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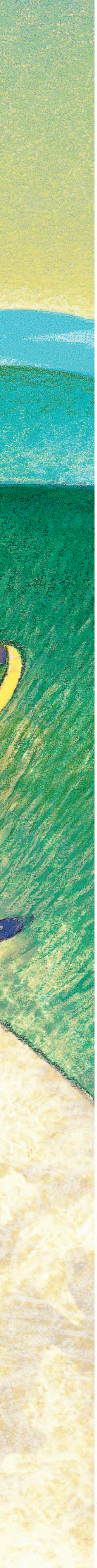

One Step Ahead

Short-Term Wind Power Forecasting and Intelligent Predictive Control Based on Data Analytics

By Ganesh Kumar Venayagamoorthy, Kurt Rohrig, and István Erlich

THE INTELLIGENT INTEGRATION OF WIND POWER INTO THE EXISTING ELECTRICITY supply system will be an important factor in the future energy supply in many countries. Wind power generation has characteristics that differ from those of conventional power generation. It is weather dependent in that it relies on wind availability. With the increasing amount of intermittent wind power generation, power systems encounter more and more short-term, unpredicted power variations. In the power system, supply and demand must be equal at all times. Thus, as levels of wind penetration into the electricity system increase, new methods of balancing supply and demand are necessary.

Accurate wind power forecasting methods play an important role in addressing the challenge of balancing supply and demand. Forecasting is required to maximize the integration of a high level of wind power penetration into an electricity system because it couples weather-dependent generation with the planned and scheduled generation from conventional power plants and the forecast electricity demand. The latter is predictable with sufficient accuracy. Even with state-of-the-art wind forecasting methods, the hour-ahead prediction errors for a single wind plant are still around 10–15% with respect to actual production. Wind power prediction determines the need for balancing energy and, hence, the cost of wind power integration. In countries such as Denmark, Germany, Spain, and the United States, wind power prediction is a critical component of grid and system control. The short-term energy balancing of existing electricity supply systems depends on automatic generation control (AGC), which cannot regulate transmission line flows. Most regional voltage controllers (RVCs) are capable of regulating only the primary bus voltage and do not result in any voltage enhancement at other buses. With a high level of wind power penetration, short-term transmission line overloads and voltage violations may occur because of the limited adaptation capabilities of the AGCs and RVCs.

A high degree of wind power integration without intelligent control may result in power system stability issues and penalties that cause wind farm owners to lose revenue. Real-time operation time frames require short-term wind power prediction on the order of seconds, minutes, and a few hours, as well as the integration of that prediction into the control room environment. Short-term wind power forecasting based on the current status of wind power plants (WPPs)—and the application of such forecasting in the development

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> Short-term wind power prediction on the order of seconds, minutes, and a few hours and its application in control centers becomes critical for the real-time operation of the electricity supply system.

of intelligent predictive optimal control of reactive power and wind power fluctuations for real-time control center operations—are discussed in this article.

Short-Term Wind Power Prediction

Short- to medium-term wind power forecasting using numerical weather forecasts and computational intelligence methods has experienced enormous progress in recent years and represents an integral part of today's energy supply. For asserting predictive control of wind farms, wind farm groups, and the associated transformer, the short-term prediction of active and reactive wind turbine power outputs is essential. Contrary to other fields of application of the prediction models for the energy market, wind farm control requires a very short forecast horizon, from a few seconds up to 15 min. The approaches used with the existing model, therefore, do not apply here. Weather pattern information will play no role in this task. Rather, it is important to estimate the electrical parameters for the near future based on recordings and analyses of the current situation of wind farms. Compiling this estimation using analytical approaches is very difficult and imposes a high computational cost; for these reasons, the use of computational intelligence methods is essential. In several studies on wind power prediction, the ability of neural networks to carry out short-term predictions from spatiotemporal information is well known.

In contrast to the previously used methods for very short-range forecasting, the proposed method uses no related numerical weather prediction (NWP) information. The active and reactive power are predicted solely based on power data measured from representative wind farms or wind turbines in a wind farm. Due to the spatial distribution of these wind farms, changes in grid areas are identified, and this information helps to predict the supply in the near future. The suitability of this spatial method for predicting wind power over very short forecast horizons is being investigated in detail. In Figure 1, the predicted outputs are active and reactive

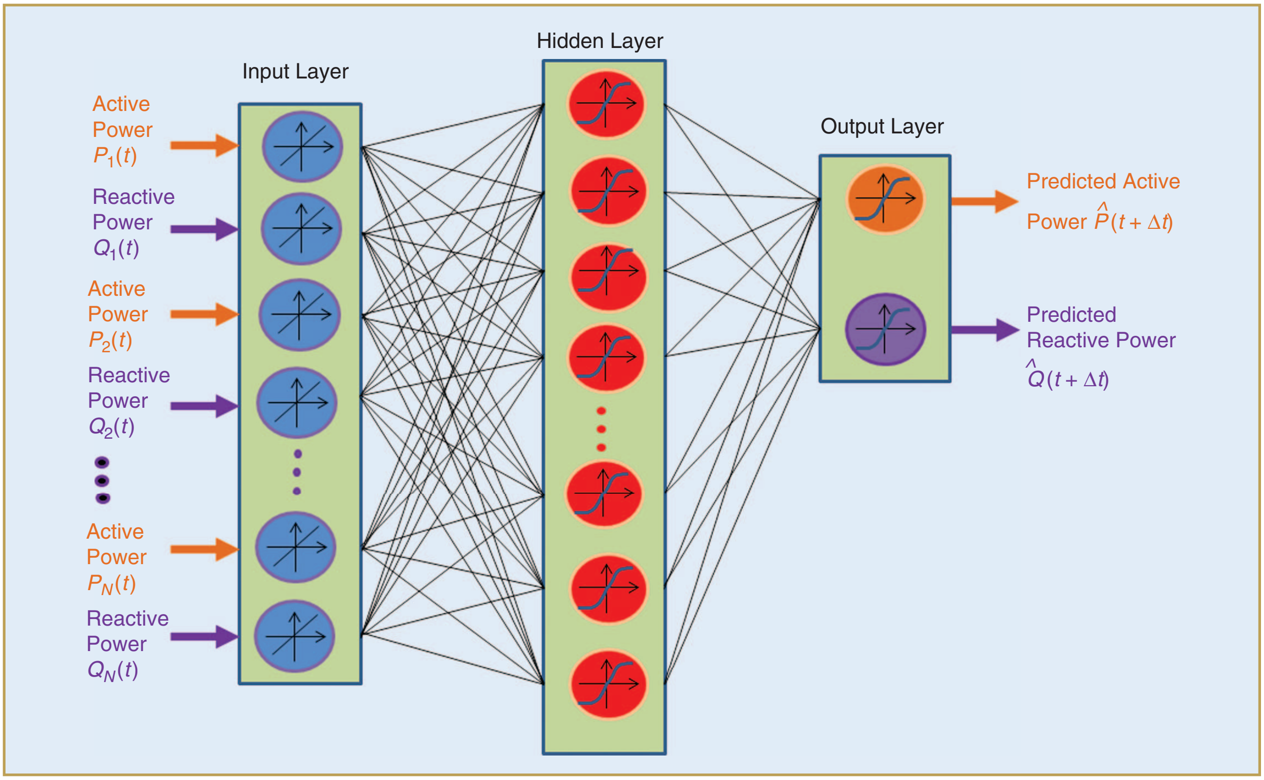

figure 1. Neural network inputs are the active and reactive power of the individual N wind turbines in a wind farm at the current time, t, and the outputs are predicted active power and reactive power of a wind farm at time $t + \Delta t$.

A high degree of wind power integration without intelligent control may result in power system stability issues and penalties that cause wind farm owners to lose revenue.

power of a wind farm at the next time interval.

The short-term active wind power forecast for one of the German network regions (TenneT), based on the measured power data of selected wind farms, is shown in Figure 2. The input data for the neural network consist of the normalized output signals representative of individual turbines or wind farms.

The figure shows the curves of the wind energy fed into a network region of TenneT compared with the one-hour forecast and the one-hour persistence. The neural network model using the spatial method is clearly predicting large fluctuations significantly better than the approximated persistence method. The root mean square error (RMSE) for the one-year period was 2.5% of the installed plant capacity, and the correlation coefficient was 0.989. Table 1 compares the forecast accuracy of the spatial method for prediction horizons from one to three hours. For the one-hour forecast, the spatial method provides a significantly better result than NWP-based models. In contrast, larger prediction horizons suffer from reduced quality compared with the NWP-based models. With these benchmarks, the neural network method based on spatial power data represents a very good solution for very short-term predictions for grid regions and wind farms.

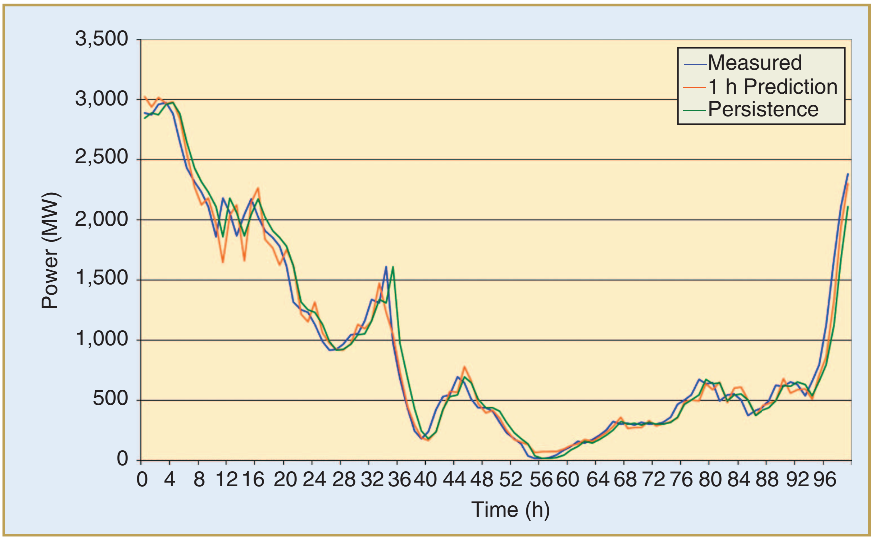

figure 2. Measured and predicted curve of active power of wind farms in a grid area of TenneT.

Predictive Wind Farm Reactive Power Control

With the increasing integration of WPPs, grid utilities require extended reactive power supply capabilities, not only during voltage dips but also during steady-state operation. According to the grid codes, the reactive power requirements are defined alternatively in terms of the power factor, the amount of reactive power supplied, or the voltage at the point of interconnection. To achieve the reactive power requirement optimally, WPP operators may consider performing reactive power optimization within their own facilities. The stochastic nature of the wind speed, however, poses a serious problem to the reactive power management of WPPs. To consider uncertainties caused by the wind, the optimization must be performed in a predictive manner for a certain future time horizon by taking into account the short-term wind forecast. This idea is depicted in Figure 3. In this approach, optimization of power flows is performed for a given scenario, which includes a set of future operating points. All of these operating points are optimized simultaneously using the objective function, which can be formulated several different ways. The simplest technique is to minimize power losses within the wind farm area. Taking into account the stepwise movement of on-load tap changers (OLTCs), the power losses and costs of OLTC movements can be considered monetarily.

The quality of the optimal wind farm operation depends on the accuracy of the wind power forecast. In the example presented herein, the forecast results shown in Figure 4 have been used.

table 1. Accuracy (RMSE and correlation) of the spatial method.

	Spatial Method	
Prediction Horizon (hour)	RMSE	Correlation
1	2.5%	0.989
2	4.2%	0.970
3	5.7%	0.953

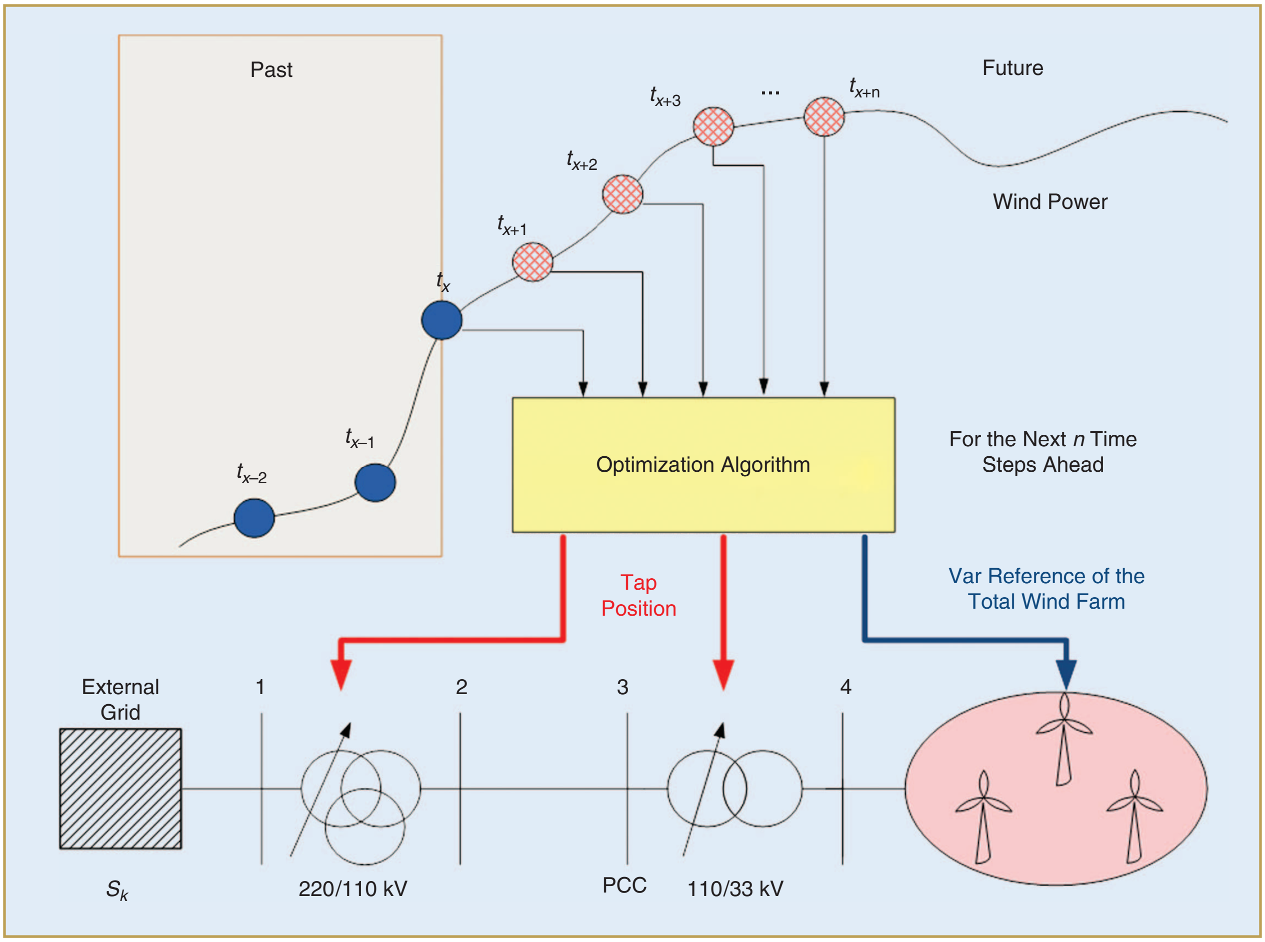

figure 3. Predictive wind farm reactive power optimization.

The optimization is carried out over the predicted time period for n discrete time steps simultaneously. Then, the optimal power flow program suggests the optimal OLTC tap settings along with the optimal reactive power references for the entire wind farm for the next n time steps. By conducting this optimization every five minutes, it can be updated if new, improved forecast results become available. The proposed predictive control optimization was tested with a real wind farm model, as depicted in Figure 3. The results are shown in Figures 5 and 6.

For simplicity, in this case study, all wind turbines receive the same optimized reactive power reference set point. Different optimization methods can be used for the described problem, but the optimization task in general is nonlinear and nonconvex.

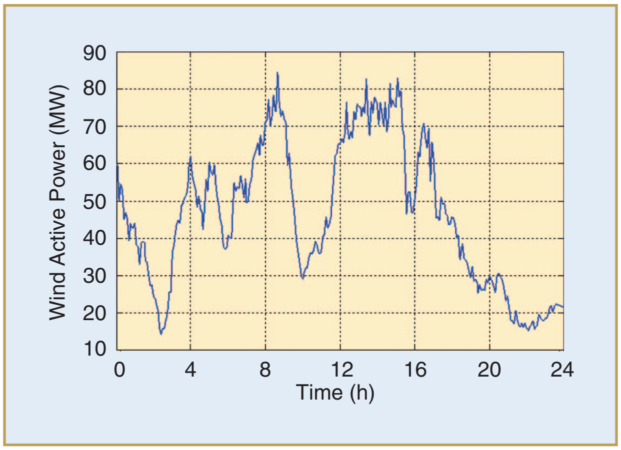

figure 4. Results of the wind power forecast using a neural network.

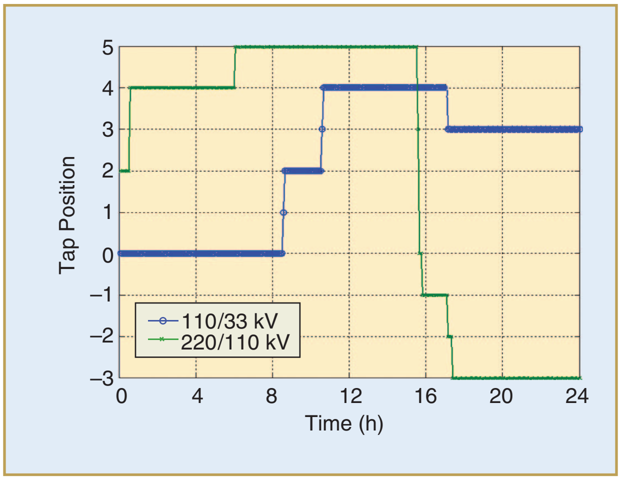

figure 5. Optimization results: OLTC stepping.

The authors therefore used the heuristic optimization algorithm called mean-variance optimization (MVO), also referred to later as the mean-variance mapping optimization (MVMO), which demonstrates excellent convergence properties.

Large wind farms connected to high-voltage transmission grids must either deliver a certain amount of reactive power or control the voltage at the point of interconnection. Often, the reactive power demand is derived from the voltage according to a given characteristic. Alternative methods may exist, but the basic task always remains the same and can be described by the reactive power demand that the wind farm has to supply. To adapt the reactive power generation, usually a wind farm controller is implemented. The output of this controller is the reactive power reference to individual wind turbines or, alternatively, the local voltage reference if a voltage controller is implemented at the wind turbine level. The question that arises is how the suggested wind farm optimization can be incorporated into the common wind farm optimization loops. Figure 7 illustrates the approach used.

The optimization directly controls the OLTC positions and the shunt reactor connected to the bus bar to compensate for the capacitive charging power of the cable. The shunt reactor represents a discrete optimization variable, as it can only be switched on or off. The reactive power reference of the wind farm is usually distributed to the operating wind turbines equally, meaning that the output of the proportional-integral controller, $\triangle Q_{\text{total}}$, is divided by the number of wind turbines. This value may now be modified by distribution factors calculated based on the optimization results. The distribution factors are usually close to unity. Deviating from 1.0 will result in different var references remotely communicated to the wind turbines. The distribution factors are calculated in such a way that even if they are not uniform, the total required power $\triangle Q_{\text{total}}$ will be supplied.

The suggested control and optimization methods have been tested by simulating their behavior over 24 hours. The

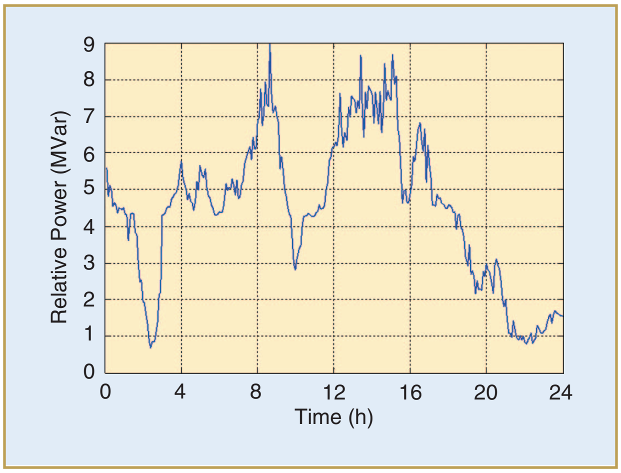

figure 6. Optimization results: wind farm var reference (sum of all wind turbine var reference set points).

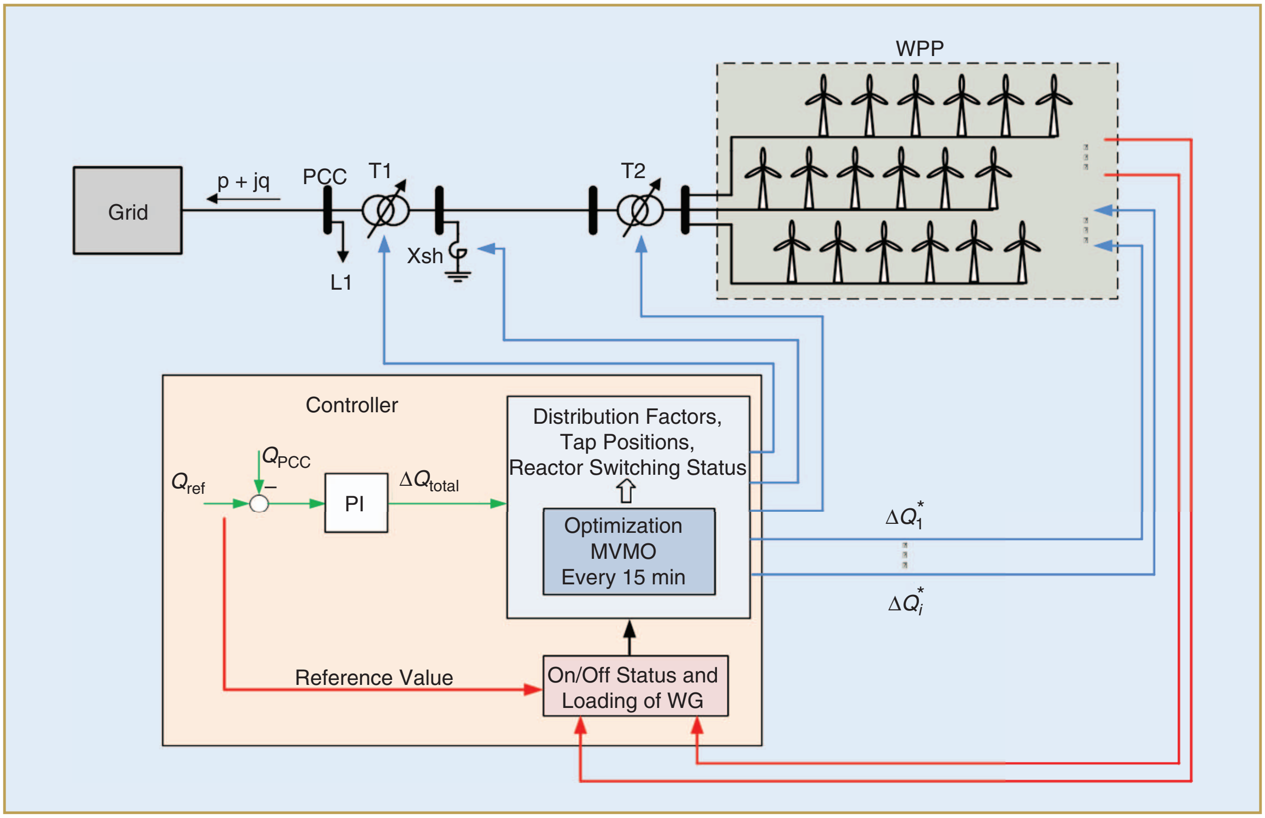

figure 7. Integration of optimization in wind farm control for reactive power control and power loss reduction.

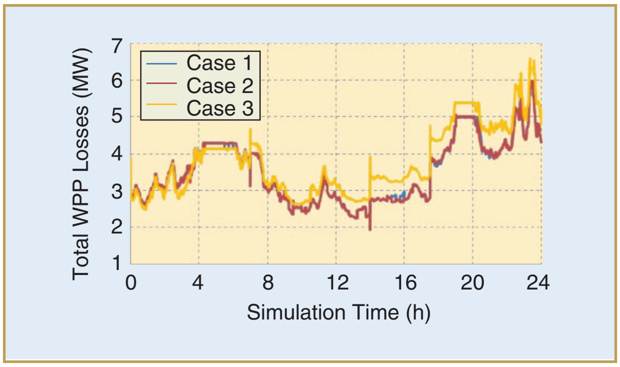

figure 8. Wind farm losses over 24 hours for three different control scenarios.

optimization is carried out every 15 min, resulting in modified distribution factors. For the simulation, it is assumed that the wind is fluctuating and that the reactive power demand is changed by the operator in a stepwise manner in the range of maximum capacitive to maximum inductive values. Wind farm losses are shown for three different cases in Figure 8. Cases 1 and 2 represent operation with optimization. In Case 1, the var references of the wind turbines are different, whereas in Case 2, all of the wind turbines have the same (but optimized) var references. Case 3 represents the state of the art as implemented in most of the wind farms without any optimization but with a wind farm controller in operation and classical voltage controllers applied to the OLTC. Clearly, the wind farm losses can be reduced considerably with optimization. On the right-hand side of the plots in Figure 8, Case 3 shows slightly smaller losses. In this case, however, the voltage limitations in the grid are violated (not shown here). Cases 1 and 2 show similar results. This is due to the fact that the wind turbines in this particular wind farm are close to each other (500–600 m), so different supplied var references will not result in considerable differences in the loss. Therefore, in this case, a uniform var generation distribution is acceptable. Optimization is required, however, for optimal control of the OLTC and the shunt reactor.

Predictive Optimal Control of Wind Power Fluctuations

The dynamic and intermittent nature of wind power causes fluctuations in transmission line flows that may result in power system instability. Power system instability can lead to cascaded outages and, eventually, a blackout. Integrating battery energy storage systems (BESSs) reduces the uncertainty inherent in wind power generation and increases grid reliability and security. In other words, it minimizes the possibility of a blackout. Wind power varies continuously, however, and in order to effectively and continuously utilize limited energy storage to mitigate the power fluctuations, it is necessary to

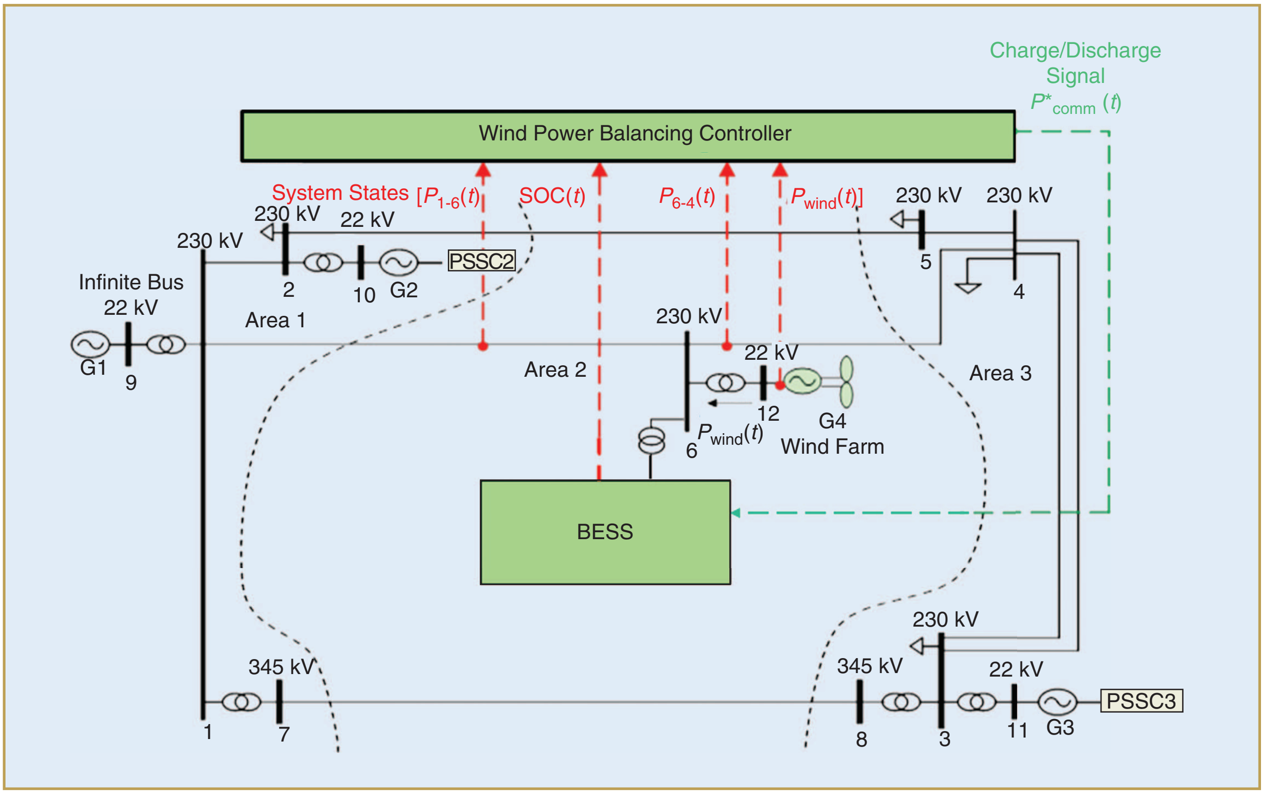

figure 9. A modified 12-bus, three-area, multimachine power system with a wind farm, BESS, and wind power balancing controller. The wind power balancing controller uses the predicted power output of the wind farm to command charging and discharging of the BESS.

carry out a real-time optimal control of the state of charge (SOC) of the battery energy storage system with variations in wind speed over a moving time window. Based on the short-term predictions of wind power over any given time window, the optimal charge and discharge power commands for the BESS are determined. In other words, without optimal control, the BESSs will lose their function as shock absorbers once their SOCs charge to their maximum limit or discharge to their minimum limit.

Adaptive critic design (ACD) is a powerful computational approach that can determine optimal control laws for a dynamic system in a noisy, nonlinear, and uncertain environment, such as the power system. Compared with classical control and dynamic programming–based approaches, ACD is a computationally inexpensive method for solving infinite-horizon optimal control problems. With ACDs, no prior information is needed about the continuously changing system to be controlled, and optimal control laws can be determined based on real-time measurements. The ACD consists of two subsystems, an actor and a critic. The actor receives the states of the system (wind speed, power flows, and so on) and dispenses the control/decision signals (BESS charge and discharge commands). The critic learns the desired performance index for some function associated with that index and evaluates the overall performance of the system, like a supervisor. The power system in Figure 9 is used to illustrate the need for intelligent optimal control of a BESS to provide maximum mitigation of transmission line power flows with wind farms. Figure 9 shows a modified 12-bus, multimachine power system with three generators (G2, G3, and G4), an infinite bus (G1), and three interconnected areas. Generator G4 is a wind farm. The BESS is connected to bus 13 in area 2 of the system. The BESS charges and discharges energy in order to reduce power fluctuations in the two transmission lines (lines 6-4 and 1-6) connected to the wind farm bus. The task of the BESS is to maintain steady-state power flows in lines 6-4 and 1-6 as much as possible with wind power variations.

In order to implement this objective, a dynamic optimal SOC controller with the ability to forecast wind power variations was developed. The actor (see Figure 10) is an MVO algorithm, which generates charge and discharge power commands ($P^*_{\mathrm{comm}}(t)$) based on the system states and feedback from the critic neural network regarding the actor's performance. The system states are measurements from the power system, which consists of the following four elements: the current SOC of the BESS ($SOC(t)$), the varying wind power ($P_{\mathrm{wind}}(t)$), and the active power flows through the transmission lines 1-6 ($P_{1\text{-}6}(t)$) and 6-4 ($P_{6\text{-}4}(t)$) connected to the wind farm.

The critic network is a neural network whose output is an approximation of the cost-to-go function of Bellman's equation of dynamic programming. The utility function in the approximation of the cost-to-go function is composed of the sum of three terms with different weightings. The first two terms are the transmission line active power fluctuations in lines 1-6 and 6-4. The third term represents the anticipated deviation in the BESS's SOC from its maximum and minimum SOC limits, which are estimated based on the predicted wind power output over the next several seconds. If the SOC of the BESS falls below the predefined minimum, the BESS will not be able to compensate for any deficit in wind power. Similarly, if the SOC exceeds the predefined maximum, it will not be able to absorb any excess wind power. Therefore, it is necessary to maintain the SOC of the BESS within its chosen dynamic range at all times. The actor based on the MVO algorithm determines the optimal charge or discharge

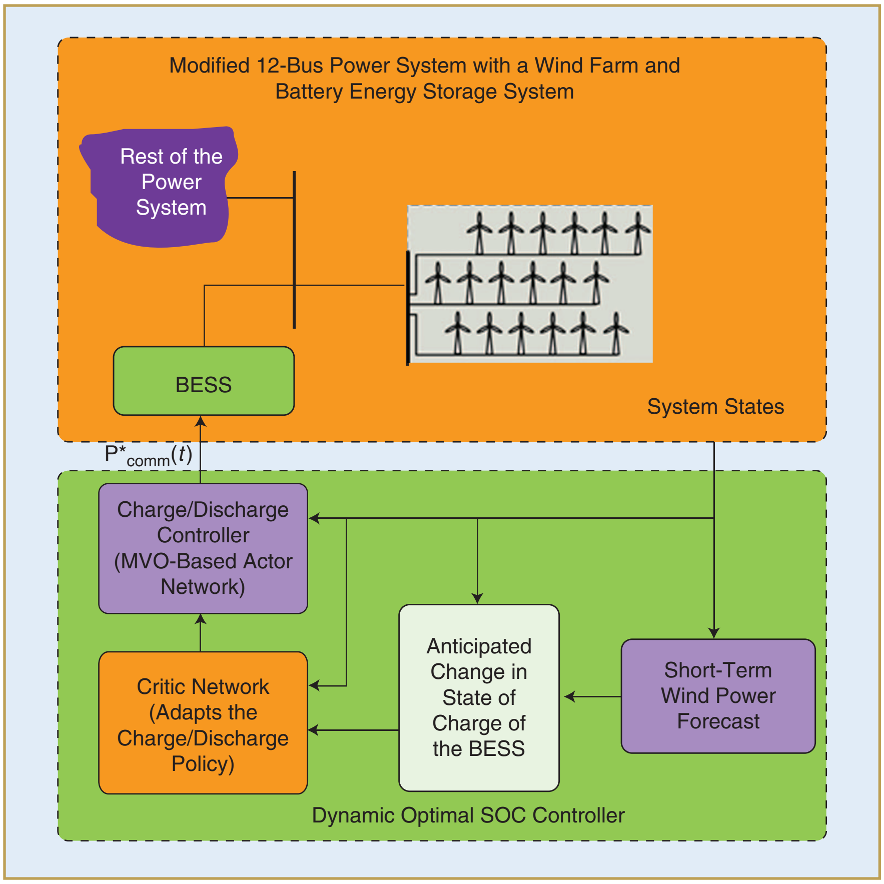

figure 10. A dynamic optimal BESS charge-discharge power command ($P^*_{\mathrm{comm}}(t)$) controller.

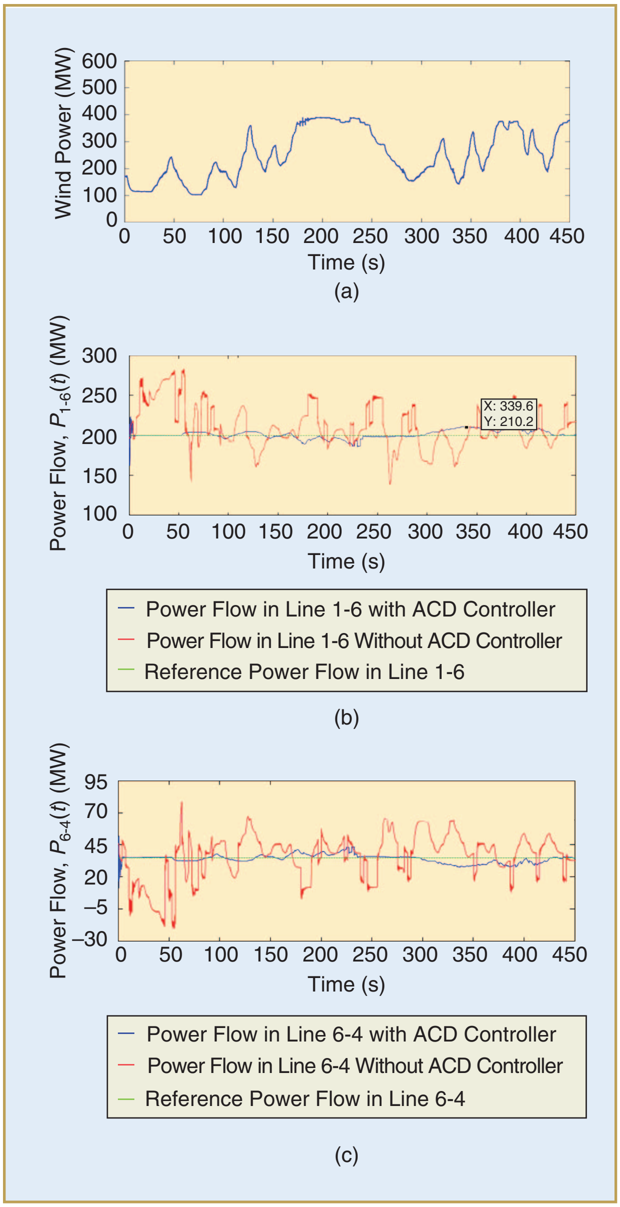

figure 11. (a) Wind power variations over a few minutes. b) Comparison of power flow in transmission line 1-6 with and without ACD controller. (c) Comparison of power flow in transmission line 6-4 with and without ACD controller.

command $P^*_{comm}(t)$. The MVO algorithm is a new, population-based stochastic optimization technique. The MVO algorithm finds the near-optimal solution and is simple to implement. The anticipated SOC deviation of the BESS is obtained using its ampere-hour rating and the forecast wind power over the next several seconds or minutes.

The active power flow fluctuations in transmission lines 1-6 and 6-4 caused by the variations in wind power over a few minutes and shown in Figure 11(a) are plotted in Figure 11(b) and 11(c), respectively. Without an ACD controller, significant power fluctuations occur in the lines, which may result in stability issues and penalties that cause the wind farm to lose revenue. The ACD controller reduces the fluctuations in the transmission lines from the reference line power flow values and, hence, minimizes the deviation penalty charged to the wind power provider. The results presented here use five steps of prediction, a total of 25 s, where each step is five seconds ahead.

Conclusions

Short-term wind power prediction on the order of seconds, minutes, and a few hours and its application in control centers becomes critical for the real-time operation of the electricity supply system as more and more wind power penetrates into it. The value of short-term wind power forecasting is high considering the reduction in power losses it offers, as is maximizing the security and stability of the power system, especially when stochastic security-constrained optimal power flow is far from reaching control centers in the near future. Even more attractive to wind power providers is that short-term wind power forecast–based system applications in control centers can result in the maximization of revenue by minimizing penalties.

For Further Reading

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