Prediction of Balancing Energy in Wind Generation using Probabilistic Weather Forecasting

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Abstract: In competitive electricity trading a group of producers, marketers, and consumers is called a 'balance circle' where a balancing mechanism is used to match supply and demand in all time periods. Fluctuations in the actual consumption are compensated by external sources or by the transmission system operator, which results in balancing charges. This paper presents an illustrative model of a balance circle, comprising a wind turbine and an electricity consumer to minimize the balancing energy costs. Since wind speed and air temperature influence the rate of generation and demand, the weather prediction affects the planned electricity purchase. Mathematical models are developed for the wind generator and the consumer loads. The application of these models allows us to predict the balancing energy requirements using deterministic and probabilistic (ensemble) weather forecasts.

Keywords: wind power forecasting, ARMA processes, Neural Networks, ensemble forecasts

1 Introduction

In market driven electricity trading the balance circle is a group of producers, marketers, and consumers where a balancing mechanism is used to match supply and demand in all time periods (e.g. every quarter hour). The difference between the actual consumption and supply is balanced by external sources or the transmission system operator, which results in the purchase costs and balancing charges [1]. In this paper an illustrative model of a balance circle is presented to plan the cost of balancing energy. The circle includes a wind turbine and an electricity consumer. The air temperature and the wind speed influence the electric loads and the wind power output, consequently, the meteorological forecasting effects the planned electricity purchase.

The ideal forecast product for the risk manager who tries to plan the balancing energy is not a probabilistic weather forecast, but a probabilistic forecast of the weather dependent economic quantity (electricity demand, wind energy production) [2]. Such forecasts attempt to transform current uncertainty in weather variables to future uncertainty in variables relevant to the market conditions.

2 Ensemble Forecast

Ensemble weather forecasting is a well-established approach in the field of numerical weather prediction. This technique involves the perturbation of the initial conditions to an extent representative of initial uncertainties. Numerical integrations are carried out forward from all perturbed conditions to arrive at a probabilistic estimate of the future state of the atmosphere (instead of a single valued estimation). It has been demonstrated that such forecasts can have advantages for the forecast users compared to the use of deterministic forecasts [3].

3 Decision Making and Risk Management

The central idea of decision making theory is utility, which is a quantification of the desirability of a particular outcome, relative to alternative outcomes [4]. Let X be a random variable and $y = u(z, x)$ the utility function of the user where z represents his decision. Denote p_k the probability of the event $P(X = x_k)$. The expected value of the utility function is given by

$$E[Y](z) = \sum_k p_k u(z, x_k).$$

In general, u is a nonlinear function of X so

$$E[Y](z) \neq u(z, E(X)).$$

If the distribution of X is known, the user can make the choice z^* that maximizes (or minimizes) the expected utility

$$E[Y](z^*) = \max_z E[Y](z).$$

4 Balancing Energy Calculation

In deregulated electricity trading the balance circle is used to match supply and demand in all time periods. Experts responsible for the power balance of the circle are required to send load schedules to the transmission system operator and to plan selling and buying electricity. The performance of a wind turbine is proportional to the third power of the wind speed. Let the power of the wind generator at time t be $p(t)$ and let the actual demand of the electricity consumer be $d(t)$, $t = 1,2,\ldots,T$. Then the balancing power in kW is given by

$$b(t) = d(t) - p(t) \quad t = 1,2,\ldots T.$$

If the actual balancing energy equals or exceeds zero, the consumer must purchase electricity at a price $\alpha(t)$ which depends on t (the price is different in peak and off-peak periods). Since the imbalance charges can greatly exceed the spot market price $\gamma(t)$ it is worth to buy electricity on the spot market to match the power supply with actual demand as much as possible. If, however, the actual difference between demand and production is negative, that is the wind generator output is higher than the demand, then the regional utility should sell the surplus energy at the price of $\beta(t)$.

If the power purchased on the spot market is equal to $s(t)$, the balancing energy can be calculated as $b(t) = d(t) - s(t) - p(t)$, $t = 1,2,\ldots,T$. The cost to maintain the energy balance in the balance circle is given by

$$c(t) = \alpha(t)b(t) + \gamma(t)s(t) \quad \text{if } b(t) \geq 0$$
$$c(t) = \beta(t)b(t) \quad \text{if } b(t) < 0 \quad t = 1,2,\ldots,T$$

where the demand and wind generation depend on the air temperature and the wind speed. Since these dependencies are nonlinear, the calculation of balancing energy costs $c(t)$ requires a probabilistic forecast. For the time period T the balancing energy costs can be calculated as

$$c = \sum_{t=1}^{T} c(t)$$

which can be considered as the utility function of the balancing strategies $c = u(s, x, y)$.

If X and Y are discrete random variables, then the distribution function of C can be computed as

$$P(C = c) = \sum_{u(s, x_k, y_j) = c} P(X = x_k, Y = y_j).$$

Let r_{kj} denote the probability of the event $P(X = x_k, Y = y_j)$. The expected value of balancing cost is given by

$$E[C](s) = \sum_k \sum_j r_{kj} u(s, x_k, y_j).$$

The nonlinearity of C suggests that balancing energy planning requires a probabilistic forecast for the weather variables; the expected value is not sufficient for a rational decision making.

5 Statistical Modeling Framework

In our study different statistical models are applied to predict wind power output and electric loads. Let $\{y_1, y_2, \ldots, y_t, \ldots, y_T\}$ denote the observations made at equidistant time intervals where y_t can be regarded as an observation at time t. Our objective is to model the series $\{y_t\}$ and to use that model to forecast beyond the last observation y_T.

5.1 Time series models

The time series model provides a description of the random nature of the stochastic process that generated the sample of observation under study [5]. A mixed autoregressive and moving average stochastic process with exogenous variables (ARMAX) can be written as

$$y_t - \phi_1 y_{t-1} - \ldots - \phi_p y_{t-p} =$$
$$= e_t + \theta_1 e_{t-1} + \ldots + \theta_q e_{t-q} + \omega_1 x_{t-1} + \ldots + \omega_s x_{t-s}$$

where e_t is a zero mean white noise sequence with unknown σ variance, p is the order of the autoregressive term, q is the order of the moving average term, $\phi_1, \phi_2, \ldots, \phi_p$, $\theta_1, \theta_2, \ldots, \theta_q$ are the model parameters and $\omega_0, \omega_1, \ldots, \omega_s$ are the coefficients of the explanatory variables.

5.2 Nonlinear system models

Both the theory and practice of nonlinear system modeling have advanced considerably in recent years. It is known that a wide class of these systems can be represented by the nonlinear autoregressive moving average time series with exogenous input [6]. These NARMAX models provide a description of the system in terms of a nonlinear functional expansion of lagged inputs, outputs and prediction errors.

Time series and transfer function models are used to infer relationships between historical input-output data and future outputs by collecting a finite number of past inputs x_t and outputs y_t into the vector φ_t :

$$\varphi_t = (y_{t-1}, y_{t-2}, \ldots, y_{t-p}, x_t, x_{t-1}, \ldots, x_{t-s})^T$$

where $(.)^T$ denotes transposed.

The forecasting problem is to give the next output y_t as a function of φ_t . To obtain this function we have a set of observed data (training set): $\{(y_t, \varphi_t)\}$. From these data we infer a relationship $y_t = g(\varphi_t)$. Typically, a function expression of the type

$$g(\varphi_t, \alpha) = \sum_k \alpha_k g_k(\varphi_t)$$

is used, where $d = p + s$, $g : R^d \to R$, and α_k is the k -th component of the parameter vector α . Using a special nonlinear relationship in the basic functions of the expansion we have

$$y_t = g(\varphi_t) = \sum_k \alpha_k \vartheta(\beta_k^T \varphi_t + \gamma_k)$$

where β_k is a parameter vector of size $\dim \varphi$, α_k and γ_k are scalar parameters. The most common choice for ϑ is

$$\vartheta(z) = \frac{1}{1 + \exp(-z)} .$$

This model is referred to the feed-forward, three-layer neural network where the output layer has only a single node [7].

6 Wind Energy Production

Two wind power units, with nominal capacities of 600 kW, are set up on the north-western part of Hungary in the village called Mosonszolnok. Wind speed and performance data measured at the top of the support tower sampled at 10 minute intervals were used to form half-hourly time series for modeling the units. Based on the measurement data the relationship between performance and wind speed is shown in Fig.1.

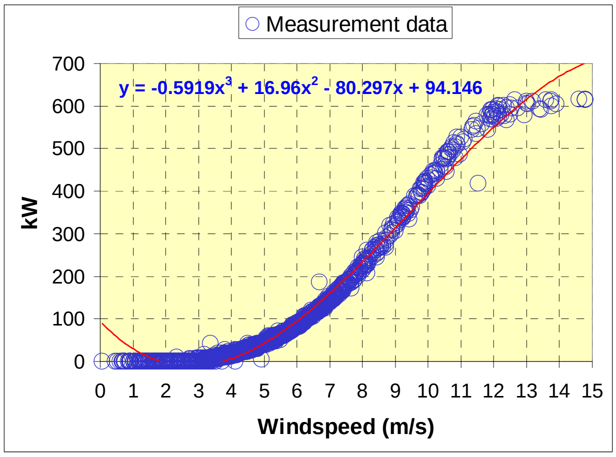

Fig.1 Relationship between wind power output and wind speed based on the measurement data.

Models were developed based on wind power and wind speed measurement data to model and predict the performance of the wind generation unit. The training period was about one month the forecasting horizon was one day ahead and hourly weather prediction data was used. In the first phase of our investigation autoregressive moving average models with external parameters (ARMAX) were used, considering the wind speed as an external parameter. The final model we applied for the calculation of balancing energy was a NARMAX model using artificial neural network technique. During the training, features from the historical data (wind power output and wind speed) are entered into the network's input layer. The neuron activation in the input layer is fed forwards through the network and the final outputs are compared with the known unit performance values. The observed and calculated data of the wind generator output applying the model can be seen in Fig.2.

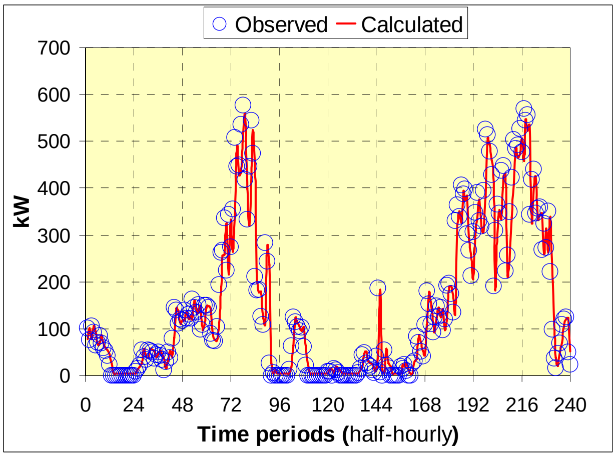

Fig.2 Observed and calculated wind unit's performance using the wind power forecasting model.

7 Electricity Demand

The electricity consumer in our balance circle was a medium size shopping center with a maximum load of about 400 kW in the north-western part of Hungary. Electricity demand was sampled at 15 minute intervals from which we formed half-hourly time series to model the demand of the balance circle. The ambient temperature data were observed on an hourly basis. Based on the metering data the relationship between the daily average load and air temperature is shown in Fig.3.

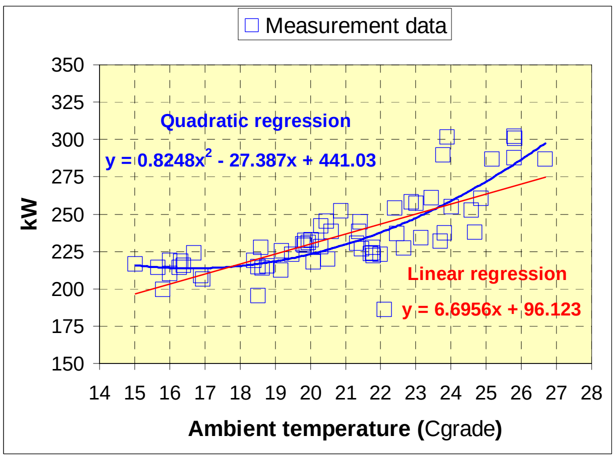

Fig.3 Relationship between consumer's loads and air temperature based on the measurement data.

To forecast the electricity demand a multivariate linear regression model was used. Historical data (loads and temperatures) for the two months training period was entered into the regression model. This regression model was applied to forecast the demand of the supermarket one day ahead. The observed and calculated data are shown in Fig.4.

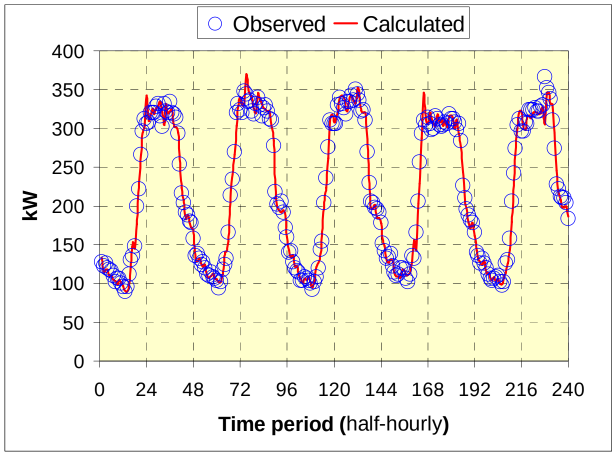

Fig.4 Observed and calculated consumer's loads using the electric load forecasting model.

8 Balancing Energy Planning

For the fictitious balance circle the task is to determine the minimum value of balancing costs taking into account the balancing conditions. In those periods where the consumer's demand exceeds the amount of the generated wind power the consumer must buy extra electricity at the imbalance price. In our study we set the imbalance price 97.6 EUR in the peak period and 48.8 EUR in the off-peak period. For the study period the daily average EEX (European Energy Exchange) spot market prices were about 36 EUR and 26 EUR in the peak and off-peak period, respectively. Since the balancing charges can greatly exceed the spot market price it is worth to cover the difference between the actual demand and wind power output as closely as possible by spot market trading. In our calculations the EEX hourly spot market prices were used. If the wind power is greater than the demand, the supply company in the region of the balance circle is forced to buy the surplus energy at the price 7.2 EUR in the peak period and 4.1 EUR in the off-peak period.

8.1 Weather forecasts

The historical and forecasts data were observed and forecast for the temperature at height two meters and for the wind speed at height ten meters in the region of the shopping center and the wind generation unit. Weather forecast data were retrieved from the Meteorological Archival and Retrieval system (MARS) of the European Centre for Medium-Range Weather Forecasts (ECMWF). The Ensemble Prediction System (EPS) was developed by ECMWF which attempts to provide different future scenarios for the state of the atmosphere instead of single value predictions. EPS has been designed to simulate the uncertainties in the initial state of the atmosphere. Uncertainties in the initial state are simulated by perturbed initial conditions using the so-called singular vector approach. This method finds those perturbations which leads to the fastest instability growth. Forecast errors resulting from approximations in the model are simulated by stochastically perturbing the overall effect of physical parameterizations. The EPS is capable of providing the time evolution of the probability density function of the atmospheric state [8].

8.2 The Method for the Calculation of Balancing Energy Costs

Based on the developed mathematical models and the meteorological forecasts we computed consumer's electric loads and wind generator performance one day ahead on half-hourly basis. From this calculation the required spot energy purchase can be scheduled for the next day. A good schedule for this external electricity sourcing results in cutting down the balancing energy costs.

One of the main aim of this paper is to demonstrate that the probabilistic forecasts based on the ECMWF ensembles can give better decision making (scheduling strategy for energy purchase on the spot market) for balancing energy planning in comparison with using ensemble mean forecasts.

In the first step of the calculation we computed the load patterns for the purchased electric energy using ensemble as well as ensemble mean weather forecasts. Using the ensemble forecasts and the mathematical models for the wind generator and the electric loads of the shopping center, the probability distribution of the balancing costs can be calculated (Fig.5).

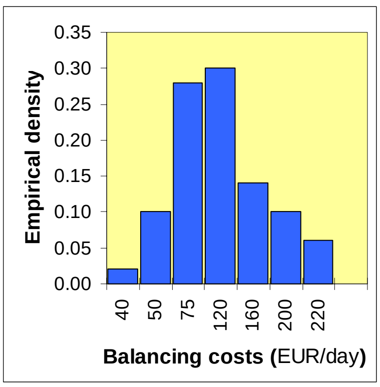

Fig.5 Probability distribution of the balancing costs using the ensemble weather forecasts.

In the second step these strategies were applied to calculate the balancing energy costs using the historical data of the wind speed and the ambient temperature for the region of the balancing circle. The results of our calculation can be seen in Table 1.

Table 1
Balancing energy costs using ensemble and ensemble mean weather predictions

26th August 2004	Temp (Cgrade)	Wspeed (m/s)	EDem	WindGen (kWh/day)	Purchase	Balancing Cost (EUR per day)
Ensemble	16.3	6.7	5251.0	3932.7	2030.0	133.7
EnsembleM					1415.0	145.1

The wind generation output, shopping center loads and weather parameters are shown in Fig.6, where the values were calculated using the historical weather components.

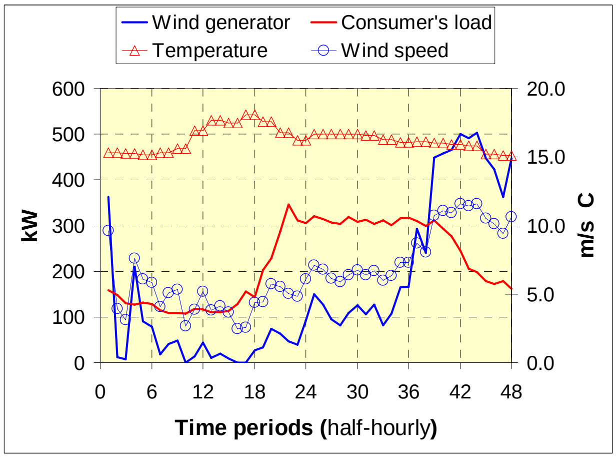

Fig.6 Calculation wind power and electric loads using the forecasting models and historical weather parameters.

9 Conclusion

The nonlinear nature of utility functions on weather dependent component in electricity trading make probabilistic forecasts essential for decision making [9]. In the case of electricity demand and wind generation forecasting ensemble forecasts can be used to improve forecasts of demand and wind power output and hence enable the balance circles to decide how much electricity they should purchase to cut the balancing energy charges. In this paper a balance circle is considered which includes a wind generator and one consumer. Since the imbalance price is much more expensive than the spot market price a good schedule of energy purchase can reduce the balancing charges. Based on the ensemble and ensemble mean weather forecasts for the wind speed and air temperature we formed two schedules for the spot energy purchases (see Fig.7). Using ensemble forecasts for the air temperature and wind speed an illustrative test example on a specific day resulted in a relative percentage saving of 8.4%.

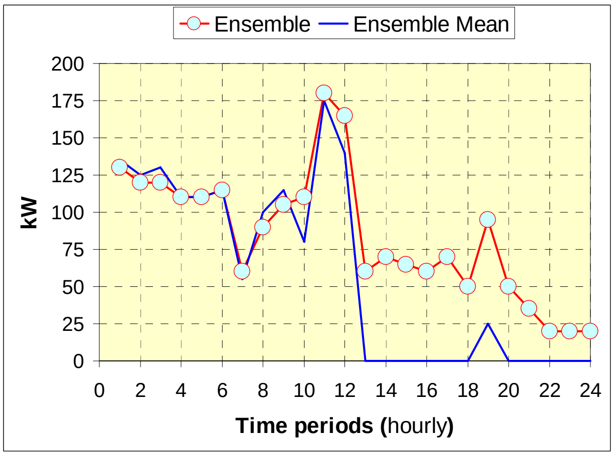

Fig.7 Spot market electricity purchase schedules using ensemble and ensemble mean weather forecasts.

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