Solar Irradiance and Load Demand Forecasts in the Supervisory Control for Off-grid Hybrid Energy System

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Abstract— Efficient operation of a hybrid renewable energy system can be achieved if the power supply from the renewable energy generator and the load demand can be predicted. The forecasts of these parameters are essential for the supervisory control planning and decision making to ensure the generator capacity on the line is sufficient to meet the load demand at a given moment. Forecast models for predicting the solar resource and the load demand are proposed. The proposed models are applied to control an off-grid Photovoltaic-Variable Speed Diesel Generators Hybrid Energy System.

Keywords - renewable resource, prediction, stand-alone hybrid energy system, remote area power supply.

1. Introduction

Forecasting methods are essential in large power plant planning and operation. Selection of a forecasting method for a particular application is based on the characteristic of a time series.[1] Autoregressive time series models have been used to forecast the solar irradiance in [2-3] and load demand [4-5]. The inconsistency of renewable energy supply and load demand patterns remain challenging in energy management of hybrid energy systems (HESs). Recently, the forecasting techniques have been extended to the hybrid power systems applications. The author has proposed a prediction method in [6-7] which is based on the three-hourly distribution of photovoltaic resource and net load demand. This method has been used to schedule the diesel generator for the next 24 hours. Forecasting has also been employed by the author in [8] for a wind-diesel HES to plan and control the operation of the diesel generators. Predictions of energy supply and demand constitute the foundation for effective diesel generators dispatch and control, as the forecast data base holds the informative historical data of power measurement. This data base is essential for the predictive control strategy in the supervisory control to determine the additional generator capacities to be brought on-line to meet the load demand in the next operating period when renewable energy is short in supply. The predictive control strategy is expected to generate data in advance for the supervisory control decision to switch a generator on-line to provide reliable system operation. While the forecasts are helpful in activating generators to satisfy the load demand, they can be applied for deactivation of a selected generator from the system operation whenever there is substantial amount of renewable energy predicted. Thus, fuel savings is achieved since the additional capacity is no more required.

The integration of the forecast system in the supervisory control which provides activation or deactivation signal to the generator in advance allows ample warm-up and cool-down period, in the range of minutes as recommended by the manufacturers. This would help in slowing down the aging of an engine by minimizing the common problems such as: hydrocarbon build-up and glazed piston and cylinder walls.

This work introduces a novel forecasting approach with the foundation of the well known single exponential smoothing (SES) method for predicting solar resource and load demand to enhance the performance of a stand-alone AC coupled Photovoltaic-Variable Speed Diesel Generators (PV-VSDGs) HES without energy storage. The recommended system configuration comprises two VSDGs and a PV generator. Further discussion by the author in other papers about the control and operation of this particular system are presented in [9] and [10]. The proposed forecasts models and their application in HES are elaborated in next sections.

2. Renewable Energy Supply and Electrical Load Demand Forecasts

2.1 Time series of Solar Irradiance and Load Demand

The average monthly solar resource and the estimated load demand data used for this work is as shown in Fig.
1 and 2. A series of synthesized hourly solar data and load demand based on these average solar resource and load demand have been generated using the Hybrid Optimization Model for Electric Renewable (HOMER) software [11].

The proposed forecast model is expressed in (2):

$$G_f(d, h + 1) = \alpha G_m(d, h) + (1 - \alpha)\mu_c(d, h + 1) \tag{2}$$

Where,

- $\alpha$ is the smoothing constant
- $G_f$ is the forecast of solar irradiance

High value of $\alpha$ indicates that the forecast value is highly correlated to the irradiance measurement in the previous period and the forecast value is averaged very little when summing up with the weighted average solar irradiance measurement in past $N$ days. Fig. 3 shows the comparison between the synthesized measured solar irradiance for a selected site with the forecast irradiance using the proposed forecast model.

For the implementation of the proposed forecast algorithm in the HES, it is more practical to measure the PV power rather than the solar irradiance. The forecast PV power can be derived based on the forecast irradiance and the mathematical model of PV as in Eq. (3) to (5) given in [12]:

$$I_{scf} \propto G_f \tag{3}$$

$$I_{pv,f} = I_{scf} - I_0 \left( e^{\frac{qV_d}{nkT}} - 1 \right) - \frac{V_d}{R_p} \tag{4}$$

$$V_{mod} = n_{cell} (V_d - I_{pv,f} R_S) \tag{5}$$

Where,

- $I_{scf}$ is the PV short circuit current
- $I_{pv,f}$ is the PV current
- $I_0$ is the diode reverse saturation current
- $k$ is the Boltzmann’s constant
- $T$ is the cell temperature
- $q$ is the electron charge
- $V_d$ is the diode terminal voltage
- $V_{mod}$ is the PV module voltage
- $n_{cell}$ is the number of cell

Fig. 1: Estimated village load profile for a selected site

Fig. 2: Average monthly irradiation for a selected site.

The generated annual time series is assumed as the measured hourly solar irradiance and load demand to be entered into the simulation to justify the proposed forecast models.

2.2 Solar Irradiance and Photovoltaic Power Forecasts

The proposed solar irradiance forecast model includes the average data of the same hour as the prediction period in the past $N$ days and also the information of the value from the recent past hour. The average solar irradiance, $\mu_c$ of the same time as the forecast hour in the previous $N$ days can be calculated using (1):

$$\mu_c(d, h + 1) = \frac{1}{N} \sum_{i=-N}^{i=1} G_m(d + i, h + 1) \tag{1}$$

Where,

- $N$ is the number of past days
- $d$ is present day
- $h$ is present hour
- $G_m$ is the synthesized measured solar irradiance
\( R_p \) is the PV cell parallel resistance  
\( R_s \) is the PV cell series resistance

By assuming constant derating factor of the PV module and average inverter conversion efficiency, the DC photovoltaic power and the converted power at the AC bus can be calculated as:

\[
P_{PVf} = V_{mod} \times I_{PVf} \times DF  \quad (6) \\
P_{PV\text{Inv}f} = P_{PVf} \times \eta_{\text{inv}}  \quad (7)
\]

Where,  
\( DF \) is PV module derating factor  
\( \eta_{\text{inv}} \) is inverter efficiency

### 2.3 Electrical Load Demand Forecast

The prediction of load demand for a large scale power system is well established and the load demand can be predicted accurately based on the electrical network statistical data. Unlike the centralised power generation plants that generate bulk supply, the remote area energy systems are designed to provide electricity to small group of inhabitants. These small scale energy systems may experience significant load changes. To achieve an acceptable forecast accuracy, the electrical load demand forecast model shall consist the average measured data in the past N days and correlated to the most recent past hourly load demand value as in the following equations:

\[
\mu_i(d, h + 1) = \frac{1}{N} \sum_{i=0}^{N-1} L_m(d+i, h+1)  \quad (8) \\
L_f(d, h + 1) = \alpha L_m(d, h) + (1 - \alpha) \mu_i(d, h + 1)  \quad (9)
\]

Where,  
\( L_m \) is the synthesized measured load demand  
\( L_f \) is the forecast load

Fig. 4 shows the synthesized measured and forecast of load demand.

![Synthesized Load Demand](image)

Fig. 4: Synthesized measurement and forecast of load demand for a selected five days.

The forecast models are applicable to any preferred site where the hourly solar irradiance and load demand data for a year are available. Both of the synthesized data for the solar irradiance and the load demand are used to demonstrate the principles of the proposed forecasts algorithm.

### 2.4 Forecast Accuracy

There are several relative measures of accuracy that facilitate the evaluation of a forecast model. To quantify the error of the solar irradiance forecast over an extended period, the forecast values are compared to the synthesized measured values and the difference between them is defined as the forecast error as in (8). The other relative measure of forecast accuracy is the mean absolute error (MAE) [3]:

\[
FE(h) = X_m(h) - X_f(h)  \quad (10)
\]

\[
\text{MAE} = \frac{1}{n} \sum_{h=1}^{n} |FE(h)| \\
= \frac{1}{n} \sum_{h=1}^{n} |X_m(h) - X_f(h)|  \quad (11)
\]

Where,  
\( X \) is the measured or forecast variable.  
\( \text{MAE} \) is the mean absolute error  
\( n \) is the number of errors

An optimum smoothing constant, \( \alpha \) can be determined by comparing the forecast accuracy for different values of \( \alpha \) and \( N \). Fig. 5 depicts the overall accuracy of solar irradiance forecast where lowest forecast error can be achieved by selecting \( \alpha = 0.5 \) and \( N = 7 \). The overall accuracy of load demand forecast is shown in Fig. 6 with \( \alpha \) ranging from 0 to 0.2 and \( N = 7 \) give low forecast errors.

![MAE vs. Smoothing Constant](image)

Fig. 5: MAE for a range of \( \alpha \) and \( N \).
3. Application of Forecasts in Supervisory Control of Hybrid Energy System

The solar irradiance and load demand forecasts are the core components of the expert system in the supervisory control for a hybrid energy system. This expert system is essential to calculate the net load demand in the next interval, so that decision can be made to determine the required diesel generating capacity to be switched on-line. Simulation results of the hybrid energy system operation using the proposed forecasting models are plotted in Fig. 7-9. The operation principle of the system is to optimally utilise the renewable energy and the unmet load demand will be supplied by the VSDGs. When the predicted renewable energy for the next period is sufficient to supply the load, the additional generator can be put off the line to achieve fuel savings. If the load demand is predicted to be greater than the power supply by the operating generators, command signal will be sent to activate the additional generator so that it is ready to be brought on-line when required. This can prevent power imbalances caused by the abrupt increased load demand or decreased solar resource. The fluctuating synthesized load demand and the PV power for a selected day is shown in Fig. 7. Fig. 8 is the average values of the predicted hourly PV power supply and load demand. Lastly, the net load for the same day is shown in Fig. 9. Only minor deviation is observed from the comparison of the measured and the predicted net load due to the selection of the most favourable smoothing constant for the prediction model discussed in previous sections.

4. Conclusions

The inclusion of forecasting in the expert system forms an advance and robust control process of the system. This allows diesel generator dispatch to be done effectively which results reliable system operation. The proposed forecast models are justified and applied in the simulation of a hybrid energy system. The models are able to predict the solar resource and load demand with marginal prediction errors. Most importantly, it was observed from the simulation results that, when applied to the supervisory control of a HES the proposed forecast models can perform satisfactorily to ensure the energy balance of the system at all time.
5. References


