Optimized Hybrid Wind Power Generation with Forecasting Algorithms and Battery Life Considerations

Abstract—**A comparative study of several forecasting schemes is performed on a dataset of a wind farm. The paper presents a generalized economy optimization of the power generated from a wind farm and batteries. These wind farms are coupled to the electrical grid to supply amount of power agreed upon a priori, irrespective of the associated penalty due to inherent randomness in the wind. The solution is to have an optimized wind forecasting technique such that the deficit power is supplied by batteries and during period of surplus power, the additional power is stored in the batteries. Economic considerations include a consumption factor that evaluates the depletion of battery life and assigns a dollar value to it.**

I. Introduction

Wind energy is one of the cheapest and most abundant renewable energy resource and is witnessing renewed efforts to harness it. Wind farms consist of wind turbines spread all over the farm that tap the wind energy and convert it to electrical energy. A major factor affecting the tapping of the wind energy is the randomness in the wind speed which prevents supply of predefined power continuously to the grid resulting in a difference of power that was to be supplied and which is supplied. One of the ways to resolve it is the use of improved wind forecasting schemes such as weighted regression, linear fitting, neural network based scheme, support vector regression and other such schemes, along with batteries.[1]

Several wind power or wind speed forecasting methods have been reported in the literature over the past few years. Soman et al. summarize forecasting techniques associated with wind power and speed, based on numeric weather prediction (NWP), statistical approaches, artificial neural network (ANN) and hybrid techniques over different time-scales. An overview of comparative analysis of various available forecasting techniques is discussed as well, and further gives emphasis on the major challenges and problems associated with wind power prediction. [10]

Wang et. al have focused on grid integration while ensuring the batteries has continuous regulation ability. The necessary storage capacity is determined from the requirements of grid integration but an estimation of remaining battery life is not provided.[7] A novel stochastic MPC controller is established to improve the wind power dispatchability and reduce fluctuations.[8] An overview of developments in the principles and practical implementation of wind forecasting is given. An accurate forecast of wind speed and power generation can help the power system operators reduce unreliability of electricity supply. Chang presents a literature survey of the categories and methods of wind forecasting and the future direction of wind forecasting.[9]

In the present study, Battery usage is optimized so as to store the surplus energy or provide the shortfall to the grid as the case may be. In certain forecast windows, especially when the required charging or discharging of the battery is large, paying the penalty may be better than using the battery. Palmgren-Miner's damage principles are used in this analysis without the need of precise knowledge of the materials or wind turbine blade structural properties.[11]

The proposed hybrid wind system consists of one or more wind turbines in a wind farm coupled with multiple batteries. A hybrid wind power system has a centralized controller consisting of a dispatch regulator, energy storage Unit, damage controller and penalty optimizer sections. Figure 1 describes a method of optimizing the wind power acquired in one or more dispatch windows. The actual wind power term represents the electrical power from the wind turbines. The actual wind power data is the time series of data for the different time slots within the dispatch window.

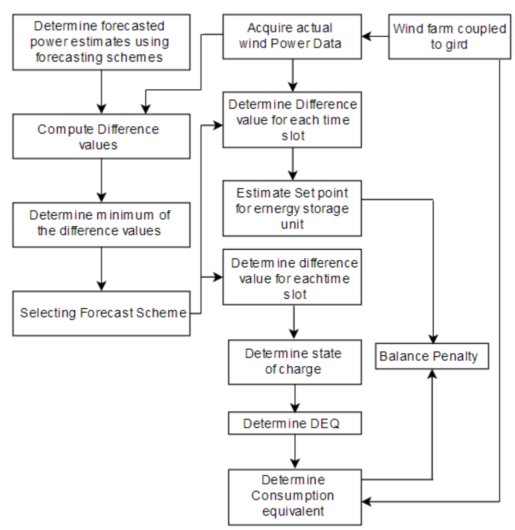

Fig. 1. Optimization of a Hybrid wind energy system.

The damage equivalent quantity (DEQ) indicates a depth of discharge value for a predefined number of battery cycles that is equal to its life consumption over a period of time. The aim of the battery damage controller is to maintain the DEQ as low as possible. Additionally, Consumption equivalent (C) corresponding to the percentage of battery life consumed is evaluated. The penalty to be paid if the wind farm fails to supply the predefined amount of power in a given dispatch window, is determined.

II. Optimization of a Hybrid Wind Energy System

The forecasted power is calculated by employing multiple forecasting schemes and the scheme that yields the minimum difference of the actual and forecasted powers is then determined for each dispatch window and the corresponding battery consumption equivalent is ascertained. Power supply to the grid uses a combination of actual wind power and supplemental support from the batteries when needed.

By using the forecasted wind farm power and actual wind power data, a difference value F_{err} is expressed as

$$F_{err} = \frac{\sqrt{\frac{1}{N}\sum_{n=1}^{N}(F_n - W_n)^2}}{\frac{1}{N}\sum_{n=1}^{N} W_n}, \tag{1}$$

where F_n is the forecasted wind farm power at time slot n corresponding in the dispatch window, W_n is an actual wind power, and N is the number of time slots within a dispatch window. Lower the value of F_{err}, greater is the reliability.

Selecting the most reliable forecasting scheme, and C is imperative for a optimized hybrid wind farm. We evaluate the penalty to the grid and balance it with life consumption of battery units. Factors such as the cost and remaining life of batteries, are critical. The next step determines the battery state of charge for each time slot. A 0% state of charge (or equivalently 100% depth of discharge) represents a fully discharged battery, whereas 100% state of charge indicates full charge. Using this value of depth of discharge, we calculate DEQ which provides a sense of damage caused to the battery life. The relation between number of cycles and depth of discharge is studied as in Figure 2.

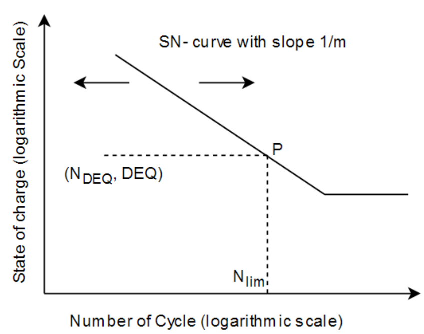

Fig. 2. S-N curve for a battery.

Using $\frac{1}{m}$ as the slope of the S-N curve and a random number of cycles, we evaluate DEQ as

$$DEQ = \left(\frac{1}{N_{DEQ}}\sum_{i=1}^{N} n_i S_i^m\right)^{\frac{1}{m}}, \tag{2}$$

where S_i is depth of discharge, n_i is number of cycles corresponding to the depth of discharge, N is the number of time slots.

If the point (N_{DEQ}, DEQ) is located on left hand side of the S-N curve, the battery still has useful life left. If the point is located on the right hand side of the S-N curve, it is an indication of battery failure. As shown in Figure 2, say the point is on left hand side. To infer consumption equivalent, we draw a horizontal line intersecting S-N curve at a point P. From P we draw a perpendicular to the X-axis representing the number of cycles. We can name the point of intersection as N_{lim} which represents the maximum number of cycles after which the battery will fail for a certain value of depth of discharge. The consumption equivalent is evaluated as

$$\mathrm{C} = \frac{N_{DEQ}}{N_{lim}}, \tag{3}$$

where $N_{lim} = k\ (DEQ)^{-m}$, $k = N\ (DOD)^m$, and DOD is depth of discharge for N number of cycles.

The number of cycles in a certain duration can be evaluated by Rainflow counting Algorithm.[12] The number of rainflow cycles is divided by $N_{lim} = 10^4$ to determine C. We assume that all the batteries would have similar DEQ and C value. Battery failure is indicated by the value $C = 1$, and if $C < 1$, the battery has useful life remaining.

III. Forecasting Methods

We now employ different forecasting schemes and check their effectiveness. We have taken the actual wind dataset consisting of wind speed data every ten minutes for the entire month of September 2016.[13] Taking the previous three value of actual wind speeds, we forecast the wind speed for the next ten minutes. In this way, we forecast the wind speed for a complete day. The actual wind power is given by

$$w = \frac{1}{2}A\rho v^3 C_p, \tag{4}$$

where w is the power output, $A(m^2)$ is the swept area of the wind turbine blades, ρ is the density of air and v is the wind speed in m/sec, and C_p is the power coefficient. Numerous forecasting methods have been used in recent years. In this paper, we have employed Persistence method and ARMA (Auto Regressive Moving Average) statistical method.

A. Persistence Algorithm Based Forecasting

The persistence method is the simplest solution for forecasting wind speed and is expressed as

$$v(t+n) = \frac{1}{n}\sum_{i=0}^{n-1} v(t+i). \tag{5}$$

We forecast the wind speed at time $t+n$ by simply taking the mean of actual wind speeds in n previous dispatch windows. In this paper, we consider three previous dispatch windows of 10 min duration each (total of 30 mins) to forecast the wind speed for the next 10 min dispatch window.

B. ARMA Model Based Forecasting

ARMA is a statistical method employed for forecasting, and is characterized by values of p, d and q where p is the order of Auto-Regression (AR), d is the degree of differencing to make the model stationary and q is the order of Moving-Regression (MA). The model is expressed as

$$y(t) = \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-i} + \epsilon_t, \tag{6}$$

where ϕ_i represents the factor of stability of the variance, i is the i^{th} autoregressive parameter, θ_j is the j^{th} moving average parameter and ϵ_t is the error term at time t. In our case we define $d = 0$ and hence we have only p and q terms.

The values of p, d and q are determined at the outset. We considered the wind data for a one week period prior to the day for which we need to forecast. The Autocorrelation and partial auto-correlation for the model are determined. This value is used to determine the Bayesian Information Criteria which results in a matrix and the least value in the matrix determines the values of p and q. The row of least value represents p and the column represents the value of q. The value of p and q were found to be 3 and 2 respectively.

Next, using Matlab or R we can find the value of estimates for the sample data considering maximum likelihood. We also determine the value of ϵ_t. The model in this case is

$$\begin{aligned} v(t) &= 1.7521\, v_{t-1} - 1.3663\, v_{t-2} + 0.5872\, v_{t-3} \\ &\quad -0.7449\, e_{t-1} + 0.3847\, e_{t-2} + 0.1448. \end{aligned} \tag{7}$$

The model constructed from seven days data is then used to forecast the wind speed for the following day. Figure 3 represents the actual wind speed compared to different forecasting schemes employed.

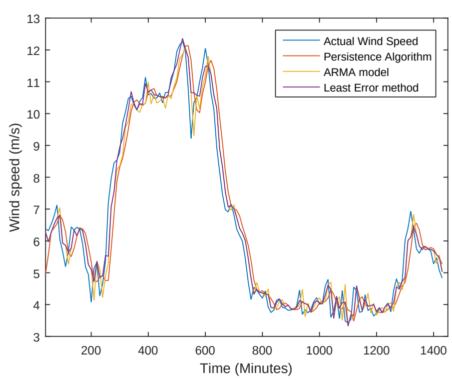

Fig. 3. Forecasting schemes compared with the actual wind speed.

In least error method, we forecast wind speed using the scheme that gives the least error of forecast in each dispatch window. Least Penalty method uses that forecasting approach which results in the minimum penalty among all the forecasting methods (ARMA and Persistence) in each dispatch window.

IV. Economy Considerations

Cost analysis is done for an optimized solution between the operation of batteries and wind forecasting scheme employed that provides most economic solution. When the forecasted wind power estimates is greater than the actual wind power, some penalty ($\$0.3\,/kWh$) is due to the grid operator. Alternatively, supplementary power can be provided from batteries. When wind speed drastically changes over successive dispatch windows, charging/discharging damages battery life, and so one is better off paying the penalty in that period in order to optimize battery life consumption.

Using (4), actual power w_a and forecasted power w_f are calculated for a dispatch window. We assume that the batteries are identical and cost $\$605$ each and the rating is $(2V, 2000A)$. The cost of penalty per unit and the cost of power units are assumed to be identical and equal to $\$0.3$ (may differ from one country to another). Broadly, there are three methods to ascertain economical usage of resources.

A. Methodology 1

In this case, battery storage is not used and penalty is paid routinely whenever there is shortfall in actual wind (w_a) over what was forecasted (w_f). Although, intuitively such a scheme is not practical it still needs to be compared with the proposed solutions. In a dispatch window, if for a given forecasting scheme $w_f > w_a$, penalty corresponding to $w_f - w_a$ is to be paid to grid operator and if $w_f < w_a$ no penalty is due. The penalty to be paid in a particular dispatch window with power shortfall, is given by

$$e_1 = \begin{cases} 0.3\,(w_f - w_a), & \text{if}\, w_f > w_a, \\ 0, & \text{otherwise,} \end{cases}$$

The net penalty E_1 for the entire duration of available data (in this case a Month) is given by

$$E_1 = 0.3 \sum_{i=1}^{r} (w_f - w_a), \tag{8}$$

where r represents the number of forecasting windows with $w_f \geq w_a$. Note that, the value of r is same for the Methodologies 1 and 2 when the same forecasting technique is applied, but changes with change in the forecasting technique, as seen in Table I.

B. Methodology 2

Whenever the forecasted wind power estimate w_f is higher than the actual wind power w_a, the difference $w_f - w_a$ is provided to the grid from the batteries, and the batteries charge when $w_f < w_a$. Battery life depends on the number of charging and discharging cycles. We consider the amount of power required for battery charging or discharging over a certain period, and accordingly select the battery power rating, accounting for a safety margin. In this scenario, the penalty is completely paid for with battery life for the four forecasting methods as shown in Table I.

The remaining useful battery life in months is indicated by the $(1 - C)$ factor. Life span of the batteries L(in yrs) is

$$L = \frac{(1 - C)\, N}{12},$$

where N represents the number of batteries required.

TABLE I
METHODOLOGY 2

Forecasting Methods	Persistence	ARMA	Least Penalty	Least Error
C	0.131	0.141	0.146	0.145
N	450	313	400	300
L	32.57	22.39	28.46	21.38
r	2209	2275	1873	2237

We calculate the power to be supplied through the batteries, and the cost E_2 is given by

$$E_2 = C\,N \times 605 \times 0.3 \sum_{i=1}^{r} (w_f - w_a). \tag{9}$$

C. Methodology 3

In this methodology, in order to avoid large charging and discharging of batteries, for a threshold w_t, if $w_f - w_a < w_t$, then $w_f - w_a$ is supplied from batteries. However penalty is paid to the grid operator whenever $w_t - (w_f - w_a) > 0$ equivalent to $w_t - (w_f - w_a)$ at ($\$0.3\,/kWh$). In this study we consider two different thresholds $w_t = 100$kW and $w_t = 200$ kW. Such dynamic threshold selection for different dispatch windows enable cost optimization with prolonged battery life and suitable dispatch failure penalty.

The life span L_i(in yrs) for $w_t = 100, 200\,kW$ and N_i, $i = 1, 2$ number of batteries, is

$$L_i = \frac{(1-C)\,N_i}{12},\ i = 1, 2,$$

respectively. Battery useful life L_i accesses long term viability of the methodology. Thresholds are set for overall optimal cost.

TABLE II
METHODOLOGY 3

Methods		Persistence	ARMA	Least Penalty	Least Error
w_t	C	0.131	0.141	0.146	0.145
100 kW+	N_1	175	150	100	125
	L_1	12.67	10.73	7.11	8.90
	r_1	193	131	99	146
200 kW+	N_2	250	175	163	125
	L_2	18.09	12.52	11.60	8.90
	r_2	27	22	32	43

We calculate the power to be supplied through the batteries, and at other times the penalty that is to be paid, and the combined cost E_{3i} is given by

$$\begin{aligned} E_{3i} &= C\,N_i \times 605 \times 0.3 \left(\sum_{i=1}^{\eta - r_i} (w_f - w_a) + \sum_{i=1}^{r_i} w_t \right) \\ &\quad + 0.3 \sum_{i=1}^{r_i} \left(w_t - (w_f - w_a) \right),\ i = 1, 2, \end{aligned} \tag{10}$$

where η is the total number of dispatch windows in the dataset considered, r_i represents the dispatch windows with $w_f - w_a \geq w_t$, $\eta - r_i$ represents the number of dispatch windows with $0 \leq w_f - w_a \leq w_t$. In this study, $\eta = 4465$ (10 min duration of dispatches for a month long data).

Tables I and II indicate that the battery life is increased by following Methodology 3 irrespective of the forecasting strategy. Using (8)-(10), the economy comparison of the three Methodologies is summarized in Table III which shows the total operational cost of operation for the forecasting schemes, a summation of cost of batteries, cost of charging and discharging per month of a single wind turbine. The results for all the techniques used to forecast indicate that Methodology 3 is effective in driving down the overall cost.

TABLE III
TOTAL COST FOR A MONTH (IN $)

Methods	Persistence	ARMA	Least Penalty	Least Error
E_1	50200	41647	33936	34034
E_2	38405	26776	35332	26499
E_{31} ($w_t = 100kW$)	28486	23025	15915	18204
E_{32} ($w_t = 200kW$)	27704	19650	17250	14000

From Table III, it is not conclusive as to which among Least error or Least Penalty approaches is ideal. An optimization technique to ascertain the ideal value of threshold w_t would be needed to address that issue decisively.

V. CONCLUDING REMARKS

A suitable dispatch regulator and forecasting scheme should be employed for having minimal cost of operation of hybrid wind energy system. Forecasting schemes like Persistence algorithm and ARMA and variations of these such as Least error and Least Penalty, are employed to forecast the wind speed. Penalty is paid directly to the grid operator, or with the help of batteries, or an optimal combination of both. We find that the overall cost of operation in paying the penalty is least in using the batteries up to certain cut-off rating and to pay the additional penalty to grid operator.

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