Potential Challenges: Integrating Renewable Energy with the Smart Grid

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Abstract— Renewable energy offers alternative sources of energy which is in general pollution free, climate friendly, sustainable and unlimited. Therefore in the starting of 21st century, Government, utilities and research communities are working together to develop an intelligent power system that has potential to better integrate renewable energy sources with the grid. However, there are a number of potential challenges in integrating renewable energy with the existing grid due to its intermittent nature. This paper investigates about the potential challenges of integrating renewable energy with the smart power grid including the possible deployment issues for a sustainable future both nationally and internationally. The paper also proposes a prediction model that informs the typical variation of energy production as well as effect on grid integration using modern machine learning techniques.

Keywords- Renewable energy; smart grid; machine learning; grid integartion.

I. INTRODUCTION

Existing power systems create environmental impacts and is a prime cause for current green house or global warming effects due to burning of fossil fuels, especially coal as carbon dioxide is emitted into the atmosphere. A recent burning issue is a need for robust, sustainable and climate friendly power transmission and distribution systems that are intelligent, reliable, and green. There is unprecedented interest in renewable energy, particularly solar and wind energy, which provides electricity without giving rise to carbon dioxide emissions. The primary national goal of Australia is to increase the use of renewable energy from present levels to 20 percent or even 25 percent of total electrical supply [1-2]. Exciting technological breakthroughs in clean energy from utility scale solar, wind, and geothermal energy and the smarter management of traditional energy sources are currently held back by the lack of supporting infrastructure. It is time to include substantial planning that includes investigation of the availability and characteristics of renewable energy sources and impact of renewable energy on transmission and distribution network and integrating with the smart power grid [1-4].

The integration of variable generation presents unique challenges on system performances, and the key factors include [5]:

- renewable energy generator's design and power movers' type
- renewable energy power generation's expected types of run
- interaction with other renewable energy sources
- the position of the grid and renewable energy plant
- the characteristics of the grid.

Issues need to be considered to integrate renewable energy sources with the power grid are efficiency, reliability and power quality (PQ), and cost of the energy conversion, appropriate load management, safety and security [5-6]. This paper presented an extensive handy survey on renewable energy and its integration techniques with the smart power systems and analyses the technical difficulties observed with their mitigation techniques. Finally, a prediction model has been presented which will be used to forecast renewable energy sources including its production of energy for appropriate load demand management system.

II. CHALLANGES TO INTEGRATE RENEWABLE ENERGY

It is a fundamental concern today, to be able to bring higher percentages of renewable electricity into the energy mix due to the variable nature of many of these resources. With the increase penetration of renewable energy to the grid the key technical potential challenges that effects quality of power observed includes: voltage fluctuation, power system transient and harmonics, reactive power, electromagnetic interference, switching actions, synchronization, long transmission lines, low power factor, storage system, load management, and forecasting and scheduling [5-7]. These problems mostly occurred for wind and solar energy. Biomass, hydro and geothermal energy sources are more predictable and they have no significant problem on integration with the smart grid [5]. Any device to be connected to the electric grid has to fulfill standardized power quality requirements. To ensure adequate PQ in the grid it is a prime concern today to mitigate these problems and Government, industries and researchers are working together for a sustainable efficient smart power grid.

Voltage fluctuation: Voltage fluctuation is a major issue particularly for wind and solar energy due to the intermittency of these resources. This happens due to the variations of wind speed and the irregular solar radiation with time. The voltage flicker caused by one machine varies inversely with the fault level at the point of grid connection, therefore is a significant issue of weak grids. Voltage fluctuation disturbs the sensitive electric and electronic equipment which leads to the great reduction in the life span of most equipment [8-9]. Periodic disturbances to the network voltage are denoted as flicker and lighting flicker is generally used to measure flicker or voltage fluctuation. The level of flicker is quantified by the short term flicker severity value P_{st} and allowable voltage change as a function of frequency is $P_{st} = 1$[10]..

Harmonic distortion: The power electronics devices, together with operation of non-linear appliances, inject harmonics to the grid which may potentially create voltage distortion problems. Operating harmonics need to be minimised to keep the total harmonic distortion within acceptable limits. Harmonic distortion is being minimized by good control algorithm design in the current control loop [5, 10]. Different types of filters are used to mitigate harmonic distortion. However, according to the IEEE standard, harmonics in the power system should be limited by the harmonic current that a user can inject into the utility system at the point of common coupling (PCC) and the harmonic voltage that the utility can supply to any customer at the PCC[11]

Reactive power compensation: The consumption of reactive power by induction generators is a common problem which affects the grid PQ. An induction generator requires an increasing amount of reactive power as the amount of power generated increases and it is essential to provide reactive power locally, as close as possible to the demand levels. Due to the fluctuations in the active and reactive power, the voltage at PCC fluctuates. A typical power compensator may be implemented by using a fixed capacitor, a switched capacitor, or static compensator [6, 8 - 9].

Synchronisation: Synchronisation of grid frequency, voltage, and phase is a promising research challenge to control PQ. The most popular grid synchronisation method is based on phase-locked loop (PLL). Other techniques for synchronization include detecting the zero crossing of the grid voltages or using combinations of filters coupled with a non linear transformation [6]. Four conditions which must be met for wind-grid integration are: the wind power frequency must be as close as possible to the grid frequency; terminal voltage magnitude must match with that of the grid; phase-sequence of the two three-phase voltages must be the same and phase angle between the two voltages must be within 5 percent [12].

Energy Storage: Energy storage is essential in ensuring the reliability of power delivery. As renewable energy have instability and uncertainty in their production storage system is useful as it can store excess energy and provide power when energy shortage. The existing energy storing technologies include battery, flywheels, super-capacitors, and superconducting magnetic energy storage **(**SMES**)** [5-6].

Forecasting and scheduling: The variability of renewable energy sources requires knowing the relevant long-term weather patterns which can be used to develop better procedures and capabilities to facilitate integration into a "smart" national power grid. To reduce intermittent energy's impacts on network security it is needed to predict renewable energy variations. Accurate forecasting and scheduling systems are essential for appropriate and satisfactory use of renewable sources and to establish sustainable load management systems for the smart power grid. Several research studies have been undertaken to assess solar irradiation and wind speed as well as production of energy from renewable energy sources. Another purpose of renewable energy's power prediction is the realization of economic dispatch, i.e., according to predicted output curves, to optimize conventional unit's output so as to realise orderly renewable energy generation combination to the grid, and achieve the goal of reducing operating costs [13].

Load demand management system: Due to the intermittent nature of renewable energy sources appropriate planning and management of load demand management is essential to ensure adequate PQ and uniform supply to the power systems. The inherent mismatch between the renewable energy sources output and the load may lead to significant energy wastage. For example, a wind-diesel hybrid power system is an autonomous electricity generating system which uses one or more diesel generators and wind turbines to supply power to a local grid. However, the contribution of wind power will vary over time based on wind speed. Thus, in high wind periods excess power may have to be dumped. Therefore a load demand management system is required to maintain appropriate power supply which increases overall efficiency and quality of the system [5, 14].

Extensive planning, design, and research need to be undertaken in different areas to mitigate the problems introduced when integrating renewable energy sources with the smart power grid. Any device to be connected to the electric grid has to fulfil standardised PQ requirements. Efficient design of electronic power converters for individual energy sources considering their physical and dynamic nature plays a key role in minimising the observed potential challenges. The main purpose of power electronic converters is to integrate the distributed generation to the grid maintaining power quality standards. However, if the inverter is not implemented properly high frequency switching of inverter injects additional harmonics to the systems that creates major PQ problems [11]. Appropriate design of electrical circuits with control systems mitigate voltage fluctuations, harmonic distortion, reactive power compensation, power factor improvements and ensure PQ improvements of the power system. New operational and optimisation tools are essential to will play a key role in minimising load demand management, scheduling and dispatching problems. Custom power devices such as shunt active power filter (static synchronous compensators STATCOMs), series active power filter (dynamic voltage regulators DVRs), and a combination of series and shunt active power filter (unified power quality conditioners UPQCs) are the latest developments of interfacing devices between grids and consumer appliance. These devices overcome voltage/current disturbances and improve the PQ by compensating the reactive and harmonic power generated or absorbed by the load [11].

This study focuses mainly on wind and solar energy and its integration with smart power grid as other sources of energy has not facing significant integration challenges. Moreover, the Australian Government is concentrating on generating more energy from wind and solar resources. The common and major potential challenges for the integration of wind and solar energy with grid are voltage fluctuations, harmonics, reactive power, forecasting and scheduling. This research focuses on mitigation of voltage fluctuation, minimising harmonic distortion and scheduling and forecasting of energy production from different renewable sources. As a work-in-progress in the next section a prediction model has been presented which will be used to forecast renewable energy sources including its production of energy for appropriate load demand management system.

III. FORECASTING ENERGY PRODUCTION

To facilitate the introduction of a large number of renewable energy sources into the grid, a careful assessment of renewable energy resource characteristics is vital, in particular variability of production of renewable energy sources with changing weather conditions. Wind and solar energy is the most promising renewable energy source which is free from green house gas emission that encourages interest worldwide. The effective utilization of wind and solar energy entails having a detailed knowledge of the wind and solar characteristics at the particular location and the distribution of wind speeds and solar irradiation is important for the design of wind farms and solar plant, and power generators. However, enough information is not always available in time on the future wind power or solar plant sites for power system planning purposes. Forecasting and real-time monitoring is needed in order to get knowledge on the geographic areas where the resource exists and the total MW possible to be implemented [15].

A. Wind Speed Data

Hourly wind speed data have been collected from the Australian Bureau of Meteorology (BOM) for the location of Yeppoon the Esplanade Weather Station (YEWS) [16]. This is located in Central Queensland, Australia with latitude -23.1364, longitude 150.7506, and height of station above mean sea level is 5.5. Data have been collected using a real time automatic system with performing quality checking. The unit of wind speed is m/s. The standard anemometer height is 10 m, however in order to produce efficient wind energy, wind speeds at heights greater than 10 m are required. The popular power law which is given in equation (i) is used to measure the hub height wind speeds at various potential sites [17].

$$\frac{v_2}{v_1} = \left(\frac{z_2}{z_1}\right)^{\alpha} \quad \text{(i)}$$

where v_2 is the extrapolated wind speed at height z_2 and v_1 is the measured speed at z_1. The exponent α depends on the nature of the roughness of the surface, wind speeds and temperature. The exponent value of 0.14 or (1/7) has widely been chosen as a good reprehensive of the prevailing conditions. In this paper, power law is used to predict the wind speed at different heights.

Power production from wind turbine is depending on wind speed (v), density of the air (ρ) and the swept area of the rotor (A). Therefore, the maximum power P, available from the wind can be represented as equation (ii).

$$P = \frac{1}{2}\rho A v^3 \quad \text{(ii)}$$

However, actual amount of energy production will be less as it is not possible to extract all available energy [17]. Standard atmospheric density may be measured from [18]. In this paper, standard atmospheric density has assumed as 1.1217 $kgm^{-3}$to calculate total wind power. From equation (ii) it has seen that wind speed has a significant role in producing energy from wind source.

B. Solar Radiation Data

Daily solar irradiation data have been collected over the year 2007 from BOM [16] for the location of RAWS. It is located in Central Queensland, Australia with latitude -23.3753^0, longitude 150.4775^0, and height of station above mean sea level is 10.4m. The unit of solar irradiation is $kWh/m^2/day$.

Today, roughly 1,368 watts per square meter (W/m^2) of solar energy on average illuminates the outermost atmosphere of the Earth. This is also called solar constant. Earth absorbs around 70 percent of this total solar irradiance (TSI) and the rest is reflected into space [19] and 58% of the radiation intercepted by the Earth [20]. However, it also depends on the distance between Sun and Earth. As the surface of a sphere has an area four times great as the area of a disk of the same radius, energy reduced to 342 W/m^2 for our spherical planet. Another explanation is that half of the Earth's surface (the night side) is in the dark, while areas near the edges of the planet are receiving reduced amounts of energy per unit [21]. The total energy production from Sun is given in equation (iii) [20].

$$E = 0.58 * 3.6 * 10^{-9} S n \pi r^2 \quad \text{(iii)}$$

where E is the solar energy in EJ, S is the solar constant in W/m^2 , n is the number of hours and r the Earth's radius in km.

Therefore this study has been predicted wind speed and solar irradiation as well as energy production respectively from wind and solar sources to develop a prediction model for the future renewable energy management system. Precise solar-radiation and wind flow estimation techniques are critical in the design of renewable energy systems. Machine learning techniques play a major role in forecasting solar irradiation and wind speed. Prediction models have been proposed using ten popular regression algorithms to predict variable wind speed and solar irradiation. In the same time typical variation of energy production from renewable energy sources also estimated. The most suitable algorithm has been proposed based on the performance metrics of the algorithms.

Regression analysis is the most significant and popular machine learning area for future decision making or forecasting of data or any incidents. Currently various statistical forecasting and regression approaches and learning algorithms are used to forecast weather pattern, solar radiation and wind speed. Meta-based learning Random Sub Space (RSS), and RegressionByDiscretization(RegDes), Regression-based learning linear regression (LR), simple linear regression (SLR), Statistical learning based algorithm sequential minimal optimisation (SMO) regression (SMOReg), and Neural Network based multilayer perception (MLP), RBFNetwork (RBFN), Lazy-based learning IBK, Tree-based learning M5Rules and RepTree with bagging techniques [22-23] are considered in this study to develop prediction models. A set of attributes to measure the estimation techniques performance rather than a single attribute have been considered includes correlation coefficient (CC), mean absolute error (MAE), root mean square error (RMSE).

Models have been developed using above regression algorithms to predict daily distribution of wind speed and solar irradiation with the help of popular WEKA learning tools [24] which is the extended works of the earlier work in [25]. From the preliminary results, extensive statistical analysis has been undertaken to select the most suitable prediction model for this application. The ranking performance has been estimated for a given algorithm based on CC, MAE and RMSE. The best performing algorithm on each of these measures is assigned the rank of 1 and the worst is 0. Thus, the rank of the *j*th algorithm on the *i*th dataset is calculated as stated in Reference [23]:

$$R_{ij} = 1 - \frac{e_{ij} - \max(e_i)}{\min(e_i) - \max(e_i)} \quad \text{(iv)}$$

Finally, the relative weighted performance was measured for all of the algorithms with two different weights for ranking performance and computational complexity using equation (v).

$$Z = \alpha a_i + \beta t_i \quad \text{(v)}$$

Here α and β are the weight parameters for ranking average against computational complexity. The average accuracy and computational complexity are denoted as a_i and t_i respectively. Relative weighted performance was calculated by assuming $\alpha = 1$ and β is from 0.4 to 2.

IV. RESULTS AND ANALYSIS

Proposed algorithms with classical data splitting options were used to predict the daily distribution of solar irradiation and hourly distribution of wind speed. This study is very important as now-a-days renewable energy sources are the emerging resources to build environment friendly sustainable power systems for future.

A. Hourly Wind Speed

Models were developed using ten regression algorithms with the collected hourly wind data to predict hourly distribution of wind flow. Model results showed that overall prediction accuracy is fairly similar; however no algorithm performs the best for all of the estimated attributes. It has shown that IBK, RBFN and RegDes predicted with highest accuracy and actual and predicted value were identical. CC is the least for the model develop with LR. In terms of MAE and RMSE model developed with RepTree with Bagging techniques is the best. Figure 1 shows the performances of different models.

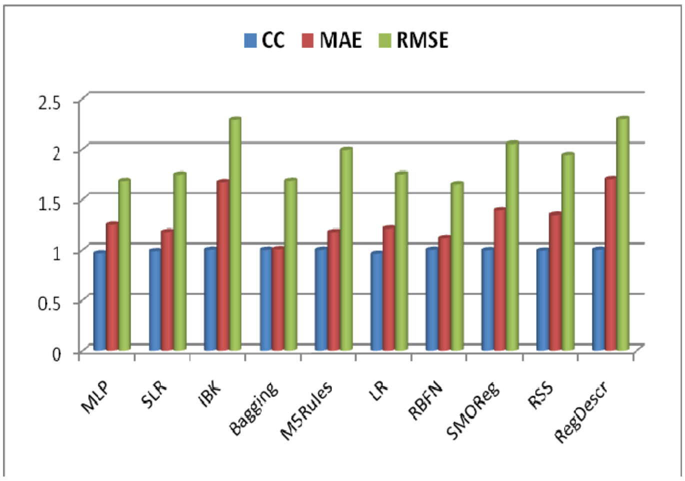

Figure 1: Comparisons of performance metrics with different algorithms for prediction of houlry wind speed

Therefore to select the most suitable model for this application ranking performance is measured based on equation (iv). From Figure 2 it is observed that Bagging technique has ranked 1, while RBFN has ranked 2 and RegDes has ranked 10.

Finally, relative weighted performance has been measured considering average ranking accuracy and computational complexity using equation (v). From Figure 3 it is shown that considering computational complexity and average accuracy Bagging technique is the best choice for all β values and RBFN is the second for this application. The model develop with RegDes performs the worst for this application. It has also been observed that MLP requires more computational time compare to other algorithms.

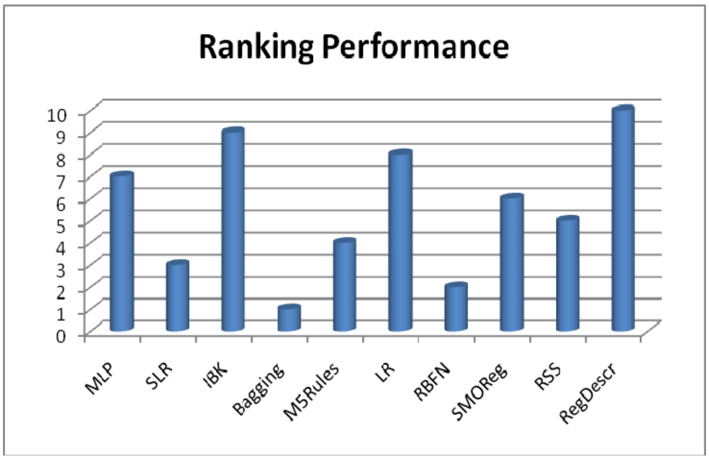

Figure 2: Ranking performances of different algorithms

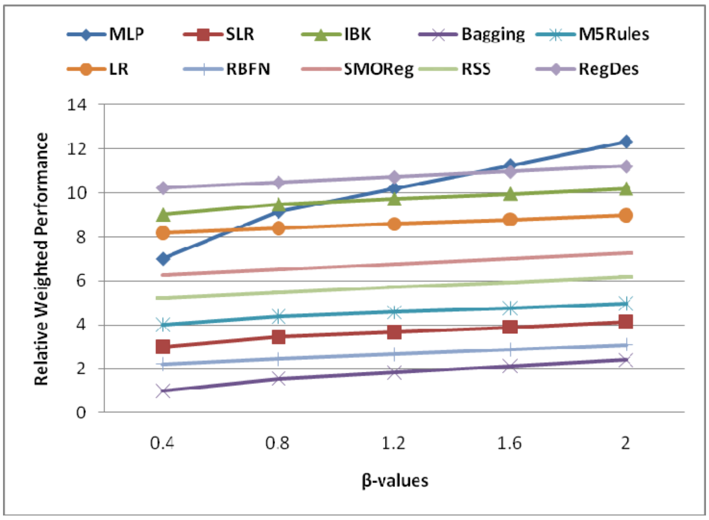

Figure 3: Overall weighted performance of the algorithms with respect to β for wind speed data

B. Daily Solar Radiation

To forecast daily distribution of solar radiation ten models have been developed using popular regression algorithms. Initially CC, MAE, and RMSE have been measured for each of the models. From Figure 5, it has seen that in terms of CC, the model develops with RSS performs the best. For RMSE measures SMOReg is the best performing algorithm while MLP is the worst. Therefore it is really difficult to select the most suitable algorithm for this application.

To select the most suitable model for this application ranking performance for a given model has been estimated using equation (iv). From statistical analysis it has shown that for CC measures RSS is the best performing algorithm and IBK is the worst performing algorithm. For MAE and RMSE measures SMOReg is the best performing algorithm. Finally, the effect of ranking average and computational complexity was observed by changing the values of β. Relative weighted performance has been measured using equation (v). Figure 5 shows the relative weighted performance of different models with respect to different β values. It has observed that considering computational complexity and average accuracy RSS is the best performing algorithm for all β values and Bagging technique with RepTree is the second performing algorithm. It has observed that computational complexity has not played a significant role in this analysis.

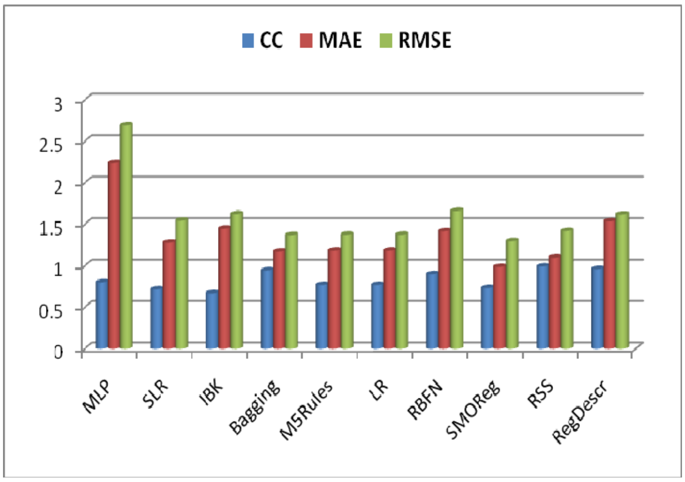

Figure 4: Comparisons of performance metrics with different algorithms for prediction of daily solar irradiation

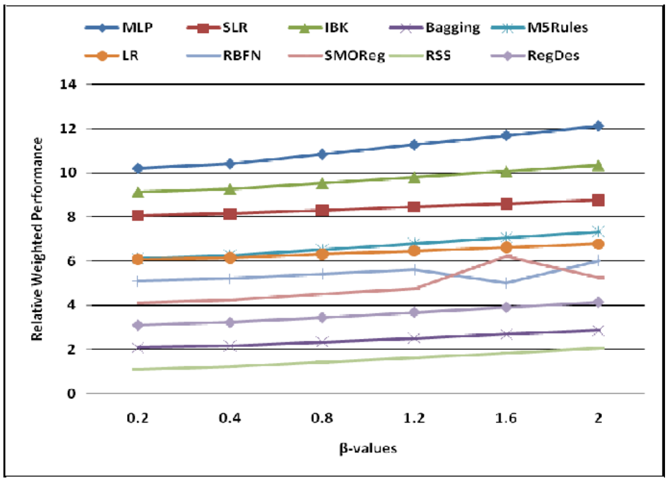

Figure 5: Relative weighted performance of the algorithms with respect to β for prediction of solar irradiation

Finally, it was concluded that Bagging technique with RepTree is the most suitable and RBFN is the second choice for predicting hourly distribution of wind speed as well as production of wind energy. The model developed with RSS is the most suitable and Bagging technique with RepTree is the second choise to predict daily solar irriadiation as well as solar energy production. From this prediction model wind speed and solar radiation data as well power generation will be available in advance for a particular location.

V. Conclusions

Recent environmental awareness, resulting from the coal fired power station, has encouraged interest in the development of modern smart grid technology and its integration with climate friendly green renewable energy. However, integration of renewable energy with the grid introduces enormous technical difficulties due to its nature which need to overcome to obtain a sustainable, climate friendly power system for the future. This article presents a handy survey of the potential challenges observed with available solutions to integrate renewable energy with smart power grid.

In this paper, a forecasting approach has been developed that predicted daily distribution of solar irradiation and hourly distribution of wind speed that will help to build a green power system for the community and utilities. Models have been developed for both solar and wind energy using ten popular regression algorithms. Ranking performances and average weighted performances have been estimated to select the most suitable algorithm for this application. Finally it has observed that models with Bagging technique and RBFN are suitable to forecast hourly distribution of wind flow. On the other hand, RSS and Bagging are suitable algorithms to forecast daily distribution of solar irridiation.

This technology has just emerged and needs to be developed in different areas. Therefore further investigations are suggested on the following areas:

- Analyse the characteristics and availability of renewable energy sources with varying weather conditions
- Analyse voltage fluctuation and ensure power quality of the smart power grid.

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