Research Article
LS-SVM Based AGC of an Asynchronous Power System with Dynamic Participation from DFIG Based Wind Turbines

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Abstract: Modern power systems are large and interconnected with growing trends to integrate wind energy to the power system and meet the ever rising energy demand in an economical manner. The penetration of wind energy has motivated power engineers and researchers to investigate the dynamic participation of Doubly Fed Induction Generators (DFIG) based wind turbines in Automatic Generation Control (AGC) services. However, with dynamic participation of DFIG, the AGC problem becomes more complex and under these conditions classical AGC are not suitable. Therefore, a new non-linear Least Squares Support Vector Machines (LS-SVM) based regulator for solution of AGC problem is proposed in this study. The proposed AGC regulator is trained for a wide range of operating conditions and load changes using an off-line data set generated from the robust control technique. A two-area power system connected via parallel AC/DC tie-lines with DFIG based wind turbines in each area is considered to demonstrate the effectiveness of the proposed AGC regulator and compared with results obtained using Multi-Layer Perceptron (MLP) neural networks and conventional PI regulators under various operating conditions and load changes.

Keywords: Automatic generation control, doubly fed induction generator, RBF kernel, support vector machines

INTRODUCTION

There is a worldwide trend toward cheaper and cleaner sources of the energy in the generation mix to meet ever rising energy demand in an economical manner. Among various sources of energy, wind is one of the most important and promising source of renewable energy. With increasing wind energy penetrations to the modern power system, it is essential to explore the possibility of wind turbines such as DFIGs in frequency control besides conventional generators. Considering this aspect, few studies have been presented by Keung *et al.* (2009) and Morren *et al.* (2006). AGC is one of the most important issues in electric power system design and operation. The main objective of AGC is to maintain the nominal frequency and to keep tie-line power close to the scheduled values by adjusting the MW outputs the AGC generators so as to accommodate the change in load demands. Extensive researches have been made in the design and development of AGC using different control techniques. The power systems are highly non-linear systems and contain different kinds of uncertainties due to changes in system parameters, error in modeling and load variations. Further, operating points of system change very much randomly during daily cycle and therefore, fixed controllers based on classical theory is

unsuitable for AGC problem as presented by Cavin *et al.* (1971). Many advanced control techniques have been developed for AGC problem of modern power systems and some of them are presented by Demiroren and Yesil (2004) and Mohamed *et al.* (2011). The robust control techniques for solution of AGC problem have been presented by some of the authors i.e., Wang *et al.* (1993) and Shayeghi and Shayanfar (2002). However, these controllers are linear and fixed therefore, cannot take into the large parametric variations and disturbances due to diverse operating conditions of practical power systems.

In recent years applications of ANN have been widely explored to design AGC regulators as reported by Ahamed *et al.* (2006). The ANN overcomes the drawbacks of insufficient data availability in real time and improves power system dynamic performance over a wide range of operating conditions. The success of ANN based regulators depends on the type, structure and training algorithm besides reliable training data. Support Vector Machines (SVMs) is another class of machine learning techniques which has excellent function approximation and classification capabilities as reported by Vapnik (1998). The SVM has better generalization capability than the conventional neural networks. Basically this network uses a kernel to map the data in the input space to a high dimensional feature

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space in which the problem becomes linearly separable. has high precision and fast convergence as compared to traditional SVMs as reported by Boolchandani *et al.* (2011). In the view of above discussion, a new non-linear LS-SVM regulator has been designed for solution of AGC problem of an interconnected power system. The proposed AGC regulator is trained for a wide range

LS-SVM is an advancement of traditional SVMs and of operating conditions and load changes using an off-line data set generated from the robust control technique. The motivation of using robust technique for training of the proposed AGC regulator is to consider the large parametric uncertainties and modeling error into account. To improve the dynamic performance of
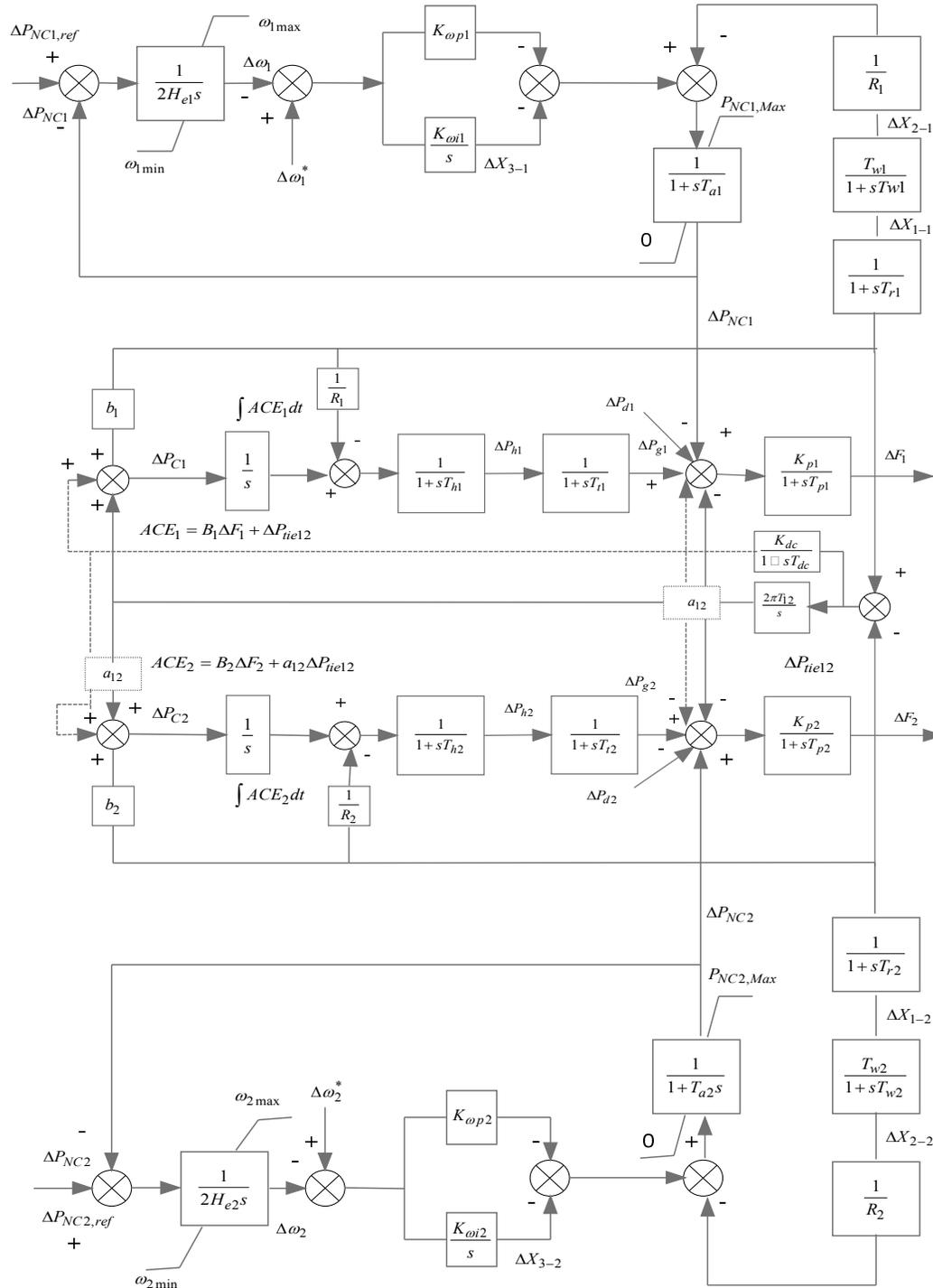
Fig. 1: Transfer function model of a two-area interconnected power system with DFIG based wind turbines considering parallel AC/DC tie-lines

the power system, the LS-SVM based AGC regulator has been reconstructed with applying the robust control technique to power system in the different operating points under various load disturbances by using the learning capability of LS-SVM network. This newly developed regulator combines the advantages of the LS-SVM and robust control techniques to achieve the desired level of robust performance for all uncertainties, load disturbance and wide operating conditions of the real world complex power systems. The designed LS-SVM based AGC regulators are tested on a two-area power system connected via parallel AC/DC tie-lines with dynamic participation from DFIG based wind turbines in each area. A performance comparison between LS-SVM, MLP NNs and conventional PI based AGC regulators are carried out to show the superiority of the proposed control strategy for different cases of the plant parameter changes under various area load disturbances.

METHODOLOGY

Power system model under investigation: The study has been carried out considering the following power system models.

Power system model-1: The Two-Area Interconnected Power System (TAIPS) is consisting of identical thermal power plants with non-reheat turbines interconnected via AC transmission line. The governor dead-band non-linearity is also considered in the dynamic model of the power system.

Power system model-2: The TAIPS is consisting of identical plants with non-reheat thermal turbines and DFIG based wind turbines in each area. The parallel AC/DC tie-lines are used as an area interconnection between two control areas. The governor dead-band effects are also considered in the modeling of the power system. The transfer function model of the power system is shown in Fig. 1.

DFIG modeling: The development of transfer function model of DFIG based wind turbines when participating in AGC in the wake of load disturbance is described in (Morren *et al.*, 2006).

Dynamical model of the system under investigation: The state variables and control inputs of the LS-SVM based AGC regulators are as follows.

Power system model-1:

$$[X_1]^T = [\Delta F_1\ \Delta P_{h1}\ \Delta F_2\ \Delta P_{h2}\ \Delta P_{tie12}\ \Delta P_{d1}\ \Delta P_{d2}],$$

$$[u_1] = \begin{bmatrix} \Delta P_{c1} \\ \Delta P_{c2} \end{bmatrix}.$$

Table 1: Parametric uncertainties of the system

	Lower bound parameters	Nominal parameters	Upper bound parameters
$1/T_{Pi}$	0.02500	0.05000	0.0750
K_{Pi}/T_{Pi}	4.80000	6	7.2000
$1/T_{ti}$	1.60000	2	2.4000
$1/R_iT_{hi}$	0.83330	1.04170	1.2500
$1/T_{hi}$	2	2.50000	3.0000
T_{12}	0.27250	0.54500	0.8175
b_i	0.34000	0.42500	0.5100
$1/T_{ri}$	8	10	12
$1/T_{wi}$	0.13328	0.16660	0.1999
$1/T_{ai}$	4	5	6
$1/2H_{ei}$	0.11428	0.14285	0.1714

Power system model-2:

$$[X_2]^T = [\Delta F_1\ \Delta P_{h1}\ \Delta F_2\ \Delta P_{h2}\ \Delta P_{tie12}\ \Delta P_{dc}\ \Delta P_{d1}\ \Delta P_{d2}],$$

$$[u_2] = [u_1].$$

Design of robust controller: The design of robust controller is available in Wang *et al.* (1993). Table 1 shows the parametric uncertainties of the system with their nominal, lower bound and upper bound values respectively. The range of system parameter variations are obtained by simultaneously changing of T_P, T_{12} by 50% and all other parameters by 20% from their original values.

LS-SVM regulator design for AGC: The SVMs are the advanced class of NNs. SVMs is a class of supervised learning model with associated learning algorithm that analyzes data and recognizes patterns. It has excellent pattern recognition and function estimation capabilities. In LS-SVM, the training data are mapped from the input space into the higher dimensional feature space via kernel function in which the problem can be implemented in the linear form. There are many kinds of kernels that can be used, such as polynomial and Radial Basis Function (RBF) kernels. The least square loss function is used in LS-SVM to construct the optimization problem based on equality constraints. This function requires only the solution of linear equation set instead of long and computationally hard quadratic programming as in case of traditional SVMs.

The LS-SVM equation for function estimation can be written as (1) (Boolchandani *et al.*, 2011):

$$y(x) = \sum_{k=1}^{N} \alpha_k K(x, x_k) + b \tag{1}$$

where, α_k is the weigh factor, K (x, x$_k$) is the kernel mapping function between the training sample *x* and support vector x$_k$, *b* represent bias and *N* represent the total number of training samples. The architecture of LS-SVM network is shown in Fig. 2.
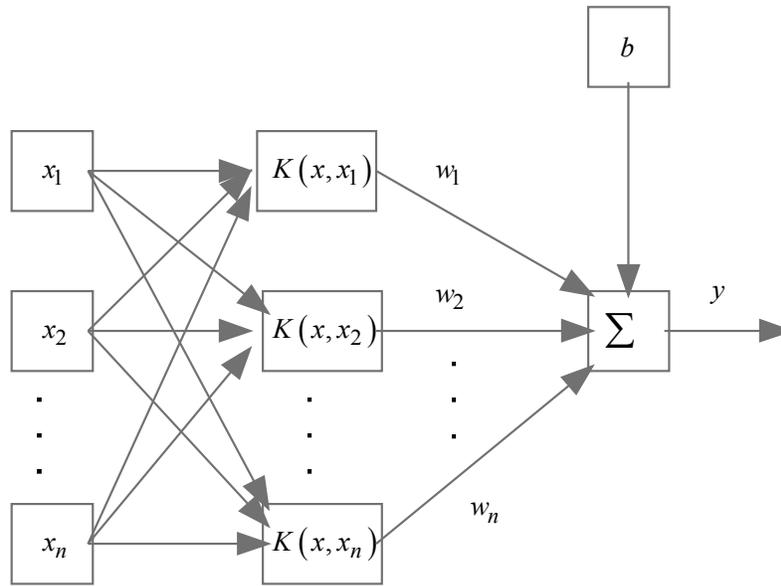
Fig. 2: The structure of LS-SVM network

The RBF kernel is used for SVMs and can be written as (2):

$$K(x, x_k) = \exp\left(-\frac{\|x - x_k\|^2}{2\sigma^2}\right) \qquad (2)$$

SIMULATION RESULTS AND DISCUSSION

In the present study, LS-SVM interfaced with standard MATLAB software is used for function estimation. During regression model generation, the LS-SVM accepts the training data set (i.e., 4500 samples) which is generated from the robust control strategy in which the uncertainties are directly introduced in the power system model and provides the values of vector α and bias b as stated in (1). These values can be use to estimate the function using (1). The LS-SVM was trained using RBF kernel and the kernel should satisfy the Mercer's condition which is necessary for the problem to be convex and provides unique and optimum solution. By proper selecting the two parameters, the kernel function variable σ and an adjustable constant γ, the desired level or the robust performance can be achieved. The parameter, γ determines the trade-off between the training error minimization and model complexity. On the other hand σ is kernel width parameter.

The LS-SVM based AGC regulators are trained from an off-line data set generated by designing and implementing the robust controller for power system model in different operating points with various load disturbances to achieve the desired level of robust performance by using the learning capability of LS-SVM network. A two-area power system with and without DFIG based wind turbines connected via parallel AC/DC tie-lines is considered to demonstrate the effectiveness of the proposed AGC regulator. Furthermore, the governor dead-band non-linearity is also considered in the power system models, so that the test system will be more close to the real power systems. The designed LS-SVM based AGC regulator is tested for nominal, upper bound and lower bound parameters under various area load disturbances and results are compared with that obtained using conventional PI and MLP based AGC regulators.

Case 1: We will test the dynamic performance of both the power system models with nominal parameters as given in Table 1 and apply load changes of $\Delta P_{d1} = 0.01$ p.u. MW in area-1. An investigation of time response plots of Fig. 3a and b reveal that the LS-SVM based AGC regulator is successful in providing the smooth settling of the system dynamic responses for both power system models. However, an incorporation of DFIG based wind turbines in a two-area power system with parallel AC/DC tie-lines offers fast and active power support proportional to frequency deviation. The dynamic responses are settling to zero steady state value within few seconds and peak of overshoot is of least magnitude as compared to results obtained without considering the dynamics of wind turbines and parallel AC/DC link in power system model.

Case 2: The performance of the designed AGC regulator is evaluated for power system model-2 by applying the lower bound parameters as given in Table 1 for both the areas with load changes of $\Delta P_{d1} = 0.02$ p.u. MW to area-1 and $\Delta P_{d2} = 0.005$ p.u. MW to area-2, respectively. An inspection of time
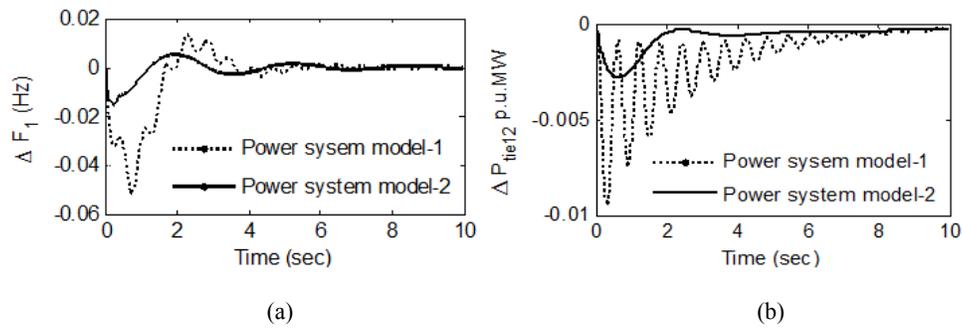
(a)

(b)

Fig. 3: Response of ΔF_1 (a) and ΔP_{tie12} (b) for case 1

(a)

(b)

Fig. 4: Response of ΔF_1 (a) and ΔP_{tie12} (b) for case 2

(a)

(b)
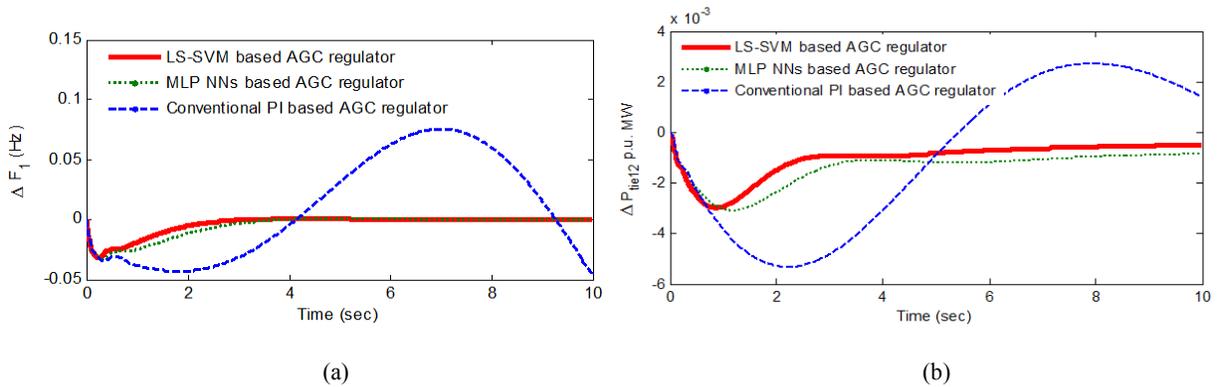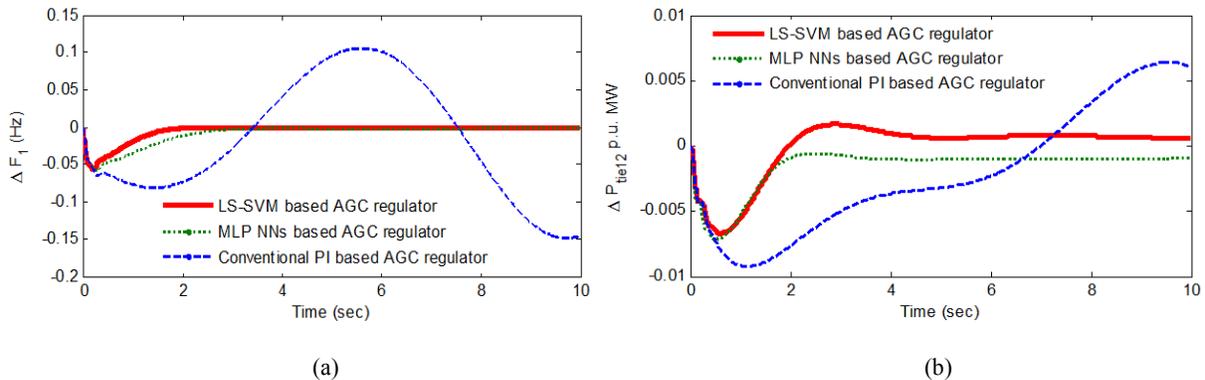
Fig. 5: Response of ΔF_1 (a) and ΔP_{tie12} (b) for case 3

response plots of Fig. 4a and b reveal that the proposed AGC regulator has better performance in terms of all response qualities as compared to MLP and conventional PI based AGC regulators.

Case 3: We choose the upper bound parameters from Table 1 and apply load changes of ΔP_{d1} = 0.03 p.u. MW to area-1 and ΔP_{d2} = 0.0193 p.u. MW to area-2 respectively. The dynamic performance of the proposed AGC regulators are evaluated for power system model-2 and the system dynamic responses are shown in Fig. 5a and b. The simulation results indicate that the proposed AGC regulator is superior to other AGC

regulators and quite robust for a wide range of operating conditions and area load disturbances.

CONCLUSION

In this study, a new non-linear LS-SVM based AGC regulator is proposed for two-area power system connected via parallel AC/DC tie-lines with dynamic participation from DFIG based wind turbines in each area. The governor dead-band effects are also considered in the power system models. The LS-SVM based AGC regulators are trained from the off-line data set generated using robust control technique for a wide

range of operating conditions and area load changes. The RBF kernel is used to train the LS-SVM network. One of the main advantages of the proposed AGC regulator is it doesn't required efficient training algorithm and no need to determine the hidden layer which is a series drawback of MLP NNs. By proper selecting the values of two parameters, the kernel function variable σ and an adjustable constant γ, the desired level of performance can be achieved and can be useful for real world complex power system.

An investigation of time response plots reveal that the proposed AGC regulator is exhibiting superior system dynamic performance when two-areas are connected via parallel AC/DC tie-lines with dynamic participation from DFIGs based wind turbines in each area as compared to those obtained without considering their dynamics in the power system model. Further, investigations reveal that the proposed AGC regulator is showing promising performance as compared to MLP and conventional PI based AGC regulators for a wide range of parametric uncertainties and area load disturbances occurring in the area of the power system.

NOMENCLATURE

a_{12} : Area size ratio coefficient
ACE_i : Area control error
B_i : Frequency bias constant
H_i : Per unit inertia constant
D_i : Load frequency constant
i : Subscript referring to area i ($i = 1, 2$)
K_{pi} : Power system gain
M_i : Effective rotary inertia
P_{ri} : Rated area power output
R_i : Speed regulation parameter
T_{12} : Synchronizing coefficient of AC tie-line
T_{hi} : Speed governor time constant of area i (sec)
T_{pi} : Power system time constant (sec)
T_{ti} : Turbine time constant (sec)
ΔF_i : Incremental change in frequency
ΔP_{Ci} : Incremental change in speed-changer position
ΔP_{di} : Incremental change in load demand
ΔP_{tie} : Incremental change in tie-line power
ΔP_{hi} : Incremental change in governor valve position of area i
$K_{\omega pi}$: DFIG proportional controller gain of area i
$K_{\omega ii}$: DFIG integral controller gain of area i
P_{mech} : Wind turbine mechanical output
T_{ai} : DFIG turbine time constant of area i
T_{ri} : Transducer time constant area i
T_{wi} : Washout filter time constant for DFIG area i
ω_i : Wind turbine speed of area i
$\omega_{i\,max}$: Wind turbine cut-out speed maximum of area i
$\omega_{i\,min}$: Wind turbine cut-out speed minimum of area i

ω_{mech} : Angular velocity of rotor rotation
$\omega_{m,\,meas}$: Wind turbine measured mechanical speed
ω_s : System frequency
ΔP^*_f : Incremental wind turbine power set point (reference) based on frequency
ΔP_{NCi} : Incremental DFIG active power output of area i
$\Delta P_{NCi,ref}$: Incremental Wind Turbine active Power reference of area i
ΔP^*_ω : Incremental Wind Turbine power set point (reference) based on speed change
$\Delta \omega_i$: Incremental wind turbine speed of area i
ΔX_{1-1} : Measured incremental frequency change for DFIG (after Transducer) area 1
ΔX_{1-2} : Measured incremental frequency change for DFIG (after Transducer) area 2
ΔX_{2-1} : Measured incremental frequency change (after wash out filter) for DFIG area 1
ΔX_{2-2} : Measured incremental frequency change (after wash out filter) for DFIG area 2
ΔX_{3-1} : Incremental DFIG active power based on mechanical speed change area 1
ΔX_{3-2} : Incremental DFIG active power based on mechanical speed change area 2
ΔP_{dci} : Incremental change in tie-line power through DC link
K_{dc} : Gain associated with DC link
T_{dc} : Time constant of DC link
H_{ei} : Wind turbine of inertia i
ΔP_{gi} : Incremental change in power generation

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