can be viewed as a collection of large number of connected prosumers, each installed with a 20 m^2 solar panel and a 2 KWh wind generator. The energy produced by the prosumers is stored in a battery for future use.

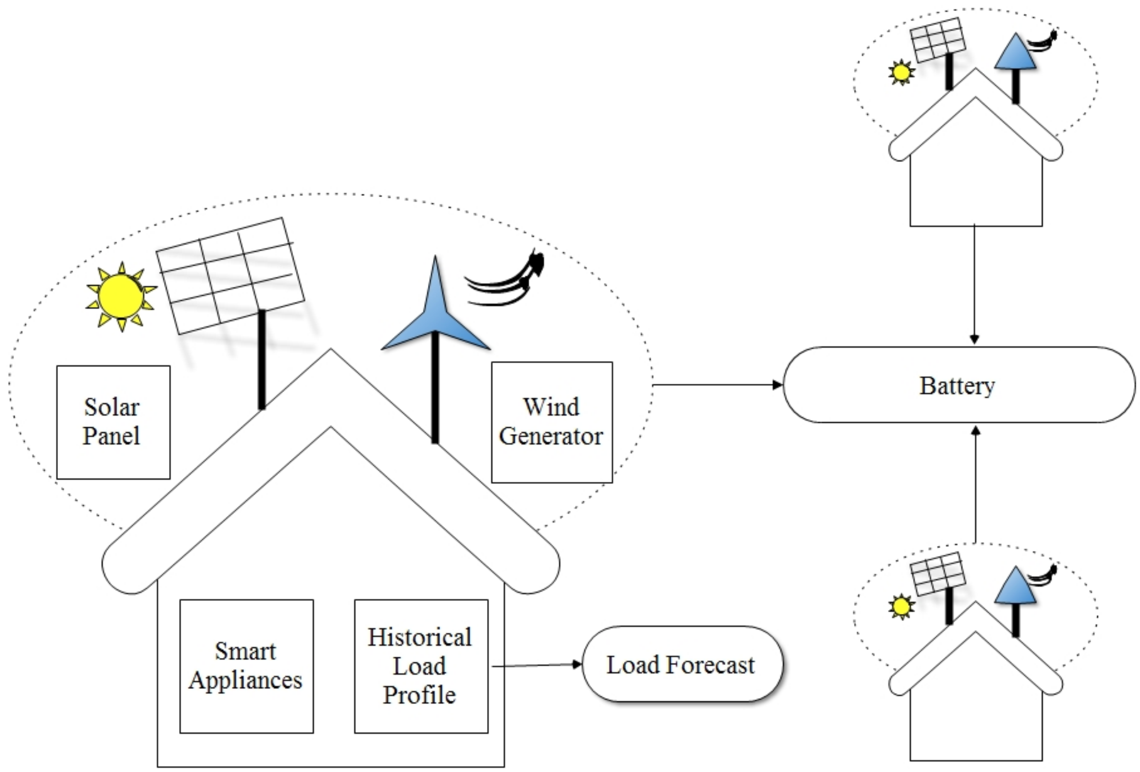

Figure 3.1: Block diagram depicting system design.

3.4 Problem Formulation

The system proposed in Fig. 3.1 is coordinated by an intelligent controller. It maximizes the RES usage in the system, to achieve self-sustainability. The day-ahead load demand for n^{th} prosumer is given as input to the controller. Using this information, the total load requirement for a system of N prosumers for the $t \in T$ is computed as shown in Eq. 3.1.

$$L_{N,t} = \sum_{n=1}^{N} l_{n,t} + \lambda \tag{3.1}$$

subject to constraints

$$L_{n,t} \geq 0 \; and \; \lambda \to 0 \tag{3.2}$$

During each interval $t \in T$, the energy harvested using wind generators and solar panels is calculated using real-time weather data, as described in section IV [29], [30]. Using this information, the cumulative RES generation of n^{th} prosumer is calculated as shown in Eq. 3.3. In the following equation, $w_{n,t}$ represents the wind energy generated by the n^{th} prosumer during time slot $t \in T$. It is calculated using Eq. 3.12 [29]. Similarly, $s_{n,t}$

represents the solar energy generated by the n^{th} prosumer during time slot $t \in T$. It is calculated using Eq. 3.13 [30] as described in sections ahead. Furthermore, γ_w and γ_s represent the errors in calculation of wind generation capacity and solar generation capacity respectively.

$$g_{n,t} = w_{n,t} + s_{n,t} + \gamma_w + \gamma_s \tag{3.3}$$

Using Eq. 3.3, the total RES generation for N prosumers during time interval $t \in T$ is calculated as shown in Eq. 3.4.

$$G_{N,t} = \sum_{n=1}^{N} g_{n,t} \tag{3.4}$$

subject to constraints

$$0 \leq G_{n,t} \leq G_{max} \ , \gamma_w \rightarrow 0 \ and \ \gamma_s \rightarrow 0 \tag{3.5}$$

For each interval $t \in T$, the controller manages the mismatch between $L_{N,t}$ and $G_{N,t}$ for a set of N prosumers. Since, RES generation fluctuates at any instant, so energy storage battery is used to smoothen the process.

3.4.1 Energy Storage Model

Battery is used as a demand-side EMS which stores energy to compensate for the mismatch between load demand and RES supply. This is achieved by storing the energy produced by RES in battery, which can be used later on as per the requirements. Let us assume that, at the beginning of time interval $t \in T$, the available energy is E_t. During each time interval, let $B_{N,t}$, shown in Eq. 3.6, be the energy charged (or discharged) from battery storage.

$$B_{N,t} = G_{N,t} - L_{n,t} \tag{3.6}$$

In case of charging, the energy is delivered to battery, i.e., $B_{N,t} \geq 0$. Similarly, in case of discharging, the energy is withdrawn from battery, i.e., $B_{N,t} \leq 0$. Hence, the battery storage model adapts according to Eq. 3.7. The objective is to achieve a trade-off between stored energy and RES generation in the current time interval $t \in T$.

$$E_t = min \ (max(E_{t-1} + B_{N,t}), 0) \ , \ E_{max}) \tag{3.7}$$

subject to constraint

$$\forall\, t \in T \ : \ 0 \leq E_t \leq E_{max} \tag{3.8}$$

If during time interval $t \in T$, the total RES generation and the available energy in the battery does not meet demand, then energy is obtained from the grid. The mismatch is depicted using Eq. 3.9.

$$M_{N,t} = E_t - (L_{N,t} - G_{N,t}) \tag{3.9}$$

During each interval $t \in T$, the objective function (ψ) is to minimize the energy drawn from grid, as shown in Eq. 3.10.

$$\psi = min(1/24 \sum_{t=1}^{24} |M_{N,t} - C_t|) \tag{3.10}$$

Eq. 3.11 depicts that the total energy produced by prosumers using RES and from battery must be greater than the total load requirements of the system. This ensures self sustainability of the system with respect to generation and consumption.

$$E_t + \sum_{n=1}^{N} (w_{n,t} + s_{n,t}) \geq \sum_{n=1}^{N} l_{n,t} \tag{3.11}$$

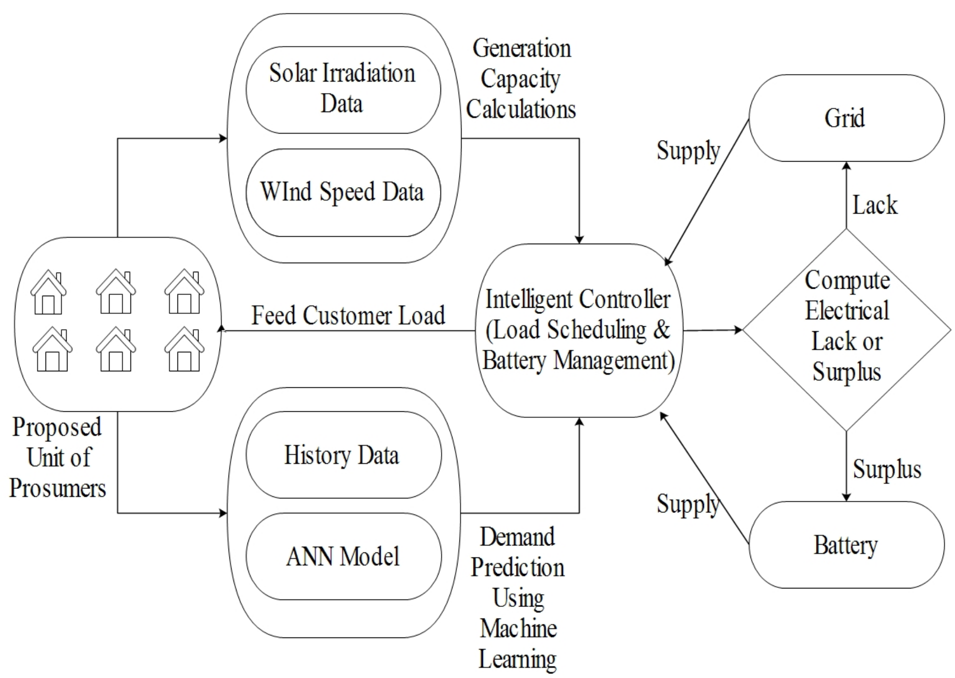

Figure 3.2: Block diagram showing flow of information in the proposed system.

3.5 Methodology

For an effective incorporation of RES in SG, a novel scheme is proposed in this paper, which uses an intelligent ANN-based controller. The working of the proposed scheme is shown in Fig. 3.2. The controller coordinates a system of connected prosumers. Each such prosumer has two parameters namely-generation capacity and day-ahead load requirements. The role of the controller is to manage the mismatch between load demand and renewable generation supply of the system. Hence, to ensure energy availability to the end users round the clock, a load scheduling algorithm based on greedy technique (GLS) is proposed. The proposed algorithm maximizes the RES usage in the system. Each component of the proposed scheme is described as follows.

3.5.1 Intelligent Controller

The working of the intelligent controller proposed in this paper is shown in Fig. 3.3. The design process of the aforementioned controller includes assessment of the system's load requirements, collection of historic load data, acquisition of real-time weather data and calculation of available generation capacity. This information helps in functioning of our proposed system which optimally schedules the incorporation of RES in SG.

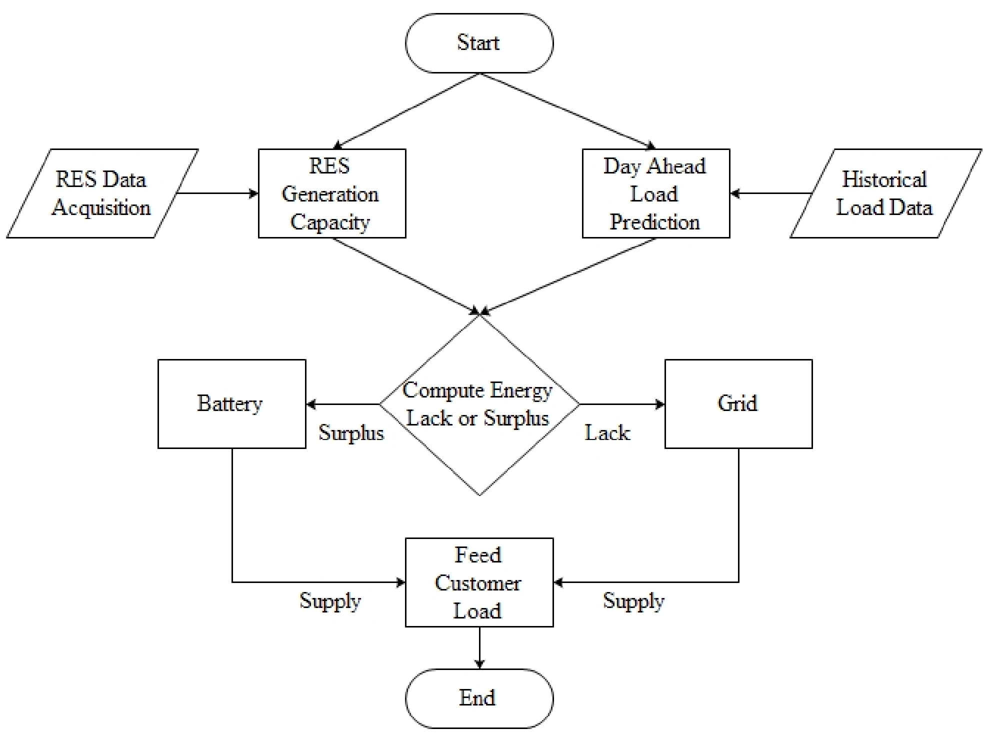

Figure 3.3: Flowchart depicting the working of the proposed controller.

First of all, the controller forecasts day ahead load requirements of a set of prosumers using ANN. Next, it uses real-time weather data to calculate the RES generation capacity of the system in an effective way. It then manages the mismatch between demand and supply. In case, there is a shortage of supply then the controller can balance it from battery storage. Battery is used as a demand-side EMS which stores the energy generated by prosumers using solar panels and wind generators. If the available energy in the battery does not meet the load requirements of the system, then it is obtained from the grid. In case, there is surplus supply then it is stored in battery for later use. In this manner, the controller performs power distribution and optimal scheduling as per the GLS algorithm. Furthermore, the controller is assumed to follow a star network topology with the prosumers as depicted in Fig. 3.4. The network is dynamic and each edge in the topology is composed of parallel physical links for bidirectional transmission of information between prosumers and controller.

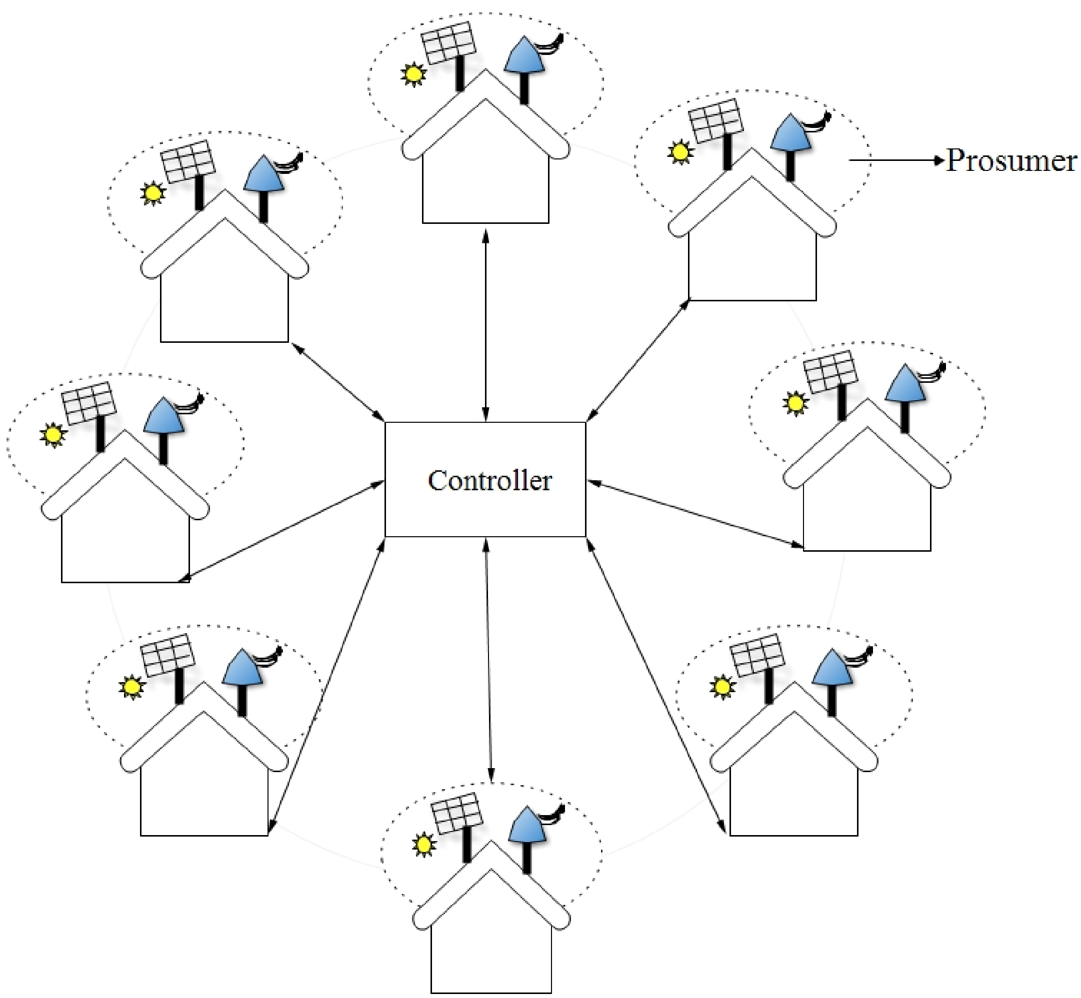

Figure 3.4: Star network transmission topology of the proposed controller.

3.5.2 Renewable Energy Generation Calculations

The proposed system is a collection of prosumers which can harness solar and wind energy using solar panels and wind generators respectively. Therefore, it is required to estimate the amount of RES generation that can be achieved. For this purpose, probabilistic calculations based on the recorded wind speed and solar irradiance data have been used as follows.

Wind Energy

Wind speed can be defined as the rate at which wind blows at a point above the surface of the earth and wind energy is a measurement of the energy that can be generated from wind. Fig. 3.5 shows the average wind speed variation of a typical day for the city of Patiala, Punjab.

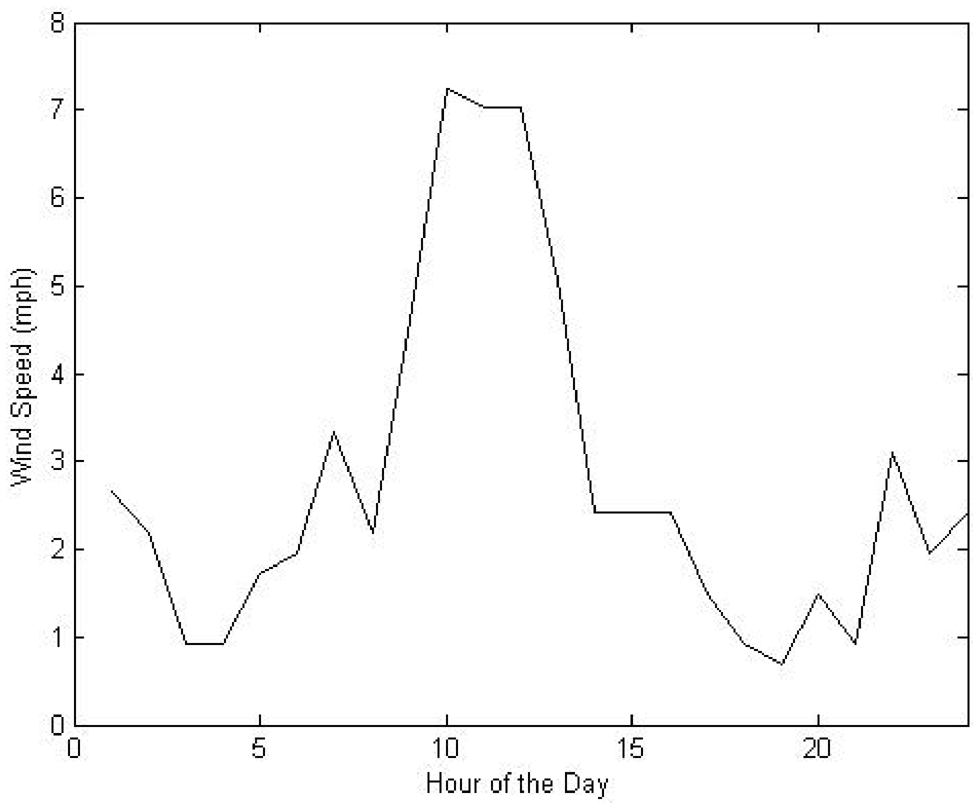

Figure 3.5: Mean wind speed variation (in miles per hour) of a typical day.

Eq.3.12 shows the relation between wind speed and wind energy [29]. In Eq.3.12 "E_w" represents the wind energy generated in kW, "α" represents a constant of yield power, "θ" represents a dimensionless energy coefficient whose value ranges from 0.25 to 0.45, "ρ"

represents the air density at site, "A" represents the rotor swept area and "V" represents wind speed in miles per hour. Based on Eq.3.12, the wind energy that can be generated from a 2kW wind turbine having a rotor diameter of 4 meter is shown in Fig. 3.6.

$$E_w = \frac{1}{2}\alpha\theta\rho AV^3 \tag{3.12}$$

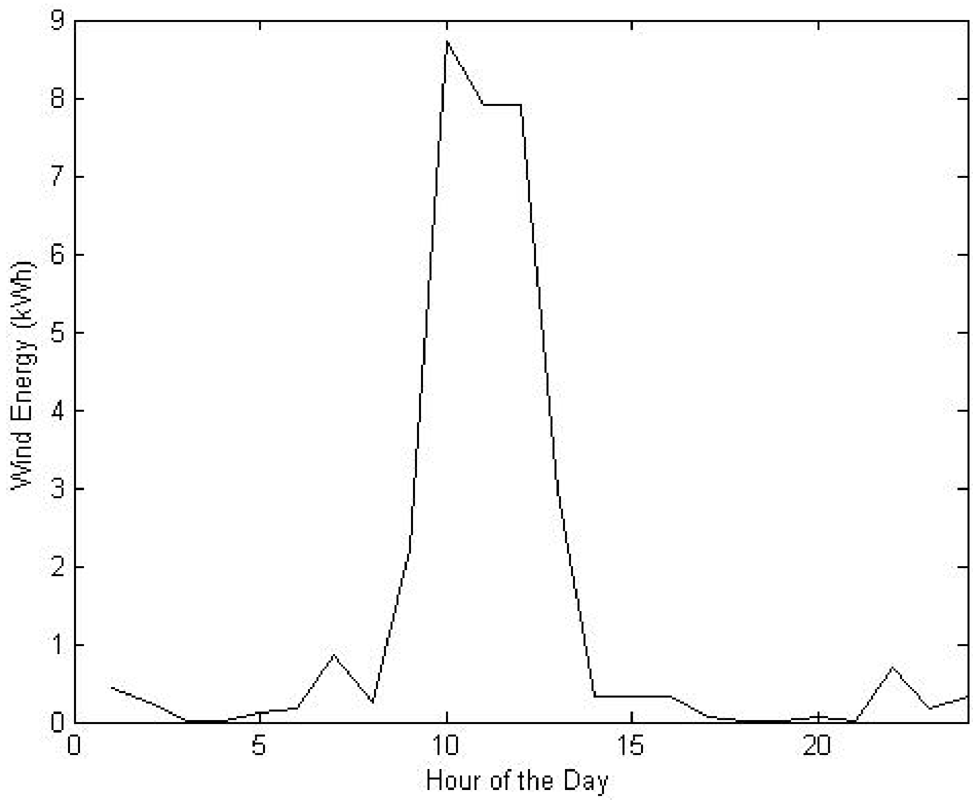

Figure 3.6: Wind energy output for a 2 kW turbine of a typical day.

Solar Energy

Solar irradiance can be defined as the measure of solar energy that can be achieved at a particular location. It varies throughout the year subject to the season and the position of the sun. The average solar insolation of a typical day is shown in Fig. 3.7. This graphical representation is constructed from 22 year averaged solar insolation measurements taken in the city of Patiala, Punjab. The city has latitude 30 19' 36" N, longitude 76 24' 1" E and as per National Renewable Energy Laboratory(NREL) the annual average Global Horizontal Irradance(GHI) estimated over 7 years (2002-08) is 5.30 kWh/m^2/day. The mathematical

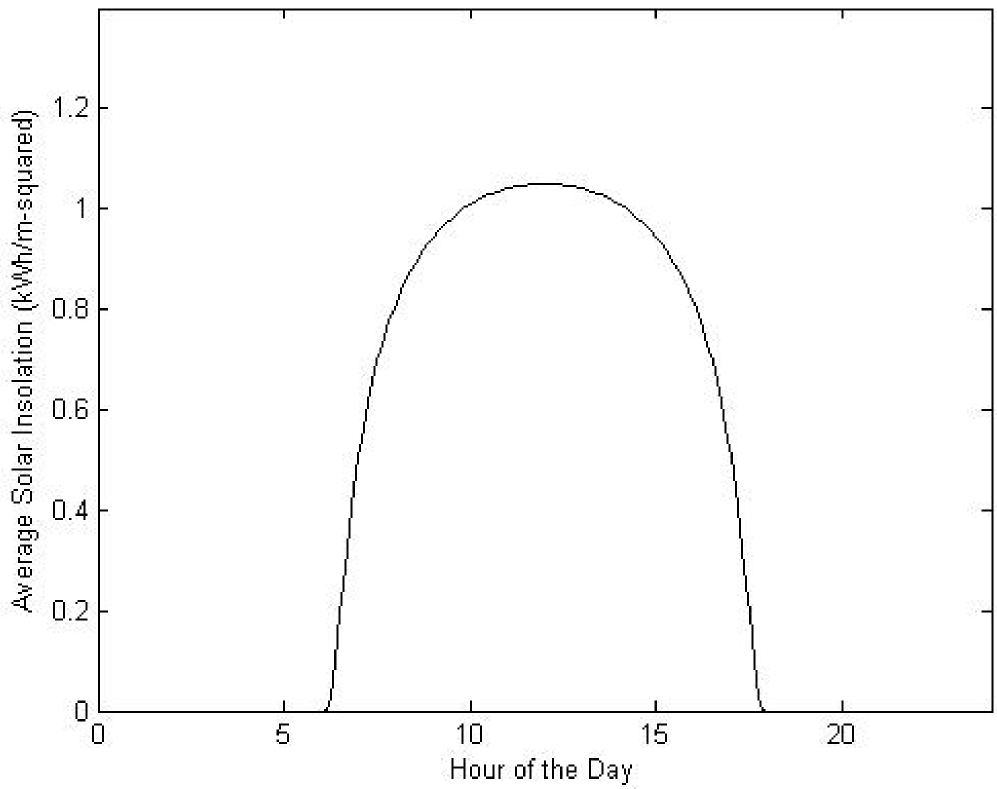

Figure 3.7: Average solar insolation (kWh/m^2).

formula to calculate the energy that can be generated from a solar panel based on the average solar insolation [30] is shown in Eq.3.13.

$$E_s = PYS\sigma \tag{3.13}$$

In Eq.3.13 "E_s" represents the energy generated in kWp, "P" represents the solar panel area in m^2, "Y" represents the solar panel yield which gives the ratio between electrical power generation and area of a single solar panel, "S" represents the average solar radiation on solar panels and "σ" represents the performance ratio which gives the quality of PV installation irrespective of orientation of the panel. Its value varies from 0.5 to 0.9. Based on Eq. 3.13, the solar energy that can be generated from a 20 m^2 solar panel having panel yield 15% and performance ratio 0.75 is shown in Fig. 3.8. The solar energy generated suffers from many losses such as-invertor loss (9%), temperature loss (12%), cable loss (2%) etc. These losses are all incorporated in the performance ratio.

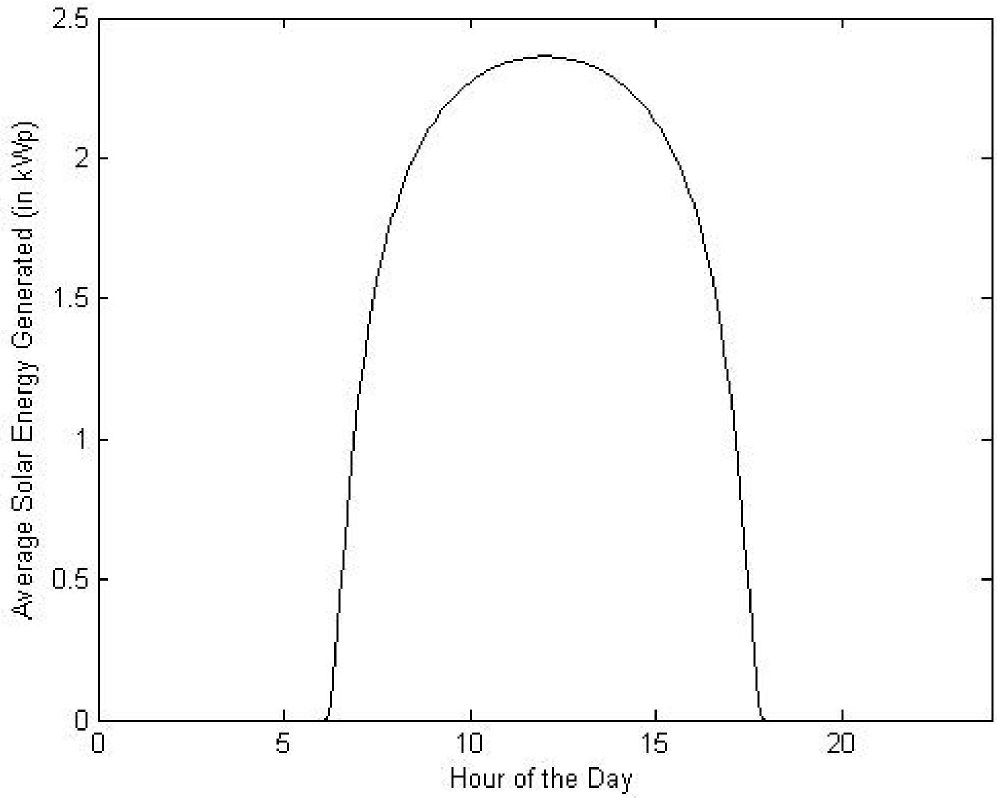

Figure 3.8: Average solar energy generated (in kW).

3.5.3 Day Ahead Load Forecasting based on ANN

Forecasting is a planning tool that tries to deal with the unpredictability of the future, depending on historical data and trend analysis. Hence, to achieve load forecast for individual prosumer, it is required to infer their behavior using historical load data. In this paper, day ahead load demand forecasting of the proposed system is performed using ANN. ANN is an adaptive system which can be viewed as a collection of neurons, i.e., processing elements connected together, to deal with specific problems. Furthermore, the property of ANN to analyze as well as learn from the information that flows through the network makes it appropriate for forecasting. The approach applied here uses feed forward ANNs with Levenberg-Marquardt Backpropagation (LMB). In a typical feed forward network, the performance function is MSE. It tries to minimize the average squared error between target (d_i) and output (o_i).

For the purpose of day-ahead load forecast of a prosumer, the basic input parameters used in this paper are the historical load demand over the past week and time slot of the day (24 slots per day) as shown in Fig. 3.9.

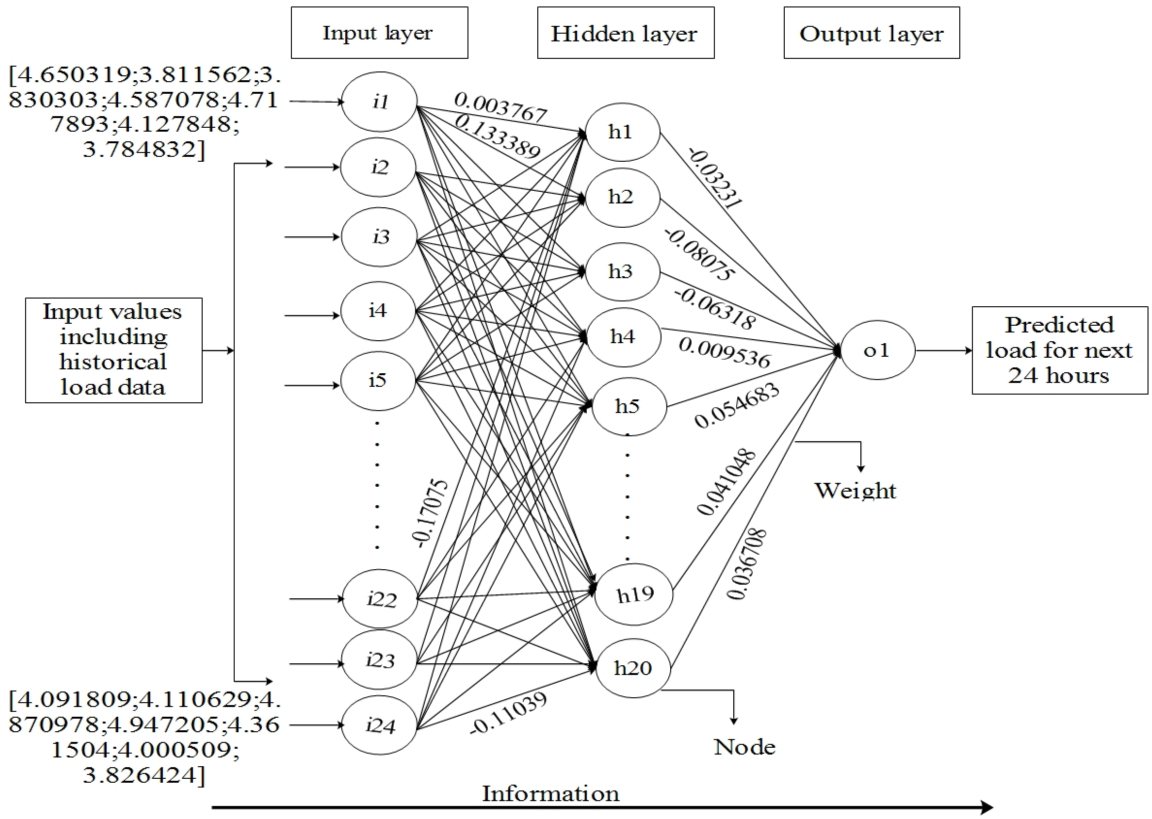

Figure 3.9: Block diagram of ANN used in the proposed system.

It has an input layer with 24 nodes, each receive historical load values from the past week. The model uses one hidden layer with 20 hidden nodes and a single output node. Each processing node in the input layer delivers the output same as the node input, since input layer nodes are passive. Furthermore, for each node h in the hidden layer, the network output is computed as summation of input value and connection weight between input and hidden nodes using Eq. 3.14.

$$o_h = \sum_{i=1}^{24} \iota_i \, w_{ih} \tag{3.14}$$

The network output for the output layer is computed using an activation function. The inputs for the aforementioned function are outputs of hidden layer and connection weights between the hidden and output layer as shown in Eq. 3.15. Here, π is the activation function used in the model, i.e., log-sigmoid transfer function.

$$o_j = \pi(o_h \, , \, w_{hj}) \tag{3.15}$$

Initially the weights in the network are assumed randomly, adapting to Eq. 3.16 and Eq.

3.17. Here, $randn(x,y)$ is the normally distributed random number function in MATLAB which returns a x-by-y matrix of random entries.

$$w_{ih} = randn(24,20) - 0.5)/10; \tag{3.16}$$

$$w_{hj} = randn(1,20) - 0.5)/10; \tag{3.17}$$

Now, for each i^{th} node in the network, error is evaluated using Eq. 3.18.

$$e_i = o_i \quad (1 - o_i) \quad (d_i - o_i) \tag{3.18}$$

Also, for the output node, the error is evaluated using summation of error in the preceeding layers, as shown in Eq. 3.19.

$$e_j = o_j \; (1 - o_j) \; \sum (e_h \Delta w_{hj}) \tag{3.19}$$

Then, the error is perpetuated backwards to update the weights of preceding layers, adapting to Eq. 3.20. Hence, the weights in the network are updated by feeding the $m \in M$ input-output patterns repeatedly.

$$\Delta w_{ij}(m) = \eta \; e_j \; o_i + \Omega \; \Delta w_{ij}(m-1) \tag{3.20}$$

This process is carried on till error is less than a desired limit and weights are stable. This allows ANN to minimize the error such that the predicted value is close to the actual value. The other parameters are learning rate (η) and momentum factor (Ω), which are system dependent. The learning rate parameter determines the influence of each updation of weight over its current value. LMB automatically adapts the learning rate. Furthermore, momentum factor ensures that the weight changes are dependent on multiple input-output patterns. Algorithm 1 is used for day-ahead load prediction using our ANN model.

Algorithm 1 Algorithm for day-ahead load prediction using ANN.

Require: Historical load for past week.

Ensure: Load prediction for the next 24 hours.

1: Initialize epoch and the number of hidden neurons.
2: **for** each neuron $\in$ input layer **do**
3:    Initialize weights w_{ih} using Eq. 3.16.
4: **end for**
5: **for** each neuron $\in$ hidden layer **do**
6:    Initialize weights w_{hj} using Eq. 3.17.
7: **end for**
8: **for** each input-output pattern m $\in$ M **do**
9:    Read input-output pattern *m*.
10:    Compute neuron output using Eq. 3.14 and Eq. 3.15.
11: **end for**
12: Compute error using Eq. 3.18 and Eq. 3.19.
13: Adjust network weights using Eq. 3.20.
14: Repeat steps 4 - 7, until error is reduced to an acceptable limit.

3.5.4 Greedy Load Scheduling Algorithm

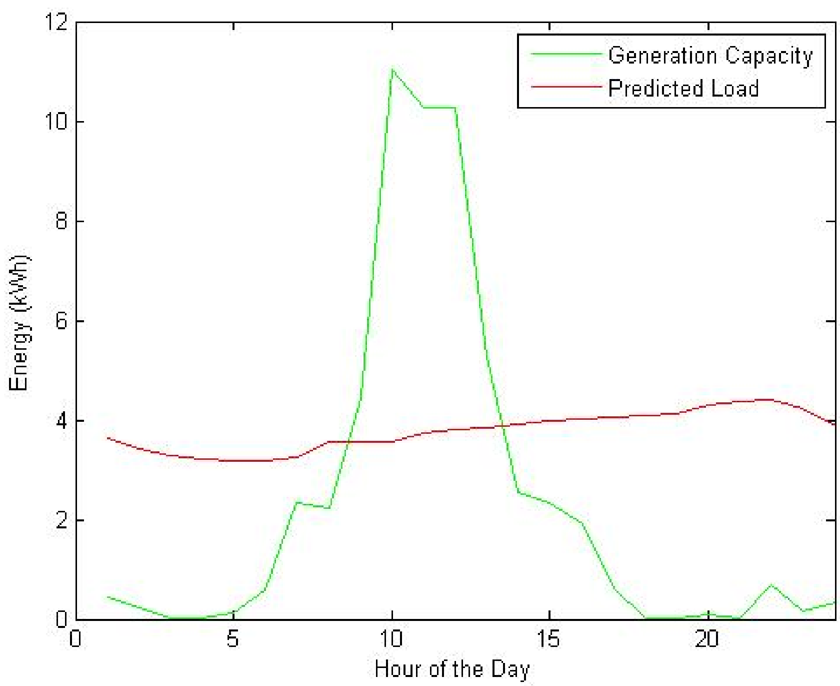

Figure 3.10: Comparison between the predicted load requirements and RES generation capacities for a 24 hour duration.

The intelligent controller proposed in the previous section aims to maximize the RES usage to decarbonize energy consumption. For this purpose, it forecasts day-ahead load requirements of a set of prosumers using ANN. Furthermore, it uses real-time weather data to calculate the RES generation capacity of the system in an effective way, as discussed in the previous section. Now, the controller is required to manage the mismatch between load demand and RES supply. This load scheduling is performed in a greedy manner, using the GSA algorithm as discussed ahead. The goal of the algorithm is described in Eq. 3.21.

$$E_t + \sum_{n=1}^{N} (w_{n,t} + s_{n,t}) \geq \sum_{n=1}^{N} l_{n,t} \tag{3.21}$$

Algorithm 2 Algorithm for load scheduling in SG environment incorporating RES.

Require: $g_{n,t}$, $l_{n,t}$, E_t.

Ensure: Energy is available at all times in the system while maximizing RES usage.

for each prosumer n $\in$ N **do**
  Adapt $w_{n,t}$ using Eq 3.12.
  Adapt $s_{n,t}$ using Eq 3.13.
  Evaluate RES generation capacity of each prosumer $n \in N$ adapting to the equation: $g_{n,t} \leftarrow \sum_{t=1}^{T} (w_{n,t} + s_{n,t}) + \gamma_s + \gamma_w$
  Evaluate RES generation capacity of the entire system of connected prosumers adapting to the equation: $G_{N,t} \leftarrow \sum_{n=1}^{N} g_{n,t}$
end for
Using ANN model predict day-ahead load for the system $L_{N,t} \leftarrow \sum_{n=1}^{N} l_{n,t}$
if $(L_{n,t} > G_{n,t})$ **then**
  if $(E_t > (L_{n,t}\text{-}G_{n,t})$ **then**
    $E_t \leftarrow E_t$ - $(L_{n,t}\text{-}G_{n,t})$
  else
    $C_t \leftarrow (L_{n,t}\text{-}G_{n,t})$
  end if
end if
if $(L_{n,t} < G_{n,t})$ **then**
  $E_t \leftarrow E_t + (L_{n,t}\text{-}G_{n,t})$
end if

Based upon the above mentioned equation, an optimal schedule would be produced, per time slot, such that maximum RES generation is used. The controller acquired real-time data to perform day-ahead load forecasting and RES generation capacity of the system. Fig.

3.10 shows the comparison of predicted load requirements and RES generation capacities for $T = 24$ hours. Based on the mismatch between demand and supply, the controller performs the task of power distribution and optimized scheduling of RES usage. As the load increases, the controller meets user load demand by selecting between the available energy options. These options include use of battery, or managing load using the energy obtained from the existing electric grid. During each time slot $t \in T$, in case, there is a shortage of supply, then the controller can balance it from battery storage. If the available energy in the battery does not meet the load requirements of the system, then it is obtained from the grid. In case, there is surplus supply then it is stored in battery for later use. In this manner, the controller performs power distribution and optimal scheduling as per the GLS algorithm. Therefore, algorithm 2 is based on heuristic greedy technique for load scheduling in a SG environment by incorporating RES. Greedy technique incorporates a heuristic problem solving approach. It finds best-possible local solutions at each step, which is extended progressively to get an optimum global solution. In the proposed work, the proposed heuristic maximizes RES usage per time slot.

Chapter 4

Results and Discussions

4.1 Numerical Dataset

In this paper, weather data is obtained from [31]. Furthermore, historical load demand values are obtained from [32]. The model is simulated in MATLAB 7.6.0 (R2012a) and its effectiveness is demonstrated in the section ahead.

4.2 Implementation and Results

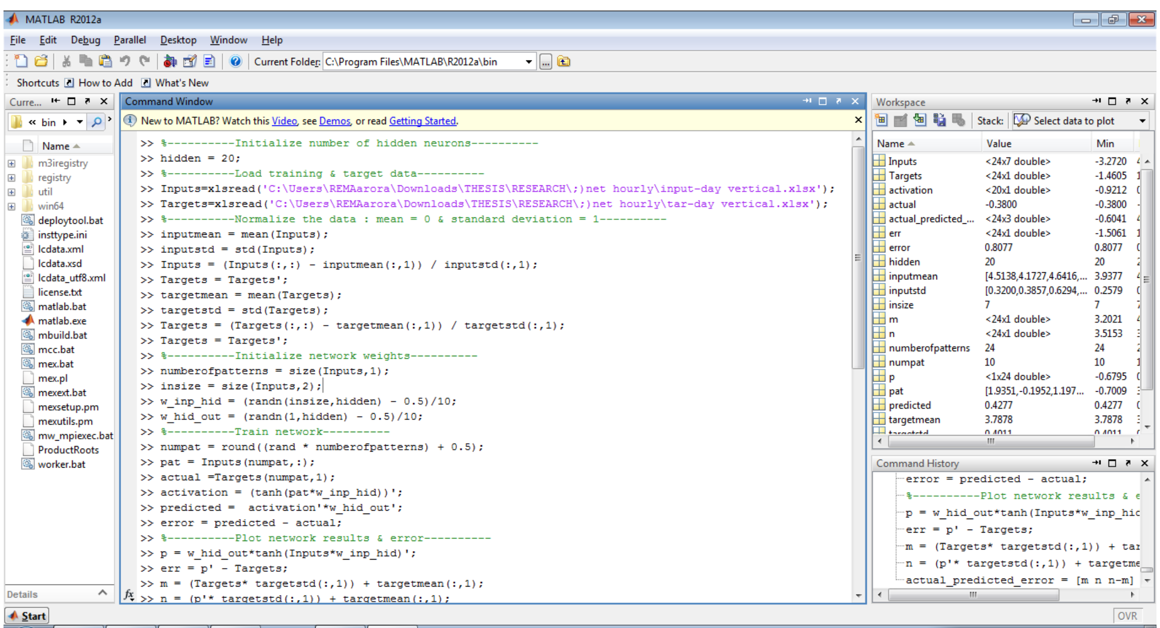

Figure 4.1: Implementation in MATLAB command window.

To obtain the results of day-ahead load forecasting, the hourly load patterns are fetched from the database and a dataset is prepared, which is then imported into the MATLAB workspace. The implementation work is depicted in Figs. 4.1 and 4.2.

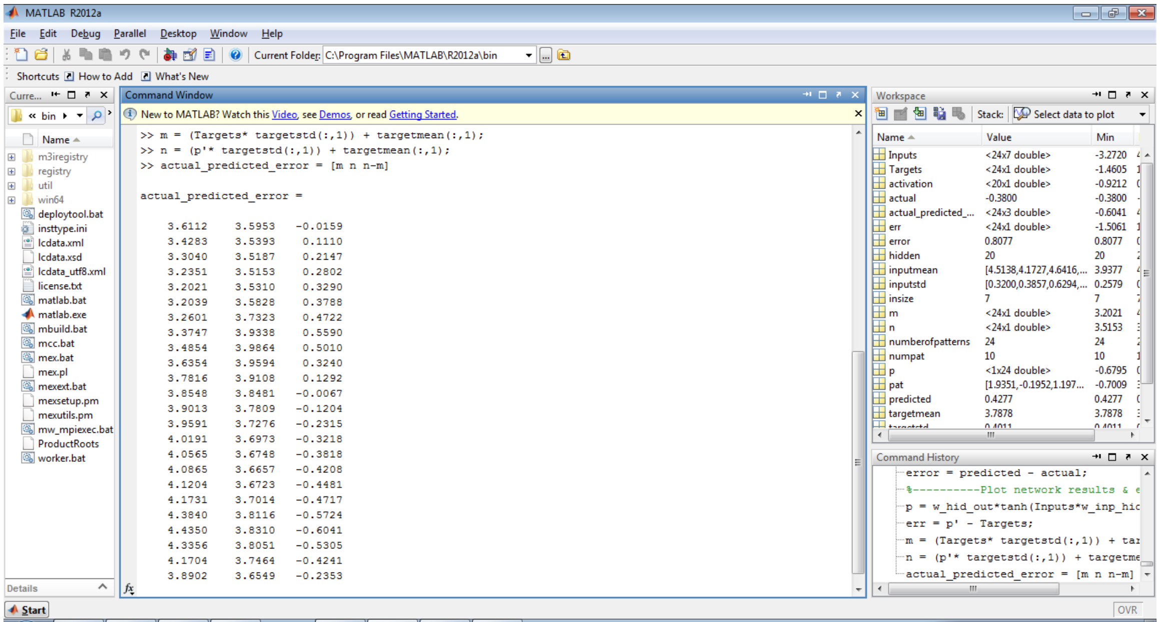

Figure 4.2: Implementation in MATLAB command window.

The forecast results for 31st January 2016 are described in Table 4.2. The graphical representation shown in Fig. 4.3 shows the comparison between target and output load.

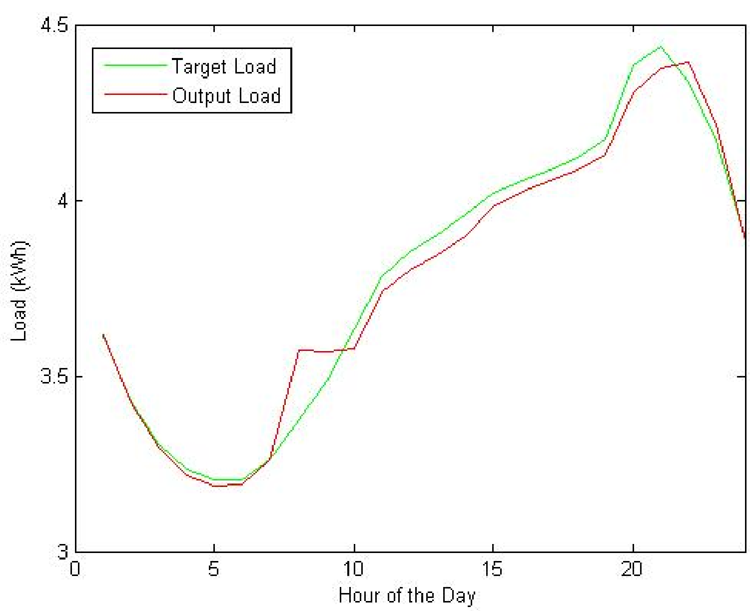

Figure 4.3: Comparison between the target and output load.

The performance evaluation of the network is depicted in Fig. 4.4. It is a plot of error versus the epoch. It shows the training, test, as well as the validation performances. Since there is a similarity between the validation and test curves, hence the plot depicts that the network has been trained well. Moreover, the accuracy of the network is investigated using regression techniques. Regression is a statistical technique to analyze the fit of the prediction model with respect to the observed dataset. Hence, the regression plot shown in Fig. 4.5 depicts the relation between the achieved outputs and desired targets. Regression value determines the degree to which these are corelated. Closer this value is to unity, the better is the fit of the prediction model. The regression plots validate network performance. In Fig. 4.5, the network output is analyzed. The perfect fit is achieved when the obtained output is equal to the desired targets, and is shown by the solid line. The training, validation and test results depicts R value higher than 0.9. Therefore, results depict that the best linear fit line is close to the perfect fit line. The aforementioned results show that the network is trained well.

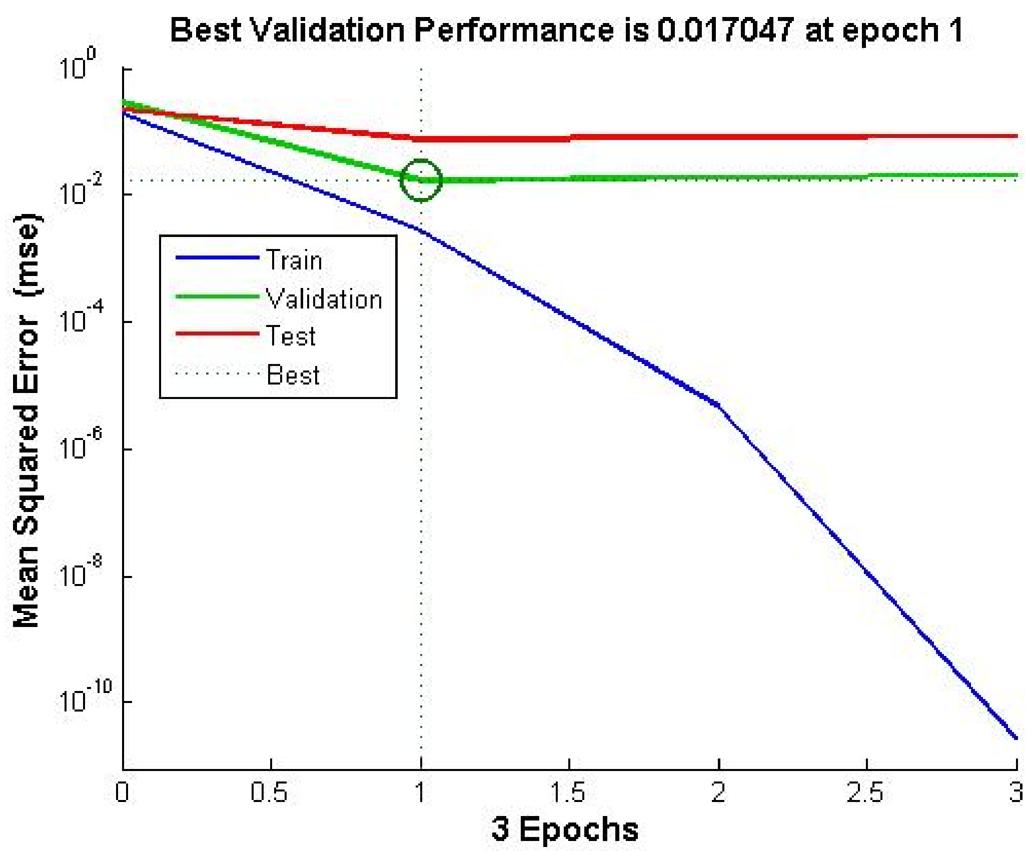

Figure 4.4: Performance plot of the trained network showing variation of MSE with respect to number of epochs.

Also, various performance metrics such as-Mean Square Error (MSE), Root Mean

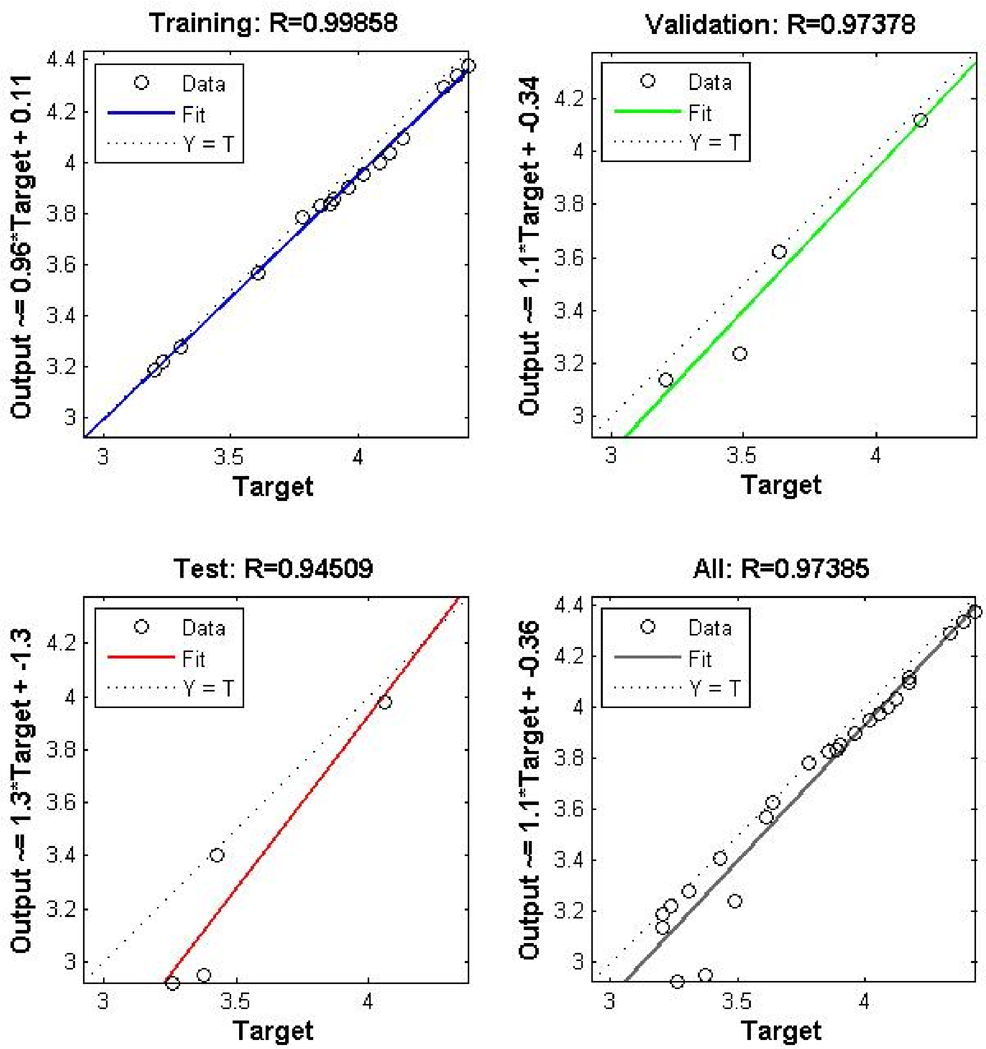

Figure 4.5: Regression plot depicting the relation between network outputs and network targets.

Square Error (RMSE), and Mean Absolute Error (MAE), have been used to evaluate the effectiveness of the proposed model. Eqs. 4.1, 4.2, and 4.3 are the mathematical formulations of the aforementioned metrics over ”m” input values.

$$MSE = \frac{1}{m}\sum_{i=1}^{m}(d_i - o_i)^2 \tag{4.1}$$

$$RMSE = \sqrt[2]{\frac{1}{m}\sum_{i=1}^{m}(d_i - o_i)^2)} \tag{4.2}$$

$$MAE = \frac{1}{m}\sum_{i=1}^{m}|d_i - o_i| \quad (4.3)$$

Using the aforementioned formulations, network accuracy was evaluated as MSE of 0.344%, RMSE of 5.869% and MAE of 4.316%. Furthermore, to demonstrate the effectiveness of the proposed neural network, day-ahead load forecasting was performed on multiple datasets of different months using the same approach, and results are listed in Table 4.1. It reveals that the developed ANN model performs well for day-ahead load forecasting.

Table 4.1: Network performance for different datasets.

Month	MSE	RMSE	MAE
January	0.344%	5.869%	4.316%
July	0.370%	6.089%	2.970%
October	0.203%	4.515%	1.461%

4.3 Case Study I

The performance of the proposed ANN day-ahead load forecasting model is compared against the existing approach demonstrated in [33]. The result is shown in Table 4.2.

The metric used for performance evaluation is mean absolute percentage error (MAPE). Its mathematical formulations over ”m” input values is shown in Eq. 4.4.

$$MAPE = \frac{1}{m}\sum_{i=1}^{m}\frac{(d_i - o_i)}{d_i} * 100\% \quad (4.4)$$

The performance evaluation reveals that MAPE of the existing ANN model in [33] is much greater than that obtained in the proposed model as shown in Table 4.3

4.4 Case Study II

For the purpose of simulation, a set of twenty-five prosumers is assumed in this paper. For simplicity, all prosumers are assumed to be identical to each other, in terms of solar panels and wind generators installed in them. Fig. 4.6 shows the variation of load, RES generation, battery storage, and grid consumption over a 24 hour duration.

Table 4.2: Comparison of load forecasting results and relative error of existing and proposed ANN model.

Hour	Existing Model			Proposed Model		
	Actual Load	Predicted Load	Error	Actual Load	Predicted Load	Error
01:00	10.4	14.3	-3.9	3.611219405	3.615128632	-0.003909227
02:00	10.7	10.7	0	3.428289838	3.4249739	0.003315938
03:00	10.26	3.7	6.56	3.304021814	3.296398857	0.007622957
04:00	12.3	10.7	1.6	3.235145928	3.216713677	0.018432251
05:00	13.6	10.3	3.3	3.202062383	3.184448554	0.01761383
06:00	14.1	11.8	2.3	3.203929421	3.190757712	0.013171709
07:00	18.2	10.2	8	3.260068628	3.261018838	-0.000950211
08:00	17.5	10.6	6.9	3.374731758	3.571083726	-0.196351968
09:00	22.5	10.4	12.1	3.485439077	3.569222005	-0.083782928
10:00	25.3	10.6	14.7	3.635420509	3.578033059	0.05738745
11:00	24.1	20	4.1	3.781616281	3.7407569	0.040859382
12:00	25.3	25.2	0.1	3.854786866	3.800448826	0.05433804
13:00	26.9	23.3	3.6	3.901283764	3.843834424	0.057449339
14:00	28.4	16.1	12.3	3.95910154	3.897275792	0.061825748
15:00	28.4	17.2	11.2	4.019119616	3.979330643	0.039788973
16:00	28.5	28.2	0.3	4.056533231	4.025042723	0.031490509
17:00	29.6	19.1	10.5	4.08650275	4.057016887	0.029485864
18:00	29.3	18.9	10.4	4.120405507	4.086283263	0.034122245
19:00	28.3	17	11.3	4.173123296	4.12966548	0.043457817
20:00	29.9	25	4.9	4.384043977	4.3044583	0.079585676
21:00	31.3	29	2.3	4.435044841	4.374800427	0.060244414
22:00	33.7	24.9	8.8	4.335642769	4.391056217	-0.055413448
23:00	31.6	25.7	5.9	4.170425273	4.21058301	-0.040157737
24:00	32.5	20.1	12.4	3.890249862	3.885013291	0.005236571

Table 4.3: Performance evaluation of existing ANN model with the proposed ANN model.

ANN Model	MAPE
Existing	1.1082%
Proposed	0.0125%

4.5 Discussions

Furthermore, the effects of incorporating RES in SG are depicted using two different cases for comparison, one without using RES, and another with usage of battery and Algorithm 2. Fig. 4.7 shows that Algorithm 2 performs dynamic demand response, while reducing the amount of energy obtained from grid by about 46.90% over a 24 hour duration. Also, the amount of energy obtained from grid is negligible during peak hours in a day, i.e., from 10:00 to 18:00. This is achieved through the use of RES and battery. Thus, the energy generated by a set of prosumers is sufficient enough to serve its load during peak hours. Therefore, incorporation of RES in SG is beneficial with respect to user as well as the environment. Fig. 4.8 depicts the energy drawn from grid for varying number of prosumers.

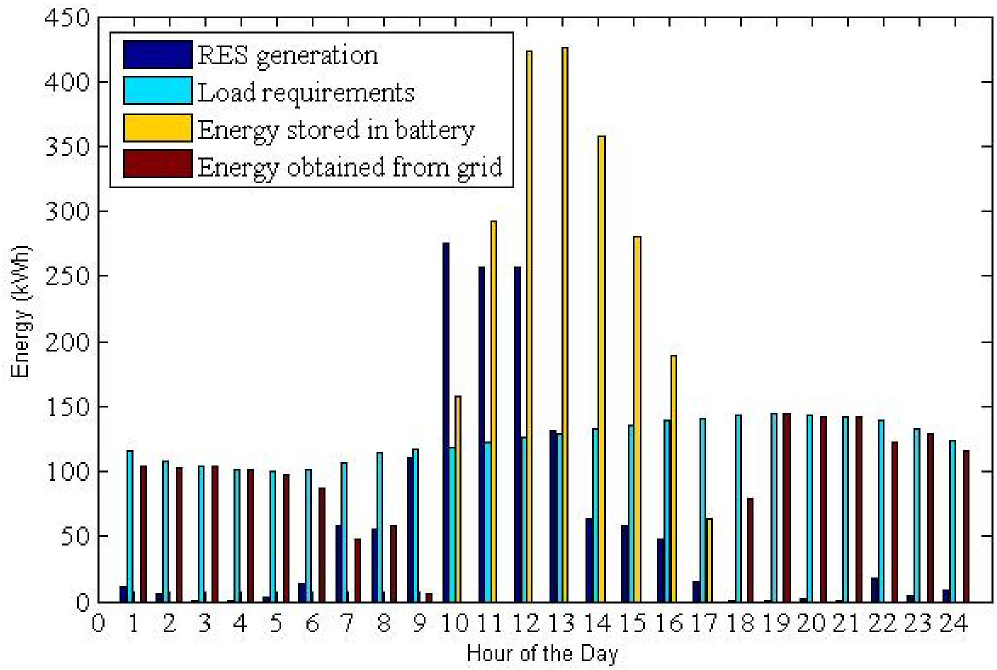

Figure 4.6: Variation of RES generation, load requirements, battery storage, and grid consumption over a 24 hour duration.

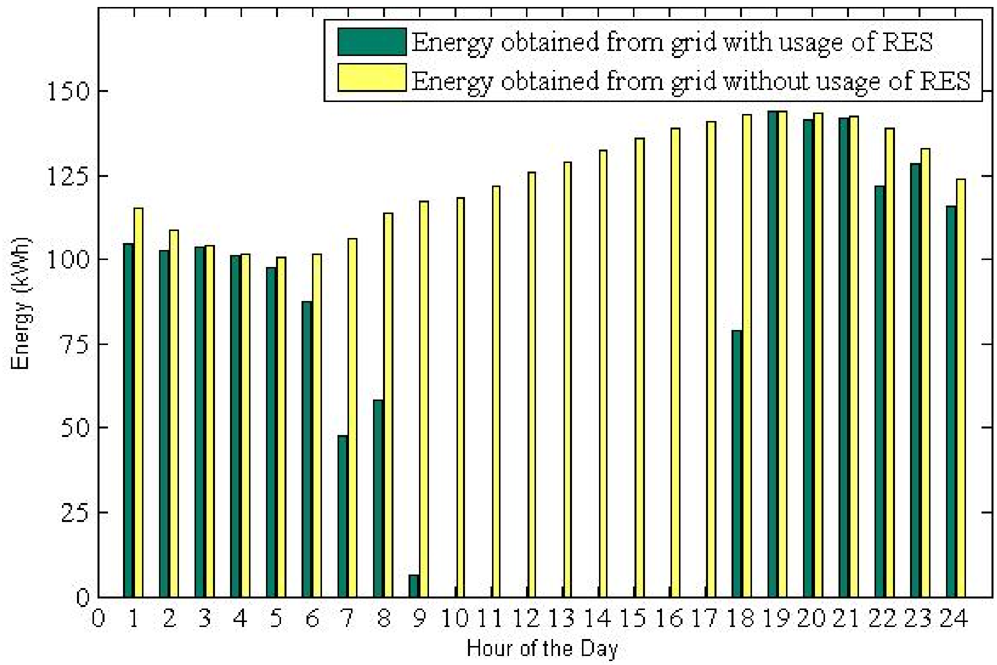

Figure 4.7: Comparison depicting the use of battery and Algorithm 2

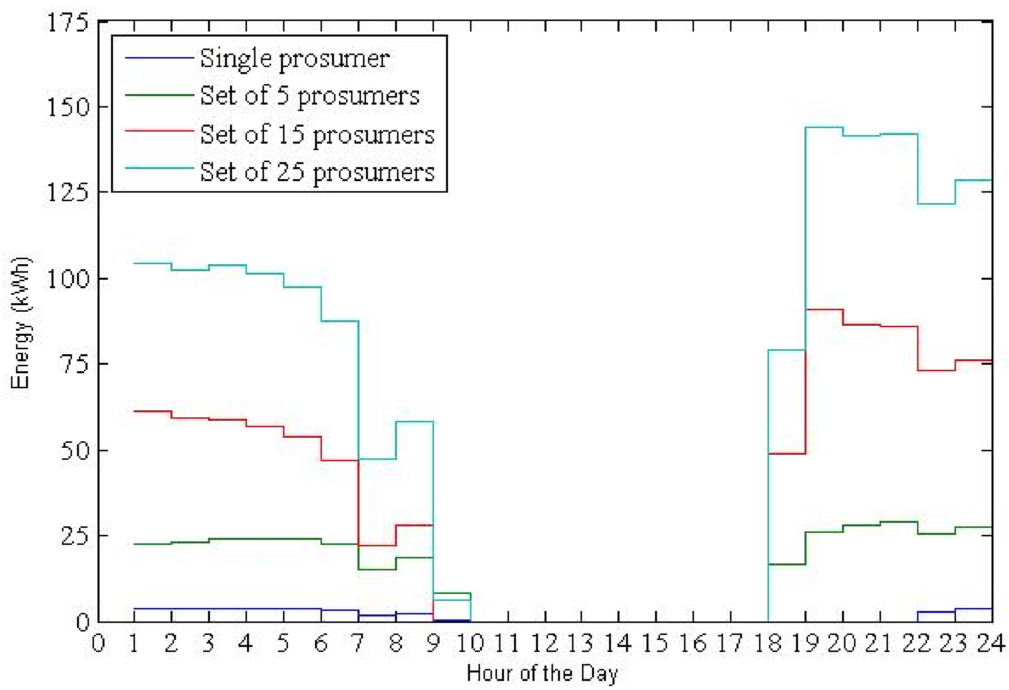

Figure 4.8: Energy drawn from grid for varying number of prosumers

Chapter 5

Conclusion and Future Scope

In this work, a novel scheme has been proposed which highlights the role of prosumers in a system performing dynamic demand response using RES. To encounter the variability of RES, battery storage is used at the point of use. The proposed system is coordinated by an ANN-based intelligent controller, which predicts day-ahead load for the system with a good accuracy. Its performance evaluation reveals the network accuracy as MSE of 0.344%, RMSE of 5.869% and MAE of 4.316%. Also, to ensure demand supply balance at all times in the proposed system, a load scheduling algorithm based on greedy technique has been proposed. The simulation of the proposed scheme for a set of twenty-five prosumers illustrates that the amount of energy drawn from grid is reduced by 46.90% over a duration of 24 hours, in comparison to the case when RES are not used. The results obtained clearly show the efficacy of the proposed scheme in real-time scenario. In the future, we will explore more techniques for integration of RES to the grid and their load management with respect to the user's demands.

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