Machine Learning Techniques for Supporting Renewable Energy Generation and Integration: A Survey

Kasun S. Perera[1], Zeyar Aung[2*], and Wei Lee Woon[2]

[1] Database Technology Group, Technische Universität Dresden, Germany
Kasun.Perera@tu-dresden.de
[2] Institute Center for Smart and Sustainable Systems (iSmart),
Masdar Institute of Science and Technology, Abu Dhabi, UAE
{zaung,wwoon}@masdar.ac.ae

Abstract. The extraction of energy from renewable sources is rapidly growing. The current pace of technological development makes it commercially viable to harness energy from sun, wind, geothermal and many other renewable sources. Because of the negative effects on the environment and the economy, conventional energy sources like natural gas, crude oil and coal are coming under political and economic pressure. Thus, they require a better mix of energy sources with a higher percentage of renewable energy sources. Harnessing energy from renewable sources range from small scale (e.g., a single household) to large scale (e.g., power plants producing several MWs to a few GWs providing energy to an entire city). An inherent characteristic common to all renewable power plants is that power generation is dependent on environmental parameters and thus cannot be fully controlled or planned for in advance. In a power grid, it is necessary to predict the amount of power that will be generated in the future, including those from the renewable sources, as fluctuations in capacity and/or quality can have negative impacts on the physical health of the entire grid as well as the quality of life of its users. As renewable power plants continue to expand, it will also be necessary to determine their optimal sizes, locations and configurations. In addition, management of the smart grid, in which the renewable energy plants are integrated, is also a challenging problem. In this paper we provide a survey on different machine learning techniques used to address the above issues related to renewable energy generation and integration.

Keywords: Renewable Energy, Smart Grids, Machine Learning

1 Introduction

The world is faced with a number of challenges related to energy sustainability and security. If not promptly addressed, these can lead to economic and political instability. The depletion of fossil fuel reserves as well as the environmental

* Corresponding author.

impact of burning these fuels have led to increased interest in developing alternative and more sustainable energy sources. Renewable energy resources like solar photovoltaic (PV), solar thermal (a.k.a. concentrated solar power, CSP), geothermal, tidal waves, wind power, and biomass have been growing rapidly in energy market [1]. Many countries and companies are seeking to diversify their energy mix by increasing the share of renewables.

In conventional energy generation process, energy production depends on the energy demand from the users, and the stability of the power grid relies on the equilibrium of energy demand and supply. When the energy demand surpasses the energy supply, it destabilizes the power grid and results in power quality degradation and/or blackouts in some parts of the grid. When the demand is lower than the supply, energy is lost incurring high unnecessary costs due to wastage. Producing the right amount of energy at the right time is crucial both for the smooth running of the grid and for higher economic benefits. To maintain this stability, much research has focused on energy supply and demand forecasting to predict the amount of energy that will be required. This will then ensure that there will be sufficient capacity to meet these requirements, but also that excess capacity and hence energy wasted will be minimized..

Renewable energy resources like solar light, solar heat and wind are highly variable and the resulting fluctuations in the generation capacity can cause instability in the power grid. This is because the energy/power output of these plants is defined by the environmental factors such as wind speed, the intensity of solar radiation, cloud cover and other factors. Another important limitation of renewable energy power plants is that they are subject to marked daily and annual cycles (e.g., solar energy is only available during the day). Thus, it is necessary to generate power when resources are available and store it for later use while using a certain portion of the generated power at the same time. Wind and solar PV energy is expensive to store, thus careful management of energy generation is needed. When the generation capacity of natural resources are insufficient to meet demand, conventional sources such as gas power plants are typically used to cover the electricity shortfall.

The above-mentioned challenges have motivated the use of machine learning techniques to support better management of energy generation and consumption. Different machine learning techniques are used in different stages of a renewable energy-integrated power grid, depending on the requirements and the characteristics of the problem. For a power grid with renewable energy sources contributing a considerable proportion of energy supply, it is necessary to forecast both short and medium term demand. This would facilitate the formulation of well informed energy policies, for example by helping to determine important parameters such as the appropriate spinning reserve levels and storage requirements. On the other hand, it is also necessary to forecast the energy output from renewable energy power plants themselves, since the energy output from these power plants depends on many environmental factors that cannot be controlled. This in turn necessitates the prediction of these environmental factors such as wind speed, direction and solar radiation in the region of the power plant. Another important use for machine learning techniques in the context of renewable energy is in determining the optimal location, size and configuration of renewable power plants. These parameters are dependent on many factors such as proximity to population centers, local climatic fluctuations, terrain, availability and costs of logistics and other facilities and many others. Yet another area for the application of machine learning methods is in the overall operations and management of the smart grid, i.e. issues such as fault detection, control and so on.

Figure 1 depicts possible areas where we can use machine learning techniques for performance improvements and better management of renewable energy. The right side of the figure depicts consumers and prosumers (who consume energy from the grid as well as produce small-scale renewable energy and feed the excessive energy to the grid). The left side depicts large-scale renewable energy producers. Conventional power plants are still involved in the grid in order to balance of demand and supply and to ensure adequate power quality.

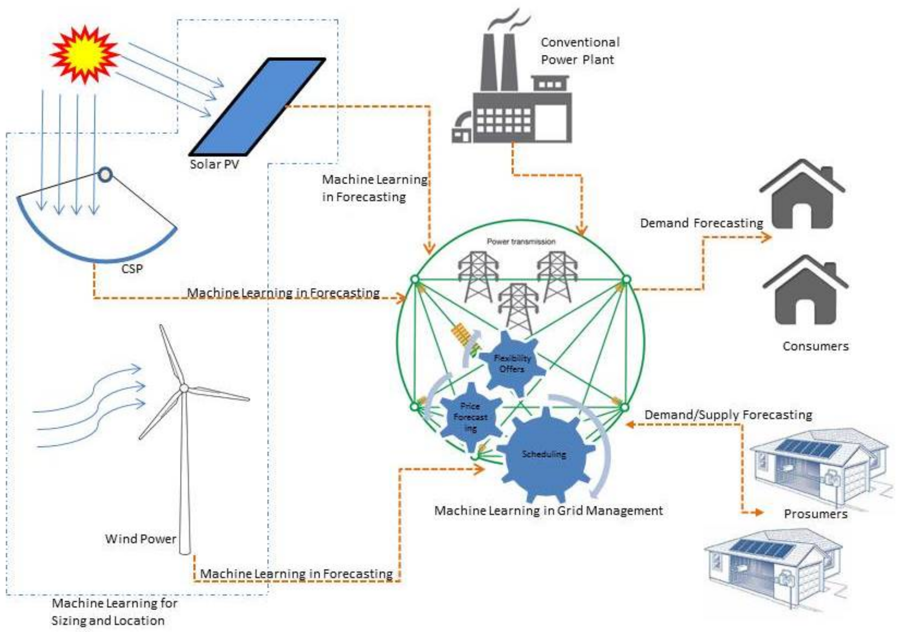

Fig. 1. Overview of power grid with integrated renewable sources and its usage of machine learning techniques in different steps.

This paper will summarize and compare the machine learning techniques that have been or can be used not just in the generation of renewable energy but also in the integration of these resources into existing power grids.

Table 1. List of acronyms.

Acronym	**Meaning**
ANN	Artificial Neural Network
AR	Additive Regression
ARIMA	Auto-Regressive Integrated Moving Average
ARMA	Auto-Regressive Moving Average
CART	Classification and Regression Trees
CSP	Concentrated Solar Power
DEA	Data Envelopment Analysis
FFT	Fast Fourier Transformation
GA	Genetic Algorithm
kNN	k-Nearest Neighbor
LLP	Loss of Load Probability
LMS	Least Median Square
LR	Linear Regression
LWL	Locally Weighted Learning
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multi-Layer Perceptron
MPPT	Maximum Power Point Tracking
MTBF	Mean Time Between Failures
NMSE	Normalized Mean Square Error
NWP	Numerical Weather Prediction
PCA	Principal Component Analysis
P&O	Perturb and Observe
PR	Pace Regression
PSO	Particle Swarm Optimization
PV	Photovoltaic
RMSE	Root Mean Square Error
RBF	Radial Basis Function
SLR	Simple Linear Regression
SVM	Support Vector Machines

The rest of the paper is organized as follows. Section 2 describes the machine learning techniques in power output prediction from different renewable sources. Section 3 discusses the techniques used in optimizing location, sizing, and configurations of renewable sources. Section 4 covers the methods in overall operations and management of a mixed-source smart grid with renewable energy playing a significant role. Finally, Section 6 concludes the paper.

2 Forecasting Renewable Energy Generation

Forecasting power output from a renewable energy power plant is crucial as this depends on many non-human-controllable factors such as environmental parameters. Depending on the energy source it uses, the power plant exhibits certain characteristics that enables the use of machine learning techniques for prediction purposes. In this section we will review the different machine learning techniques used in different types of power plants including wind farms, solar farms, and hydro power.

2.1 Wind Power Generation

Wind power generation depends on many characteristics and the power output from a wind turbine can be calculated using the Equation 1. Here A stands for area that is covered by the wind turbine blades (a circle with radius r), ρ is for air density, V is wind speed and C_p for efficiency factor usually imposed by the manufacturer.

$$P = \frac{A\rho V^3 C_p}{2} \tag{1}$$

In this equation wind speed is a significant factor as the power output is proportional to the wind speed. It also observed that there is a cutoff speed where the power output is steady after that speed (so as to ensure the safety of the turbine). Other factors such as humidity and temperature also affect the density of the air, which in turn affects the power generation. Thus, it is necessary to forecast these factors and ultimately the final power output in a wind farm. Many methods have been proposed for forecasting power generation in wind farms. Brief descriptions and reviews on them are given below.

In [2], Lei et al. presented physical and statistical-based models as two main categories of forecasting models. The physical models are more suitable for long term forecasting whereas the statistical models are used for short and medium term forecasting. Our interest lies in the statistical models as they are more closely associated with machine learning techniques.

Auto-regressive moving average (ARMA) and auto-regressive integrated moving average (ARIMA) models are presented in [3] for wind speed forecasting and then wind power forecasting by analyzing the time-series data. The authors start with the well known ARMA model and then apply ordered differential transformation to the model to get the ARIMA model. The ARMA model is a combination of AR model and MA model on the same time series data.

A Kalman filter model using the wind speed as the state variable is used in [4]. The authors suggested that this model is suitable for online forecasting of wind speed and generated power. Online forecasting of power generation is important as it can provide the most recent and updated future forecasting which then can be used for power grid management.

Comparison of the ARIMA and ANN models for wind speed forecasting in Oaxaca region in Mexico is presented in [5] by Sfetsos. Their analysis showed that seasonal ARIMA model outperformed ANN model for more accurate forecasting, but when the number of training vectors were increased for ANN model its accuracy could be improved. Using the previous ten-minute data for training, Sfetsos also presented a model [6] using ANN for wind time-series forecasting. Subsequent predictions are averaged to obtain the mean hourly wind speed and then to determine the power generation from the wind turbine.

Recurrent multi-layer perceptron (MLP) model, a variant of ANN, was proposed in [7], which employs Kalman filter based back-propagation network. The proposed model performs well in long term power generation prediction than in short term prediction.

In Mohandes et al. [8] an SVM using Gaussian kernels was used to predict the wind speed. The proposed method performed better than the MLP in terms the root mean square error (RMSE) on 12 years of wind data from Medina city, Saudi Arabia.

Fuzzy models are another way of using machine learning for prediction. In [9], Damousis et al. used a fuzzy model with spatial correlation method for wind power generation prediction. The proposed model performs well on wind turbines installed in a flat terrain, but performs poorly with respect to those installed in a deteriorated terrain. This might be due to variation of the wind speed with respect to height of the tower from the ground level as well as quality differences in the air.

Numerical weather prediction (NWP) models [10] were also used for wind forecasting and subsequently power generation prediction in many research works. In this approach, selecting an accurate NWP model is crucial as the accuracy well depends on the initial NWP model. In order to mitigate the effect of single NWP model, an ensemble method was proposed in [11]. The ensemble model allows to use same NWP with different parameters such as different initial conditions, physical parameterization of the sub-grid system or different data assimilation systems. It also can employ completely different NWP models to obtain the final ensemble learner.

Jursa and Rohrig [12] presented a mixed model using k-nearest neighbor (kNN) and ANN approaches. Their optimization model produces the results with 10.75% improvement over the benchmark model (persistence method) used with respect to RMSE. Jursa [13] also proposed the use of a variety of machine learning models. In that work, wind power forecasts were determined at 10 wind farms and compared to the NWP data at each wind farm using classical ANNs, mixture of experts, SVM and kNN with particle swarm optimization (PSO).

The main conclusion was that combining several models for day-ahead forecasts produces better results.

Foley et al. [14] provides a good survey of methods for wind power generation forecasting. It listed SVM, MLP, ANN, regression trees, and random forest as the widely-used machine learning methods in the context of wind power.

2.2 Solar Energy Generation

Solar photovoltaic (PV) usage ranges from the single household level to large solar PV plants with capacities of 1–100MW. As solar PV have been used in small domestic level for a long time, a number of research works for performance estimation for PV using machine learning techniques have been conducted in the past years.

Thermo siphon solar heater is a way of using renewable energy to get hot water for domestic usage. Kalogirou et al. [15] conducted performance prediction for these devices using ANN. The performance was measured in terms of the useful energy extracted and of the stored water temperature rise. The ANN was trained using the performance data for four types of systems, all employing the same collector panel under varying weather conditions. The output of ANN is the useful energy extracted from the system and the water temperature rise. Seven input units, 24 hidden neurons and 2 neurons as output comprises the network model with Sigmod as the transfer function.

A site specific prediction model for solar power generation based on weather parameters was proposed in [16], in which Sharma et al. used different machine learning techniques. Multiple regression techniques including least-square SVM using multiple kernel functions were used in the comparison with other models. Experimental results showed that the SVM model outperformed the others with up to 27% more accuracy. Linear least-square regression model was also used for prediction with 7 weather parameters and results indicate 165W/m^2 and 130W/m^2 RMSE for validation and prediction sets respectively. For the SVM-based model they tired linear, polynomial and RBF kernels, and chose the RBF kernel for the final SVM model (as the first two did not perform well). Further improvement to the model was made by using principal component analysis (PCA), thus by selecting the first 4 features from the ranked output features from PCA.

A hybrid intelligent predictor for 6 hour ahead solar power prediction was proposed in [17]. The system used an ensemble method with 10 widely-used regression models namely linear regression (LR), radial basis function (RBF), SVM, MLP, pace regression (PR), simple linear regression (SLR), least median square (LMS), additive regression (AR), locally weighted learning (LWL) and IBk (an implementation of kNN). Their results showed that, with respect to MAE and MAPE, the top most accurately performing regression models are LMS, MLP, and SVM.

Diagne et al. [18] recently provided a survey of solar energy forecasting methods covering various physical and statistical/machine learning techniques.

2.3 Hydro Power Generation

Hydro power is the most widely used and one of the most established renewable energy sources. Due to its characteristics and economic viability, many third world countries depend on extracting energy from their available water sources. As hyrdo power uses running water or stored water sources which depend on the rainfall in the region, it is obviously affected by non-human controllable weather parameters which need to be forecasted for better planning and management.

Recurrent ANNs [19–21] as well as SVMs have been widely used for rainfall prediction. In [22], Hong presented the use of a combination of recurrent ANN and SVM to forecast rainfall depth values. Moreover, chaotic PSO algorithm was employed to choose the parameters for the SVM model. With the 129 data points provided to the model, the resulting performance of the model in terms of the normalized mean square error (NMSE) values were 1.1592, 0.4028 and 0.3752 for training, validation, and testing sets respectively.

An ensemble learning model for hydropower energy consumption forecasting was presented in [23], where Wang et al. used a seasonal decomposition-based least-squares SVM mechanism. The original time series data was decomposed into regional factors (which demonstrate seasonal effects/trends) and irregular components, and then all of them were used for least-square SVM analysis. This least-square SVM model was used to predict the three main components known as trend cycle, seasonal factor, and irregular component which were in turn fed into another least-square SVM to combine the prediction values. The authors stated that the model outperformed the other benchmark models by providing accurate results when seasonal effects and irregularities were presented in the input time-series.

Lansberry and Wozniak [24] used a genetic algorithm (GA) to support optimal governor tuning in hydro power plants. The authors investigated the GA as one possible means for adaptively optimizing the gains of proportional-plus-integral governors. This tuning methodology was adaptive towards changing plant parameters-conduit time constant and load self-regulation.

Djukanovic et al. [25–27] presented an ANN-based coordinated control for both exciter and governor for low head hydropower plants. Their design was based on self-organization and the predictive estimation capabilities of ANN implemented through the cluster-wise segmented associative memory scheme [25].

3 Determining Plant Location, Size, and Configuration

Unlike natural gas, diesel or coal fired plants, renewable energy power plants require a huge area for their operation. For example, Shams-1, which is the biggest CSP power plant in the world opened recently in Abu Dhabi, UAE, occupies an area of 2km^2 and generates 100MW of electricity. A conventional power plant of similar capacity only takes a few square meters space. Thus, it is necessary to analyze the required size of the renewable energy power plant with respect to the energy requirements. Power plants like solar PV and CSP also exhibits special requirements of location selection and orientation selection as solar panels need to be faced to solar irradiation to absorb the optimal energy. Thus, machine learning techniques play a crucial role in assisting these decision making steps.

Conventional methods for sizing PV plants have generally been used for locations where the required weather data (irradiation, temperature, humidity, clearness index, wind speed, etc.) is available and so is the other information concerning the site where the PV plant is to be built. However, these methods could not be used for sizing PV systems in remote areas where the required data are not readily available, and thus machine learning techniques are needed to be employed for estimation purposes.

Mellit et al. [28] developed an ANN model for estimating sizing parameters of stand-alone PV systems. In this model, the inputs are the latitude and longitude of the site, while the outputs are two hybrid-sizing parameters (f, u). These parameters are determined by simple regression of loss of load probability (LLP) as shown in Equation 2.

$$f = f_1 + f_2 \log(LLP) \quad and \quad u = e^{(u_1 + u_2 \cdot LLP)} \tag{2}$$

These parameters allow the designers of PV systems to determine the number of solar PV modules and the storage capacity of the batteries necessary to satisfy demand. In the proposed model, the relative error with respect to actual data does not exceed 6%, thus providing accurate predictions. In addition, radial basis function network has been used for identification of the sizing parameters of the PV system. Their model, depicted in Figure 2, has been evaluated on 16 different sites and experimental results indicated that prediction error ranges from 3.75%–5.95% with respect to the sizing parameters f and u.

Seeling-Hochmuth [29] presented research into the optimization of PV-hybrid energy systems. The proposed method optimizes the configuration of the system and the control strategy by means of a GA. The control of the system is coded as a vector whose components are five decision variables for every hour of the year.

Senjyua et al. [30] also developed an optimal configuration of power generating systems in isolated islands with renewable energy using a GA. The hybrid power generation system consisted of diesel generators, wind turbine generators, PV system and batteries. The proposed methodology can be used to determine the optimum number of solar array panels, wind turbine generators, and battery configurations. The authors argued that by using the proposed method, operation cost can be reduced by about 10% in comparison with using diesel generators only.

Similarly, Yokoyama et al. [31] proposed a multi-objective optimal unit sizing of hybrid power generation systems utilizing PV and wind energy.

Hernadeza et al. [32] presented a GA-based approach to determining the optimal allocation and sizing of PV grid connected systems in feeders that provides the best overall impact on the feeder. The optimal solution is reached by a multi-objective optimization approach. According to the authors, the results obtained

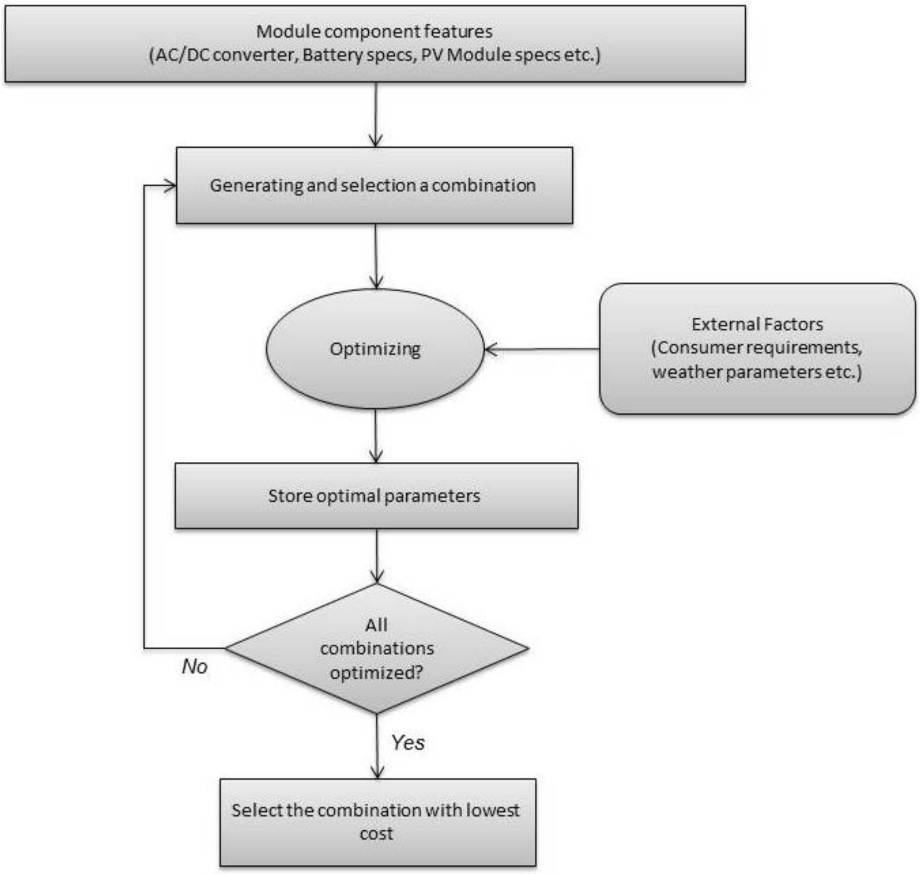

Fig. 2. The overview of the sizing, configuration, and optimizing of a PV plant [28].

with the proposed methodology for feeders performed well when compared with the results found in the literature.

A flexible neuro-fuzzy approach for location optimization of solar plants with possible complexity and uncertainty was described in [33]. The flexible approach was composed of ANN and fuzzy data envelopment analysis (DEA). In the model, first fuzzy DEA was validated by ordinary DEA, and then it was used for ranking of solar plant units and the best α-cut was selected based on the test of normality. Several ANN models are developed using MLP and the network with minimum MAPE was selected for the final model building.

Maximum power point tracking (MPPT) in solar PV is essential as it helps to extract the maximum energy in a given time period. Rotational non-static PV panels are employed with intelligent mechanisms for sun tracking. An intelligent MPPT was outlined in [34], which used fuzzy logic approach with the perturb and observe (P&O) algorithm. The subjective fuzzy model of the system was designed based on prior expert knowledge of the system. The Fuzzy logic controller was divided into four sections: fuzzification, rule-base, inference and defuzzification.

4 Managing Renewable Energy-Integrated Smart Grid

As rapid advancements in the power grid continue to make it smarter, its users/stakeholders expect more efficient and effective operation and management of the grid. Since more and more stakeholders take part in the power grid, managing such a big network becomes harder. Thus, intelligent techniques are required to cater the better management of the smart grid. In this section we will outline some problems the power grids are facing, namely supply/damand balancing, grid operations and management, grid's data management, and the proposed machine learning solutions to them. In addition, we will briefly describe a promising approach for the grid's data management problem.

4.1 Balancing Supply and Demand

When a power grid is integrated with renewable sources, it is even more important to accurately forecast energy generation as well as energy consumption. Fluctuations and intermittent behavior of solar and wind power plants imposes vulnerabilities to the power grid, thus by destabilizing the grid. Therefore, in order to maintain the stability of the grid, it is necessary to connect to the conventional power generation in time, disconnect malfunctioning wind power plants/turbines, or use smoothing techniques for the solar PV plants and grid connection. To identify those factors affecting the grid's stability and to ensure its good management, various machine learning techniques were employed.

The MIRABEL [35] system offers forecasting models which target flexibilities in energy supply and demand, thus helping to manage the production and consumption in the smart grid with renewable energy plants. The forecasting model can also efficiently process new energy measurements to detect changes in the upcoming energy production or consumption and to enable the rescheduling of flex-offers if necessary. The model uses a combination of widely adopted algorithms like SVM and ensemble learners. In order to better manage the demand and supply depending on the time domain, it employs different models for different time scales.

In a near future, the smart grid will consist of many individual autonomous units such as smart households, smart offices or smart vehicles. These users on the demand side pose a varying demand on the grid as their requirements are changing over the time and their life styles. Moreover, the demand is also affected by pricing regulations of the grid, as the smart grid employ deregulated pricing mechanisms at many levels. This deregulated market offers a flexibly to the users, thus allowing them to bid for energy that they need. Forecasting those flexibility offers is crucial in the smart grid systems today. Barbato et al. [36] and Reinhardt et al. [37] forecasted t he energy demand through meter readings from households. This provides detecting the flexible energy usage from the connected autonomous users in the demand side. Kaulakiene et. al. extended that idea in [38] by suggesting methods to extract the flexibilities from the electricity time series.

On the energy supply side, since there are different stakeholders with different characteristics, predicting energy supply can be a very challenging task. Use of multiple models to predict the energy supply is a common approach among the users. This impose another challenge as there is no systematic method to select which models to use when necessary. Ulbricht et. al. [39] presented a systematical optimized strategy to select suitable models from a model pool to use for solar energy supply forecasting.

4.2 Grid Operations and Management

For the operations and management of the grid itself, an overview of machine learning techniques used in New York City power grid was provided in [40] by Rudin et al. The system consisted of many different models for forecasting in different levels of the entire power grid. These models can be used directly by power companies to assist with prioritization of maintenance and repair work. Specialized versions of the proposed process are used to produce 1) feeder failure rankings, 2) cable, joint, terminator, and transformer rankings, 3) feeder mean time between failures (MTBF) estimates, and 4) manhole events vulnerability rankings. In their model, the authors used approximately 300 features generated from the time series data and associated parameters. SVM, classification and regression trees (CART), ensemble learning techniques such as random forests, and statistical methods were used for model building.

4.3 Grid Data Management

As smart grid deployments continue to expand via the addition of more users, it often requires information to be exchanged amongst different stakeholders. Many users generated frequent data that need to be shared among interesting parties to help make decisions for better management of the smart grid. So, it is required to employ a efficient and effective methods to share the smart grid's data.

Compression is a widely used technique to help data exchange when it has to deal with large quantities of data. Louie and Miguel [41] presented a lossless compression of wind plant data by using characteristics related to the wind plants. They suggests two methods to use with grid based wind plants and unordered wind plants. The authors claimed the superiority of their methods having 50% more compression than state-of-the-art methods and managed to achieve ∼1.8 times compression rate. In simple terms 1.8 compression rate means 1.8GB of data compressed to 1GB data, thus, user only has to work on 1GB data instead of 1.8GB of data.

Reeves et. al. [42] described a model-based compression of massive time series data. The authors presented a method employing fast Fourier transformation (FFT), filtered spikes and random signal projection to represent the original time series data. The method achieved a data reduction rate of 91.5%. The method was a lossy compression but still preserved the important information.

Here, we suggest that a similar model-based data representation method be used for smart grid data as it can potentially provide many advantages.

1. Model-based representation provides low memory footprint while maintaining the same required information.
2. It also provides efficient method to exchange information, since it does not need to exchange raw data, but can exchange the representation model.
3. Models provide efficient query processing when compared to query processing on raw data.

We envision that the smart grid will greatly benefit from model-based data representation. Further analysis and results will be included in the upcoming research papers.

5 Conclusion

Due to the depletion of conventional energy sources like natural gas, crude oil and coal and to mitigate the environmental effects of the burning of fossil fuels, governments and companies are focusing increasingly on developing renewable energy sources. Hydro power is a good example of a renewable source that has been successfully used for many decades. Wind and solar are also promising renewable sources that have experienced a fast pace of growth in the recent years. An inherent feature of these resources is that the energy production capacity is not fully controllable or even predictable, thus necessitating the use of proper forecasting and management techniques to ensure smooth integration with the power grid. A smart power grid that incorporates renewable energy sources needs to be constantly monitored and need to have the forecasting ability to predicting sudden changes in the power supply and demand. The studies reviewed in this paper analyze the different machine learning techniques used for supporting the generation of renewable energy and more importantly their integration into the power grid. It is very difficult to generalize the machine learning models for each and every aspect of renewable energy generation and integration into the grid, but a strong coordination is necessary among the different prediction and decision making models to better enhance the grid's overall efficiency and effectiveness.

In addition, machine learning techniques have been successfully used in the planning of renewable energy plants based on available data with reasonable accuracy. Published literature on location, sizing, and configuration of wind and PV systems based on machine learning techniques underline their popularity, particularly in isolated areas. This shows the potential of machine learning as a design tool in strategic planning and policy making for renewable energy.

References

1. United States Department of Energy: 2012 renewable energy data book (2012) http://www.nrel.gov/docs/fy14osti/60197.pdf.
2. Lei, M., Shiyan, L., Chuanwen, J., Hongling, L., Yan, Z.: A review on the forecasting of wind speed and generated power. Renewable and Sustainable Energy Reviews **13** (2009) 915–920
3. Guoyang, W., Yang, X., Shasha, W.: Discussion about short-term forecast of wind speed on wind farm. Jilin Electric Power **181** (2005) 21–24
4. Ding, M., Zhang, L.j., Wu, Y.c.: Wind speed forecast model for wind farms based on time series analysis. Electric Power Automation Equipment **25** (2005) 32–34
5. Sfetsos, A.: A comparison of various forecasting techniques applied to mean hourly wind speed time series. Renewable Energy **21** (2000) 23–35
6. Sfetsos, A.: A novel approach for the forecasting of mean hourly wind speed time series. Renewable Energy **27** (2002) 163–174
7. Li, S.: Wind power prediction using recurrent multilayer perceptron neural networks. In: Proceedings of the 2003 IEEE Power Engineering Society General Meeting. Volume 4. (2003) 2325–2330
8. Mohandes, M.A., Halawani, T.O., Rehman, S., Hussain, A.A.: Support vector machines for wind speed prediction. Renewable Energy **29** (2004) 939–947
9. Damousis, I.G., Alexiadis, M.C., Theocharis, J.B., Dokopoulos, P.S.: A fuzzy model for wind speed prediction and power generation in wind parks using spatial correlation. IEEE Transactions on Energy Conversion **19** (2004) 352–361
10. Giebel, G., Badger, J., Landberg, L., et al.: Wind power prediction ensembles. Technical Report 1527, Ris National Laboratory, Denmark (2005)
11. Al-Yahyai, S., Charabi, Y., Al-Badi, A., Gastli, A.: Nested ensemble NWP approach for wind energy assessment. Renewable Energy **37** (2012) 150–160
12. Jursa, R., Rohrig, K.: Short-term wind power forecasting using evolutionary algorithms for the automated specification of artificial intelligence models. International Journal of Forecasting **24** (2008) 694–709
13. Jursa, R.: Wind power prediction with different artificial intelligence models. In: Proceedings of the 2007 European Wind Energy Conference and Exhibition (EWEC). (2007) 1–10
14. Foley, A.M., Leahy, P.G., Marvuglia, A., McKeogh, E.J.: Current methods and advances in forecasting of wind power generation. Renewable Energy **37** (2012) 1–8

15. Kalogirou, S.A., Panteliou, S., Dentsoras, A.: Artificial neural networks used for the performance prediction of a thermosiphon solar water heater. Renewable Energy **18** (1999) 87–99
16. Sharma, N., Sharma, P., Irwin, D., Shenoy, P.: Predicting solar generation from weather forecasts using machine learning. In: Proceedings of the 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm). (2011) 528–533
17. Hossain, M.R., Amanullah, M.T.O., Shawkat Ali, A.B.M.: Hybrid prediction method of solar power using different computational intelligence algorithms. In: Proceedings of the 22nd Australasian Universities Power Engineering Conference (AUPEC). (2012) 1–6
18. Diagne, M., David, M., Lauret, P., Boland, J., Schmutz, N.: Review of solar irradiance forecasting methods and a proposition for small-scale insular grids. Renewable and Sustainable Energy Reviews **27** (2013) 65–76
19. Kechriotis, G., Zervas, E., Manolakos, E.S.: Using recurrent neural networks for adaptive communication channel equalization. IEEE Transactions on Neural Networks **5** (1994) 267–278
20. Jordan, M.I.: Attractor dynamics and parallelism in a connectionist sequential machine. In: Proceeding of 8th Annual Conference of the Cognitive Science Society (CogSci). (1987) 531–546
21. Williams, R., Zipser, D.: A learning algorithm for continually running fully recurrent neural networks. Neural Computation **1** (1989) 270–280
22. Hong, W.C.: Rainfall forecasting by technological machine learning models. Applied Mathematics and Computation **200** (2008) 41–57
23. Wang, S., Tang, L., Yu, L.: SD-LSSVR-based decomposition-and-ensemble methodology with application to hydropower consumption forecasting. In: Proceedings of the 4th International Joint Conference on Computational Sciences and Optimization (CSO). (2011) 603–607
24. Lansberry, J.E., Wozniak, L.: Optimal hydro generator governor tuning with a genetic algorithm. IEEE Transactions on Energy Conversion **7** (1992) 623–630
25. Djukanovic, M., Novicevic, M., Dobrijevic, D.J., et al.: Neural-net based coordinated stabilizing control for the exciter and governor loops of low head hydropower plants. IEEE Transactions on Energy Conversion **10** (1995) 760–767
26. Djukanovic, M.B., Calovic, M.S., Vesovic, B.V., Sobajic, D.J.: Neuro-fuzzy controller of low head power plants using adaptive-network based fuzzy inference system. IEEE Transactions on Energy Conversion **12** (1997) 375–381
27. Djukanovic, M.B., Calovic, M.S., Vesovic, B.V., Sobajic, D.J.: Coordinated-stabilizing control for the exciter and governor loops using fuzzy set theory and neural nets. International Journal of Electrical Power and Energy Systems **19** (1997) 489–499
28. Mellit, A., Benghanem, M., Hadj Arab, A., Guessoum, A.: Modeling of sizing the photovoltaic system parameters using artificial neural network. In: Proceedings of the 2003 IEEE International Conference on Control Application (CCA). (2003) 353–357
29. Seeling-Hochmuth, G.C.: Optimisation of hybrid energy systems sizing and operation control. PhD thesis, University of Kassel, Germany (1998)
30. Senjyua, T., Hayashia, D., Yonaa, A., Urasakia, N., Funabashib, T.: Optimal configuration of power generating systems in isolated island with renewable energy. Renewable Energy **32** (2007) 1917–1933

31. Yokoyama, R., Ito, K., Yuasa, Y.: Multiobjective optimal unit sizing of hybrid power generation systems utilizing photovoltaic and wind energy. Journal of Solar Energy Engineering **116** (1994) 167–173
32. Hernádeza, J.C., Medinaa, A., Juradob, F.: Optimal allocation and sizing for profitability and voltage enhancement of PV systems on feeders. Renewable Energy **32** (2007) 1768–1789
33. Azadeh, A., Sheikhalishahi, M., Asadzadeh, S.M.: A flexible neural network-fuzzy data envelopment analysis approach for location optimization of solar plants with uncertainty and complexity. Renewable Energy **36** (2011) 3394–3401
34. Revankar, P.S., Thosar, A.G., Gandhare, W.Z.: Maximum power point tracking for PV systems using MATLAB/SIMULINK. In: Proceedings of the 2nd International Conference on Machine Learning and Computing (ICMLC). (2010) 8–11
35. Boehm, M., Dannecker, L., Doms, A., et al.: Data management in the MIRABEL smart grid system. In: Proceedings of the 2012 Joint EDBT/ICDT Workshops. (2012) 95–102
36. Barbato, A., Capone, A., Rodolfi, M., Tagliaferri, D.: Forecasting the usage of household appliances through power meter sensors for demand management in the smart grid. In: Proceedings of the 2011 IEEE International Conference on Smart Grid Communications (SmartGridComm). (2011) 404–409
37. Reinhardt, A., Christin, D., Kanhere, S.S.: Predicting the power consumption of electric appliances through time series pattern matching. In: Proceedings of the 5th ACM Workshop on Embedded Systems for Energy-Efficient Buildings (BuildSys). (2013) 30:1–30:2
38. Kaulakienė, D., Šikšnys, L., Pitarch, Y.: Towards the automated extraction of flexibilities from electricity time series. In: Proceedings of the 2013 Joint EDBT/ICDT Workshops. (2013) 267–272
39. Ulbricht, R., Fischer, U., Lehner, W., Donker, H.: First steps towards a systematical optimized strategy for solar energy supply forecasting. In: Proceedings of the 2013 ECML/PKDD International Workshop on Data Analytics for Renewable Energy Integration (DARE). (2013) 14–25
40. Rudin, C., Waltz, D., Anderson, R., et al.: Machine learning for the New York City power grid. IEEE Transactions on Pattern Analysis and Machine Intelligence **34** (2012) 328–345
41. Louie, H., Miguel, A.: Lossless compression of wind plant data. IEEE Transactions on Sustainable Energy **3** (2012) 598–606
42. Reeves, G., Liu, J., Nath, S., Zhao, F.: Managing massive time series streams with multi-scale compressed trickles. Proceedings of the VLDB Endowment **2** (2009) 97–108