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Load and Renewable Energy Forecasting for a Microgrid using Persistence Technique

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Abstract

A microgrid system, be it connected to the utility grid or an independent system, usually consists of a mix of generation - renewable and non-renewable; loads - controllable or non-controllable and Energy Storage Systems (ESSs) such as batteries or flywheels. In order to determine how much power is utilized from the controllable resources such as ESS, diesel generators, micro-turbines or gas turbines, we first need to determine how much the demand is or how much the renewable energy sources are generating is which is accomplished using forecasting techniques.

Due to the intermittent nature of renewable resources such as wind energy or solar energy, it is difficult to forecast wind power or solar power accurately. These forecasts are highly dependent on weather forecasts. It is evident that forecast of any data based on forecast of other parameters would lead to further inaccuracy, even if the relation between the inputs and output maybe predetermined through regression methods. Therefore, this paper illustrates an approach to use historical power data instead of numerical weather predictions to produce short-term forecast results.

The concept is based on persistence method presented in [1]. This method uses the "today equals tomorrow" concept. From [2], we know that persistence technique produces results that are more accurate as compared to other forecasting techniques for a look-ahead time of 4-6 hours. Both [1] and [2] were based on wind power forecasting. In this paper, we investigate persistence method for short-term electrical demand, solar PV (Photovoltaic) power and wind power forecasting. Since the forecasts are dependent on historical averages of the data in the 'near' past, the accuracy is inversely proportional to the variation of power between the historical data and the actual data.

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1. Introduction to Power Forecasting in a microgrid Energy Management System (EMS)

The main function of a forecasting algorithm in a microgrid is to predict the demand of the loads in the microgrid network or the power generated by renewable energy connected to the network for the near future. This is necessary for determining how much power is utilized from the controllable resources such as Energy Storage Systems (ESS), diesel generators, micro-turbines or gas turbines. In other words, the optimization algorithm of the microgrid EMS utilizes the load and renewable energy forecasts to schedule in advance the power generated by distributed generators (DGs) or charged/discharged by storage devices, in an optimal manner.

Based on the design of the EMS, it may have other functions such as:

- predicting active and reactive power of PQ buses with loads or renewables to be used for power flow analysis
- acting as pseudo-measurements for bus with no measuring devices for calculation of distribution state estimation results
- determining user-defined constraints such as variable battery State-of-Charge (SOC) limits or distributed generation ON/OFF patterns.

Nomenclature

Distributed Generators	power generators at the point of consumption. E.g. diesel generators, micro-turbines or gas turbines
Power Flow	method for determining magnitude and phase angle of each bus voltage in the network
Pseudo-measurements	low accuracy bus generation and load measurements, required to complete the observability of the system in state estimation

2. Forecasting algorithms

For microgrid applications, the generation and load forecasts required are usually short-term forecasting. Any forecast performed in the order of hours or days in advance may be categorized as short term forecasting. Since the load and generation are dependent on several weather conditions, historical measurements, special events, time of the day, the inputs used for short-term load and generation data are Numerical Weather Prediction (NWP), past load or generation data and time-related data. Most forecast use NWP as the main input for generation forecast. The problem with this method is that the generation forecasts are based on weather forecasts, which may lead to further inaccuracy.

2.1. Review of other algorithms

Some of the popularly used methods for short-term power forecasting are:

- **Autoregressive Integrated Moving-Average (ARIMA)** is a stochastic method whose basic principle is that the forecasts for the later hours will be based on the forecasts for the previous ones [3]. Even though it is a simple model, it is based on approximation and the true model of the forecast is unknown.
- **Advanced Neural Network (ANN)** is a mathematical tool originally inspired by the way the human brain processes information [3]. The neuron receives information (weather, time, and historical data) through a number of input nodes, processes it internally, and puts out a response. The model is based on a black box

approach and may lead to overfitting. Fuzzy neural models are a combination of fuzzy logic and ANN concept where the fuzzy pre-processing helps to reduce the number of inputs to the ANN algorithm.

- **Kalman Filter method** is one where the load/generation is modeled as a state variable using state space formulation, which is designated by the system state equations and the measurement equations. It is very attractive for online prediction because of the recursive property of the Kalman filter. The drawback of the method is that the model has to be known prior to using the Kalman filter [4].
- **Multiple Linear Regression (MLR)** is a straightforward time-series technique to model the set of load or generation data as a linear curve. But, due to the intermittent nature of data, in reality, the models are non-linear.

2.2. Persistence Algorithm

Persistence is a direct method of forecast following the basic rule of: today equals tomorrow, and was selected based on the discussion of various forecast methods above. The persistence method assumes that the conditions at the time of the forecast will not change [5]. It is said to have higher accuracy compared to other complex forecast algorithms for a look-ahead time of up to 4-6 hours [2]. It also allows us to investigate the changes in the error distribution with changing forecast scenario. In Figure 1(a) from [6], Fuzzy neural method has been compared to persistence algorithm and shows that for wind forecasting of an offshore wind farm in Denmark, the persistence method is as accurate for small look-ahead times as Fuzzy- NN model.

Persistence method is largely adopted for short term wind forecasts. The reason behind this is that the wind power varies very frequently and there is no fixed daily pattern for wind generation. Hence, using immediate past data for forecast would yield more accurate results compared to dependence on the weather forecast. In this paper, this method has been tested for load and PV forecast for its directness in implementation. The main process of persistence forecast is to use average of historical power for forecast of future power.

The formula used for forecast is as follows [1]:

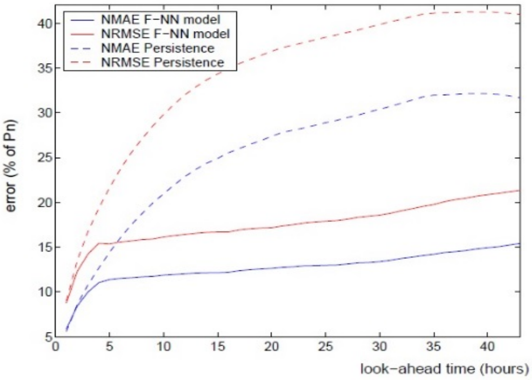
$$P(t+k \mid t) = \frac{1}{T}\sum_{i=0}^{n-1} P(t - i\Delta t) \tag{1}$$

where $P(t + k|t)$ is the forecast for time t+k made at instant t; T is the prediction interval length; n is the no. of historic measurements; $P(t-i\Delta t)$ is the measured power for time t and previous i time steps within T; and Δt the time step length of the measured time series.
During implementation of the forecast algorithm, data is available for every minute for 24 hours.

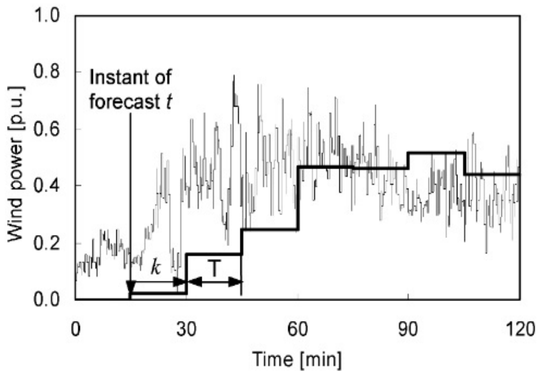
Three cases have been considered to test the algorithm:

1) k = 15 mins, i.e. k=T: The forecast is done 15 minutes ahead of time for the next 15 minutes using the average of past 15 minutes. E.g. we are forecasting the load/ generation for 10:30-10:45 am using the average load/generation from 10:00 to 10:15 am. This forecast could be done any time once all the data is available for the time sample 10:00 to 10:15 am. Figure 1(b) shows the pictorial representation for the same concept.
2) k = 0: The forecast is done for the immediate next 15 minutes. So, to predict values for 10:30-10:45 am, we use the average load or generation from 10:15 to 10:30 am. Hence, this forecast should be done immediately after capturing the value for 10:30 am.

3) k = -15 mins: This scenario is not applicable in real life and is only to demonstrate that the load or generation during a time period does not differ much from the average value for the time period. This forecast is done using average values from 10:30-10:45 am and compared for the sampled values during the same time period.



(a)



(b)

Fig. 1. (a) Comparison of Persistence and Fuzzy-NN model performance [6]; (b) Wind power forecast using persistence for k=T from [1]

3. Forecast Results

3.1. Observation

For calculating forecast values using persistence method, Equation (1) was used and the concept was tested for three cases with three different sliding windows, also described in Section 4.5.2. The test for considering 30 minutes look-back time (k=T), 15 minutes look-back time (k=0) and real time calculation (k=-T). Δt is taken as 1 minute.

To explain further, for case 1, we are predicting for time instant t+k, k being 15 minutes. So, for time from t+k to t+2k, according to Equation (1), it is taking the average of P(t-14) to P(t) as the forecast which is similar to the example above where time instant at 10:15 AM is t and at 10:30 AM is t+k.

Here t refers to the beginning of the hour, Δt is 1 minute and all the numbers are in minutes.

Figure 2 shows the forecast results for typical PV generation data for simulation using Matlab/Simulink. The PV data was obtained from a demo Matlab/Simulink model named “power_microgrid” [7]. The algorithm took the first half an hour data as historic data and predicted for the next 23.5 hours. The three graphs depict the actual and forecast results for a look-back time of 30 minutes (k=T), 15 minutes (k=0) and 0 (k=-T). The third case was performed for proof of concept and is difficult to achieve in real life, even if we consider moving averages. It is evident that nearer is the look-back time, closer is the forecast to the actual value.

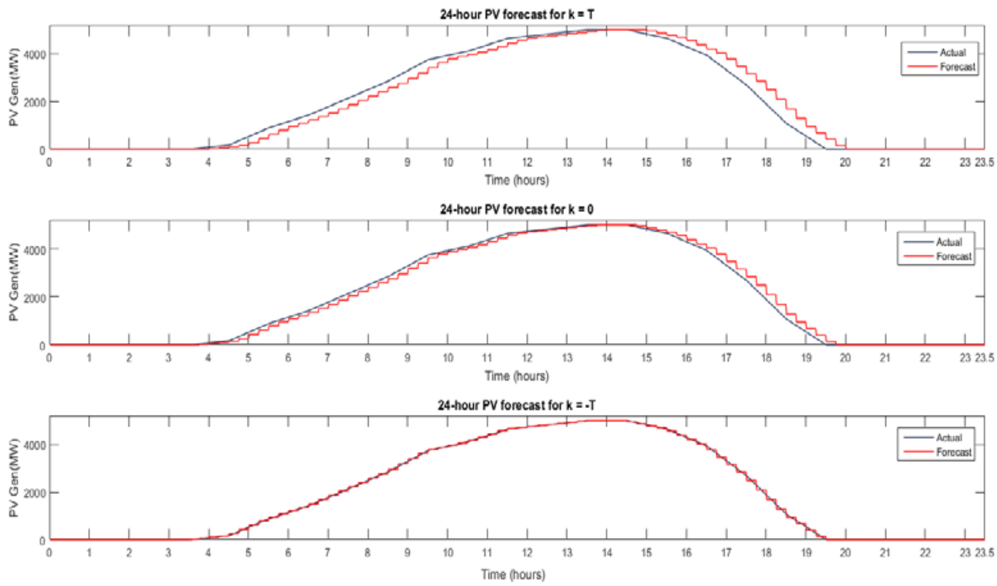


Fig. 2. PV Power forecast results for three cases for 23.5 hours

3.2. How the forecasts were evaluated

MAPE (Mean Absolute Percentage Error) is the mean of all the error in forecasts compared to actual values in terms of percentage [8]. The formula for the same is shown in Equation (2).

$$MAPE = mean\left(\frac{|Forecast - Actual|}{Actual}\right) X100\% \tag{2}$$

MAPE is easy to compute and most commonly used for evaluating forecast errors. But when the actual value is zero or a very small number then the MAPE tends to be very large as it has the actual value as the denominator. That is why, for PV power forecast, we cannot use MAPE since at nighttime the PV power output is zero or nearly zero. Thus, the MAPE for PV forecast is infinity or close to infinity.

RMSE (Root Mean Square Error) is a good measure of how accurately the model predicts the response, and is the most important criterion for fit if the main purpose of the model is prediction. It is the variance of residuals of the forecast as shown in Equation (3).

$$RMSE = \sqrt{\frac{\sum_{t=1}^{n} (\hat{y}_t - y)^2}{n}} \tag{3}$$

where n is the number of data samples and $\hat{y}_t$ - y is the difference between actual and forecast [9].

RMSE is scale dependent and the lower is its value, the better. It ranges from 0 to infinity. So in PV forecast if the RMSE is 3 and the PV power scale is MW then the average error is 3 MW.

The forecasts were performed for load and PV data from “power_microgrid” model and wind data from NREL website [10]. The MAPE and RMSE was evaluated for the above mentioned three cases and are listed in Table 1. It shows that the more recent is the historic data, the more is the forecast accuracy.

Table 1. MAPE and RMSE for load, PV and wind power forecasting for three cases

	k=T	k=0	k= -T
Load (Peak = 2500 MW)	MAPE= 18.19%, RMSE= 239.4 MW	MAPE = 9.28%, RMSE = 126.84 MW	MAPE = 2.42%, RMSE = 36.54 MW
PV (Peak =5000 MW)	RMSE = 308.9 MW	RMSE=160 MW	RMSE = 44.7 MW
Wind (Peak = 400 MW)	RMSE = 27.86 MW	RMSE = 15.9 MW	RMSE = 5.52 MW

4. Conclusion

In this paper, persistence technique was chosen as the forecast algorithm for two reasons: it is simple to implement and unlike most other forecast algorithms, it relies neither on weather forecast data nor on in-built toolboxes in software for implementation. Due to this reason, if we desire to embed the algorithm into hardware, it is more straightforward to do so for persistence technique than other algorithms.

It was seen from the forecast results that the accuracy of forecast depends on two factors: the look-back time and the extent of change of the data over time. E.g. if due to cloud cover, the PV generation suddenly drops, the persistence algorithm will not be able to anticipate the large decrease in generation, as the forecast is based on the average of historical data.

The optimization algorithm should compensate the large forecast error by adjusting the reference power for the controllable devices to calculate the final dispatch power. In addition, for load and PV forecasts, the existing persistence algorithm may be improved by using previous day patterns along with more recent historic data and assigning weighting factors to account for variation of data over time.

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