Chapter 25
Machine Learning-Based Solar Energy Forecasting: Implications on Grid and Power Market

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1 Introduction

In modern world, electrical power is a primary need and is counted in basic needs of society. With the increase of residential and industrial loads, generation (or supply) must increase at same rate to balance demand-supply. Conventional power plants (thermal) have been employed since various decades to satisfy energy requirements. It was a thinking that coal (fuel) is in abundance and it will never get exhausted. Apart from it, supply from conventional generation increases greenhouse gas (GHG) to atmosphere. However, there are methods to control/reduce GHG in conventional plants but it will be better option that fossil fuel plants may be replaced by renewable energy resources.

As of now, solar and wind energy generations are developed technology. They have been installed and maintained on a large scale for power production. Despite of intermittent nature of output power, lot of resource on their design and development are considered by various nations.

Solar energy is vast and spread over every part of land and water on earth, but it is not constant. It varies with respect to place and time due to geographical factors, atmospheric conditions, etc. Global solar power installation has reached above 500 GW, with annual increase of 100 GW only in year 2018. India has also increased its installation of 10.8 GW in year 2018, and adding total solar capacity to 33 GW [10].

Now a day's most of electrical grids are centralized in various nations. They transfer power from power plants (mainly thermal) to consumer end; however, decentralized dispatch scenario is increasing significantly due to extension of renewable generation (or distributed generation). There is a need to increase electricity generation amongst grid at different levels and this may be challenging to grid management.

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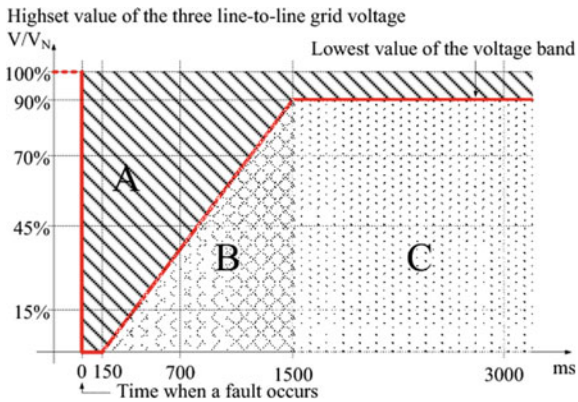

Fig. 1 Low voltage ride through requirement for grid connection

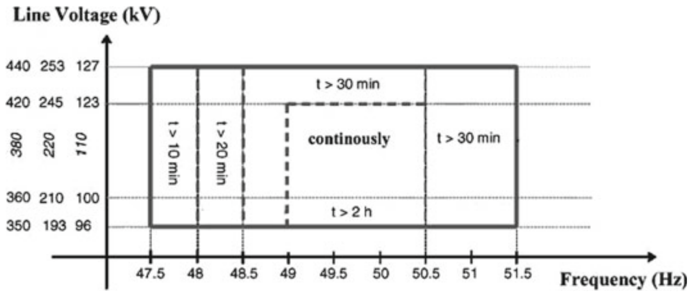

Fig. 2 Line voltage and frequency operating limits of generating unit

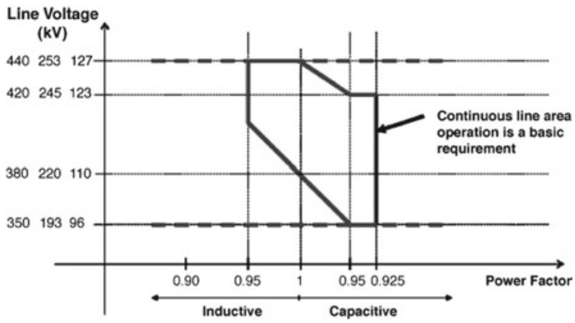

Fig. 3 Voltage and power factor operating limits for generation unit

The challenge for electrical grid operators will be to optimize generation location and dispatch to balance demand with energy supply and also maintain stability.

In solar technology, flat-panel PV, Concentrated Solar Power (CSP) and concentrated PV (CPV) system are mostly employed. They have ability to compete with

Table 1 Forecasting methods for the optimization of power output/Irradiance

Author	Forecasting time horizon	Methods	INPUT Parameters	OUTPUT
1zgi et al. [1]	0–60-min ahead	Artificial Neural Network—Levenberg Marquardt Back-Propagation Algorithm	750 Wp solar PV Panel—Ambient and cell temperature —Diffuse solar Irradiation	Solar power
Kardakos et al.[2]	Day and Intra-day ahead	Seasonal-Autoregressive Integrated Moving Average —Artificial Neural Network with multiple input	Solar radiation	PV power
Mellit et al. [3]	Hourly	Artificial Neural Network—Multi Layer Perceptron Architecture	Solar irradiance —Air temperature	Power of PV modules
Yona et al. [4]	24-h ahead	Based on insolation forecasting by utilizing weather reported data, fuzzy theory, and Radial Basis Neural Network	Weather reported data (Humidity, cloud amount, and temperature) —Insolation forecast data with fuzzy	PV power output
Almonacid et al. [5]	1-h ahead	Dynamic Artificial Neural Network: Non-linear Autoregressive Neural Network	Global solar irradiance —Air temperature —PV power output Module	PV power output generator

(continued)

fossil fuel-based production in near future. However, natural variability (intermittency) of the solar power and high cost of energy storage raises concerns regarding reliability and feasibility of this technology.

2 Technical Issues with Grid

Grid interconnection (loading) and disconnection (unloading) of generation units is one of the technical issues that needs to be considered for power dispatch.

The incoming generation unit and existing power-sharing (supplying) system have to adjust their power output such that dynamics at the point of interconnection would remain within limits. If new power generation unit is added it should synchronize

Table 1 (continued)

Author	Forecasting time horizon	Methods	INPUT Parameters	OUTPUT
Cornaro et al. [6],	24-h ahead	Statistical Model (ST) and Model Output Statistics (MOS) based on an ensemble Artificial Neural Networks by master optimization process	Statistical model: STNNS —Ordinal day number —Daily irradiation —Average daily temperature —Clearness index MOS model: ECMWF-MOSNNS —Ordinal day number —Daily irradiation —Average daily temperature —Clearness index —Daily irradiation prediction provided by	Global horizontal irradiance
Lima et al. [7]	24-h ahead	NWP-WRF model by using Artificial Neural Networks	Weather forecast outputs supplied by WRF model —Observational ground data	Surface solar irradiance
Hossain et al. [8]	Day ahead —1-h ahead	Extreme Learning Machine (ELM)	Daily average solar irradiance —Ambient temperature —Module temperature —Wind speed —PV output data	PV power
Mellit, A. MassiPava, V. Lughi [9]	Hourly and Daily	Adaptive feed-forward back-propagation network (AFFNN)	Solar Insolation time series	Hourly Insolation

its voltage, frequency, phase sequence as per grid codes. It also has to maintain his loading gradually and reach up to sharing limit of power allocated. It is so because ramp rate of loading has to maintain in limits, this ensures safety of generation equipments. The active and reactive power controlled by DC to DC converters and inverters at point of connection. These converters maintain parameter dynamics in range. In wind energy system, back to back converters are used to control dynamics.

Generation unit is also required to operate in normal and faulty conditions. In case of high transients/dynamics of grid or generation parameters, generation unit is made to trip. There are standard conditions when generation could remain connected to grid. This is fault ride through requirement.

It can be observed from the figure that generation unit may remain connected if fault is cleared within 150 ms. Also if voltage due to fault restore its operating magnitude in specified time (as straight line), then generation remains in operating mode, otherwise unit may be disconnected from grid [11].

Frequency and voltage operating range must be in limits for continuous operation of generation unit. In the figure, standard line voltages are 110, 220 and 380 volts and their range of continuous operation is 100–123, 210–245 and 360–420, respectively, if frequency is maintained 49–50 Hz. Deviation from standard magnitudes increases dynamics/disturbance in system, hence more deviation in parameters will lead to more disturbance of system. This gives less time for system to withstand disturbances. Hence system becomes prone to tripping of generation unit [12].

These disturbances in voltage and frequency create flicker. When load changes are more dynamically and demand–supply difference (changes) becomes fast then power fluctuation arises. This creates power quality problems.

Uneven demand pattern and less regulated generated power (especially in case of renewable) create grid instability in terms of frequency limit violation.

Reactive power is regulated to maintain system voltages within limits. In case of faults, voltage is restored by increasing reactive power to the system. The reactive power supply is provided by generator units, static capacitor banks, FACTS, etc.

In the figure, generation units supplying inductive VARs increases voltage magnitude and capacitive VARs decreases voltage [12].

Now all problems start with demand–supply difference, it is needful that load demand information must be specified. As the consumer is free to vary its load, therefore, there is only left provision to study its demand pattern/behavior. Hence power is regulated with respect to demand pattern of consumer.

It is a common practice to forecast demand behavior and manage supply resource accordingly.

If power forecasted becomes same to that needed by consumer, then generator, then load flow analysis can be carried out for stability analysis of Grid easily. Also there will be better stability condition as power injection is defined and maintained at a same level.

In thermal, energy/power output is controlled/regulated and fed to injection point of grid in order to obtain stable grid interconnection.

If solar power could be predicted, then interconnection will be more reliable. For controlling power, power electronics devices can be employed to obtain stable interconnection.

For solar DC to DC converters, grid inverter controls parameter of solar power with respect to Grid parameters. The power electronic devices selected must have burden as that of installed solar capacity.

3 Forecasting and Power Market

Solar energy is highly dependent on weather conditions especially cloud structure and day/night cycles. Clouds cause significant ramps in solar insolation and PV power output. Therefore, integration of electricity produced by solar power systems requires accurate energy evaluation and time horizon forecasts. Overall energy production pattern does not follow the energy forecasted.

Solar forecasts on multiple time horizons play a fundamental role in

1. Storage management of PV systems.
2. Control systems in buildings, such as solar thermal plants
3. Power scheduling and regulation.

It allows grid operators to study load pattern in order to optimize power wheeling and plan maintenance activities at the production sites and take necessary measures to protect production from extreme events.

Depending on the purpose, different information are needed, such as

1. Long-term historical data of expected energy yield (to assess sites where solar power is abundant)
2. Real-time data set of energy yield (optimizes real-time energy production management)
3. Forecasted site irradiance data.
4. Real-time datasets on weather conditions.

If generation accuracy increases, it can be compared with conventional generation resources that are scheduled and dispatched for power market.

Overall, accuracy in short-term forecasting yields:

(i) Exact Supplier (power) bidding in market and forecast returns from it.
(ii) Exact change in grid condition/grid parameter (such as frequency, reactive power, voltages) for which a load flow study program can be run and take an observation of grid parameter, which leads to grid stability.

Forecasting of supply is needed for ensuring power to be traded in power market. The Generation supply bids have power (in MW), time span (for dispatching) and price of power in bidding offer. Better forecasting ensures estimation of real-time magnitude of power. More the reliable prediction, more reliability to market players. Hence economic efficiency/incentives of transactions increase. There are various methods for estimation/predication of power generated with respect to state variables such as global irradiance, humidity, cloud, etc.

Apart from grid interconnection, grid stability is also essential; stability refers to frequency regulation, voltage regulation, energy imbalance, contingency analysis in case of outage, etc. Frequency regulation is maintained by demand supply balance. Hence reserves are needed to balance them. These reserve services are also traded apart from real power market.

Price bidding is normally for centralized market. In Indian system, discoms and few retailers along with some big industries are “buyer” and all generations units are "seller." Here power bid is placed by every generator (government/private) in market and buyers fulfill its power requirement and place his bid (prices and MW). Market settlement is made by government entity and then transmission lines are ensured/scheduled for bulk power transmission [13].

The generation price bid must be such that it becomes economical and reliable to buyer. Here cost of power is overall components of various costs, such as capital cost of installation, operation and maintenance, along with market returns (profit) whereas reliability depends on technology of generation [14]. Solar technology produces intermittent power that is not reliable in power market (in terms of fixed MW placed).

Hence solar power bid can be placed in market as minimum limit value of range in which generated solar power varies. But as difference between minimum and maximum is very large, therefore, this is another challenge to estimate about magnitude of power placed in power market.

If forecasted solar power is close to real power produced then power placed in market will be a curve of "power vs. time." This variation of power can be managed by system operator in its load flow studies. At last, payment for power transaction will be on the basis of total energy transaction at the end of schedule.

4 Machine Learning-Based Solar Generation Models

As power output of solar PV modules depends on atmospheric and geographical conditions, its power output can be predicted. There are various scenarios in which PV modules behave in different way. These behaviors are modeled by different methods, some of these methods are persistence method, statistical method, machine learning approach and hybrid approach [15].

In persistence model, solar insolation and climatic conditions of each day are considered to be same. Daily pattern of solar irradiance throughout the day of same geographical location is fixed. It does not depend on change of climatic conditions such as temperature, pressure, cloud variation, humidity, wind flow, suspension particles of air, etc. This method gives standard data that may be different from power output of module of next coming day. These data are used as benchmark for the analysis of power output when metrological data are considered in input.

In statistical model, more than one variable is considered for evaluation of power output. The solar insolation variable is combined with one of the above mentioned metrological variables and then power output of PV modules is determined. There are various models in which various combination of temperature, pressure, cloud variation, humidity, etc., are made with solar irradiance data (throughout the day) of a particular geographical location, and used as input variables for power output function.

The accuracy of this method depends on the accuracy of metrological data and method of regression used. The simple and multiple regressions give better results than single input (persistence model) method [16].

As the input data of solar irradiance and metrological have nonlinear nature, nonlinear approaches of determination of relation or functions are used further for better results. Artificial neural network is one of the approaches, which consider wide range of nonlinear inputs and determined by different models. These models are trained by real-input and -output data. Input data consist of more than one input and activation function is selected on behalf of nature of nonlinearity of input and output data. There are no assumptions made for training of models, therefore, they produce better output than statistical methods.

In this method, there is input layer that accepts input data, hidden layers (which may be more than one) determine the effect of input on output defined by weights and bias. Output layer produces output data in the neural network model.

Initially, these weights are randomly selected for training of model and activation function squeezes sum of all signal and sent to output layer. For training, reference input–output data are used. Output of model is compared with reference output, further weights and bias are modified and again output is determined. The weights are modified so as to reduce error between new output and reference output than previous error. In this process, weights are modified each time to obtain better output and it continues till the obtained output matches with reference output. On completion of training, weights are obtained that validate reference input–output data. After training of model, it can be used to obtain output from new set of input data. There are various types of neural network layer interconnection or architecture, some of them are multilayer perceptron, multilayer feed forward neural network, radial basis function neural network, recurrent neural network, adaptive neuro-fuzzy inference systems (ANFIS), etc. These architectures have been used for solar power output analysis. Auto-regressive integrated moving average (ARMA), Support vector machine (SVM), ANFIS are frequently used for forecasting [15]. Some of the details of forecasting methods have been tabulated for the optimization of power output/irradiance.

Above methods have been used for various inputs at different geographical locations to forecast hourly power output of PV modules. Machine learning refers to methods to analyze real-time response to real-time changes in defined inputs, the methods are normally combination of regression, neural, fuzzy, genetic, recognition of weather input, etc., also reinforcement learning method. Reinforcement learning normalize inputs and information is processed. Its decision-making system performs action/evaluation and output is obtained, the environment (inputs and state variables) respond on output produced. This information policy reward makes tuning in decision strategy/action to tune new output [17]. New output is a function of change in input and state variables. This method may include above different machine learning techniques to produce outputs constraint to environment limits.

5 Conclusion

As solar power is essential to be utilized for generation expansion, its intermittent nature should be controlled to regulated output. Grid integration is controlled by power converters, relevant algorithms are employed for gate signal of converters to control voltage, frequency, etc. Accuracy in forecasting infers to reliability in power market trade and less congestion conditions in transmission. As solar power output is forecasted correctly, overall power market economics improves. This may be achieved by machine learning algorithms while incorporating solar insolation, weather data for short-term forecasting. There are various methods that have reduced error in forecasted output to great extent. When neural, fuzzy and GA are combined with one another and implemented to analyze the effect of weather on power output, they have determined almost same output as real power produced in some cases. SVM and reinforced learning along with previous algorithms are recent areas for forecasting power output.

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