Spatial Correlation Based Adaptive Control of Wind Turbines for Improved System Frequency

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***Abstract*- This paper is focused on the problem of electrical frequency stabilization in microgrids and small scale power systems with high penetration of wind power. Higher quality of system frequency is ensured by using adaptive controllers on wind turbines. The existence of spatial correlation between wind speeds at different locations in the grid is deployed to design an adaptation mechanism for turbine controllers. Spatial correlation coefficients are calculated for each pair of wind turbines by using measurements or estimates of wind speed. These coefficients are then used to adjust the gains of the controllers at each wind turbine. The controllers are initially designed as decentralized and only the computation of spatial correlation is performed in cooperation between turbines.**

Keywords—Wind turbine, frequency control, spatial correlation

I. Motivation

PENETRATION of wind power in electricity grids has increased significantly over the past decade. Unpredictable and intermittent nature of wind considerably influences the quality of grid frequency [1-3] necessitating reliable and effective regulation and stabilization services more than ever. If controlled poorly, frequency variations could lead to reduced power quality, or in worse case, instability and blackouts [4-6]. The impact of renewables on the system frequency is further amplified in the relatively low inertia systems, such as microgrids.

In order to keep grid frequency stable, production of electrical energy has to balance demand closely and instantaneously. Inevitable mismatch from anticipated values of generation and consumption is handled by frequency regulation. In conventional power grids, which are predominantly equipped with synchronous generators, regulation of frequency is performed using speed governors [7]. In microgrids on the other hand, considerable contribution to the total generation profile comes from resources based on inherently different energy conversion processes, e.g. photovoltaics and induction wind turbines. As such generation profile significantly differs from the one of the traditional power systems, new regulation and stabilization solutions are needed to achieve satisfying power quality and maintain high system efficiency. In this paper, we focus on the problem of frequency stabilization in microgrids and small scale power systems with high penetration of wind power.

Frequency stabilization using wind turbines has been extensively discussed in literature. Some approaches for frequency support include pitch angle control [8-9], use of kinetic energy stored in rotating masses of wind turbines [9-10] and combination of wind turbines and fuel cells [11]. Our approach extends on the work on designing primary frequency control which adjusts pitch angle of the rotor blades. We propose an adaptive mechanism to retune controllers on wind turbines in response to the change in wind patterns.

In particular, we exploit the existence of spatial correlation between wind speeds at locations of different turbines in a microgrid to adjust controllers. It was shown in [12-13] that spatial correlation of wind speed exists across relatively small geographical regions, such as those of a microgrid. As denoted therein, the strength of spatial correlation varies across different frequency components and depends on factors such as wind direction and season. Spatial correlation information has already been used to improve wind power forecast [14-15] and to obtain more accurate economic dispatch results [16]. Although results presented in this paper are valid for a small scale system, the same rationale can be used when designing controllers across smaller geographical regions in a large scale system.

II. Problem Description and Proposed Approach

Power output of wind generators can change significantly due to the unpredictable wind gusts. Consequently, higher deviations from expected wind speed could lead to emerging transient behavior of the grid dynamics. Although transient analysis is usually concerned with split-second time scale phenomena, we focus our attention on dynamically slower deviations of the electrical grid frequency. The influence of wind power on dynamics of grid frequency is intensified further if the deviations of wind speed at locations of different turbines are correlated.

To illustrate this interdependence, we look at the behavior of the grid frequency of the IEEE 14 bus system with three wind turbines in response to uncorrelated and correlated wind sequences given in Fig. 1. In order to unambiguously show the effect of correlation, we use the same sequence of white noise to generate the correlated and uncorrelated wind sequences. As claimed earlier and as shown in Fig. 2, higher wind speed correlation results in larger deviations of grid frequency. This observation is used to propose an adaptation mechanism for wind turbine controllers.

A wind turbine controller is designed as a linear quadratic regulator (LQR) with adaptation mechanism based on spatial correlation. As the physical model of wind turbine is nonlinear, and controllers of the LQR type are designed for linear state space models, linear wind turbine model is derived around working point of interest.

Coefficients of the standard LQR controller are modified based on values of spatial correlation between wind speeds. Such improved controller uses less control effort when spatial correlation between wind speeds is low and system frequency is less disturbed, and more control

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effort when spatial correlation is high and system frequency is highly affected. This paper shows that the proposed controller significantly improves system frequency response while limiting control effort of the pitch angle actuators.

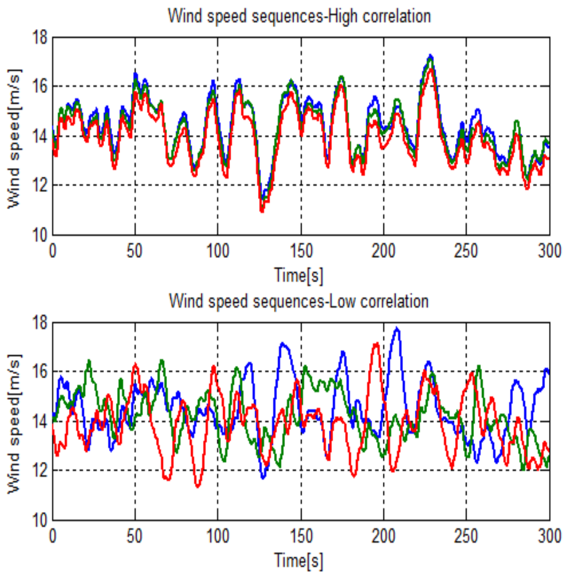

Fig 1. Wind speed sequences

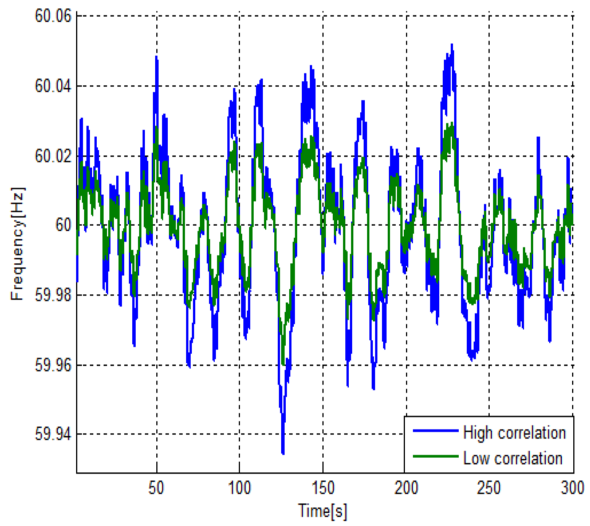

Fig 2. System frequency deviations

In this paper, the LQR controllers are designed and implemented for each individual wind turbine as decentralized, assuming infinite bus grid equivalent. Only the computation of pairwise spatial correlation coefficients is performed in a coordinated manner.

The effects of spatial correlation of wind speeds on the system frequency and the improvement obtained by our controller are shown in a simulation of a medium size microgrid. As a microgrid example, we use standard IEEE 14 bus system.

The rest of the paper is organized as follows. In Section III, spatial correlation is introduced. The linear state space model of wind turbine is derived in Section IV. Controllers are described in Section V, while simulations and results are presented in Section VI. Finally, Section VII summarizes concepts and results presented in the previous sections.

III. Spatial Correlation

Spatial correlation refers to similar readings of nearby wind speed sensors [17]. Since wind speed at certain location behaves as a stochastic process, a good way to determine the level of similarity between two wind speeds is by computing their cross correlation function [18].

According to [19], for short time intervals, wind speed $\bar{v}(t)$ is modeled as a sum of constant mean value v_0 and stochastic deviation from the mean value $v(t)$:

$$\bar{v}(t) = v_0 + v(t) \tag{1}$$

We model deviation of wind speed $v(t)$ between two consecutive adaptations as a zero mean, wide sense stationary process. If we denote with $v_x(t)$ and $v_y(t)$ deviations of wind speed from the mean value at locations x and y, cross and auto correlation functions of these signals are defined by:

$$r_{xy}(\tau) = E\{v_x(t)v_y(t+\tau)\} \tag{2}$$

$$r_{xx}(\tau) = E\{v_x(t)v_x(t+\tau)\} \tag{3}$$

Cross and auto correlation function measure resemblance between signals in the time domain. Since our goal is to calculate spatial correlation, i.e. correlation between wind speeds at different locations at the same time instance, value of cross correlation between two wind speeds $r_{xy}(0)$ is computed.

If the measurements of wind speeds are collected with sampling period T, values of cross and auto correlation function $r_{xy}(0)$ and $r_{xx}(0)$ can be estimated in the following way:

$$\hat{r}_{xy}(0) = \frac{1}{N_s}\sum_{i=1}^{N_s} \tilde{v}_x(iT)\tilde{v}_y(iT) \tag{4}$$

$$\hat{r}_{xx}(0) = \frac{1}{N_s}\sum_{i=1}^{N_s} \tilde{v}_x(iT)\tilde{v}_x(iT) \tag{5}$$

where N_s is a total number of collected measurements. Estimates of wind speed could also be used for this purpose.

Value $\hat{r}_{xy}(0)$ might be similar when deviations of wind speed are higher and less correlated and when deviations of wind speed are lower and more correlated. In order to distinguish between these two cases, instead of $\hat{r}_{xy}(0)$, we use correlation coefficient $\hat{\rho}_{xy}$ (CC) given in Equation (6). The value of CC is always between -1 and 1. We only look at the positive values of this coefficient. A value close to 1 indicates strong resemblance between signals, while a value close to zero means that such resemblance is indistinguishable by using CC. In Section V, we show how CC can be used to enhance controllers on wind turbines.

$$\hat{\rho}_{xy} = \frac{\hat{r}_{xy}(0)}{\sqrt{\hat{r}_{xx}(0)\hat{r}_{yy}(0)}} \tag{6}$$

IV. State Space Dynamic Model of Horizontal Axis Wind Turbine With Doubly Fed Induction Generator

Linear quadratic regulator is used in this paper as a controller of wind turbines. In order to implement an optimal controller, a linear state space model is needed and derived in this section.

Modelling of wind turbines [20-22] and wind farms [19] has been heavily discussed in literature. In this paper we consider horizontal axis wind turbines with doubly fed induction generator (DFIG). The model for such turbine is described in detail in [22].

For the purpose of this paper, the model from [22] is adopted and modified. All the variables are scaled to per unit system and stator resistance is neglected for the sake of simplicity.

Stator dynamics of an induction generator is much faster than its rotor dynamics. Therefore, it is common to define the stator circuit by a pair of algebraic equations:

$$V_{qs} = -X_s' I_{ds} + E_{qr} \quad (7)$$

$$V_{ds} = X_s' I_{qs} + E_{dr} \quad (8)$$

The rotor circuit is defined by two first order differential equations:

$$T_0 \dot{E}_{qr} = -\left(E_{qr} + (X_s - X_s') I_{ds}\right) + T_0 \left(\omega_s \frac{X_m}{X_r} V_{dr} - \omega_s(\omega_{sys} - \omega_r) E_{dr}\right) \quad (9)$$

$$T_0 \dot{E}_{dr} = -\left(E_{dr} - (X_s - X_s') I_{qs}\right) + T_0 \left(-\omega_s \frac{X_m}{X_r} V_{qr} + \omega_s(\omega_{sys} - \omega_r) E_{qr}\right) \quad (10)$$

where ω_s is the base frequency equal to 120π, and ω_{sys} is the observed system frequency in p.u.

Differential equation describing mechanical rotor speed is given by:

$$2H\dot{\omega}_r = T_m(\theta, v_{wind}, \omega_r) - E_{dr} I_{ds} - E_{qr} I_{qs} \quad (11)$$

Torque T_m is a nonlinear function of pitch angle θ, wind speed v_{wind} and electrical rotor speed ω_r defined by following three nonlinear equations [22]:

$$T_m(\theta, v_{wind}, \omega_r) = \frac{\rho \pi R^2 \omega_b}{2 S_b \omega_r} C_p(\lambda, \theta) v_{wind}^3 \quad (13)$$

$$C_p(\lambda_i, \theta) = 0.22\left(\frac{116}{\lambda_i} - 0.4\theta - 5\right) e^{-\frac{12.5}{\lambda_i}} \quad (14)$$

$$\lambda_i = \left(\frac{1}{\lambda + 0.08\theta} - \frac{0.035}{1 + \theta^3}\right)^{-1} \quad (15)$$

The states of the wind turbine model from Equations (9-11) are direct and quadrature component of the voltage behind transient reactance, E_{qr} and E_{dr}, and electrical rotor speed ω_r while pitch angle θ is considered as the control signal u (17). Linear model of the wind turbine is given in (16) where the system matrix A and the input matrix B are given by (18) and (19). Subscript zero in these equations marks the equilibrium value of the state and input variables.

$$\dot{x}(t) = Ax(t) + Bu(t) \quad (16)$$

$$x(t) = \begin{bmatrix} E_{qr}(t) \\ E_{dr}(t) \\ \omega_r(t) \end{bmatrix} \quad u(t) = \theta(t) \quad (17)$$

Linearization of this model is performed assuming that the wind turbine is connected to an infinite bus. Such assumption is commonly made in practice when parameters of the grid are unknown. Therefore, stator voltages V_{qs}, V_{ds} and system frequency ω_{sys} are taken as constants.

$$A = \begin{bmatrix} \frac{-X_s}{T_0 X_s'} & \omega_s(\omega_{r0} - \omega_{sys0}) & \omega_s E_{dr0} \\ \omega_s(\omega_{sys0} - \omega_{r0}) & \frac{-X_s}{T_0 X_s'} & -\omega_s E_{qr0} \\ \frac{-V_{ds0}}{2H X_s'} & \frac{V_{qs0}}{2H X_s'} & \frac{1}{2H}\frac{dT_{m0}}{d\omega_r} \end{bmatrix} \quad (18)$$

$$B = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{2H}\frac{dT_{m0}}{d\theta} \end{bmatrix} \quad (19)$$

V. Adaptive Control Design

A linear quadratic regulator with an adaptation mechanism based on spatial correlation is used for control of wind turbines. Before we explain how adaptation is done, we introduce some basic terms concerning LQR which are used afterwards. More about LQR can be found in variety of textbooks such as [23].

A. Linear quadratic regulator

Classical LQR is an optimal controller for linear state space model (16). The goal of the controller is to minimize deviation of states with a minimal control effort. The cost function is defined by:

$$J = \int_0^{+\infty} \left(x(t)^T Q x(t) + u(t)^T R u(t)\right) dt \quad (20)$$

where weight matrices Q and R are positive definite. Solution which minimizes this cost function is given by:

$$u(t) = -Kx(t) \quad (21)$$

where K is obtained from the solution of algebraic Riccati equation.

The role of matrices Q and R is to determine the nature of control signal. If $Q >> R$, emphasize is given to keeping states of the system tightly controlled. This formulation yields large and fast control signals because of the small weight given to control effort. When $Q << R$, control effort is penalized yielding lower and slower control signal and larger deviations of the states from the equilibrium.

The goal of the controller is to keep electrical frequency of the grid between certain bounds. In order to reduce changes of system frequency, controller should keep states of wind turbine close to the nominal value resulting in reduced fluctuations of power output. A trivial solution is the one for which $Q >> R$.

Such solution results in a high gain control. Large and fast changes in values of the control signal reduce life cycle of the actuator equipment. Therefore, it is critical to keep control signals as low as possible while having satisfying system frequency response.

To that end, we propose adaptation of control gain matrix K based on values of spatial correlation between wind speeds.

B. Adaptation mechanism

Adaptation mechanism should ensure less control effort for low values of spatial correlation, and more control effort for high values of spatial correlation.

Adaptation is done on every T_s minutes. Period T_s should be large enough so that values of CC-s are accurately estimated, and small enough so that assumption about wide sense stationarity holds. Between two consecutive adaptations, the level of spatial correlation is computed by estimating CC-s using (6) for each pair of sequences of wind speeds.

Matrix R is modified using spatial correlation while matrix Q is kept constant. In the case of low spatial correlation between wind speeds, system frequency deviations are small and matrix R is kept near its nominal value R_{nom}. R_{nom} is chosen to obtain satisfying dynamic performance of a controlled stand-alone wind turbine without information about spatial correlation. In the case of high spatial correlation, matrix R is modified towards R_{min} so that more control effort is used to suppress wind gusts. Matrix R_{min} is chosen to obtain maximal control effort of a pitch angle controller.

In the case that system consists of N wind turbines, matrix R of i-th turbine is adjusted using CC-s between *i-th* wind turbine and all other wind turbines in the system as:

$$R_i = f_i(\hat{\rho}_{i1}, \hat{\rho}_{i2,} \dots, \hat{\rho}_{iN}) R_{inom} \tag{22}$$

where f_i is a scaling function that takes higher values when correlation is low, and lower values when correlation is high. In order to show the proof of concept, we choose a scalable power law function for f_i as:

$$f_i(\hat{\rho}_i) = a_i + (1 - a_i)(1 - \hat{\rho}_i^{\ \gamma}) \tag{23}$$

where

$$\hat{\rho}_i = \frac{\sum_{j=1}^{N} \hat{\rho}_{ij} - \hat{\rho}_{ii}}{N - 1} \tag{24}$$

Coefficient a_i is chosen so that the following equation holds

$$a_i R_{inom} = R_{imin} \tag{25}$$

Real coefficient γ is used to adjust the shape of function $f_i(\hat{\rho}_i)$.

In the next section we show results obtained by using the aforementioned adaptation principle for a 14 bus system with three wind turbines.

VI. Simulation Results

The IEEE 14 bus system is chosen as a test example of a microgrid. Generators at buses 1 and 2 are kept as synchronous generators while generators at buses 3, 6 and 8 are replaced by three wind turbines as shown in Fig. 3.

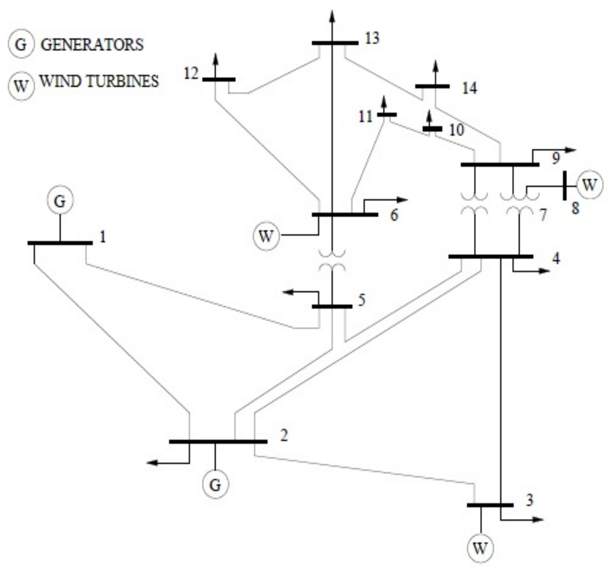

Fig 3. IEEE 14 bus system

Generators 1 and 2 are equipped with standard IEEE type 1 exciters whose parameters can be found in [24]. Additionally, generator 1 is equipped with a governor whose purpose is to keep the system frequency at its reference value of 60Hz.

The nominal power injections are chosen to have 44.3 % of total generation coming from wind power plants. Amounts of power produced by different generators in the equilibrium are given in Table I. Simulations are conducted for the values of correlation coefficients between wind speeds given in Table II. The results presented in this section are obtained for γ=1 unless stated otherwise.

In order to test controllers for different values of spatial correlation and in the absence of wind speed measurements, wind speed time sequences are generated by filtering previously colored white Gaussian noise. The white noise is colored using correlation coefficients from Table II. Resulting wind sequences are shown in Fig. 4.

The goal of the controller is to keep frequency in the interval [59.08, 60.02] Hz. Frequency response of the system without wind turbine controllers is shown in Fig. 5 to illustrate the base case. This figure shows that frequency deviations are reaching values above 60.04 Hz and bellow 59.96 Hz. After implementing controllers on wind turbines, frequency deviations have considerably decreased as it can be seen in Fig. 6. The goal of keeping frequency in the interval [59.08, 60.02] Hz is achieved.

TABLE I
Overall Power Production of Each Generator

Generator type	Bus	Percent of overall power [%]	Power [MW]
Synchronous Generator 1	1	30.7	0.64
Synchronous Generator 2	2	25.0	0.52
Wind turbine1	3	15.4	0.32
Wind turbine2	6	14.9	0.31
Wind turbine3	8	14.0	0.29

TABLE II
Correlation Coefficients

CC	Case				
	1	2	3	4	5
$\hat{\rho}_{12}$	0.002	0.33	0.66	0.99	0.66
$\hat{\rho}_{13}$	0.002	0.33	0.66	0.99	0.002
$\hat{\rho}_{23}$	0.002	0.33	0.66	0.99	0.002

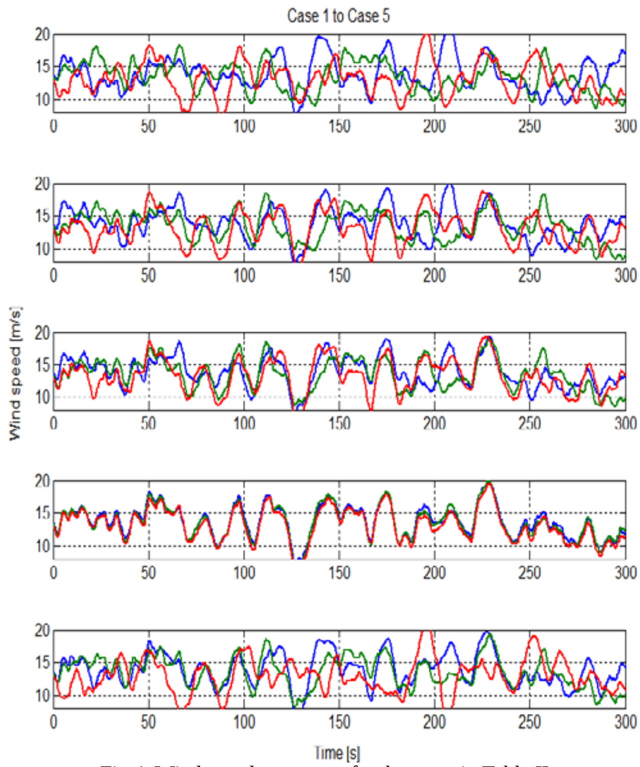

Fig 4. Wind speed sequences for the cases in Table II

Control effort is measured by the scaled integral given in (26), where u_0 is nominal value of the pitch angle. Fig. 7 to Fig. 9 graphically show control effort values for all three turbines as the function of time. All three controllers exhibit higher effort when the wind sequences are correlated.

$$I_u = \frac{1}{I_{max}} \int_0^t |u(t) - u_0|\, dt \tag{26}$$

Next, we compare results for different values of coefficient γ. For values of γ smaller than 1, frequency deviations reduce, while control effort increases. In order to reduce control effort, adaptation should be done with coefficient γ higher than 1. To illustrate this point, Fig. 10 and Fig. 11. compare frequency deviations and control efforts for different values of γ.

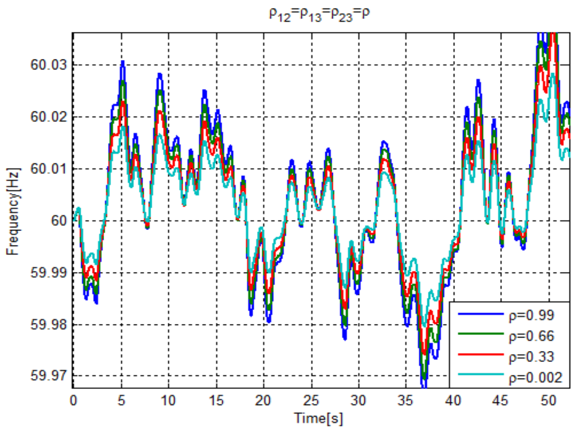

Fig. 5. Grid frequency without controllers

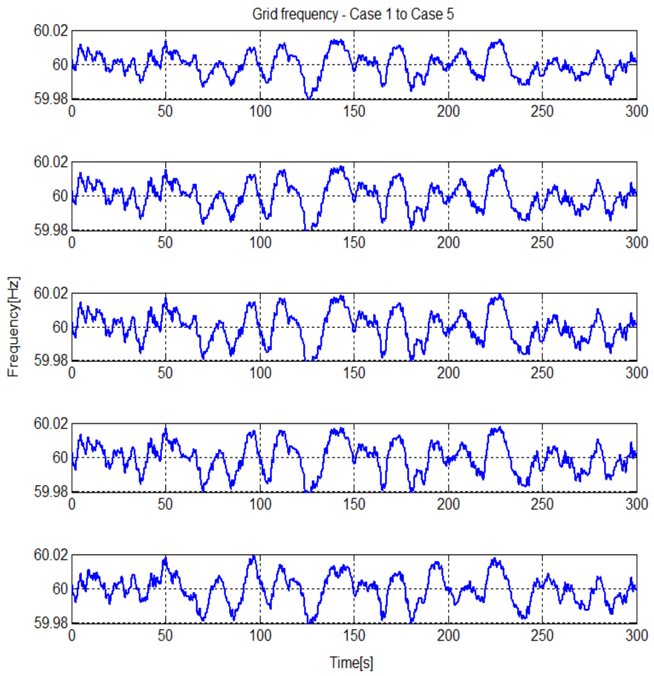

Fig. 6. Grid frequency with pitch control

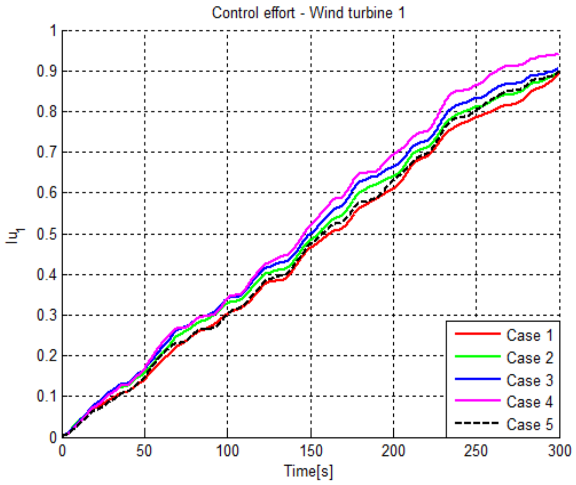

Fig. 7. Control effort – Wind turbine 1

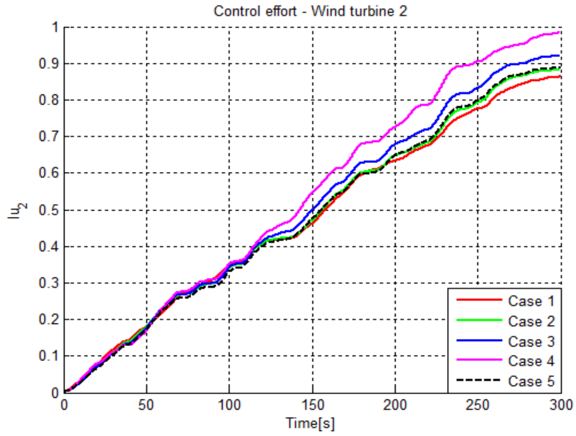

Fig. 8. Control effort – Wind turbine 2

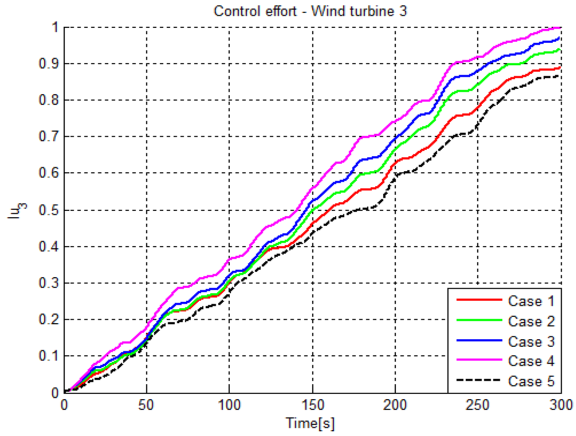

Fig. 9. Control effort - Wind turbine 3

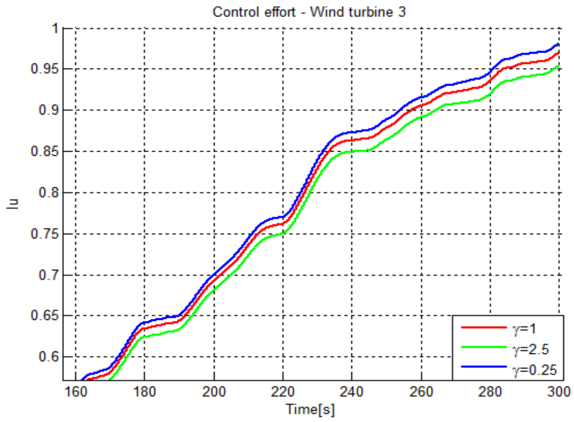

Fig. 10. Control effort for different values of γ - Wind turbine 3

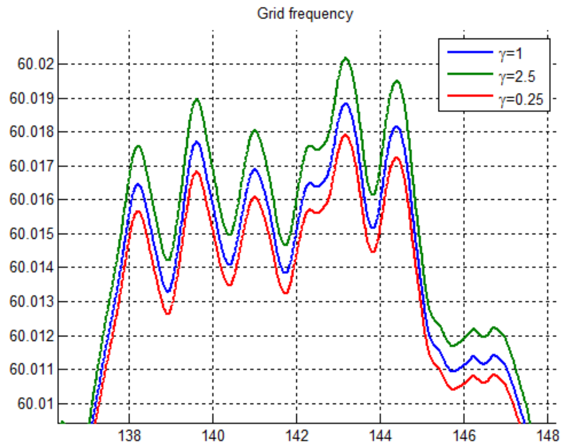

Fig. 11. Grid frequency for different values of γ

CONCLUSION

In this paper, spatial correlation between wind speeds is used to adjust controllers of wind turbines. We proposed an approach to integrate spatial correlation value with the LQR controller. Effects of spatial correlation among wind speeds and improvements obtained by our controller were simulated using IEEE 14 bus system with high percentage of power production coming from wind turbines. Simulation results showed that the proposed controller significantly improves system frequency response while limiting control effort of pitch angle actuators. Future work will consider integration of spatial correlation with other types of controllers, such as PID.

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