USE OF NEURAL NETWORK BASED PREDICTION ALGORITHMS FOR POWERING UP SMART PORTABLE ACCESSORIES

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ABSTRACT

USE OF NEURAL NETWORK BASED PREDICTION ALGORITHMS FOR POWERING UP SMART PORTABLE ACCESSORIES

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In the current technological era, the use of smart portable accessories are accelerating and with that the concern of powering them in an efficient way is becoming an important challenge. Unlike the traditional fossil fuel based resources, renewable energy sources have paved the path in making use of these accessories more sustainable and improving the life style of individuals at the same time. Prediction of the output power and energy from the hybrid PV-wind renewable system poses many challenges and is of paramount importance. In the field of renewable energies, this study focuses on the prediction, monitoring and analysing of the performance indicators, majorly focusing on the hybrid PV-wind system integrated with Raspberry Pi 3 module to power small portable accessories. In order to design a robust and precise prediction model, three of the popular prediction algorithms are compared and analysed for an efficient decision support system. Levenberg-Marquardt (LM), Bayesian Regularization (BR) and Scale Conjugate Gradient (SCG) are the prediction algorithms which are used to develop a Shallow Neural Network (SNN)-time series prediction. The proposed SNN model uses a closed-loop NARX recurrent dynamic neural network to predict the active power and energy of a hybrid system based on the experimental data of solar irradiation, wind speed, wind direction, humidity, precipitation, ambient temperature and atmospheric pressure collected from Jan 1st 2015 to Dec 26th 2015. The historical hourly metrological data set which is to be analyzed have been acquired from calibrated sensors deployed at Middle East Technical University (METU), NCC (latitude $35^o15'N$, longitude $33^o00'E$). The smart portable accessory considered in this study is an umbrella with an integrated Raspberry Pi module to fetch the weather data from the current location and store it in cloud to be processed using SNN classified prediction algorithms. The best harvested prediction result is in turn adopted by the Smart Umbrella System (SUS) to power the smart portable accessories in a smart and efficient way.

Keywords: energy harvesting, renewable energy sources, shallow neural network, prediction algorithm, smart umbrella system, Raspberry Pi

ÖZ

AKILLI TAŞINABİLİR AKSESUARLARI GÜÇLENDİRMEK İÇİN SİNİR AĞI TABANLI TAHMİN ALGORİTMALARININ KULLANIMI

Qadir, Zakria
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Mevcut teknolojik çağda, akıllı taşınabilir aksesuarların kullanımı hızlanıyor ve bu sayede onları verimli bir şekilde güçlendirme endişesi önemli bir sorun haline geliyor. Geleneksel fosil yakıt bazlı kaynakların aksine, yenilenebilir enerji kaynakları, bu aksesuarları daha sürdürülebilir hale getirme ve aynı zamanda bireylerin yaşam tarzlarını iyileştirme yolunu açmıştır. Çıkış gücünün ve enerjisinin hibrit PV-rüzgar yenilenebilir sisteminden öngörülmesi birçok zorluk yaratır ve büyük önem taşır. Yenilenebilir enerjiler alanında, bu çalışma büyük ölçüde küçük taşınabilir aksesuarlara güç sağlamak için Raspberry Pi 3 modülü ile entegre hibrit PV-rüzgar sistemine odaklanarak performans göstergelerinin tahmini, izlenmesi ve analizine odaklanmaktadır. Sağlam ve kesin bir tahmin modeli tasarlamak için, popüler tahmin algoritmalarından üçü etkin bir karar destek sistemi için karşılaştırılır ve analiz edilir. Levenberg-Marquardt (LM), Bayesian Regularization (BR) ve Scale Conjugate Gradient (SCG), Shallow Neural Network (SNN) zaman serisi tahminini geliştirmek için kullanılan tahmin algoritmalarıdır. Önerilen SNN modeli, güneş ışınımı, rüzgar hızı, rüzgar yönü, nem, yağış, ortam sıcaklığı ve toplanan atmosferik basıncın deneysel verilerine dayanarak bir hibrit sistemin aktif gücünü ve enerjisini tahmin etmek için bir kapalı devre NARX tekrarlayan dinamik sinir ağı kullanır. 1 Ocak 2015 - 26 Aralık 2015 tarihleri arasında. Analiz edilecek tarihi saatlik metrolojik veri seti, Orta Doğu Teknik Üniversitesi (ODTÜ), NCC'de (enlem $35^o15'N$, boylam $33^o00'E$). Bu çalışmada ele alınan akıllı taşınabilir aksesuar, hava durumu verilerini mevcut konumdan almak ve SNN sınıflandırmalı tahmin algoritmaları kullanarak işlenmek üzere bulutta saklamak için entegre bir Raspberry Pi modülüne sahip bir şemsiyedir. En iyi hasat tahmin sonucu, akıllı taşınabilir aksesuarlara akıllı ve verimli bir şekilde güç sağlamak için Akıllı Şemsiye Sistemi (SUS) tarafından benimsenmiştir.

Anahtar Kelimeler: enerji hasadı, yenilenebilir enerji kaynakları, sığ sinir ağı, tahmin algoritması, akıllı şemsiye sistemi, Raspberry Pi

To Allah Almighty for bestowing me with strength to apprehend His numerous creations

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LIST OF ABBREVIATIONS

ICT	Information and Communication Technology
AI	Artificial Intelligence
ML	Machine Learning
FFNN	Feed-Forward Neural Network
GRNN	Generalized Regression Neural Network
ANS	Artificial Neural System
RNN	Recurrent Neural Network
DNN	Dynamic Neural Network
PV	Photo voltaic
LM	Levenberg-Marquard
BR	Bayesian Regularization
SCG	Scale Conjugate Gradien
SNN	Shallow Neural Network
SUS	Smart Umbrella System
IEA	International Energy Agency
GWEC	Global Wind Energy Council
GW	Giga Watt
kW	Kilo Watt
BP	British Petroleum
toe	tons of equivalent
TEG	Thermal Energy Generato
NN	Neural Network
IoT	Internet of Things
EMG	Electromyography

ECG	Electrocardiogram
3D	3 Dimensional
CNN	Convolutional Neural Network
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
MBE	Mean Bias Error
R	Correlation Coefficient
MSE	Mean Square Error
MLP	Multilayer Perceptron
ELM	Extreme Learning Machine
ARMA	Auto Regressive Moving Average
ARIMA	Auto Regressive Integrated Moving Average
ANN	Artificial Neural Network
KNN	K-Nearest-Neighbour
ADP	Adaptive Dynamic Programming
SE	Standard Errors
S_i	Solar Irradiation
W_s	Wind Speed
T_a	Ambient Temperature
H	Humidity
R_a	Precipitation
P_a	Atmospheric Pressure
W_d	Wind Direction
STC	Standard Test Conditions
NOCT	Nominal Operating Cell Temperature
NARX	Non-linear Auto-Regressive with External input
NAR	Non-linear Auto-Regressive

SVM	Space Vector Modulation
SVR	Space Vector Regression
SOM	Kohonen's Selforganizing Map
BRANN	Bayesian Regularised Neural Network
FBNN	Feed Backward Neural Network
RNN	Recurrent Neural Network
SLP	Single-Layer Perceptron
MLP	Multi-Layer Perceptron
HMM	Hidden Markov Model
E	Error Signal
DLS	Damped Least Square
G	Error Gradient
BP	Back Propagation
GPS	Global Positioning System
USB	Universal Serial Bus
DC	Direct Current
LED	Light Emitting Diode
GHG	Green House Gas
GA	Genetic Algorithm

CHAPTER 1

INTRODUCTION

The rapid elevation in the energy consumption along with the rise in conventional fuel cost has lead to an awareness for many environmentalist, scientist and economist to contribute in the field of renewable energy [1, 10]. However, the renewable energy usage also impose some additional factors like higher global energy demand whihc is caused by the drastic increase in population growth and economic expansion [11]. In the last two decades, it is observed that the investments in the installation of photovoltaic (PV) systems and wind turbines have sustained a remarkable growth rate as compared to fossil fuels like coal and natural gas [12]. One of the most important needs for the era we are living in is to use renewable energy sources and get rid of the high dependency on fossil fuels which are badly affecting our environment [13]. The popularity of renewable energy resources have been increased at a global level, influenced by the energy policies and legislation imposed by the government and non-government bodies. For the aforementioned reason, European Union (EU) set a political agreement with European Council, Parliament and Commission on 14 June 2018 to set forth new grounds to elevate the usage of renewable energy, leading towards a cut of carbon-dioxide emissions by at least 40% in Europe by 2030 [14]. The target set by the EU in renewable energy share is predicted to be 32% by 2030 and can be increased further as specified in the revision clause by the year 2023 [15] . Main precedence of these renewable energy resources from fossil fuels resources is that they are environment friendly, sustainable, cost effective and can regenerate energy in a shorter time-frame through the use of indispensable types of energy [16–19]. Moreover, in terms of economical development, the energy produced by these renewable resources ensure less dependence on imported fossil fuels and provide safe and secure energy supplies by saving traditional resources [20].

According to the report generated by International Energy Agency (IEA) from 2000 to 2011, globally installed capacity of the PV system has increased from 1 GW to 67 GW [21]. On the other hand, for the wind turbine systems, the globally installed capacity has surpassed 50 GW according to Global Wind Energy Council (GWEC) in 2017 [22]. Moreover, according to the British Petroleum (BP) Statistical Review of World Energy, an unexpected amount of 69.4 tons of equivalent (toe) rise in the growth of renewable power has been observed in 2017, where toe represents the total amount of energy released during burning of one tone of crude oil [23].

Solar irradiance, wind speed and other weather factors poses great importance in many of the prediction applications, such as environmental impact analysis, thermal load on buildings, meteorology and renewable energy power plants [24–26]. The commonly used applications in recent studies are mostly related to the daily or yearly based solar irradiance data for a PV power plant or wind speed for a wind turbine [27,28]. Based on these weather factors the energy output of the hybrid PV-wind system varies and to predict the renewable energy output is quite challenging [29].

1.1 Background

The popular term Internet of Things (IoT) was co-founded by Kevin Ashton and the main concept lies in the connectivity of small objects through internet. According to the report generated by Cisco, approximately 50 billion devices will be merged with the internet by 2020 [30]. Moreover, the number of smart meters installed will be increased to 1.1 billion by 2022 as reported by Navigant [31]. The internet based connectivity of cars will drastically elevate from 23 million in 2013 to 152 million in 2022 according to Automotive News report [32]. IoT is a fast growing field and can be integrated with any kind of environment as per application requirement such as smart industry [33], smart health [34,35], smart cities [36,37], smart building [38,39], smart grid [40, 41], smart transportation [42, 43] and smart homes [44, 45] as shown in Fig. 1.1.

The rapid growth of the IoT field and the advancement in the Communication technologies have enforced the physical world to interlink with other computation elements like sensors, actuators while keeping the network connectivity continuous [46]. The integration of these sensors and processors into everyday object had enabled new horizons for the Information and Communication Technology (ICT). The ICT is a broader topic and the tremendous advancement in this area such as smart portable accessories and devices, machine learning based prediction models, wireless mobile communication and sensor area networking portrays a clear picture to make the dream of smart world a reality [47]. The commonly used term smart particularly portrays the autonomous capability to acquire and apply that knowledge to the surrounding environment. In a smart world, the sensor-enabled devices connected together work simultaneously to make human life comfortable as per their needs. The AI-driven edge computed mechanism along with the integration of IoT enabled portable devices are quite promising and has the capability to deal with most relevant constraints at a global scale. The main constraint is the power consumption, high computational complexity and short battery life of the IoT-enabled portable devices.

This thesis is structured as follows. Chapter 1 discusses an overview of the previous research studies related to smart wearable accessories, efficient prediction algorithms and neural network based models. The literature review is followed by the design methodology. Chapter 2 describes the design methodology and all the approaches to harvest the best prediction results for SUS in order to power the smart portable accessories in a smart and efficient way. In Chapter 3, the prediction results and discussion is presented based on the historical hourly based data collected from calibrated sensors in METU, NCC. Chapter 4 covers the conclusion and future works.

1.2 Related Work

The smart wearable accessories are often considered together with studies focusing on IoT and related applications. Perera et al. [48] surveyed around hundred of the smart IoT solutions and classify them into five different groups such as smart wearable, smart environment, smart home, smart city and smart enterprise. The authors further investigate the effectiveness and efficacy of these solutions on consumers' lifestyle and society in general. In [48], authors also claim that the proposed solutions can aim to contribute at large scale industries, but they did not clearly mention about how to

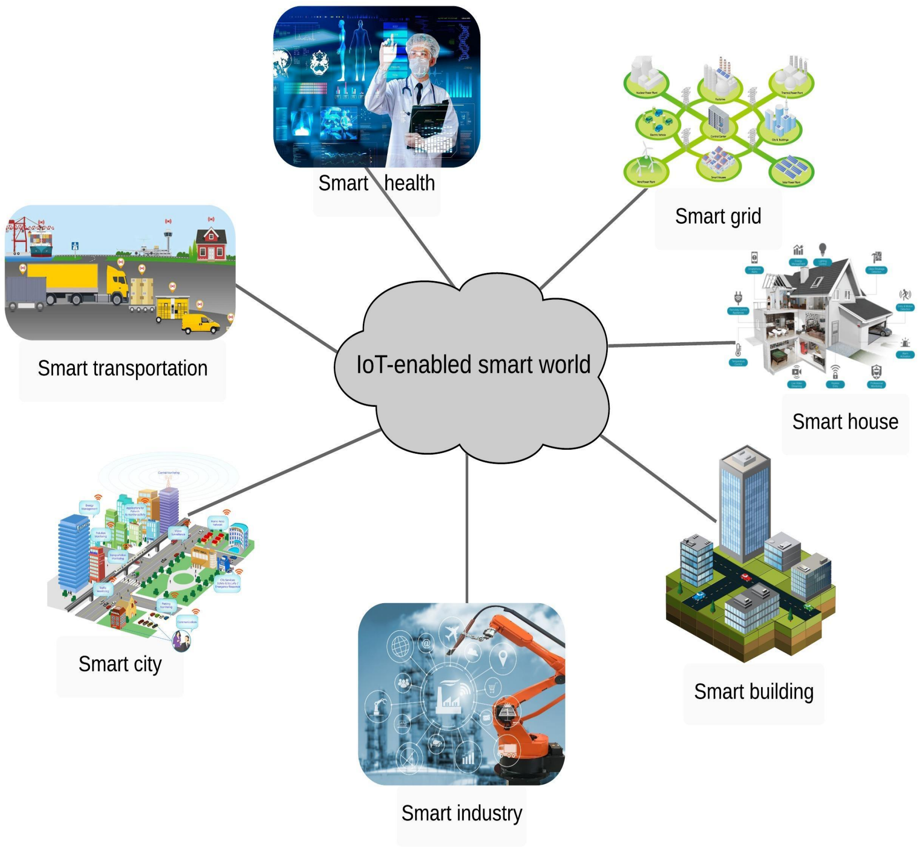


Figure 1.1: IoT-enabled smart world

optimize the industry performance through monitoring, real time data collection and reasoning.

In Myers et al. [49] authors propose an analytical method to analyze the effects of human and different environmental factors on thermal energy generator (TEG). For this purpose, a TEG is developed in a wearable form to investigate the energy harvested during human trial under different environmental conditions. The results depict that the humidity levels don't have a pronounced impact on the thermal energy harvesting, however the body movement and wet-bulb temperature affects the process. The authors also emphasize that the proposed system introduces a unique self-powered design that can be used with wearable device for different applications. However, the authors did not examine the practical applicability of self-powered design that can be used with wearable device for different applications.

In Thielen et al. [50] authors investigate the effect of human body heat and the power conversion circuitry to design a self-sustained wearable device for different applications. This study mainly focuses on the interaction between TEG and DC-DC conversion circuit. For this purpose, two approaches are compared based on the I/O voltage and thermal resistance coupled with inductor based DC-DC converter. The results depict that in terms of output power and total conversion efficiency the mTEG can perform as good as or even better than µTEG.

Similar to studies presented in [49, 50], in this study as well an infrastructure and a novel design is presented to make energy harvesting possible. Instead of focusing on thermal energy and body heat, possibilities of using solar and wind energy together with a proactive learning infrastructure is investigated.

In [51], authors presented two user studies consisting a total of 30 participants in order to analyze the design possibilities and preferences for smart handbags. A co-design approach was assimilated. First the users draw a template individually and then through co-design workshops a prototype of the smart handbags are created. While the authors recommended ten of the best suited designs for the smart handbags in terms of shape, size, color and texture, however, the energy efficiency of these portable accessorie s are not discussed.

In [52], a novel smart eyeglass design is proposed which monitors the dietary patterns of a human being using Electromyography (EMG) electrodes mounted on smart eyeglasses. The authors analyze food pieces (banana, cucumber and carrot) of three hardness levels. Please note that the wearable considered in [52] is similar to our work since both use energy harvesting for facilitating different applications. In [52] the results show that harder food pieces cause higher EMG harvesting.

A prototype is proposed in [53] for monitoring real time heart rate and electrocardiogram (ECG) using a 3-D smart phone case. Moreover, this smart accessory consist of two dry electrodes embedded at the bottom of the 3-D case which does not require any extra circuitry leading to an affordable, light in weight and user friendly health monitoring system. The experimental results evaluated for the ECG measurements in this study are closely related to the medical grade and can be improved further.

An optical accessory integrated with an android smartphone is introduced in [54] to catch early stage cervical cancer in one of the Africa's rural clinics. The authors use convolutional neural network (CNN) and train approximately 0.1 million images of cervixes (healthy tissue, precancerous and suspected cancer) from U.S. National Cancer Institute.

Unlike the studies considered above, energy efficiency is considered in [55] with introduction of a self-sustained wireless bracelet design which is powered through the use of flexible solar energy harvester. The authors illustrate that the designed system is efficient and helpful in many healthcare applications for patient and elderly people. The results retrieved from the designed model show that the power produced is 16mW when exposed to sun, while it is 0.21mW when used indoor on a test application using Bluetooth wireless technology.

Predicting the conditions for a proactive approach of energy harvesting to be used together with accessories and wearables has the potential to significantly improve the efficiency and usability. Ramsami et al. [56] formulates a hybrid model which they named as stepwise regression-feedforward neural network and is considered to be the best approach for predicting the PV system energy output. The data collected for this study is from 2012 to 2013, in Newquay, Cornwall, UK. The authors depict that using hybrid neural network models provide slightly better prediction results as compared to single stage models. The proposed hybrid model provide Root Mean Square Error (RMSE) of 2.74, mean absolute error (MAE) of 2.09, mean bias error (MBE) of 0.01, and correlation coefficient (R) of 93.2%, respectively. However, the data collected is on daily basis and the hybrid model do not show a significant difference than a single stage model in terms of RMSE and R.

A Multilayer Perceptron (MLP) model is proposed by Mellit et al. [57] to predict 24h ahead solar irradiance based on the data collected for mean solar irradiance and air temperature. For testing the efficacy of the proposed model, it is cross-validated using the K-fold model. According to the results obtained, the authors claim that the regression results were quite promising, achieving between 98-99% for sunny days and 94-96% for cloudy days. However, in this study only cloudy and sunny days were considered based on the data availability.

The PV plant active power and active energy prediction is considered in [58] by considering the solar irradiance,wind speed, wind direction,humidity and ambient temperature as the input variables. The function fitting neural networks are analyzed with three different algorithms LM, BR and SCG on daily basis data collected in the year 2014, Romania. The authors also compare 39 different neural networks and based on their results BR algorithm provides the best results having R of 95.6% and MSE of

0.198. However, the main shortcoming of this study is that the computational time and output errors are not analyzed.

In [59] an extreme learning machine (ELM) integrated with employed cuckoo algorithm is addressed for data preprocessing in a hybrid prediction system. The authors mainly focus on surpassing all the shortcomings in the standard ELM models. In order to lessen the input parameters, a standard genetic algorithm is used, whereas, for correcting errors auto regressive moving average (ARMA) is employed.

Boroojeni et al. [60] models the historical load data in order to predict the electric power demand using multi-time-scale modelling. Short term and medium term horizon are covered for predicting the power demand. Moreover, the authors consider two type of components. The first one deals with the power demand prediction by using ARMA for the historical load data, while the second one predicts the power demand profile without using additional weather data, as it is often unavailable. Two approaches are used by the authors to evaluate the data modeling accuracy namely Bayesian quantification method and the Akaike, based on the model complexity and accuracy.

Ye et al. [61] proposed an optimized Levenberg Marquardt-back propagation (LM-BP) NN integrated with Quasi-Newton and gradient descent method to enhance the prediction of electricity demand of a shopping mall in China. For finding the best prediction model, both BP and LM-BP NN are compared based on the actual results and simulation results for electricity consumption. The authors also demonstrates that the proposed LM-BP NN forecasting model provide better performance in terms of stability and accuracy for predicting both real-time and short-term electricity consumption. However, this study doesn't consider other seasonal climatic factors that can effect to predict long-term energy consumption.

In [62] authors proposes a ANN prediction model based on the hourly and daily readings to predict the diffused solar radiation. The authors also analyzed and differentiate the performance parameters based on two linear regression models integrated with ANN. The output prediction results demonstrates that the ANN model surpass the regression model both in terms of standard errors (SE) and RMSE.

Similarly, İzgi et al. [63] propose an ANN model to predict the shortest time duration for energy generated by a 750 W of solar PV panel. The authors observe that the best energy generated prediction results are for 3 to 5 min (short time duration) during the month of April and 35 to 40 min (medium time duration) during the month of August. However, during these two months the RMSE between measured and tested values vary between 33-63W, respectively.

Many of the studies have been performed to predict solar power output by comparing the statistical performance parameters using climatic factors. In [64] authors analyze the annual energy output of a PV plant by comparing ANN with three different mathematical models. The authors claim that the prediction results for ANN model outperforms the classical models. Besides the temperature and irradiance losses, second order energy losses because of certain factors such as shading and spectral effects also contributed to lessen the accuracy of these mathematical models.

Pedro and Coimbra [25] proposed a 1-h ahead (short-term) power output prediction for a 1MW PV plant in California. For this purpose, they compared five different models, namely ANN, k-nearest-neighbour(KNN), AutoRegressive Integrated Moving Average (ARIMA), hybrid genetic algorithm-ANN and ANN. The author observe that ANN performs well than other prediction techniques, having a RMSE and R of 0.1142 and 97%, respectively. Significantly, this accuracy can be increased by the use of genetic algorithm as claimed by the authors.

For improving the prediction accuracy of the ANN based predicton model, several input parameters can be applied. Azadeh et al. [65] propose a ANN model using seven metrological input parameters to predict the solar output of different geographical locations in Iran.

The most influential input climatic parameters are also determined in fewer studies that can be directly fed to ANN prediction models. Similarly, Marquez and Coimbra [66] selects and analyze the most relevant input variables from several climatic parameters using Gamma test based strategy. Later on, a genetic algorithm search is also included for speeding the process and finding the relevant combination of input variables. The experimental results depict that the selected inputs are temperature, precipitation, cloud cover and solar geometry. Moreover, by using these inputs , the values of R, MBE and RMSE comes out to be 94.7%, -0.6 and 0.177 respectively.

The use of additional input climatological factors is investigated by Sfetsos and Coonick [67] for predicting the solar power output. Analyzing the trial and error method the two-step technique was taken into account by the authors. In this technique, minimal errors are achieved initially by training the model. Significantly, the influence of input parameters is abolished by changing it with either zero or mean value.

Implementation issues can be faced while integrating several input variables to an ANN model. The foremost one is the elevation in computation time which is consumed during the training process. Additionally, it can also increase the risk of having redundant parameters which may complicates the training process and can cause a drastic increase in the prediction errors [68]. This scenario is most common while using MLP, as each of the hidden neuron is multiplied by the input variables leading to a complex network. To recapitulate, additional dimension to the output space is caused by the addition of variable in the input data and in order to represent the mapping relationship, the training stage will need more data to occupy the space densely [69]. Currently, the development of smart solutions as well as implementation of various applications using smart wearables and accessories are being investigated quite extensively [51–54]. Furthermore, various processes of predicting the energy output of a PV and wind plants as a standalone system has also been considered in various studies [70, 71].

In the current state of knowledge, the scientific studies conducted in the literature review depicts that still a research gap exists regarding the prediction algorithm that can compute results with less computational time, higher correlation coefficient (R), least MSE and least hybrid output errors. Moreover, the further extension of ANN which is known as SNN is discussed in more detail in Chapter 2. Several hidden layers in DNN requires more computational power and time, and may also lead to over-fitting where the dataset is in millions. However, as compared to DNN, SNN model is used to deal with medium-size datasets utilizing less power and computational time and is quite efficient in providing the best prediction accuracy for the collected weather dataset. For processing the prediction algorithms, MATLAB 2018b software is analyzed on a Windows 7 Operating System with Intel Core i5-3470, 3.20GHz-3.19 GHz and 8GB RAM. Moreover, lightweight portable accessories are used for the design of SUS framework.

1.2.1 Artificial Neural Network

ANN are the models inspired from human nervous system to assimilate themselves in any environment and perform different activities as shown in Fig. 1.2. The most common task that an ANN can perform are pattern recognition, prediction, image classification, clustering, signal processing, social networking, machine learning techniques [72–77]. Currently, ICT host a lot of hot topics related to artificial intelligence (AI), such as machine learning, deep learning, neural networks, cloud computing, big data and information security [78–81]. Under the umbrella of ANNs lies data analysis factors, such as computational time, accuracy, performance, latency, scalability and fault tolerance [82, 83].

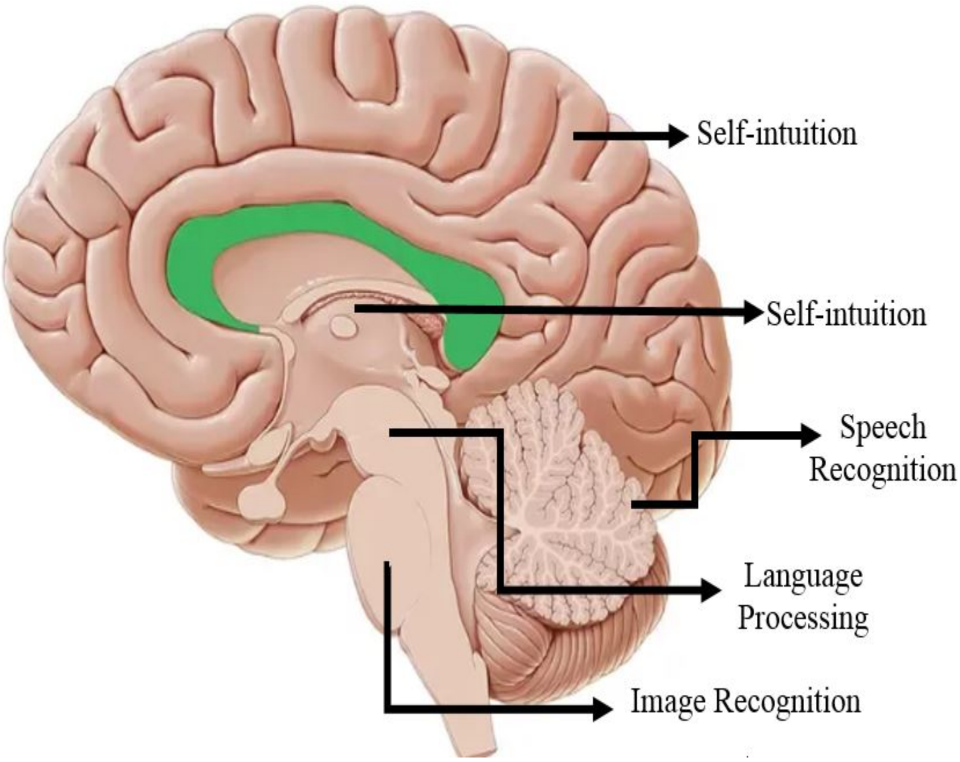


Figure 1.2: Human brain structure with performance capability [2]

ANN have high speed performance capability in massive parallel implementation heightening the need to do comprehensive research in this domain [84]. In numerical paradigm, ANN are widely used in universal function approximation because of their unique capability of adaptivity, self-learning, fault tolerance, advancement and non-linearity in input to output mapping [85]. Moreover, for handling complex and non-complex problems, these data analysis factors provide a clear picture. Therefore, ANNs are preferred to be used (effectiveness, successfulness and efficiency) in providing high data handling capability.
An ANN consist of highly interconnected elements (nodes) known as neurons, which

look like a human or animal (biological) natural neurons from brain [2,86–90]. These nodes are connected via weights and operate in parallel, similar to the case with synapsis, where the message is transmitted from one node to another. A simple ANN architecture is illustrated in Fig. 1.3. The neurons (also known as artificial neurons) collects this message, process it and again transmit it to neighboring nodes. During the learning process, the weights of these artificial neurons and nodes are adjusted in order to speed up the process. In most cases, the output neurons are computed as a non-linear function depending on the input message during ANN implementation. According to the task performed on the inputs, the neurons assimilated themselves into different layers, thus starting from the input layer- each message (signal) passes to the output layer.

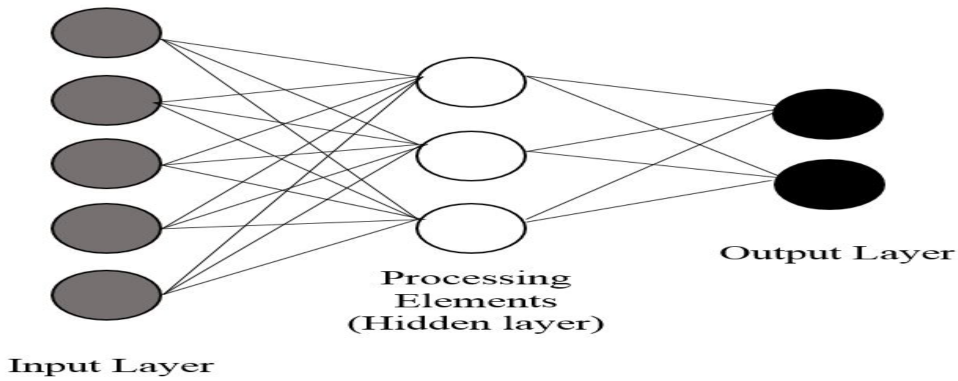


Figure 1.3: Architecture of ANN [3]

Certain algorithms are used to train ANNs and the best training algorithm in terms of computational time and accuracy depends on many factors, such as size(dimension) of the data set, different weight and biases of network, number of delays, network complexity and its architecture, splitting of data set for training, validation and testing purpose and last but not the least is the acceptable errors (error histogram) and auto-correlation between training and test data. ANN energy prediction pipeline consist of five basic steps to select accurate prediction model. The input data from the given data base is splitted into training and testing according to the type of problem being addressed. In the second and third step, feed-forward or feed-back connections are selected along with the parameters to train ANN model. In the forth and fifth step, the error values are calculated based on R, RMSE,MSE, MAPE, and the prediction model is selected based on least errors and higher accuracy as shown in Fig. 1.4.

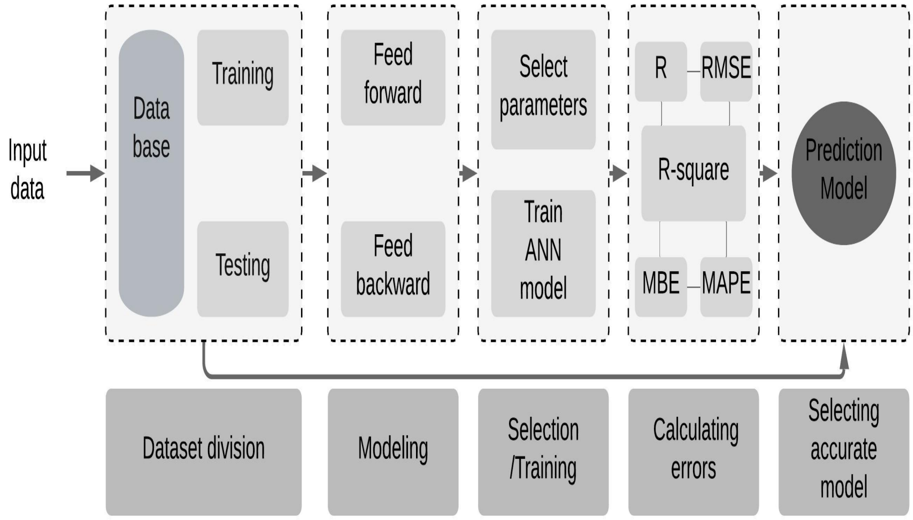


Figure 1.4: ANN energy prediction pipeline [4]

There are several problems related to time-consumption convergence, variable quantization and artificial neural system (ANS) using supervised learning that needs to be addressed. This study highlights some of these shortcomings as follows:

- Improving the prediction capability of ANNs and making them robust. Additionally, training generalized range of data in order to enhance the prediction accuracy [91, 92].
- Complete knowledge retrieval from trained ANNs and model transparency in order to deeply understand the data transfer and processing from input to output layer.
- Enhancing the extrapolation ability of ANNs in order to design a model that can predicts the outward range of data accurately.
- Improving efficacy of ANN prediction algorithms to avoid uncertainity.

1.2.2 ANN Applications

Researchers interest in ANN applications has exploded over the past years. Many of the new applications are introduced primarily focusing on technological and de-

Table 1.1: Results related to classification, pattern-recognition and prediction in several ANN Applications [1]

ANN Applications in different sectors	Classification	Pattern recognition	Prediction	Total
Agriculture	2	3	3	7
Energy	2	15	5	22
Engineering	2	7	22	31
Environmental	2	15	10	27
Finance	2	15	10	27
Management	2	2	40	44
Manufacturing	5	15	12	32
Medical science	2	5	10	17
Mining	2	15	2	19
Policy	2	2	2	6
Science	2	25	25	52
Security	2	18	20	40
Weather and climate	2	15	2	19
Other fields	10	11	52	71

velopment issues related to ANN. These applications are not limited to one area but submerges many fields such as agriculture production and environment, energy generation, engineering and science, finance and management, policy and security [93–96]. While the other fields are related to stock market, banking, quality prediction of crude oil, money laundering, water treatment, crime detection etc. The relationship among these ANN applications with classification, pattern-recognition and prediction is summarized in Table.1.1 and .

As ANN is a vast field and has the capability to solve any problem related to different sectors. Different framework, models, algorithms and scheme are always available to predict, classify or recognise patterns in any emerging field. Fig. 1.5 reveals diverse sectors in which ANN applications are applied. However, there is an utmost need for robust ANN prediction models related to energy sector that can be analyzed to utilize energy in much sustainable and efficient way.

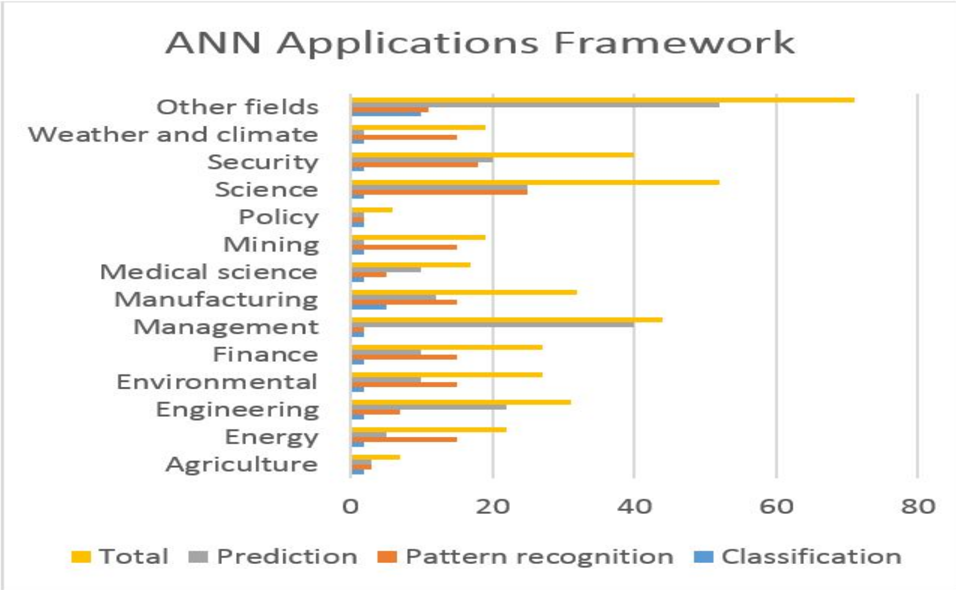


Figure 1.5: ANN Applications in diverse sectors [1]

1.2.3 ANN Classification

ANN are classified into two main categories. The first category is the feed-forward neural network (FFNN), where the data flows in only forward direction. Moreover, it consist of single or multiple hidden layers which encompasses several hidden neurons to process any arbitrary function under different scenarios [97–101]. The FFNN is further divided into single or multiple layer perceptron and radial basis function as shown in Fig. 1.6.

The second category is the feed-back neural network (FBNN) or recurrent neural network (RNN), in which data can flow in either direction. The main purpose of using FBNN is that the output can be again feedback to the input in order to process it again and make the network more robust and error-free [102–104]. The bayesian regularised neural network (BRANN) is one of the commonly used feedback networks that uses more computational time but gives the best prediction results as illustrated in Fig. 1.6.

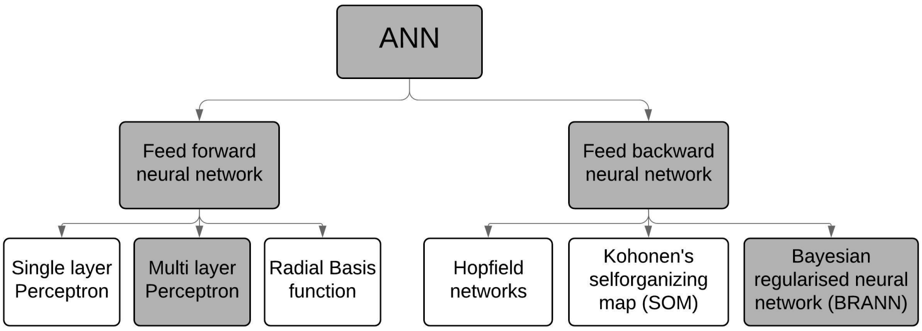


Figure 1.6: ANN Classification [5]

The FFNN and FBNN are further explained in this section.

1.2.3.1 Feed-Forward Neural Network

The first developed type of ANN is the feed-forward neural network (FFNN), where the information flows unidirectionally and no feedback connection is present.
FFNN can be classified as multilayer perceptron (MLP), where every neuron in the adjacent layers are interconnected as illustrated in Fig. 1.7. The weights are adjusted during training between the neurons to match the network output with desired target. The main purpose of these FFNN is that they have the capability to fit any kind of finite input-output problem by encompassing enough neurons in a single hidden layer.

1.2.3.2 Generalized Regression Neural Network

The modified type of ANN is generalized regression neural network (GRNN). These networks are probabilistic-based and performs regression rather than classification tasks. For activation function, GRNN uses a popular kernal known as Gaussian in the hidden layer [105, 106]. These NN are a four layered network, which comprise of pattern and summation layer instead of hidden layer as shown in Fig. 1.8. Clustering is performed on the training data in the pattern layer, while the extra neuron in summation layer are used to calculate the probability density of the function [107, 108]. The new inputs are generalized for adequate training patterns and is equated in 1.1

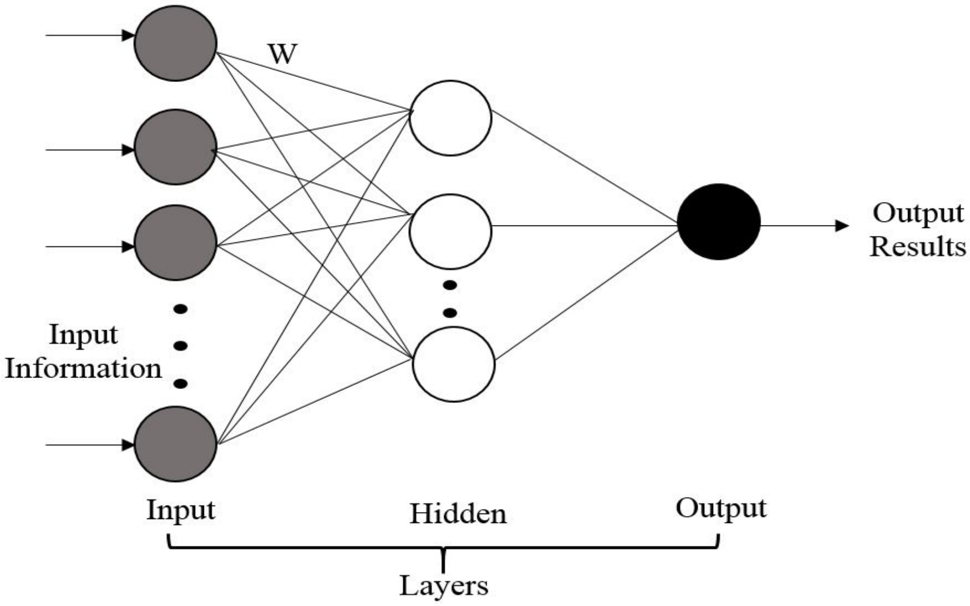


Figure 1.7: Architecture of FFNN [6]

and 1.2 respectively.

$$\mid D \mid_k = (X - X_k)^T (X - X_k) \tag{1.1}$$

$$Out = (\sum_{k=1}^{N} Y e^{-|D|_k / 2\sigma^2}) / (\sum_{k=1}^{N} e^{-|D|_k / 2\sigma^2}) \tag{1.2}$$

where $\mid D \mid_k$ represents the Euclidean distance between the training samples (input=X, output=Y) and input X_k. While, σ is the smoothing parameter for GRNN.

1.2.3.3 Feed-Backward Neural Network

FBNN or RNN are used in many applications related to pattern recognition, medicine, mathematical proofs, classification, data fitting and the time-series prediction. Fig. 1.9 shows a connection between nodes that particularly demonstrates the terrestrial dynamic behavior for a timing sequence. For this purpose, FBNN uses some memory element to store the previous output and feedback it to the input with in concurrent time steps. For this study, Recurrent dynamic neural networks are considered for

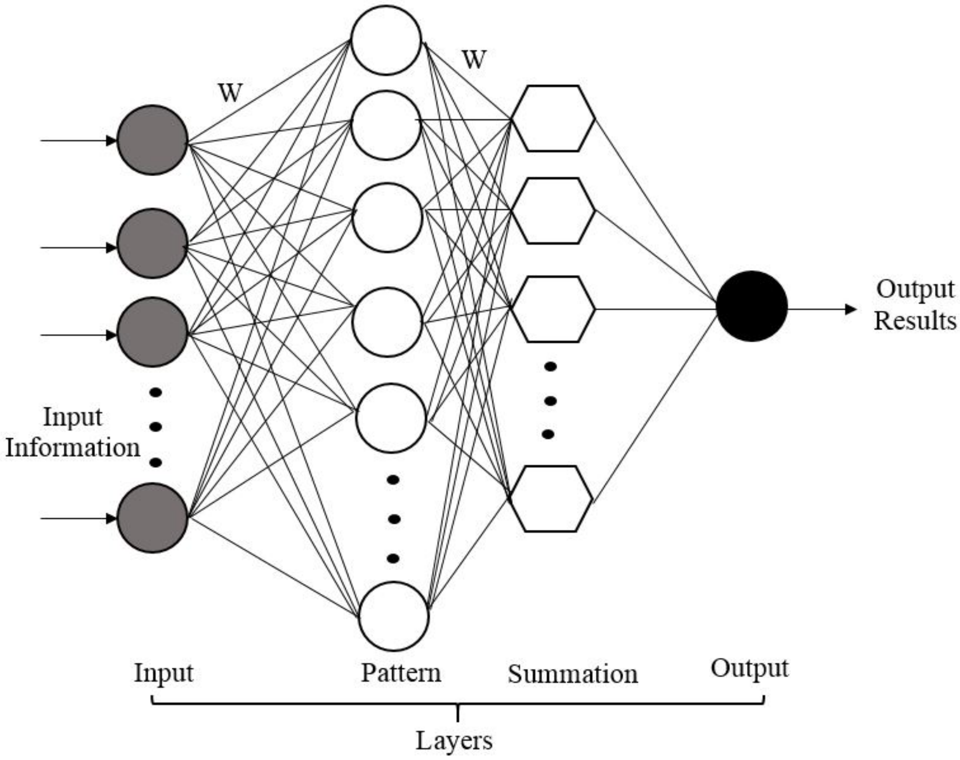


Figure 1.8: Architecture of GRNN [7]

predicting the hybrid energy to energize the portable accessories and is explained in Chapter 2.

1.3 Database Description

In the design of the Smart Umbrella System (SUS), a 100W flexible PV sheet (RNG-100DB-H) [109], and a 10W vertical wind turbine (FLTXNY FS-VM7) [110], are employed. The specifications of these components are provided in Table 1.2. A comprehensive study is conducted, in which all the metrological factors are considered that can affect the output power and energy of the SUS. In turn, the system model illustrated in Fig. 1.10 is acquired, where the output power and energy of the hybrid system are considered to be dependent variables, whereas, the input metrological factors to be independent variables.

The varying weather condition data which are considered for forecasting the output

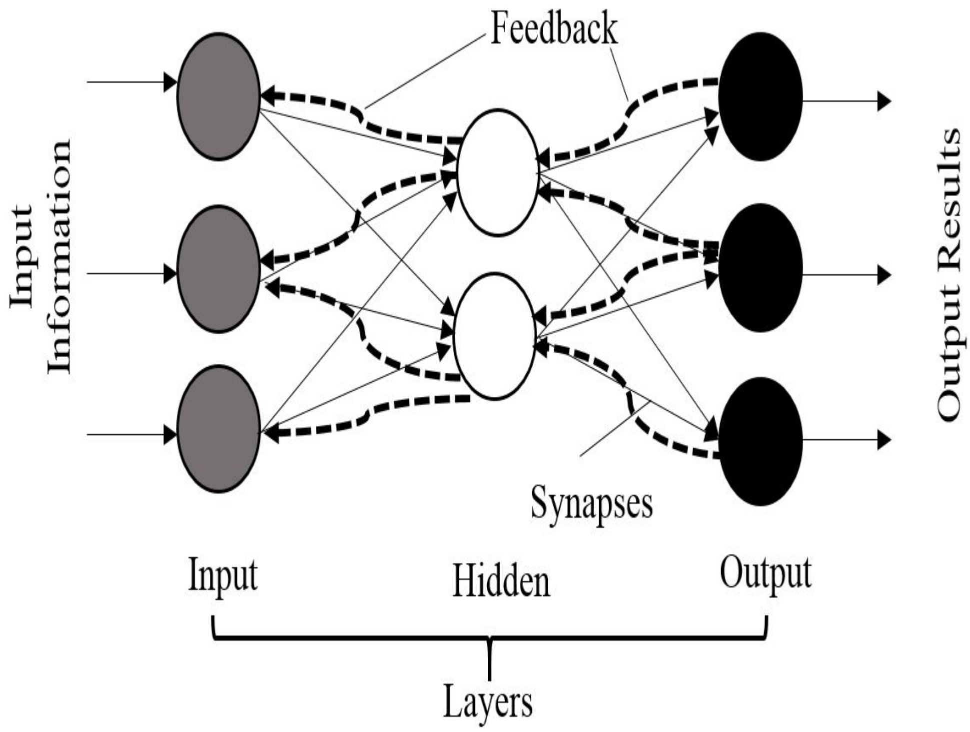


Figure 1.9: Architecture of FBNN [8]

power and energy of a SUS are: the Solar Irradiation (Si), Wind Speed (Ws), Ambient Temperature (Ta), Humidity (H), Precipitation (Ra), Atmospheric Pressure (Pa) and Wind Direction (Wd). Fig. 1.11 shows the calibrated sensors inside the solar plant to measure the weather data and it is recorded based on hourly timescale from Jan 1st 2015 to Dec 26th 2015 in METU, NCC.

1.4 Problem Statement

The need of proactive approach for optimizing the cost of energy harvesting techniques is of paramount importance. The use of two most commonly used renewable energy; either solar or wind energy to power appliances is becoming popular and to harvest this energy in an efficient way is the need of this hour. Currently, the advancement in ICT field improves the life time of batteries to power smart accessories but energy harvesting is still the main concern that needs to be addressed. This study emphasizes on accuracy and portability by analyzing the available prediction

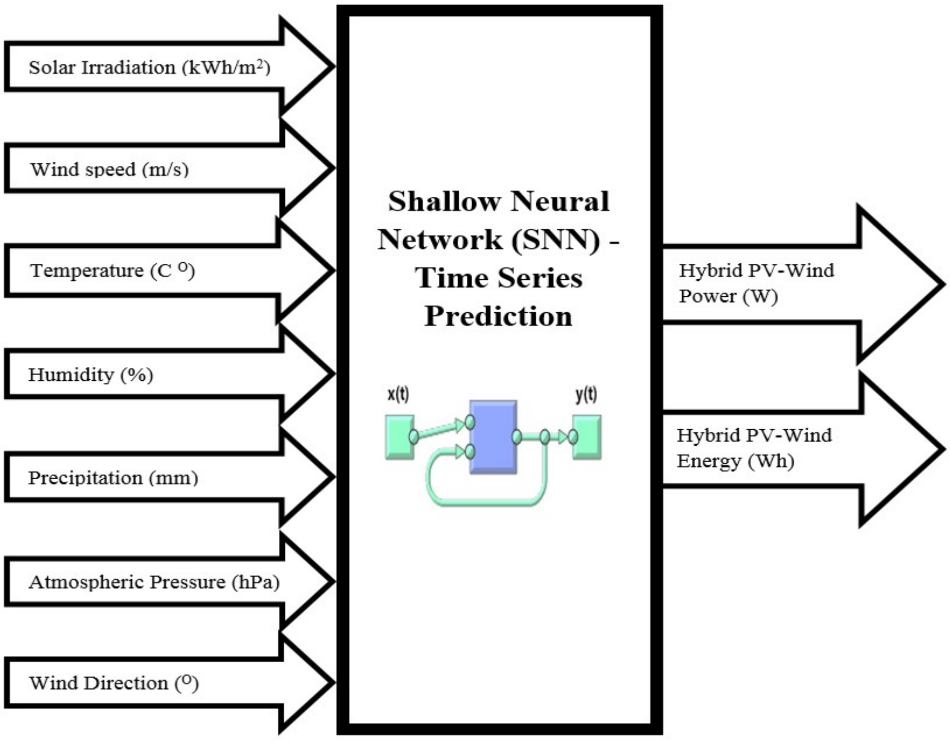


Figure 1.10: Proposed SNN Model

methods. Moreover, to make it more time and energy efficient, SUS framework is introduced where the computation takes place in the cloud. The aforementioned system framework ensures prediction accuracy in less computational time which as a result consumes less energy and provides better energy harvesting.

1.5 Main Aim and Objectives

The main aim of this study is to develop a novel Smart Umbrella System (SUS) which is mainly attached to two most common solar and wind renewable energy technologies. The SUS infrastructure is integrated with Raspberry Pi in such a way to power smart portable accessories such as, charging cellular devices, operating a cooling fan, torch and energizing the raspberry pi board itself. Neural Network (NN) based prediction algorithms i.e., LM, BR, and SCG are compared with each other in order to evaluate the prediction results for output power and energy of the hybrid PV-wind system, based on different weather factors, and a historical data set of weather condi-

Table 1.2: Flexible Solar Panel and Vertical Wind Turbine Specifications

RNG-100DB-H PV Panel		**FLTXNY FS-VM7 Wind Turbine**	
Operational data		**Operational data**	
PV module rated power	100 W	Turbine rated power	10 W
Isc	5.75 A	Nominal power wind speed	20 m/s
Voc	22.5 V	Cut – in speed	1.5 m/s
Imp	5.29 A	Rated Speed	100 - 6000 rpm(10.4 m/s)
Vmp	18.9 V	Efficiency	91.6 %
Efficiency at STC	14.88 %	**Alternator**	
No. of cells	36	Generator	Wind Power Generator
NOCT	45 oC	Output voltage (DC)	0.01V - 5.5V
Irradiance at STC	1000 W/m2		
Solar collector area	0.6 m2	**HUB**	
Mechanical Characteristics		Type	Vertical
Type	Monocrystalline Silicon	Size	(3.94in x 3.15in x 3.15in)
Length	1.2 m	Weight	0.1 Kg
Weight	1.8 Kg	Blade Material	Plastic
Width	0.5 m	Shaft Material	Stainless Steel

tions. The foremost objectives of this study are stated as follows:

- A novel hybrid PV-wind system is presented as an engineering application with the help of an SNN and prediction algorithms with a real test bed implementation.
- To the best of my knowledge, this proposed model is the first smart accessory implementation with a proactive approach in which the prediction is extensively used for the decision of best energy harvesting method.
- The system implemented considers seven of the main weather factors that can vary the power and energy produced by the hybrid system.
- Three different prediction algorithms are compared and the prediction accuracy obtained is sufficient for portable accessories with energy harvesting technique.

1.6 Contributions and Novelties

In this study, the design and implementation of smart portable accessories is considered. Prediction, monitoring and analysis of the performance indicators are employed together with algorithms to decide on the optimum strategy for energy harvesting. The devices, circuits and systems employed are tested extensively for verification of the employed approaches particularly for the prediction part. In order to design a robust and precise prediction model, three of the popular prediction algorithms Levenberg-Marquardt, Bayesian Regularization and Scale Conjugate Gradient (SCG) are compared, analyzed, and used to develop a Shallow Neural Network (SNN) time series prediction.

To the best of my knowledge, this is the first smart accessory implementation with a proactive approach in which the prediction is extensively used for the decision of best energy harvesting method.

The promising results depict that using the proactive approach of SNN-SCG together with real time data, we can have high precision predictions to choose the correct method for energy harvesting depending on the geographical location of the accessories considered.

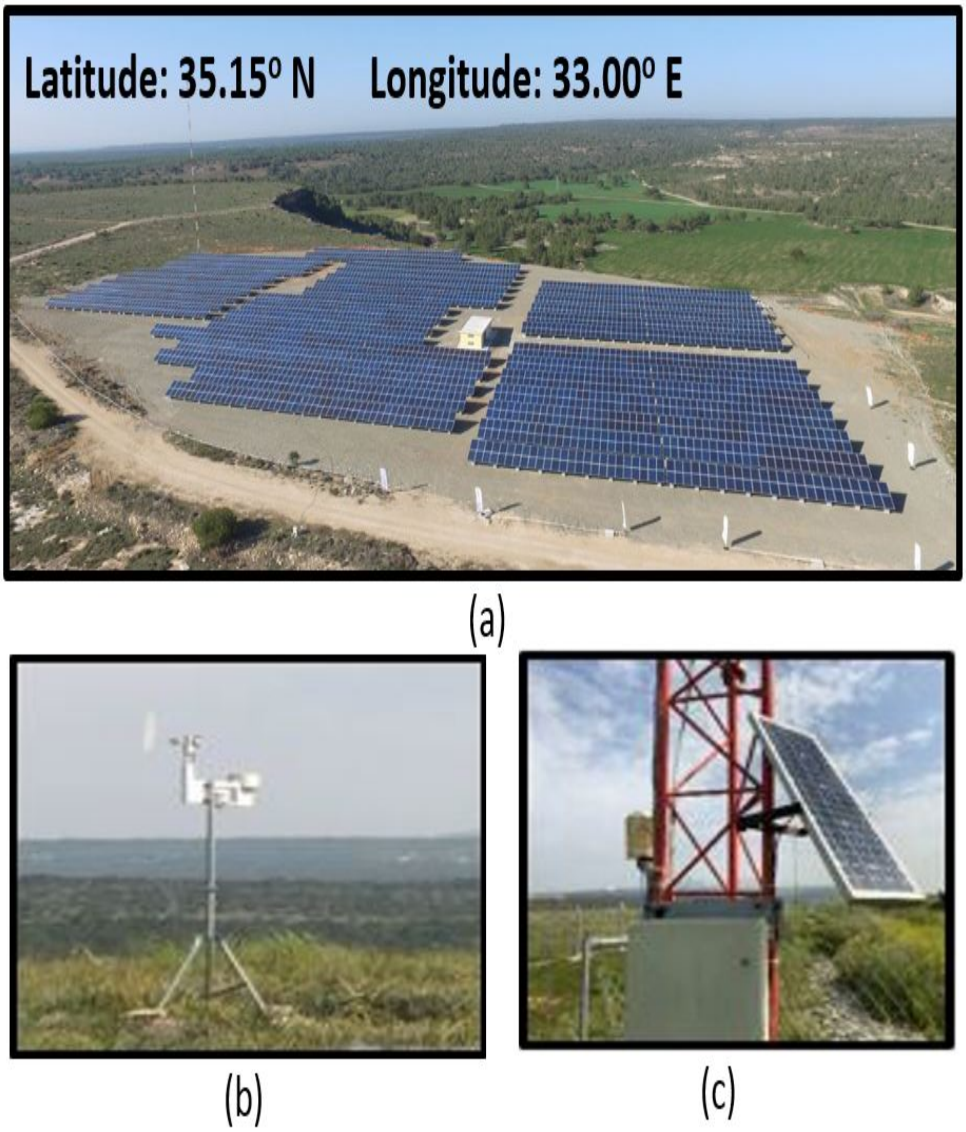


Figure 1.11: METU, NCC, TRNC Solar plant (a) Solar panels and Wind Tower, (b) wind sensor at 2m height, (c) solar sensor

CHAPTER 2

METHODOLOGY

2.1 The Recurrent Dynamic Neural Network

Two of the widely used neural network categories are explained in this section for time series prediction analysis; static and dynamic [111, 112].

2.1.1 Static Neural Network

The static networks do not involve any feedback or delays connections and the output is calculated based on the current input via a feed-forward network [113–115]. The dynamic networks on the other hand are feed-backward network along with tapped delay lines. Considering dynamic networks, the output relays on both the previous and the current values of input and output. Moreover, the dynamic networks are recurrent networks which can work both as feedback or feed-forward networks. In static networks, back propagation algorithm is considered to compute the error function gradients, which are mainly required for training the gradient based algorithms as illustrated in Fig. 2.1 [116].

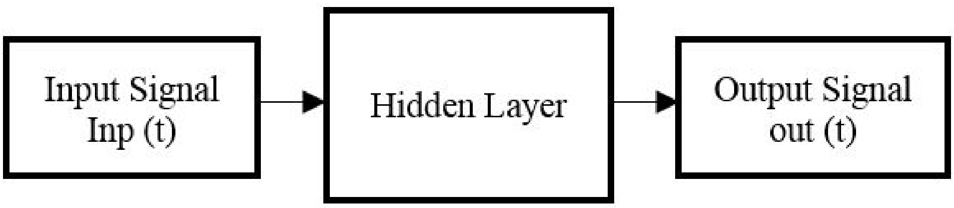


Figure 2.1: Static Neural Network

2.1.2 Dynamic Neural Network

Contrary to the static networks, dynamic networks are comparatively robust and powerful as they have the feedback connection as shown in Fig. 2.2 [117, 118]. Although dynamic networks are considered to be more difficult to train, it is still possible to train them to learn complex time varying or sequential patterns. Dynamic networks can be deployed to various applications like predicting the failure of a jet engine, annual profit in a business, stock rate fluctuations in financial markets, effect of climatic factors on renewable energy generation and many more [119, 120].

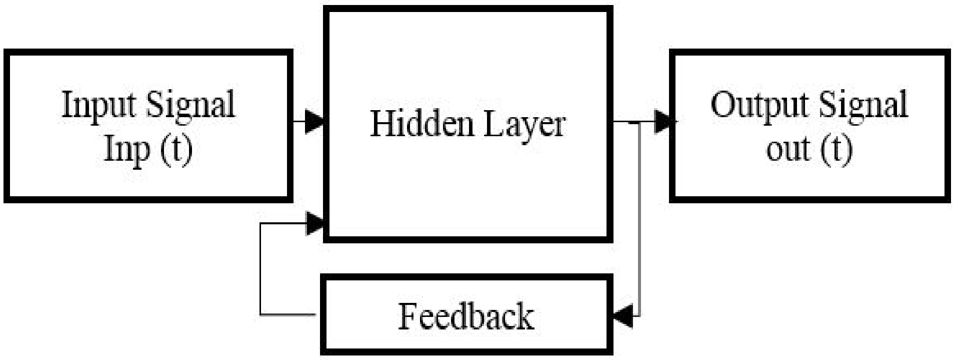


Figure 2.2: Dynamic Neural Network

2.2 The Proposed System Architecture

2.2.1 NARX Model

For the proposed model, the Non-linear Auto-Regressive with External input (NARX) which is an accurate recurrent dynamic neural network is used for solving the non-linear time-series problems [121, 122]. The NARX model which is used widely for time-series problems provide promising outcomes based on the lagging input-output variables and prediction errors as discussed in these studies [123–125]. In contrary to the conventional recurrent neural network (RNN), the NARX network provides optimal prediciton performance for amost every non-linear function with negligible or no computational losses [126]. Previous studies uses NARX model for different applications [127–130]. The network architecture for SNN based on NARX is comprised of a two-layer feedforward network. One of the layers is the hidden layer having sigmoid transfer function and other is the output layer constitute of linear transfer function. SNN-time series prediction model uses NARX network with feedback connections enclosing the hidden layers [131]. Based on the previous values of input signal inp (t), this closed loop network predicts the future values output signal out (t). The output signal can be expressed as:

$$out(t) = f(out(t-1), out(t-2), \ldots, out(t-n), inp(t-1), inp(t-2), \ldots, inp(t-n)) \tag{2.1}$$

The proposed network architecture consists of seven of the input metrological parameters and the two output parameters (power and energy) of the hybrid system. The output parameters are feedback to the input of the NARX model enclosing 10 hidden neurons, 2 delay stages as shown in Fig. 2.3.

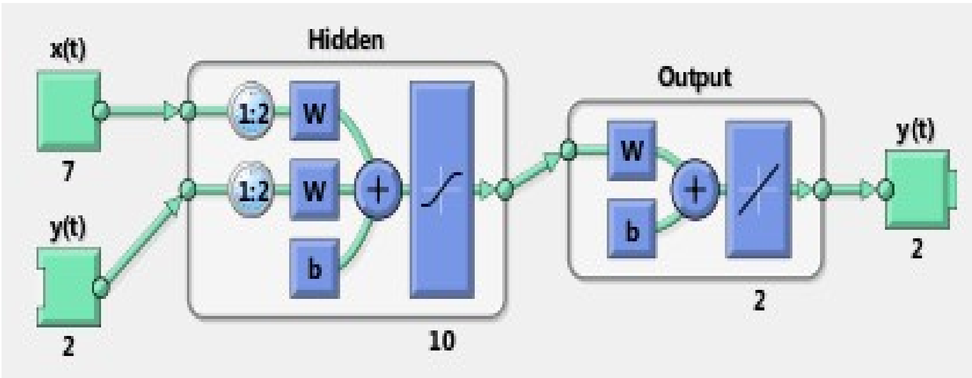


Figure 2.3: Implementation of NARX Model

2.2.1.1 Why SNN?

Deep Neural Networks (DNN) are most effective for complex real-world AI applications, dealing with classification framework where data is in millions or billions, such as, pattern recognition, voice recognition or image classification [132–135]. Moreover, to solve complex problems DNN consist of several hidden layers as shown in Fig. 2.4, however, SNN network consist of several neurons in a single hidden layer that can be varied according to the complexity of the analyzed problem as shown in

Fig. 2.5.

As DNN architecture consist of many number of several hidden layers and in order to train such a network more computational power and time is consumed. Moreover, DNN requires large data set for training the networks which may also lead to over-fitting [136–139]. Subsequently, for this study where the data set is in thousand, SNN will provide the optimal results, requiring lower computation time and the best prediction accuracy can be achieved with minimal power consumption.

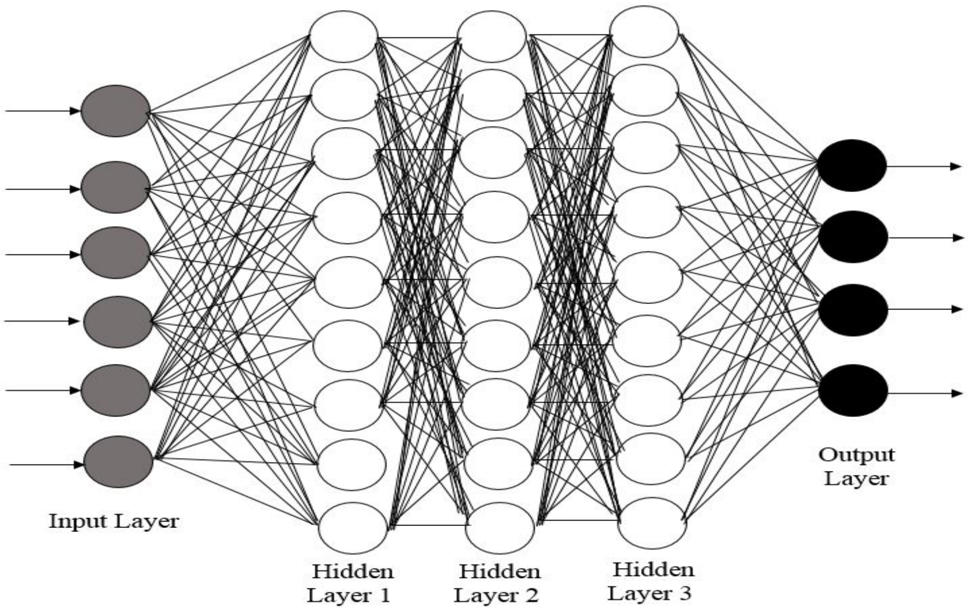


Figure 2.4: Architecture of DNN

2.2.1.2 SNN Time-Series Prediction Modeling

The hierarchy of SNN time series prediction modeling is presented in Fig. 2.6. A Shallow neural network (SNN) uses dynamic time series application where three of the models can be selected as per the scope of the problem being addressed. The three models are NARX, NAR and nonlinear input- output respectively. In the next step, the selected data is analyzed based on the target and input values. After data selection, it is separated into training, validation and testing phase. For setting the delays and the number of hidden neurons, the model completely depends on training data set. Both of the hidden neurons and delays are updated till desired results are

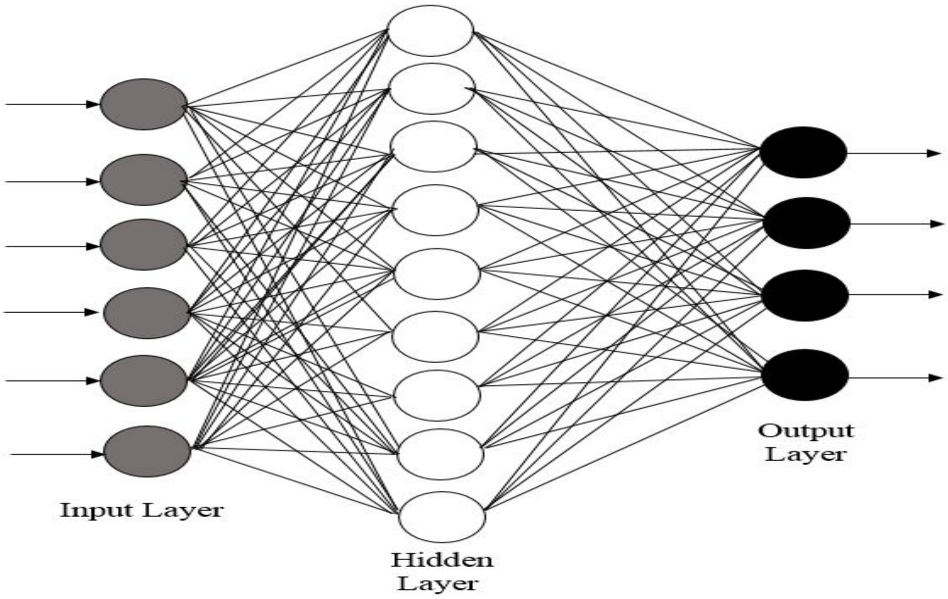


Figure 2.5: Architecture of SNN

achieved. Three of the most popular algorithms LM, BR and SCG are trained and retrained till the best prediction results are achieved in terms of MSE, Epoch/time, R and hybrid energy output error values.

For the historical hourly based data set of seven of the most relevant climatological factors, dynamic time series neural network along with NARX model is selected. NARX model is selected for this study as it provides a feedback connection and proved to be the best model in various studies. The input sample consist of seven climatological factors and the target sample consist of hybrid power and energy output. The concise data division was achieved by setting the training to 75%, validation and testing to 15% respectively. The network architecture consist of 10 hidden neurons, as SNN only have 1 hidden layer and number of delays to be 2. The training algorithms were analyzed base on the accuracy, computational time and errors to achieve best prediction results.

2.3 Proposed Supervised Learning Algorithms for Smart Accessory System

Supervised learning algorithm is a mapping function Y=f(X), where the main goal is to predict the output variable (Y) from the input data (X). It generalizes the training

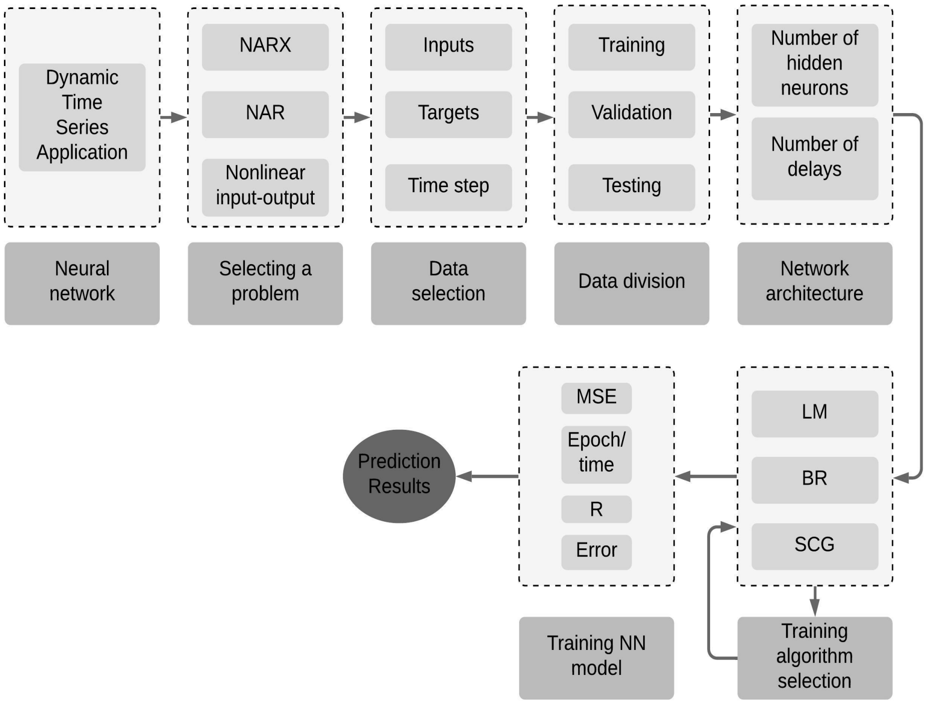


Figure 2.6: Hierarchy of SNN Time-Series Prediction Modeling

data to any unseen situation in a reasonable way [140]. Classification and regression are the two main categories of supervised learning as shown in Fig. 2.7 [141]. The supervised ANN include linear classifiers [142, 143], single layer perceptron (SLP) [98, 144]and multilayer perceptron (MLP) [145, 146]. Additionally, it also includes SVM [147,148], kNN [149], bayesian statistics [150] and decision trees [151]. However, the unsupervised ANN uses clustering approach and the most common methods include hierarchical, hidden Markov model (HMM) [152]and K-means/ k-Medoids [153–158].

In this study, regression learning is considered for various weather condition data. In order to train a SNN, back propagation (BP) technique is quite important and useful [159, 160]. Most commonly it is integrated with optimization technique, where error signal (E) propagates backward to compute the weight(Δw_{ij}^{l}) as:

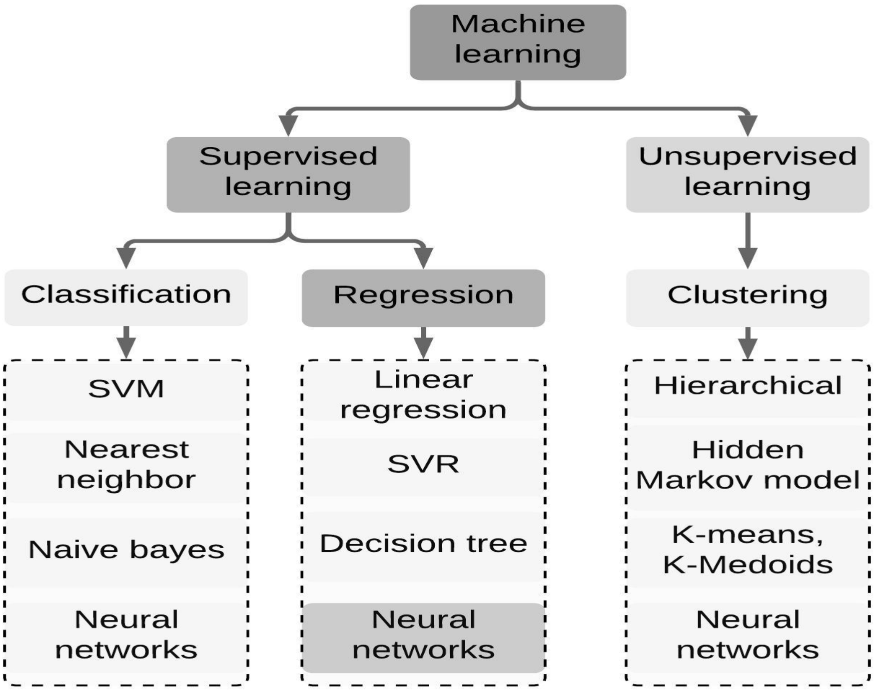


Figure 2.7: Classification of Machine learning [9]

$$\Delta w_{ij}^{l} = \eta \frac{\partial E}{\partial w_{ij}^{l}} \tag{2.2}$$

where, E is the error and η is the learning rate, Δw_{ij}^{l} can be derived from the chain rule.

LM, BR and SCG are compared based on regression (R), mean square error (MSE), output error and time. The best prediction algorithm is chosen based on the prediction result accuracy.

2.3.1 Levenberg-Marquardt Algorithm

LM algorithm is normally used for mathematical or computational problems, which are not much complex. The commonly used name for these algorithms are damped least square (DLS) and are used to confront non-linear least square problems quite efficiently [161]. However, these algorithms are mainly used for curve fitting problems providing a local minimum [162]. Two minimization methods are used for generalizing the LM algorithms [163].

The first one updates the parameters in order to reduce the least square function, as parameters are far from optimal value is known as Gradient descent method [164], whereas, the second one assumes the least square function to be quadratic and computes the minimum of quadratic known as Gauss-Newton method. The reduction is in turn achieved as the parameters are close to their optimal values [165]. The main purpose of the nonlinear least square minimization problem is to minimize a function f which is described as follows:

$$f(x) = \frac{1}{2} \parallel r(x) \parallel^2 \tag{2.3}$$

where, x= (x1,x2,..,xn), r(x)= r1(x), r2(x),. . . , rm(x)=R^n.

In terms of residual function, it can be further expressed as:

$$f(x) = \frac{1}{2} \sum_{k}^{m} r_k^2 \tag{2.4}$$

where, rk is the residual function, Moreover, taking the differential of the residual with the input variables can provide the Jacobian matrix, which is calculated based on predefined limits of k and I, as follows:

$$J(x) = \frac{\partial r_k}{\partial x_i} (1 \leq k \leq m, 1 \leq i \leq n) \tag{2.5}$$

where, J(x) represents the Jacobian Matrix. Based on the previously calculated Jacobian Matrix, Hessian matrix is derived by multiplying the Jacobian matrix with its transpose as illustrated in 2.6 [166]. However, for the back propagation technique, the output is propagated backwards towards the input as equated in 2.7.

$$H = \nabla^2 f(x) = J(x)^T J(x) + \sum_{k}^{m} r_k(x) \nabla^2 r_k(x) = J^T J \tag{2.6}$$

$$x_{i+1} = x_i - (J^T + \mu I)^{-1} J^T(x_i) r(x_i) \tag{2.7}$$

The main shortcoming of LM algorithm as compared to the other two is that whenever we have to deal with large residual problems, it always produce poor results [167].

2.3.2 Bayesian Regularization Algorithm

BR algorithm uses a cost function that sums up the squared weights and squared errors, targeting to minimize this function as follows [168]:

$$C(i) = \alpha.S_w + \beta.S_e \tag{2.8}$$

The main aim of this algorithm is to improve the generalization qualities [169]. The Jacobian matrix is computed based on both the LM and back propagation techniques with respect to weights and biases as follows:

$$G = \nabla f(x) = J^T J \tag{2.9}$$

where, the Jacobian is computed first using chain rule and then error gradient (G). Moreover, as the Jacobian is calculated, the Hessian matrix is again approximated based on the product of Jacobian with its transpose as shown in equation 2.10. Furthermore, the initially calculated cost function is updated with respect to weights as illustrated in 2.11.

$$H = J^T J \tag{2.10}$$

$$(H + \lambda I)\delta = g \tag{2.11}$$

where, δ is used to update weight. Following this, the cost function is computed again and the neural network is retrained.

The main advantage of BR over the other two algorithms is that it saves the cost during validation process and even reduce the testing of different hidden layers [170, 171].

2.3.3 Scale Conjugate Gradient Algorithm

SCG algorithm combines the approach of conjugate gradient and LM, which makes it quite efficient in terms of computation time [172]. BP technique is commonly conjugated with optimization technique such as gradient descent, which allows comparison of weights with the gradient objective function to minimize it [173]. The gradient of objective function is calculated based on the input and corresponding output values to determine BP error [174]. However, along the negative of gradient, the objective function decrements abruptly which occurs in accordance with the descent direction of the network weights as illustrated in equation 2.12. Whereas, the optimal distance is calculated using equation 2.13 and the new search direction is conjugated to the previous one for new steepest descent direction as formulated in equation 2.14.

$$\rho_o = -g_0 \tag{2.12}$$

$$x_{i+1} = x_i + \alpha_i g_i \tag{2.13}$$

$$\rho_i = -g_i + \beta_i g_{i-1} \tag{2.14}$$

The previously used algorithms, such as, Rumelhart's standard back propagation algorithm, Johansson's conjugate gradient algorithm and Battiti's one-step quasi-Newton algorithm uses line search technique, thus making the process more time consuming [175]. However, SCG algorithm is fully automated and it avoids user dependent parameters, such as step size, that otherwise may consume a lot of time [176].

2.4 Hybrid Model Implementation

The SUS consist of a flexible solar sheet of 100 W and a vertical wind turbine of 10 W, which is mounted to the top of the umbrella as shown in Fig. 2.8. The raspberry pi board integrated with this SUS will collect the current location weather data using the Global Positioning System (GPS) technology and store it in the cloud. In order to connect the MATLAB software to the raspberry pi board, MATLAB support package is used. The real time information is communicated to the services provided within the cloud and processed in the SNN. MATLAB software is employed for the implementation of SNN as well.

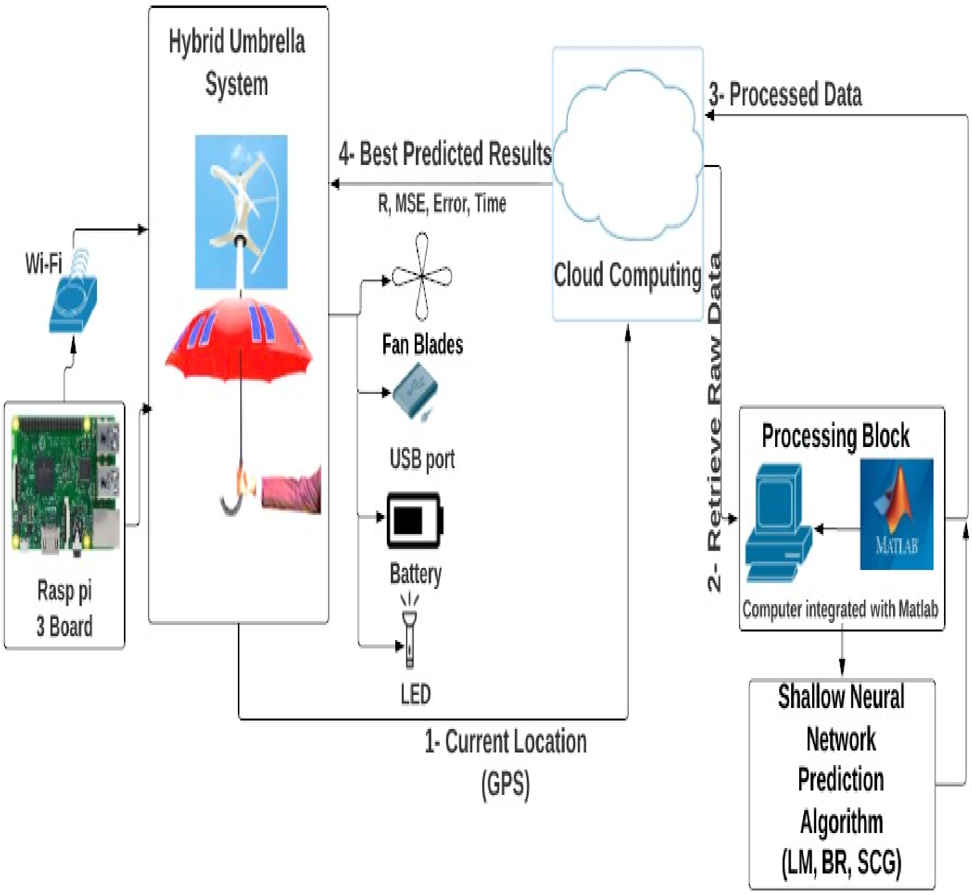


Figure 2.8: Hybrid Umbrella system integrated with Raspberry pi board

Algorithm 1: Pseudo-code for Best Prediction Algorithm

Function: Integrating Raspberry pi hardware with SNN

1. **Input**
2. Climatic Data based on current location
3. **Output**
4. Best prediction algorithm for hybrid system
5. **Begin**
6. Initialize
7. Clear if any previous raspberry pi module is connected
8. Obtain the new IP address
9. Get the current location(GPS)
10. Retrieve the climatic data and send it to cloud (cloud computing)
11. Stored data is processed in MATLAB using SNN-time series prediction
12. Prediction results are stored in cloud and compared
13. Decision is made based on the Best prediction results for Hybrid system
14. **END**

2.4.1 Prediction Algorithm for Hybrid output

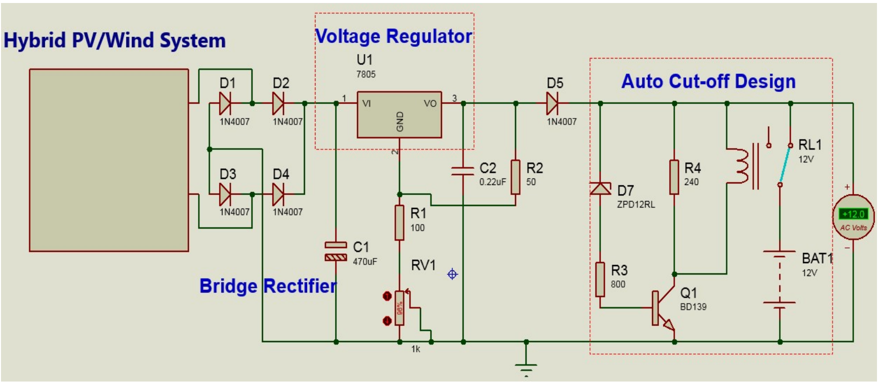
In this study, various algorithms are considered comparatively in order to identify the best supervised learning approach that can be employed. As the data processed is saved in the cloud, the values of regression, MSE, output error and computation time are compared to evaluate prediction results based on the varying input weather conditions and desired output energy of the hybrid system. The best prediction results are in turn analyzed in order to classify the best harvesting approach for that particular day. In other words, using the historical information together with real time feedback, a smart prediction approach is employed for energy harvesting. In turn, the renewable energy is converted into electricity to power the small accessories like fan, USB port (cellular devices), torch and many more in a sustainable way. The overall process used for evaluation of the learning algorithms is illustrated in Algorithm 1.

2.4.2 Hybrid controlled circuit for Powering Accessories and Battery charging

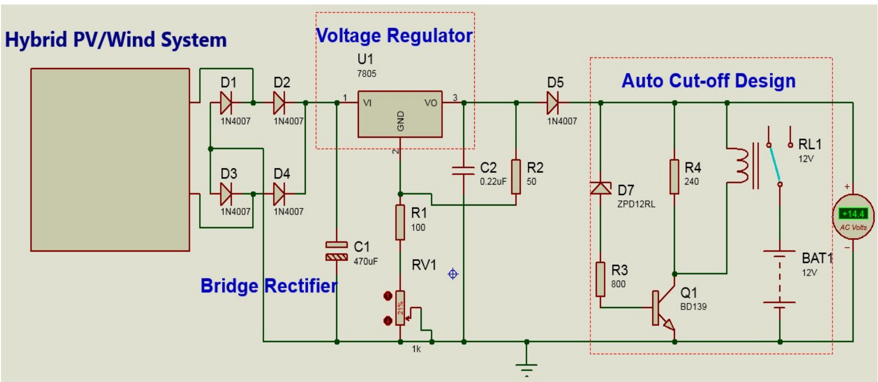
The test-bed uses a rechargeable Li-Ion Battery of 15 Ah (12.6 V, 1-2.4 A) to store the excess amount energy generated from the hybrid system. The total charging time for the battery is 8 h and it can energize the portable accessories when none of the renewable energies are available. When the output power produced by the hybrid PV-Wind system fluctuates, a controlled circuit is introduced to stabilize it. The stable output is used to power the accessories and charge the battery having a fixed voltage of 12 V and 2 A of current. The arrangement of bridge rectifier, voltage regulator and auto cut-off design is shown in Fig. 2.9a.

The bridge rectifier consist of four IN4007 diodes assembled in such a configuration allowing only two of the diodes to work in either direction. The 7805 IC regularizes the voltage depending on the value of potentiometer connected to its ground terminal. Before the voltage regulator polarized capacitor is used for filtration purpose. The auto cut-off design consist of relay, battery, zener diode, resistors and transistor. For the cases where the hybrid output voltage exceeds the required voltage, the auto cut-off design in Fig. 2.9b is employed to energize the relay and disconnect both the battery (as it is fully charged) and the accessories.

These approaches allow us to design a long lasting batteries and prevent the portable accessories from any plausible damage. The battery introduced can be used to power the accessories when the renewable energy sources are not available.



(a) Stable output voltage



(b) Relay disconnected during high voltage input

Figure 2.9: Hybrid battery charging control circuit

CHAPTER 3

RESULT AND DISCUSSION

Three of the main objectives are considered in this section. The first objective is to deal with the practical applicability of the proposed hybrid umbrella system for real time powering accessories. The second one is to focus on the level of prediction accuracy via the SNN based prediction algorithms and the third one is to design an android application that provides ease for the user to access the energy generated and consumed by the SUS.

3.1 Proactive Practical Applicability of Hybrid System

A Subsequent evaluation is taken into account to verify the practical applicability of the proposed system. The learning algorithms implemented using MATLAB are located in cloud rather than in raspberry pi, which has very limited resources in terms of energy and computation power. For designing a proactive model, the weight, robustness, considerable losses and reliability of the hybrid system are also very important. The testbed employed is illustrated in Fig. 3.1.
The portable accessories considered for the practical applicability of the proposed hybrid system along with their energy consumption are shown in Table 3.1. The accessories taken into account are, DC fan in scorching sun, USB port to power smart cellular devices, LED torch for visualization at night and Raspberry pi board for collecting the weather data. The total average daily power consumption of these accessories are calculated to be 176.5 Wh per day.

The total energy generated from the proposed hybrid system using the historical information for 15th June 2015 is illustrated in Fig. 3.2. Furthermore, all the con-

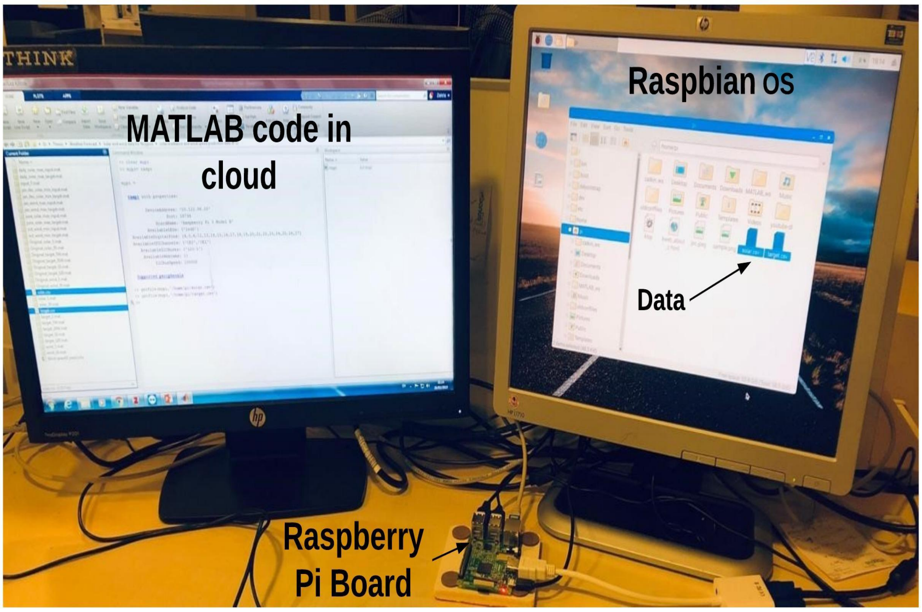


Figure 3.1: Test Bed for cloud computing

siderable power losses like solar insolation (30%), operating temperature (10%), tilt angle and electronic components (2%), cabling loss (5%), ageing and cell mismatch (5%) [177, 178] are also evaluated and the nominal power is calculated for the hybrid system as shown in Table 3.2. All these losses are considered to check the reliability, robustness and efficiency of the proposed model for a single day in powering the portable accessories. The total average energy generated from the hybrid system which comprise of the solar panel and wind turbine is computed as 669 Wh for 15th June 2015.

Table 3.1: Energy Consumed by the Portable Accessories

Load	Ref	Rated power(W)	Operating Hours	Power Consumption (Wh/d)
DC Fan	[58]	3.5	4	14
USB port	[59]	10	6	60
LED Torch	[60]	10	5	50
Raspberry pi Board	[61]	10.5	5	52.5
Total Avg Daily Energy Consumption by Portable accessories (Wh/d)				176.5

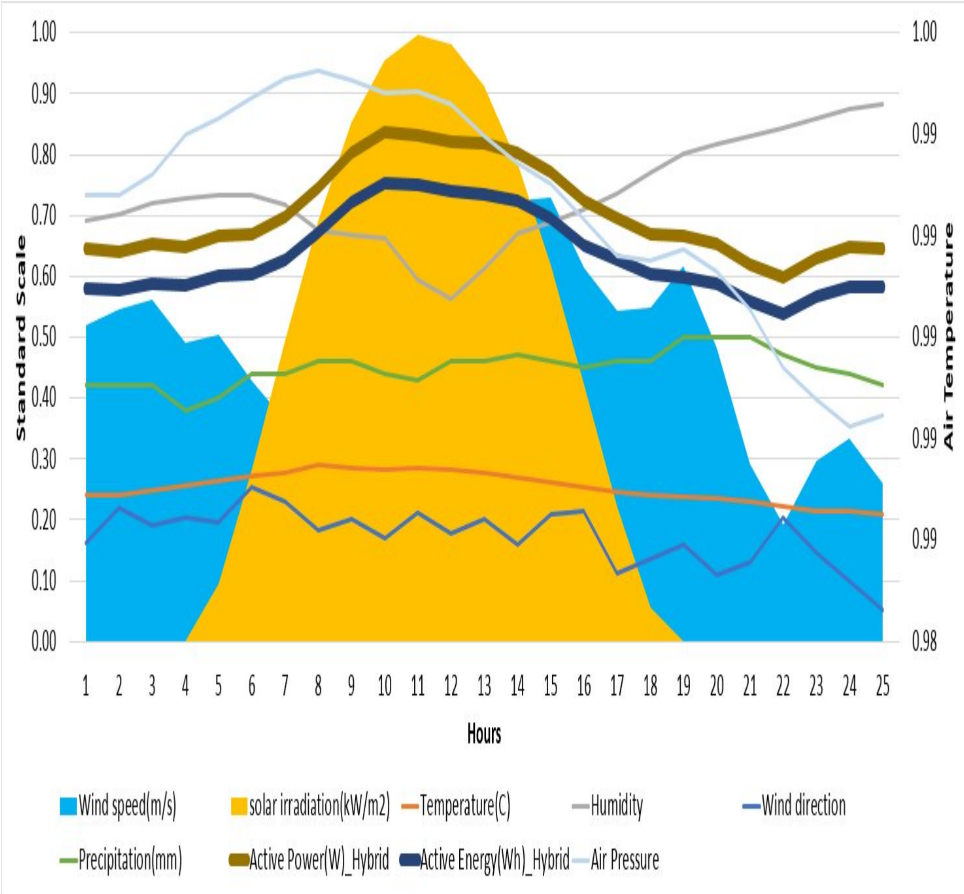


Figure 3.2: Power generated by hybrid system on 15th June 2015

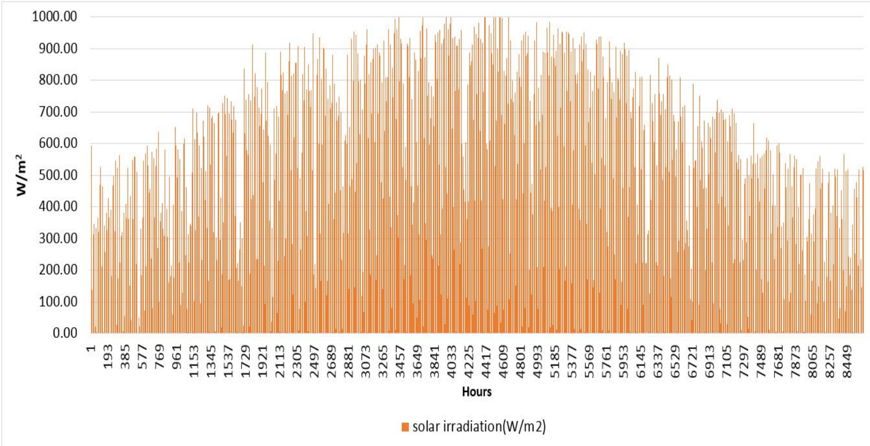
3.2 Prediction Accuracy

The target time steps analyzed in this work are training, validation and testing. Training adjusts the data sets according to the errors, whereas, validation measures the network generalization and halts the training when further generalization stops improving. However, testing is independent of the training and measures overall network performance. Table 3.3 shows the comparison between LM, BR and SCG prediction algorithms for the yearly, monthly and daily datasets evaluated using SNN. In total, 77,688 samples are collected from the year 2015 based on seven input weather parameters and two hybrid output parameters on hourly basis as shown in Fig. 3.3 and Fig. 3.4, respectively. The SNN model using the three algorithms is further trained with monthly data set comprising of 6,480 samples from Jan (Max. wind speed), Oct (Min wind speed) and June (Max solar irradiance), as well as the period of Jan-Dec (Min

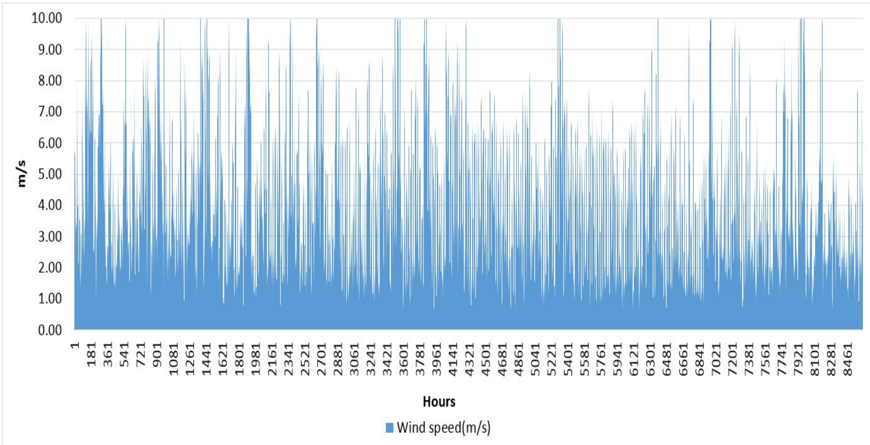
Table 3.2: Energy Generated by the Hybrid System

Renewable Source	Rated power (W)	Nominal Power (W)	Avg Max Sunshine (Hours)	Avg Max Wind Speed (Hours)	Average Energy Generated (Wh/d)
Solar Panel	100	79	7.5	-	592.5
Wind Turbine	10	9	-	8.5	76.5
	Total Avg Daily Energy Generated by the Hybrid system (Wh/d)				669

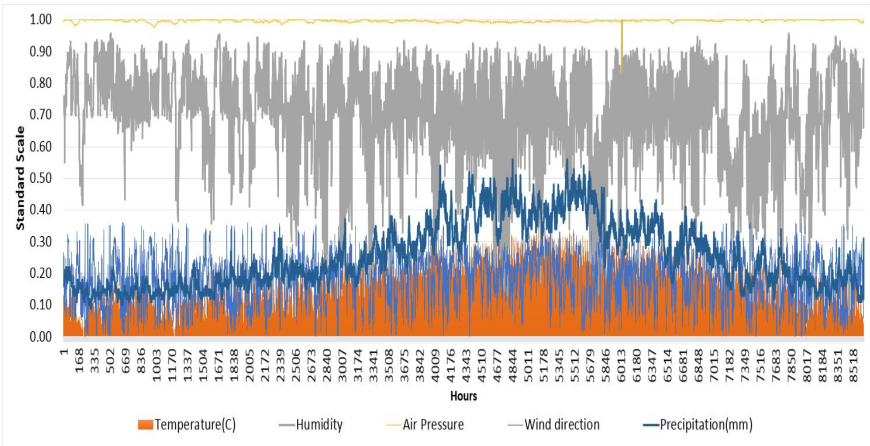
solar irradiance). Furthermore, to analyze the efficacy of our proposed model, daily data comprising of 216 samples are also examined for 15th June 2015. The input and target values are divided into three sets based on the data sets to be evaluated. The first 75% of the total data set is used for training, which is around 58,266 samples, while the validation and testing are assigned 15% of the total data set, comprising of 11,653 samples from a total of 77,688. Several other proportions for training, validation and testing have been analyzed but the aforementioned proportion avoids over-fitting and also provide an improved SNN generalization.



(a) solar irradiation



(b) wind speed



(c) five other weather factors

Figure 3.3: Input weather parameters

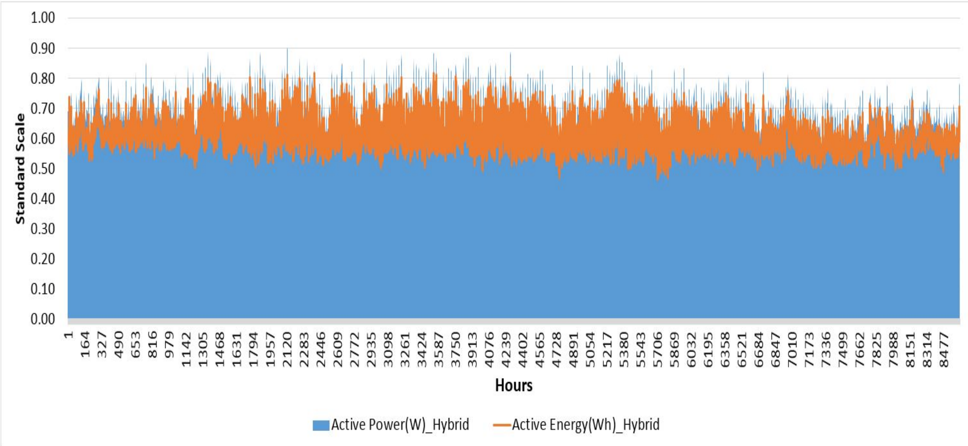


Figure 3.4: Hybrid power and energy output

Table 3.3: Comparing LM, BR and SCG Prediction Algorithms using SNN

Hybrid (PV+WIND)	SNN	Year- 2015	Jan -2015 (Max Wind speed)	Oct -2015 (Min Wind speed)	Jun -2015 (Max Solar irradiance)	Jan_dec-2015 (Min Solar irradiance)	15th June-2015
MSE	LM	3.90E-05	3.10E-05	4.20E-05	9.00E-05	4.90E-05	0.48 e-4
	BR	3.80E-05	1.20E-05	2.30E-05	7.60E-05	2.10E-05	2.50E-05
	SCG	4.30E-05	2.30E-05	4.40E-05	1.04E-04	5.30E-05	8.50E-05
EPOCH/ Time(sec)	LM	26th / 137	6th / 27	6th / 18	8th / 25	4th / 13	2nd / 7
	BR	186th / 1510	153rd / 110	233rd / 72	240th / 80	81st / 62	25th / 14
	SCG	80th / 135	93rd / 25	40th / 16	98th / 20	49th / 12	20th/ 6
Regression	LM	0.9614	0.9821	0.9324	0.9953	0.9297	0.9776
	BR	0.9614	0.9841	0.9324	0.9953	0.9476	0.9711
	SCG	0.956	0.9812	0.9249	0.9944	0.924	0.9865
ERROR (Hybrid Output)	LM	-0.069, 0.061	-0.04631, 0.04878	-0.05329, 0.05067	-0.1077, 0.0991	-0.0719, 0.0850	0.00224
	BR	-0.046, 0.045	-0.0391, 0.03736	-0.0409, 0.0456	-0.0881, 0.0889	-0.0502, 0.0594	0.00194
	SCG	-0.043, 0.034	-0.02835, 0.02807	-0.0327, 0.0414	-0.0690, 0.0730	-0.036, 0.04835	0.00269

In this study, SCG algorithm is preferred to be used over LM and BR, as this algorithm uses gradient calculations rather than the Jacobean. The gradient calculations are the most memory efficient since it requires less memory as well as less computation time. Moreover, when the generalization stops improving, it allows the training to automatically stop as stipulated by the elevation in the MSE of the validation samples. Network training provides MSE and R values for the output and target, based on the input dataset. MSE also provides the average mean square difference between target and output values, where zero indicates no error. R values indicate the correlation between the targets and outputs, where one means close relationship and zero means random relationship.

Examining the results obtained, it can be observed that the hybrid umbrella system depicts the best prediction accuracy for the following SNN model considering the year 2015, 77,688 samples that are collected on hourly basis from the calibrated sensors for different weather parameters. BR prediction algorithm achieves an MSE of 0.000038 (lowest as compared to other algorithms) and hybrid error output of 0.001, whereas the R is 0.9614 (higher compared to SCG but equal to LM) but the main shortcoming is the higher training time which is 1510 s as shown in Fig. 3.5.

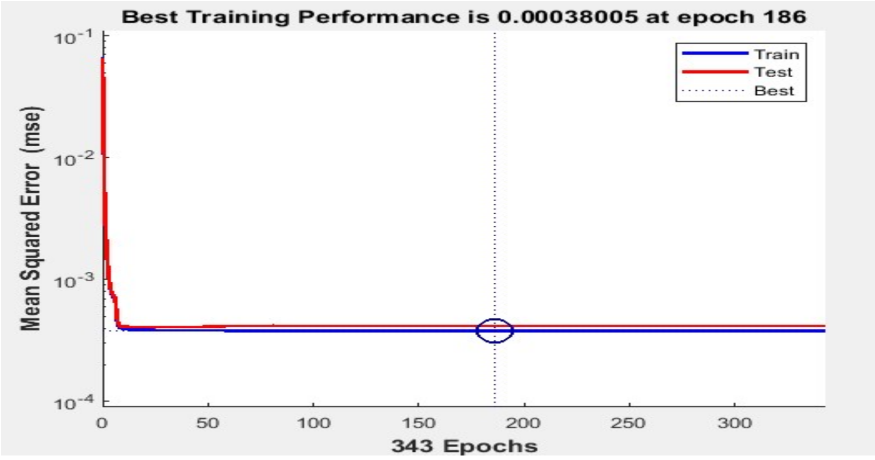
Analyzing the dataset for the month of January-2015, where high wind speeds are experienced, the prediction results obtained for 6,480 samples shows that BR algorithm predict better than LM and SCG in terms of MSE and R, having values of 0.000012 and 0.9841, respectively. Contrarily, SCG outperforms the other two algorithms in terms of computation time and hybrid output error, having values of 25 s and 0.00028, respectively as shown in Fig. 3.6. However, in October, the low wind speeds are recorded and again SCG prediction algorithms beats the other two in terms of computation time, having value of 16 s, while that for R is 0.925 -which is close to the values obtained using LM and BR. In order to train the proposed SNN model, the devised methodology have been applied, where the important parameters considered are MSE, R, training time and hybrid output power and energy errors- which are computed for the entire dataset based on year, months and daily weather parameters.

The results obtained for the proposed model show that as the hidden neurons increased from 10 to 20, the overall computation time and MSE also elevates rapidly.

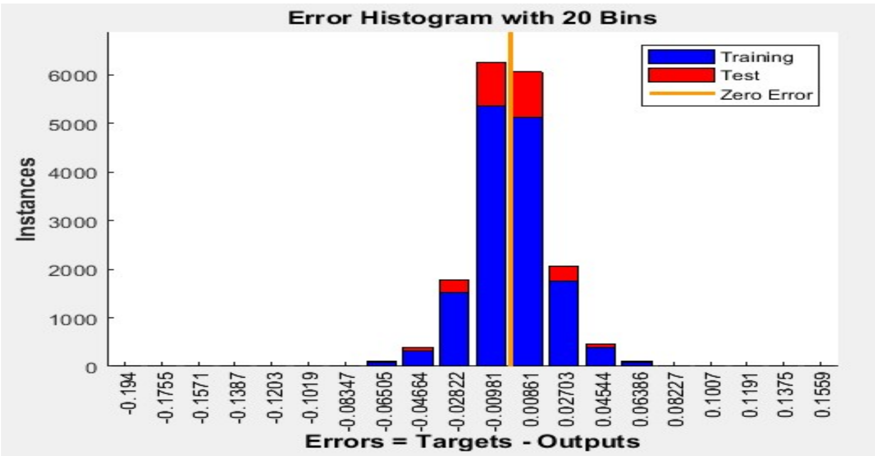
This tends to worsen the overall performance of the SNN model. Therefore, the neuron size for the hidden layers are kept constant that is 10 and the training, validation and testing percentages are 75, 15 and 15, respectively.
Maximum solar irradiance is recorded for the month of June. BR algorithm predicts the best results in terms of MSE of 0.000076 and R of 0.9953 (nearly close to one). Whereas, in terms of computation time SCG algorithm beats the other two with training time duration of 20 s as illustrated in Fig. 3.7. Starting from December 15th till January 15th, minimum solar irradiance is experienced, where the sky is mostly covered with clouds. Subsequently, BR algorithm predicts the best results with an MSE of 0.000025 and R of 0.9476, while for training time SCG again outperforms the other two having value of 12 s.

In order to check the efficacy, robustness and reliability of the proposed SNN model, June 15th (a single day) is taken into consideration. For SCG prediction algorithm the MSE is somehow little higher than BR and LM, having value of 0.000085, however it is negligible The best prediction results in terms of R (0.9865) and the time consumed during training (is just 6s), show that SCG algorithm is much faster as compared to LM and BR as shown in Fig. 3.8.

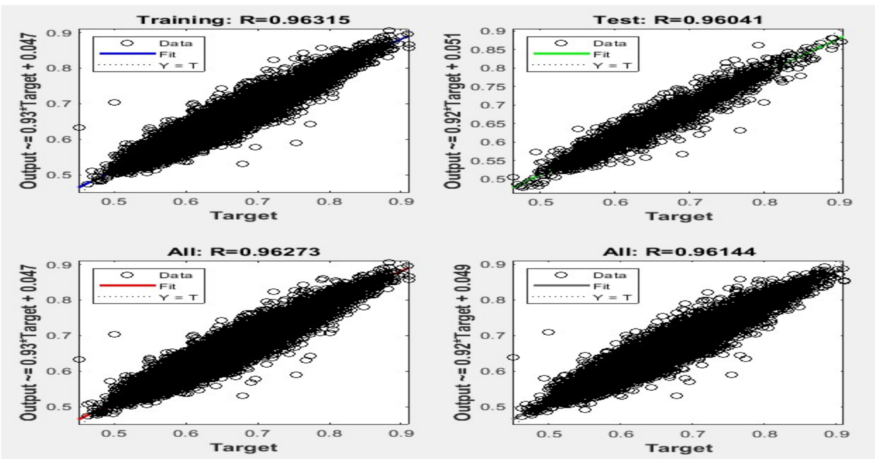
When the three prediction algorithms are compared, even though the performance in terms of MSE and R for the SCG algorithm is negligibly lower as shown in Fig. 3.11, it outperforms LM and BR algorithm in terms of computation time and hybrid output errors as illustrated in Fig. 3.9 and Fig. 3.10, respectively. For the proposed SUS, the time and hybrid output error parameters are considerably much more important. Therefore, SCG algorithm provides the most convenient and efficient prediction results for the proposed SUS-SNN model, since we require higher computational speed and low memory consumption.
The results indicates that for both yearly and monthly data the proposed model which uses 100 W flexible solar panel and 10 W vertical wind turbine provide efficient prediction for output active power and energy of a hybrid system.



(a) Best training performance

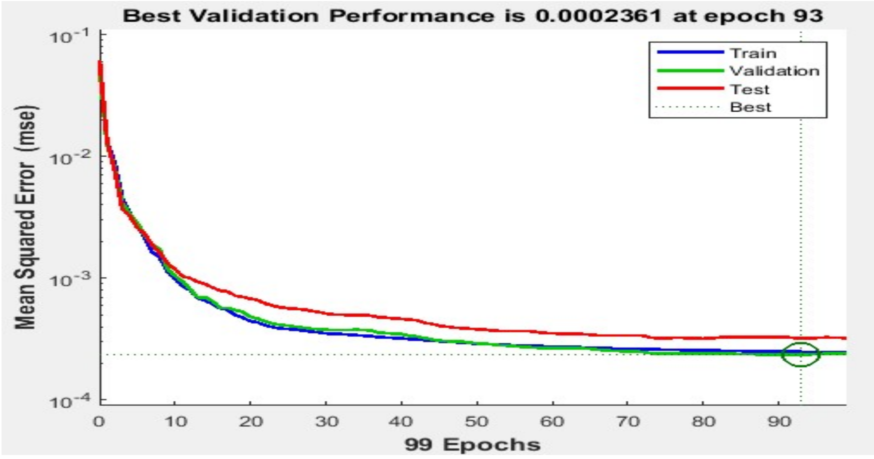


(b) Error Histogram

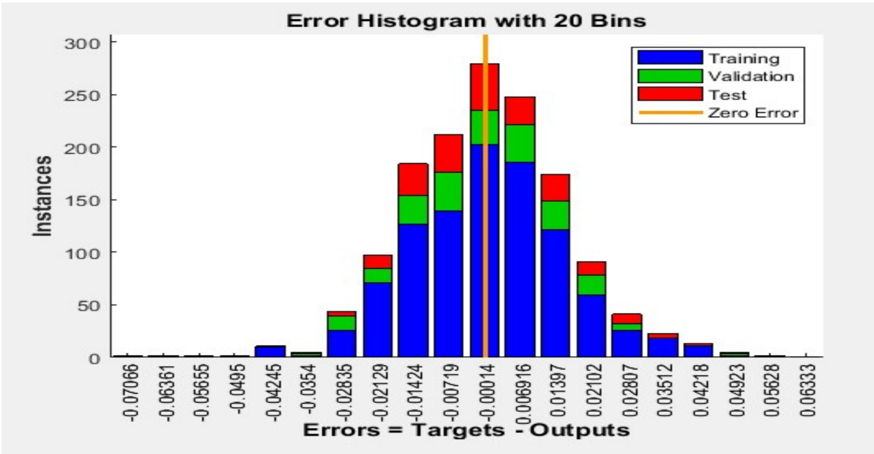


(c) Regression between network output and target

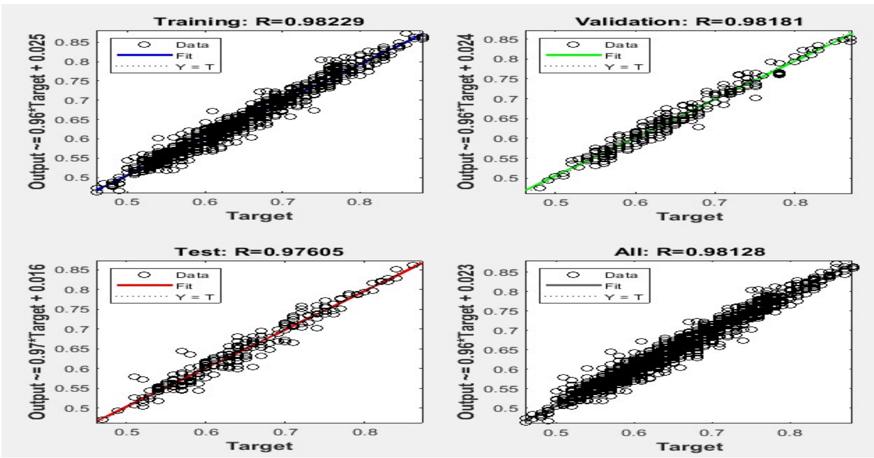
Figure 3.5: Performance characteristic of SNN-BR algorithm for year 2015



(a) Best training performance

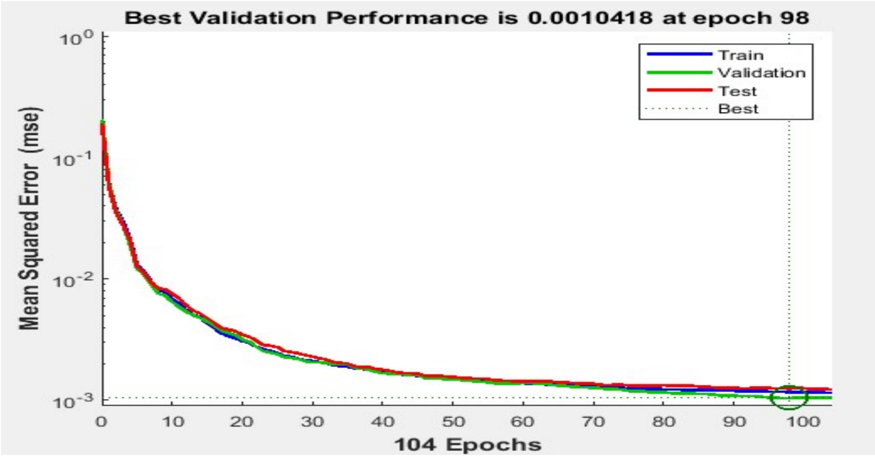


(b) Error Histogram

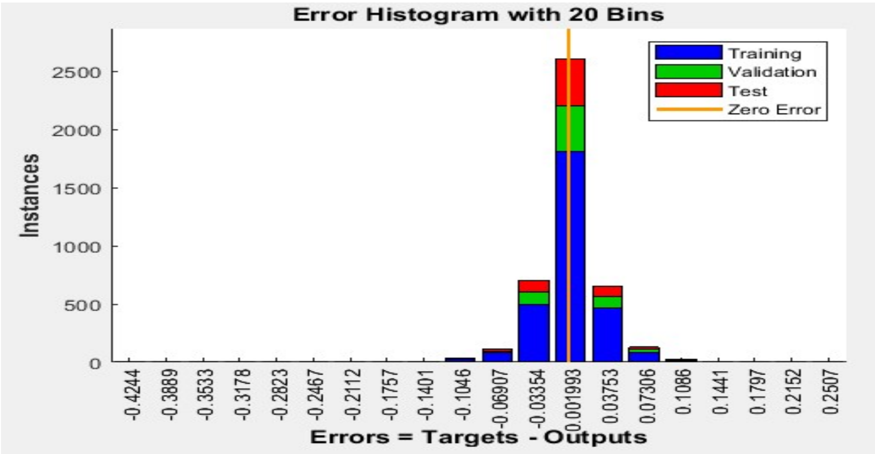


(c) Regression between network output and target

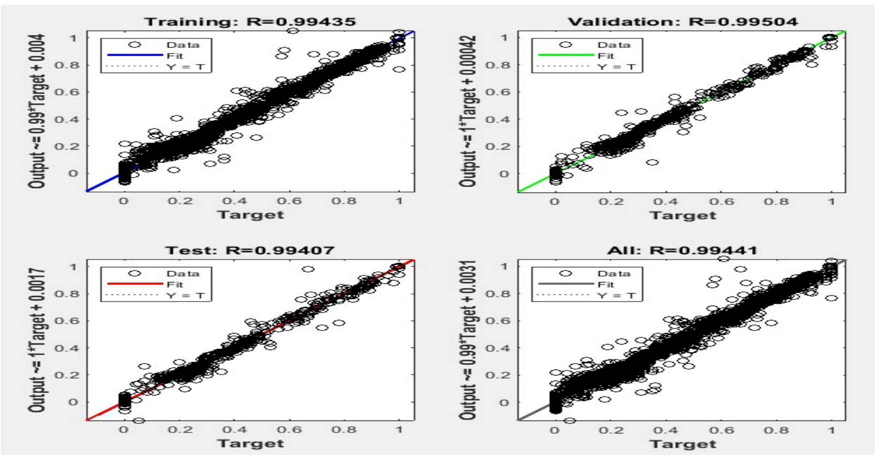
Figure 3.6: Performance characteristic of SNN-SCG algorithm for the high wind speed in the month of January, 2015



(a) Best training performance

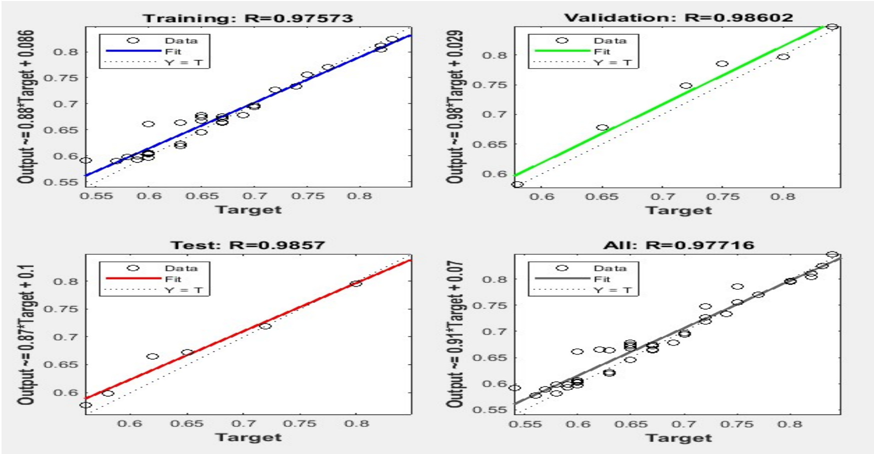


(b) Error Histogram

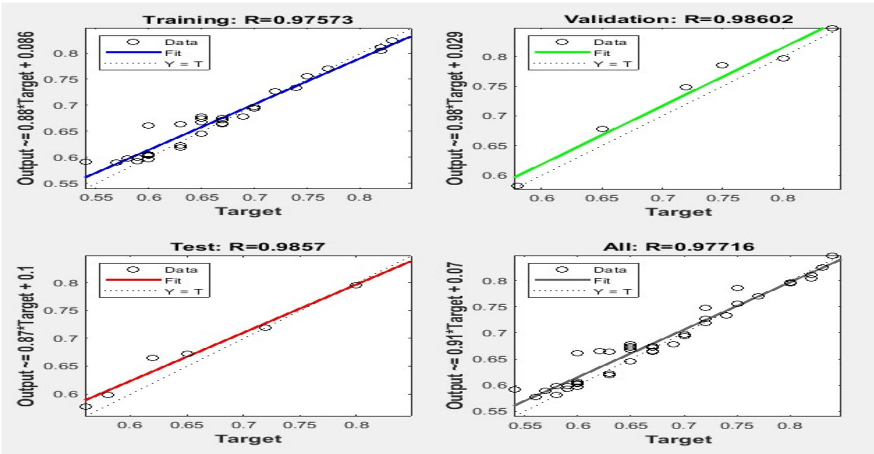


(c) Regression between network output and target

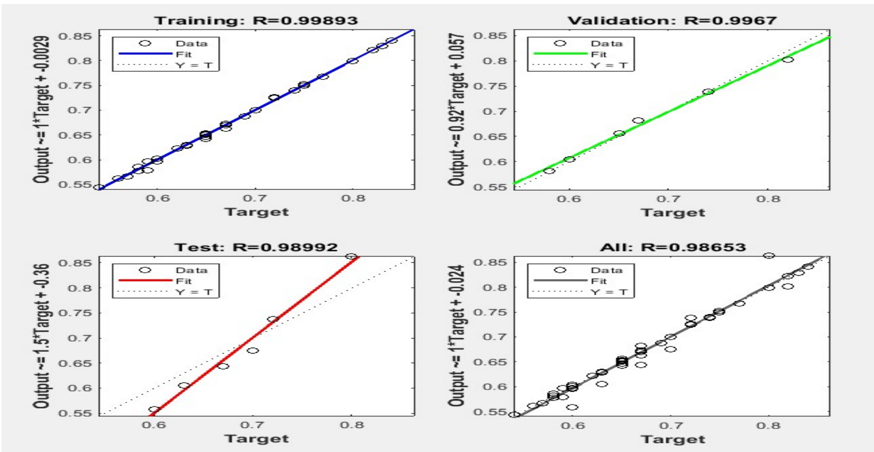
Figure 3.7: Performance characteristic of SNN-SCG algorithm for the max solar irradiance in the month of June, 2015



(a) LM



(b) BR



(c) SCG

Figure 3.8: Comparison between Regression values of LM, BR and SCG algorithms on 15th June 2015

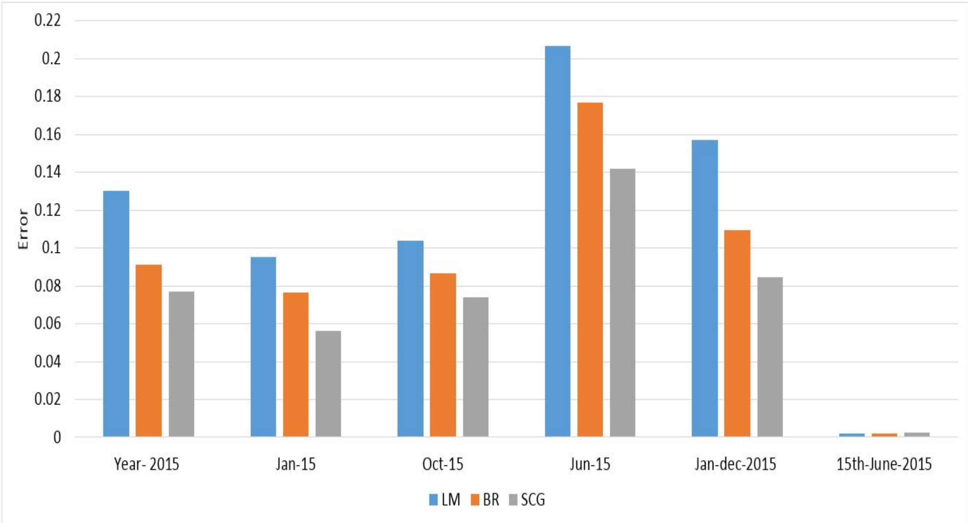


Figure 3.9: Comparison between Hybrid PV-Wind output Error

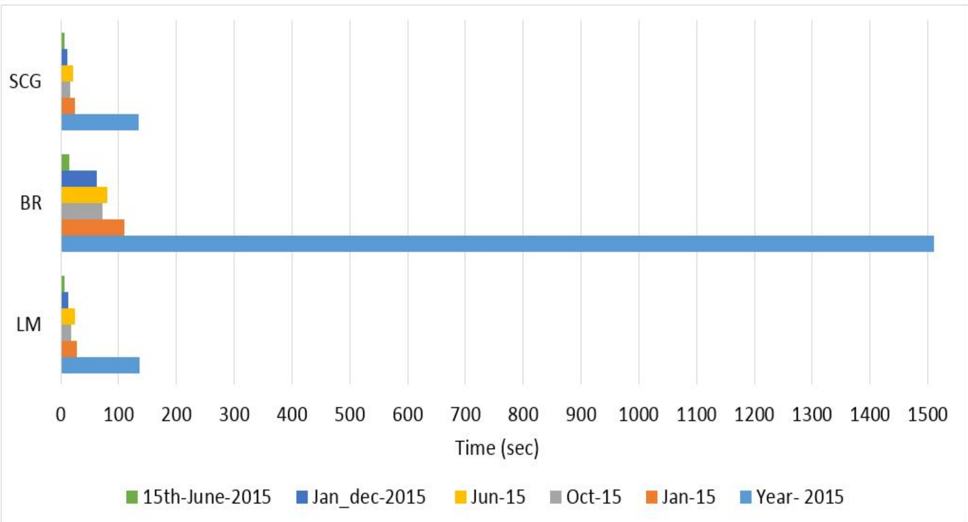


Figure 3.10: Time Comparison between LM, BR and SCG algorithms

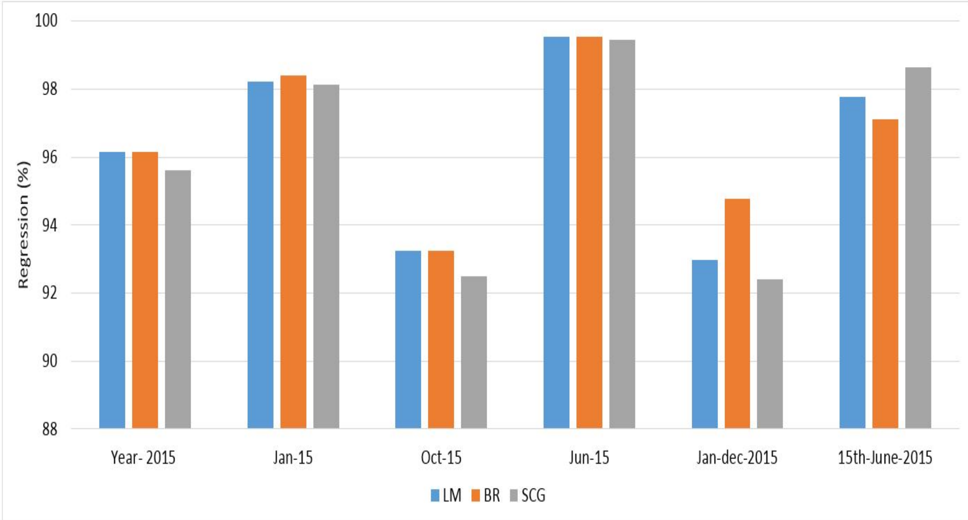
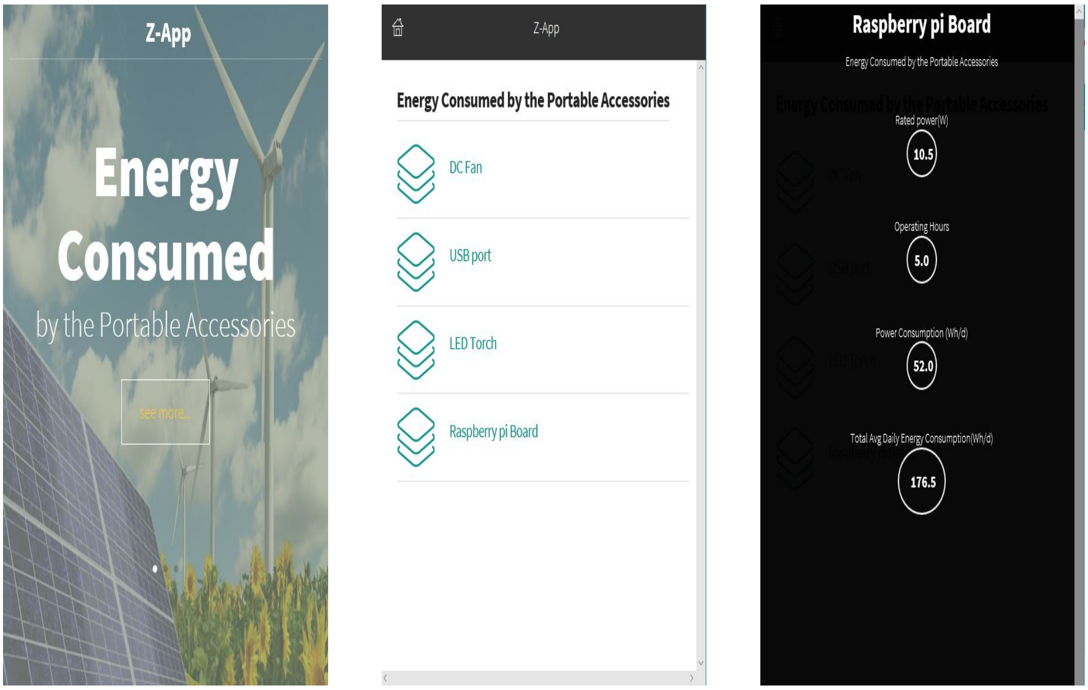


Figure 3.11: Regression Comparison between LM, BR and SCG algorithms

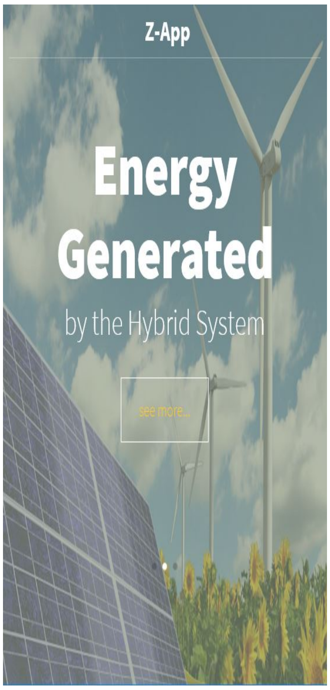
3.3 Software Implementation

An android application is implemented to make the proposed proactive approach promising and user friendly. The main purpose is to provide ease to a user which can access the amount of energy consumed and generated by the smart portable accessories and hybrid system as shown in Fig. 3.12 and 3.13. The comparison between the proposed algorithms LM,BR and SCG for all the data retrieved from the sensors for the historical hourly metrological factors is also displayed in Fig. 3.14. The prediction results can be easily accessed based on the R, MSE, Epoch/time and hybrid energy output. Significantly, if the error percentage is more and the prediction accuracy is the least, depicting that there are less chances to extract power from the renewable sources, the battery can be charged as a backup source as it can provide the necessary energy to the portable accessories in worst case scenario.

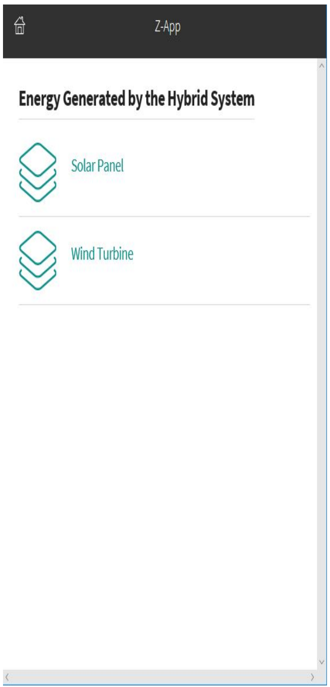


(a) (b) (c)

Figure 3.12: Energy Consumed by Portable Accessories



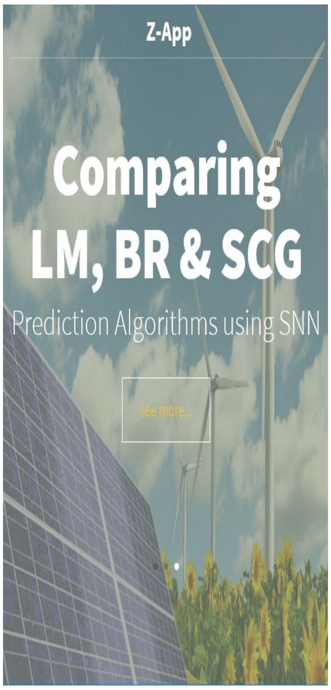
(a)



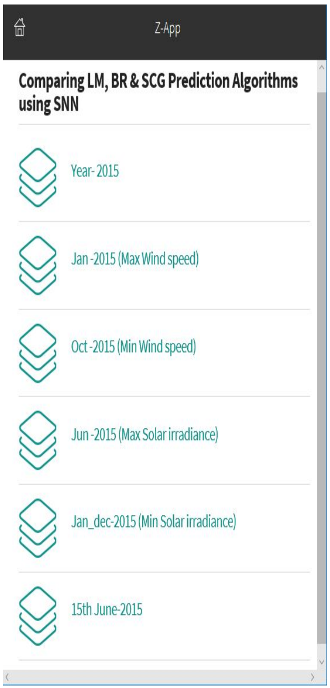
(b)

(c)

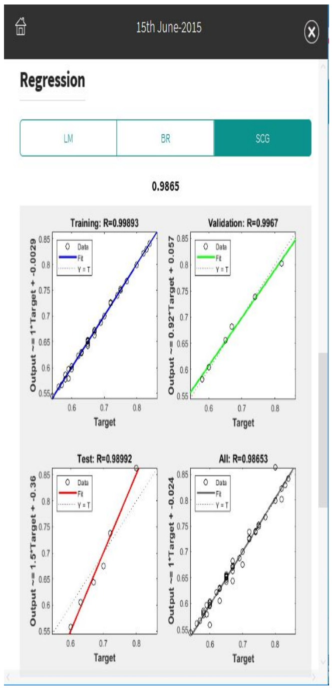
Figure 3.13: Energy Generated by the Hybrid System



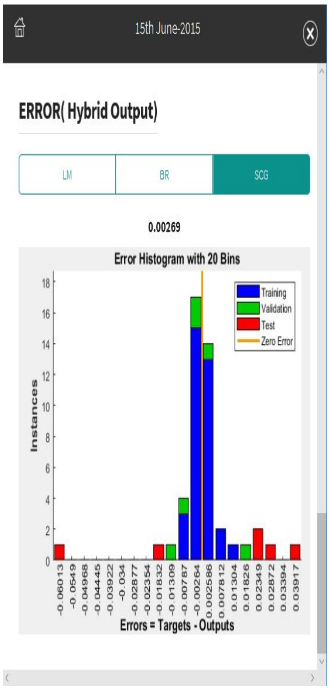
(a)



(b)



(c)



(d)

Figure 3.14: Energy Consumed by Portable Accessories

CHAPTER 4

CONCLUSION AND FUTURE WORKS

Neural Networks integrated with Hybrid Solar-Wind power systems have recently gained popularity and a lot of research can be performed in this area. It is possible to use this research area in the elimination of the haphazard caused by Green House Gas (GHG) emissions. Moreover, these renewable energy technologies should be considered and new technologies should be introduced to make them more efficient, which will help reducing the dependency on fossil fuels.

Based on the paramount analytical factors such as computational time, output error, accuracy, performance and latency a comparison is done between three of the commonly used prediction algorithm integrated with SNN model. This study presents a novel implementation of NARX network with in SNN framework for forecasting energy produced by the SUS architecture. After processing the historical hourly based data for climatological factors in MATLAB, the best prediction results are taken into account in terms of energy output for powering smart portable accessories.

We believe that using the proactive approach of SNN-SCG together with real time data, we can have high precision predictions to choose the correct method for energy harvesting depending on the metrological location of the accessories considered. In this study, all these state of the art prediction methods are employed together with a smart wearable accessory proposal. A prototype has been designed, developed and tested to show the energy efficiency of the proposed prototype and accuracy of the employed proactive approaches.

The results obtained show that the SNN model integrated with SCG algorithm outperforms other algorithms in terms of computation time, and prediction errors having values of 20 sec, and 0.004 respectively for the month of June, where more sunny days were experienced. However, BR algorithm provides better results in term of

MSE and R having values of 0.000012 and 98.4 % for the month of Jan, where more windy days were experienced.Moreover, an android application is designed to make the proactive approach more robust and provide user friendly environment to encourage the use of renewable energy source instead of fossil fuels.

In future studies, more complex prediction systems can be investigated by the use of extended AI techniques like reinforcement learning and genetic algorithms (GA). New hybrid neural network models can be explored to improve the performance regarding efficacy and efficiency. Stability analysis of SNN can be further addressed as it is becoming a hot research area in many AI applications. New models needs to be designed which can provide best prediction results by processing fewer training data. For intelligent optimization, the adaptive dynamic programming (ADP) performance can be further enhanced. Automatic input variables selection can be investigated to choose the most relevant input parameter which can be directly fed to the network in order to forecast time series problems.

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