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Introduction

Demand of renewable energy is continuously increasing around the globe due to increase in population, industrialization and urbanization. The conventional energy is used to fulfil domestic and industrial demand at the cost of environment and ecosystem of the earth. Not only that there is a problem of limited resources but also the uses of conventional energy lead to environmental health hazards. Today, India and other developing countries more relies on fossil fuels to meet the energy requirements for domestic uses and contribute to heavy pollution. In India, 37.8 % of the total greenhouse gases, released in the atmosphere are due to electricity generated by burning fossil fuels . World Health Organization (WHO) conducted a study for the period of 2010 to 2016 and reported that India has 14 out of the 15 most polluted cities in the world in terms of PM 2.5 concentrations. To reduce the dependency on conventional energy, fight against climate change and holding the increase in the global average temperature to well below 2^oC, researchers, industries and government organizations are working hard on alternate fuels, which must be less pollutant, cost effective, easy to use and abundant in nature. Thus renewable energy like solar energy, wind energy, and bio fuel are more suitable for energy security as these energy sources are unlimited, eco-friendly and provide energy with negligible emissions of air pollutant and greenhouse gases. In addition to this, the cost of solar energy generation has reduced drastically in last ten years. Looking at the challenges as opportunity India has set ambitious target under Jawaharlal Nehru National Solar Mission to increase the renewable energy more than five fold by 2022 and intend reach up to 175GW. Out of 175GW, the contribution of solar set as to 100GW. Solar energy can be utilized mainly in two different ways, solar thermal and solar photovoltaic. Solar thermal uses the sun's heat and converts thermal energy to produce electricity. Solar photovoltaic (PV) works on the principle of photoelectric effect and uses solar energy to directly produce electricity. Solar PV is highly influenced by the cloud and produces high variable output. The electricity produced by solar is intermittent in nature and depends on the availability of the solar radiation. There are few major challenges for widespread solar utilization which include but not limited to grid parity, generation cost, efficient overnight/overcast energy storage system, variability smoother (short term storage) and improvement in energy quality for grid integration for which efficient radiation forecasting is one of the prominent solutions. This gives rise to the promising research problems in the field of solar forecasting. Some of them are listed below:

1. How well can we model and forecast the solar irradiance or output power ?
2. How can we use the forecast information for better management of solar power utilization ?
3. How can we reduce the cost of intermittent resources by using detailed knowledge of both short-term and long-term behaviour ahead of time at production, utility, regulatory and energy trading stages ?

Solar energy produced from PV needs to be appropriately predicted in order to integrate with the grid so that it can provide stability and ensure quality of generation. For these reasons, irradiance forecasting becomes extremely important for solar PV generation. The generated power of PV arrays is proportional to the solar irradiation at earth's surface [Luque and Hegedus, 2011]. Therefore, in this thesis, solar irradiation is considered as the primary variable for PV array output power forecasting.

1.1 OBJECTIVES OF THESIS

The chapters of the thesis are clustered into two main objectives.

1. To develop hybrid model to precisely forecast solar irradiance. The idea is to leverage advantages of standalone models to build a hybrid model which is more efficient than any of the standalone model. Number of machine learning algorithms have been used to pre-process and analyze data.

2. To analyse the performance of solar PV systems. Several parameters are used to analyze the performance of two solar PV systems of 43 kW grid-connected amorphous-silicon system and 58 kW multicrystelline-silicon grid-connected PV systems.

1.2 MOTIVATION AND APPLICATION

1.2.1 Motivation

Output of renewable energy generation systems is mainly dictated by weather variation. Variations in irradiance depend on daily sun cycle, cloud cover, sun elevation, wind speed and several other factors. Change in the cloud cover and other atmospheric conditions can cause drop in solar irradiance and manifest as significant drops in generated power output. Sudden change in power output contributes to solar intermittency and may cause issues such as power quality and stability of grid. It can further manifest as local voltage and frequency issues in the strong grid and weak grid respectively [West *et al.*, 2014; Barnes *et al.*, 2014; Lonij *et al.*, 2012; Schittekatte *et al.*, 2016,?; Tao *et al.*, 2010; Lu and Shahidehpour, 2005; Femia *et al.*, 2005]. Several research outcomes confirm that integration of intermittent renewable energy sources in power grids will have adverse impacts on the power quality, regulation, load following and unit commitment (Table 1.1). It creates a demand of forecast over a wide horizon for various purposes; for example, immediate short-term forecast for operational purposes, mid-term forecast for scheduling, dispatching and trading purposes and long-term forecast for investment and planning purposes. Solar forecast information can help to counter the issues caused due to intermittency and inform preventive measures to the solar operators. Hence, solar radiation forecasting has become essential to deal with the huge integration of renewable energy generation in the power grid. In brief, some objectives of solar irradiance forecasting can be summarized as follows:

1. Maximizing the solar based renewable energy generation and minimizing the impacts of solar variability to ensure its optimal use.

2. To help grid operations, network management, market planning, plant operations by giving forecast information in advance.

3. To extract the information of solar irradiance over a time period for selecting appropriate solar energy conversion technology and project location.

4. To extract the information of real-time demand and generation.

5. Moreover, the solar operators may also be informed to take preventive measures.

Table 1.1 : Forecast horizon of various solar forecasting applications [Sayeef *et al.*, 2012]

Time-scale of intermittency	Potential impact
Seconds	Power quality (e.g. voltage flicker)
Minutes	Regulation reserves
Minutes to Hours	Load following
Hours to Days	Unit commitment

Table 1.2 : Application of forecast information they can apply to, motivation and their corresponding examples [West *et al.*, 2014]

Application category	Motivation	Examples
Production	To understand solar energy generation in advance for technical or market benefits	1. Solar farm operator to maximize energy market spot trade market 2. To charge/discharge energy storage 3. Home-owner to alter or control consumption depending on network prices
Network information	To get prior information about quantity and impact of solar energy on the power grid	1. Help market players in decision making regarding bidding, buying and generation. 2. Utility can use the information to take preventive action against voltage and frequency fluctuation and reverse power flow. 3. Increased load-following duties 4. Ancillary services
Compliance	To curtail operation within system limits	1. Ramp rate control 2. Real/reactive power control 3. Fulfilment of energy, power or technical commitments.

1.2.2 Applications of solar irradiance forecasting

Forecast information about solar availability and variability can help in ensuring stable grid operations, maintaining quality of supply and efficient supply-demand management. For example, utilities and market operators need demand related information in advance to maximize solar energy penetration, optimize infrastructure utilization while maintaining grid reliability, stability, quality of supply etc. Forecast information is required to prevent equipment damage and outage costs caused due to supply interruption, equipment failure and system instability. The forecast applications can be categorized into three broader categories, depending on the applicability of information; production, network information and compliance [West *et al.*, 2014], see Table 1.2.

Major electricity stakeholders/market players with their purpose of utilizing the forecast information are listed below:

1. **System operators:**

   To understand plant generation profiles for monitoring market actions, maximizing infrastructure utilization and complying with operational limits. For example, forecast information can be used to control market approach and pricing behaviour such as maximizing cost of solar energy on a spot trade market. Information can also be used to improve the operation of ancillary services, inverter settings and to curtail operations within ramp rate limits.

2. **Utility:**

To understand load and generation behaviour for grid reliability, stability and quality of generation. For example, solar forecast information can be used to measure the impact of solar energy on the electricity grid in order to support grid stability.

3. **Energy markets:**

   To dispatch and maintenance planning of solar generation and to maximize the revenue. For example, solar forecast information on the quantity and variability can be applied as an intelligence tool to support energy trades. Competing market players can use aggregate solar forecasting information to make strategies for bidding, buying and generation.

4. **Consumer:**

   Consumers can alter their demand to minimize supply cost or to maximize generation to ensure higher returns by understanding demand and generation patterns. For example, home owners may wish to alter their consumption in accordance with network prices offered.

5. **Green policies:**

   Solar forecasting can be used to maximize solar energy penetration and to minimize costs as these sources are unlimited, eco-friendly and provide energy with negligible emissions of air pollutant and greenhouse gases.

1.3 LITERATURE REVIEW

Researchers have developed various forecasting models, for the purpose of solar forecasting, including regressive models, statistical models and hybrid models. In this section, we review some of the significant contributions in the recent years and leading forecasting methods used in this field, their limitations and findings.

1.3.1 Autoregressive moving average (ARMA)

ARMA models have been applied in wide areas of research including solar radiation prediction and modelling. Reikard [Reikard, 2009] compared ARMA models with various other nonlinear models, including neural networks and hybrid models, at resolutions of 5, 15, 30 and 60 minutes using Global Horizontal Irradiance (GHI). He concluded that, in nearly all the cases, performance of ARMA model is better. Perdomo et al. used daily solar radiation data obtained from Bogotá, Columbia, between 2003 to 2009 for predicting daily mean GHI using ARIMA(1, 0, 0) model [Perdomo *et al.*, 2010]. ARMA model recently found many applications in the construction of hybrid systems [Ji and Chee, 2011; Voyant *et al.*, 2012; Bouzerdoum *et al.*, 2013; David *et al.*, 2016]. Hybrid of ARMA and time-delay neural networks (TDNN), along with several detrending models for hourly solar radiation prediction models were introduced by [Ji and Chee, 2011]. The data was collected from Nanyang Technological University, Singapore with sampling interval 10 min. Bouzerdoum et al. proposed hybrid of seasonal ARMA and Support Vector Machine (SVM) for short-term power forecasting of a small-scale grid-connected photovoltaic plant [Bouzerdoum *et al.*, 2013]. Probabilistic forecasting of solar irradiance with recursive ARMA and GARCH models for very short-term solar forecasting, from 10 minutes to 1 hour, applied for six different locations, is introduced by. [David *et al.*, 2016].

1.3.2 Exponential smoothing (ES)

Recently, ES found many applications in the construction of hybrid models with other models in the field of renewable energy [Dong *et al.*, 2013; Yang *et al.*, 2015; Dong *et al.*, 2014].

Dong et al. applied exponential smoothing state-space model for short-term solar irradiance forecasting [Dong *et al.*, 2013]. The study employs two sets of data, one from the meteorological station Singapore and another from a rooftop station Colorado, USA. Authors proposed Fourier trend model to stationarize the solar irradiance data before applying linear time series models and compared the performance with another state of the art models using residual analysis and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) stationarity test. They compared the performance with ARIMA, linear exponential smoothing (LES), simple exponential smoothing (SES) and random walk (RW) using the same data samples. Yang et al. in 2015 proposed three hybrid frameworks based on seasonal and trend decompositions using loess (STL) decompositions and exponential triple smoothing (ETS) [Yang *et al.*, 2015]. In the first model, STL was used to decompose the GHI into seasonal, trend and residual series. The residual series was then used as an input for prediction using ETS. Final forecast of global horizontal irradiance (GHI) is obtained by aggregation of these results and the seasonal components. In the second model, direct normal irradiance (DNI) and diffuse horizontal irradiance (DHI) were decomposed by STL and forecast of two residual series were separated by ETS. Final forecast of GHI was obtained by closure equation of aggregation of two forecast results and their respective seasonal components. In the third proposed method, cloud cover index was also considered as one of the variables to forecast GHI. Dong et al. [Dong *et al.*, 2014] proposed hybrid forecast framework comprise of satellite image analysis and exponential smoothing state space (ESSS)/ artificial neural networks (ANN). Self-organizing maps (SOM) were used to classify cloud cover index which was forecasted using ESSS. Multilayer perceptron (MLP) was used to derive the solar irradiance from cloud cover index. The author finally compared the results of the proposed model with ARMA, linear exponential smoothing (LES), simple exponential smoothing (SES) and random walk (RW).

1.3.3 Artificial neural networks (ANN)

Many researchers used the family of ANNs as a predictor for solar irradiance. Early use of ANN by Al-Alawi and Al-Hinai is seen for climatological variables as inputs to forecast monthly values of GHI over a year [Al-Alawi and Al-Hinai, 1998]. Sfetsos and Coonick proposed a hybrid framework for mean hourly GHI prediction using feedforward, recurrent and radial basis ANNs and compared the results with traditional linear methods [Sfetsos and Coonick, 2000]. The improved results produced by ANN motivated many researchers to implement it in the field of renewable energy [Paoli *et al.*, 2010; Gutierrez-Corea *et al.*, 2016; Guarnieri *et al.*, ????; Wang *et al.*, 2012; Sfetsos and Coonick, 2000; Mellit and Pavan, 2010; Hocaoğlu *et al.*, 2008].

ANN also found many applications in the construction of hybrid framework with several other methods in recent years [Cao and Cao, 2006, 2005; Mellit *et al.*, 2006; Cao and Lin, 2008; Theodosiou, 2011; Ji and Chee, 2011; Voyant *et al.*, 2012; Yacef *et al.*, 2012; Benmouiza and Cheknane, 2013; Aguiar *et al.*, 2015; Dong *et al.*, 2015; Sharma *et al.*, 2016; Azimi *et al.*, 2016; Ghofrani *et al.*, 2016; Monjoly *et al.*, 2017].

Use of ANN in a hybrid framework for solar irradiance forecasting was introduced by Cao et al. in 2005 and 2006. In these two consecutive works, authors proposed a hybrid of discrete wavelet transform (DWT) and artificial neural network (ANN) [Cao and Cao, 2005, 2006]. In the next work, Cao & Cao in 2008 proposed hybrid of diagonal recurrent wavelet neural network (DRWNN) and the fuzzy network for hourly solar irradiance forecasting [Cao and Lin, 2008]. After that many researchers used the hybrid of family of ANN with wavelet transform for prediction of solar resources [Mellit *et al.*, 2006; Sharma *et al.*, 2016; Ji and Chee, 2011]. Later on researchers introduced use of machine learning techniques for data mining which laid foundation of hybrid framework of ANN with many others machine learning techniques [Benmouiza and Cheknane, 2013; Wu and Chan, 2013; Wu *et al.*, 2014; Azimi *et al.*, 2016; Ghofrani *et al.*, 2016; Jiménez-Pérez and Mora-López, 2016; Monjoly *et al.*, 2017]. K-means clustering and nonlinear autoregressive (NAR) neural network were combined to forecast hourly global horizontal irradiance by [Benmouiza and Cheknane, 2013]. A multi-model framework (MMF) was proposed, based on clustering and an appropriate predictor model by Wu et al. [Wu and Chan, 2013]. In a similar work, Wu et al. proposed genetic approach of combining multi-model framework for prediction of solar irradiance [Wu *et al.*, 2014]. Azimi et al. proposed a hybrid framework using transformation based K-means clustering, and a multilayer perceptron neural network (MLPNN) [Azimi *et al.*, 2016]. In another similar work, Ghofrani et al., in the same year, proposed a hybrid framework using clustering technique, a classification method, a cluster selection algorithm and MLPNN [Ghofrani *et al.*, 2016].

1.3.4 K-nearest neighbour (KNN)

KNN has been extensively used in the field of solar time series forecasting in many applications. Pedro et al. used KNN methodology for intra-hour GHI and DNI prediction for time horizons ranging from 5 min to 30 min, and also estimated the corresponding prediction intervals[Pedro and Coimbra, 2015]. Lora et al. used KNN for market price forecasting [Lora *et al.*, 2007]. In the applications of short-term load forecasting, Sudheer and Suseelatha used weighted KNN to forecast one of the wavelet decomposed subseries of electric load data [Sudheer and Suseelatha, 2015].

1.3.5 Support vector regression (SVR)

SVR has been used in the construction of hybrid models for solar resource forecasting [Bouzerdoum *et al.*, 2013; Mohammadi *et al.*, 2015; Dong *et al.*, 2015; Jiménez-Pérez and Mora-López, 2016]. A hybrid of seasonal ARIMA (SARIMA) and SVM was proposed by Bouzerdoum et al. for short-term power forecasting of a grid-connected PV plant [Bouzerdoum *et al.*, 2013]. Hybrid of SVM and wavelet transform (WT) was introduced by Mohammadi et al. to predict horizontal global solar radiation [Mohammadi *et al.*, 2015]. Dong et al. introduced construction of a hybrid framework based on self-organizing maps (SOM), SVR and PSO (particle swarm optimization) to forecast hourly solar irradiance [Dong *et al.*, 2015]. SOM was applied to partition the input dataset into several disjoint sub-datasets of different characteristic information. PSO was implemented to select the parameters of SVR and finally SVR was used as a predictor. Four hybrid frameworks: decision tree (DT) and ANN; DT and support vector machine regression(SVM-R); support vector machine clustering (SVM-C) and ANN; SVM-C and SVM-R for hourly solar irradiance forecast were reported by Jimenez et al. [Jiménez-Pérez and Mora-López, 2016].

1.3.6 Decision tree

The decision tree is one of the most recently used machine learning tools in the field of solar resource forecasting. Regression tree based ensemble methods for solar irradiance forecasting were discussed in [Hassan *et al.*, 2017]. A regression tree is used for estimation of prediction interval for global irradiance by [Voyant *et al.*, 2018]. Variability of solar irradiance is forecasted by using model tree [McCandless *et al.*, 2015].

1.3.7 Markov model

In solar radiation forecasting domain, the sequences of measured irradiance values are sometimes transformed into discrete states. These states are then used as radiation values between intervals that make the transition over time [Aguiar *et al.*, 1988]. Hocaoglu and Serttas developed a hybrid of Mycielski and Markov method for hourly prediction of solar radiation [Hocaoglu and Serttas, 2017]. The Mycielski algorithm finds the longest repeating sequence in the past that are present in solar radiation dataset. The Markov transition probabilities decide the foremost probable historical sub-pattern among all sub-patterns obtained from the Mycielski. The most probable historic sub-patten gave the final value of forecast. Sahin and Sen used Markov models to model and predict the wind speed of ten different cities on hourly time scale at north-western region of Turkey [Sahin and Sen, 2001]. The work of several researchers suggests that Markov models is often used for generation of wind speed time series data [Shamshad *et al.*, 2005; Carpinone *et al.*, 2015; Hocaoğlu *et al.*, 2010].

1.3.8 Hybrid model

As mentioned in the earlier sub-sections, a number of hybrid models are proposed in the literature in the field of solar irradiance forecasting by various researchers. The hybrid of different data mining techniques are proposed with various other predictive models such as ANN, SVM, ES, fuzzy networks etc. The hybrid of DWT with ANN has been discussed in many research papers on the solar irradiance forecast [Cao and Cao, 2005, 2006; Mellit *et al.*, 2006; Sharma *et al.*, 2016; Monjoly *et al.*, 2017]. The hybrid of DWT with SVM and ES were reported in [Mohammadi *et al.*, 2015] and [Sudheer and Suseelatha, 2015] respectively. Hybrid of diagonal recurrent wavelet neural network (DRWNN) and the fuzzy network for hourly solar irradiance was reported in [Cao and Lin, 2008].

Hybrid of another data mining technique, STL, with several different predictive models, was also reported in the literature. The Hybrid of STL with ANN, ARIMA and ETS were proposed in [Theodosiou, 2011], [Theodosiou, 2014; Yang *et al.*, 2012] and [Yang *et al.*, 2015] respectively. STL decomposes a time series into its three constituent time-domain components; seasonal, trend and remainder without using any deterministic function. In all these hybrid models, wavelet transform works as a data preparation technique that decomposes time series data into the time-domain and improves the accuracy of the forecast.

There are other hybrid models, based on machine learning, such as clustering with ANN, multi-model framework (MMF), non-linear auto-regressive (NAR) neural network and SVM were discussed in [Azimi *et al.*, 2016; Ghofrani *et al.*, 2016; Benmouiza and Cheknane, 2013], [Wu and Chan, 2013], [Benmouiza and Cheknane, 2013] and [Jiménez-Pérez and Mora-López, 2016] respectively. Clustering is used in all of these works to extract the underlying pattern of input data series. Finally, an appropriate predictor is applied to obtain the final forecast value of the solar radiation.

Along with this, researchers had proposed several other hybrid models with the combination of ARMA and ANN [Theodosiou, 2011; Ji and Chee, 2011; Voyant *et al.*, 2012]; ARIMA and SVM [Bouzerdoum *et al.*, 2013]; KNN and SVM [Gastón *et al.*, 2010]; SVM/ANN and evolutionary algorithm [Dong *et al.*, 2015]; Mycielski and Markov [Hocaoglu and Serttas, 2017]; DT and SVR [Jiménez-Pérez and Mora-López, 2016]; DT and Clustering [Jiménez-Pérez and Mora-López, 2016]; GA and MMF [Wu *et al.*, 2014]; so on and so forth.

A few hybrid models and their motivation behind various combinations are presented in brief in Table 1.3.

1.4 THESIS OVERVIEW AND CONTRIBUTIONS

The main contributions of the thesis are in four folds; review of the incremental work done in the past by various researchers followed by the data preparation or preprocessing techniques, two proposed ensemble forecast models and performance analysis of two solar PV systems. Solar irradiance data is highly fluctuating and non-stationary that poses various patterns like spikes, trends and seasonality. To control the outliers, seasonality and trends, various data preparation or preprocessing techniques are used which significantly enhance the forecast accuracy and help in the construction of various ensemble models after combining the predictors. In the first proposed model we implement an ensemble model that comprise of Discrete Wavelet Transform (DWT)

Table 1.3 : Hybrid models and the motivation behind ensembling

Hybrid methods	Citation	Motivation
ARIMA+ANN	[Theodosiou, 2011; Ji and Chee, 2011; Voyant *et al.*, 2012]	The underlying linear pattern of the time series data is captured by the ARIMA model, and ANN fits the underlying nonlinear pattern present in the time series data.
ARIMA+SVMs	[Bouzerdoum *et al.*, 2013]	The underlying linear pattern of the data is captured by the ARIMA and SVM is used to model the underlying deviation and nonlinear pattern of the time series data.
KNN+SVM	[Gastón *et al.*, 2010]	KNN utilizes selection criteria to determine the most suitable set of inputs. It is combined with SVM to tackle the local minima problems.
SVM+Evolutionary algorithms	[Dong *et al.*, 2015]	Self-Organizing Map (SOM) is an evolutionary algorithm, utilize to partition the input datasets into several disjoint sub-datasets and PSO (Particle swarm optimization) is implemented to select the parameters of SVR and finally, SVR is used as a predictor.
WT+SVM	[Mohammadi *et al.*, 2015]	Wavelet transform (WT) decompose the time series data into deterministic and fluctuation parts and SVR is used as a predictor to model the decomposed time series.
WT+ANN	[Cao and Cao, 2006, 2005; Mellit *et al.*, 2006; Sharma *et al.*, 2016; Monjoly *et al.*, 2017]	The WT acts as a preprocessor and decomposed the time series into sub-series with more detailed periodic information, which is easier to predict. Ann acts as a predictor which can efficiently model underlying nonlinear pattern in the data series.
WT+Exponential smoothing+WNN	[Sudheer and Suseelatha, 2015]	WT acts as a preprocessor and decomposes the time series into deterministic and fluctuation components. Exponential smoothing and WNN acts as a predictor to model deterministic and fluctuating components respectively.
K-means+ANN	[Azimi *et al.*, 2016; Ghofrani *et al.*, 2016; Benmouiza and Cheknane, 2013]	K-means clustering acts as a preprocessor which divides the data into smaller subgroup based on similarity. A Proper cluster selection algorithm used to select the most suitable clusters. The suitable cluster data is modelled using ANN.
GA+MMF	[Wu *et al.*, 2014]	The underlying patterns inside the solar radiation data is uncovered by genetic algorithm (GA) and a suitable forecasting model is implemented to forecast the solar irradiance.
STL+ETS	[Yang *et al.*, 2015]	STL decomposes the data into its time-domain constituent components; seasonal, trend and residuals with more detailed time-domain information which gives better accuracy when modelled through ETS.
STL+ARIMA	[Theodosiou, 2014; Yang *et al.*, 2012]	STL decomposes the data into its time-domain constituent components; seasonal, trend and residuals with more detailed time-domain information which gives better accuracy when modelled through ARIMA.
STL+ANN	[Theodosiou, 2011]	STL decomposes the data into its time-domain constituent components; seasonal, trend and residuals with more detailed time-domain information which gives better accuracy when modelled through ANN.
Mycielski+Markov	[Hocaoglu and Serttas, 2017]	Longest repeating sequence present in the time series data is determined by Mycielski algorithm. Then Markov transition probabilities are used to determine the most probable historical sub-pattern among all sub-patterns obtained through the Mycielski algorithm.

and Feedforward Neural Network (FFNN) and compare the results with the model that does not use DWT and uses Feedforward Neural Network (FFNN) alone. In continuation to that we propose another ensemble model that comprise of data mining techniques, DWT and STL, and uses FFNN as a predictor. Lastly we analyze the performance of two solar PV systems of 43 kW grid-connected amorphous-silicon system and 58 kW multicrystelline-silicon grid-connected PV systems. The performance indices that are used for study of systems are performance ratio, specific yield, reference yield, capture loss, system loss, system efficiency, PVUSA rating and performance indicator based on ratio of ac power at PTC to dc power at STC. Based on the discussions, we divide the work and present chapters of this thesis.

1.4.1 Preliminaries, predictive models and related work (Chapter 2)

Chapter 2 presents literature review of the related work in the context of this study. It highlights the research gaps of previous studies carried out and the need for the contribution of the present study along with some directions of future work.

1.4.2 Preprocessing techniques and error metrics (Chapter 3)

Preprocessing techniques play a vital role in the construction of ensemble framework for solar irradiance forecasting. It facilitates better understanding of the underlying patterns in the time-series and improves the forecast accuracy. Data preprocessing reduces complexity of the data. Data is better understood and subsequent data analysis is performed more accurately and efficiently. A preprocessing may help in matching the time-frequency or the scale. There are other reasons for preprocessing, such as reduction of features, handling missing informations, the effect of seasonality etc. To quantify the improvement of forecast accuracy, after using preprocessing techniques, the error metrics are used. It is also used for comparative analysis between the existing and the proposed models. Error metrics are used for accuracy evaluation and comparative analysis between the existing models and proposed model.

1.4.3 Ensemble forecasting of solar irradiance using data mining techniques (Chapter 4)

In this chapter we implement a hybrid model comprise of Discrete Wavelet Transform (DWT) and Feedforward Neural Network (FFNN). We show that this approach of hybrid model performs better for the underlying solar data. In this process, we measure the difference in forecast error with and without applying wavelet transform and highlight the improvement in forecast accuracy.

1.4.4 Short-term forecasting of solar irradiance using hybrid of wavelet transform and feedforward neural networks (Chapter 5)

The study aims at analysis and quantification of solar irradiance forecasting using two types of decomposition techniques, that is, decomposition of time series into time-domain as well as frequency-domain via locally weighted regression based on loess (STL) and discrete wavelet transformation (DWT) respectively. Hourly data from Indian Meteorological Department (IMD) Jodhpur Rajasthan of the year 2015 has been used for the analysis purpose. The forecast accuracy of the proposed model is compared with competing models. The observed results show that the hybrid of STL, wavelet transform, and FFNN outperforms (1) FFNN (2) hybrid of STL and FFNN and (3) persistence model.

1.4.5 Performance analysis of 58 kW multicrystelline-silicon and 43 kW amorphous-silicon grid connected rooftop solar PV systems (Chapter 6)

Proper analysis of PV power plant is one of the most crucial requirements for the development of technology, proper distribution and maintenance to optimize the design and for prediction of energy injected into the grid at a given PV power plant. This chapter presents analysis and comparison of performance of two grid-connected photovoltaic plants which are situated at the same place but based on different module technologies. The monitored plants are 43 kW grid-connected amorphous-silicon system and 58 kW multicrystelline-silicon grid-connected PV system.

1.4.6 Conclusions (Chapter 7)

The chapter finally concludes the thesis and provides insights of the current work that is going on in the field. The chapter also briefly mentions the scope of future work that may be done in the time to come.

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