

LS-SVM based AGC of Power System with Dynamic Participation from DFIG based Wind Turbines

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Abstract

Modern power systems are large and complex with growing trends to integrate wind energy to the grid. The penetration of wind energy has motivated researchers to investigate the dynamic participation of wind generators in load frequency control besides conventional generators. This has necessitated relooking of the classical AGC problem in the new environment. Literature surveys shows that pattern recognition techniques such as ANNs have the potential to design non linear controller for better dynamic performance in the AGC system under wide range of operating conditions. The Support vector machine (SVM) 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 capability. In this paper, a least squares support vector machines (LS-SVM) based automatic generation control (AGC) regulators have been investigated for a two-area interconnected power system with dynamic participation of doubly fed induction generator (DFIG) based wind turbines. The RBF kernel is used for support vector machines. AC tie-line is used as an area interconnection between the control areas. The designed LS-SVM based AGC regulators are implemented and the system dynamic responses for various system states are obtained and compared with that obtained using multi-layer perceptron neural networks (MLP NNs) and conventional PI based AGC regulators for various cases of plant parameter changes under diverse operating conditions.

1 Introduction

In an interconnected power system, a sudden load change in any area causes the deviation of frequencies of all the areas and also in the tie-line powers. The function of AGC is to maintain desired megawatt output and the nominal frequency in an interconnected power system besides maintaining the net tie-line power exchange between control areas at predetermined values. Modern power systems are large and interconnected with increasing trends of wind power penetrations. However, with increasing wind power penetrations, the frequency of the power system will be more vulnerable to disturbances, as wind energy converters

generally do not participate in AGC services. Extensive researches have been made in the design and development of AGC using different control techniques. Further, power system is highly non-linear, complex and contains different kinds of uncertainties due to changes in system parameters, load variations and error in modelling. With increasing wind power penetrations, the power system becomes more complex and conventional controllers based on classical control theory are unsuitable for solution of AGC problem [1]. Several kinds of machines are used in wind energy conversion system, but variable speed generators such as DFIG are gaining momentum worldwide. Considering this aspect, some studies are available in the literature pertaining to wind generator participation along with conventional generators in AGC services [2-5]. A method based on inertial control, power reserve control and control through communication method is available in [2]. In [3], an additional inertial control loop with a suitable gain of 2H is introduced, which is sensitive to the frequency of the system and releases the kinetic energy from the DFIG to support system inertia. Primary frequency is controlled with DFIG by injecting the active power during frequency excursion. The capability of the DFIG in frequency control is exploited through the combinations of static converters and pitch control. The active power and rotor speed were adjusted according to the de loaded optimum power extraction curve in [4] to extract maximum power. In [5] the dynamic participation of the DFIG in frequency control is analyzed by a frequency control support function that responds to deviation in frequency and uses the kinetic energy of turbine blades to improve the system frequency. Different controllers based on advanced control techniques such as model predictive control, optimal control etc. [6-8] have been developed for AGC problem. The optimal AGC regulators design requires availability of all the state variables directly or through state reconstruction procedures. Further, it needs an exact state space model of the power system. Therefore, the design of these AGC regulators is quite impractical for use in real world power system. In [9] a robust fixed linear-feedback controller is designed, using the Riccati-equation approach for AGC of power system. The designed controller can ensure the stability of the overall system for all admissible uncertainties. However, this controller is linear and fixed therefore, cannot take into the large uncertainties and disturbances due to multivariable operating conditions and load changes in real time applications of power system operation and control. In recent years applications of ANN

have been explored to design AGC regulators [10-11]. The ANN overcomes the drawbacks of insufficient data availability in real time and improves the dynamic performance of the power system over a wide range of operating conditions. The success of these regulators depends on the type, structure and training algorithm besides reliable training data. Support Vector Machines (SVMs) are advanced class of machine learning techniques which has excellent function approximation and classification capabilities [12]. SVM has better generalization capability than conventional ANN. Basically this network uses a kernel to map the data in the input space to a high dimensional feature space in which the problem becomes linearly separable. LS-SVM is an advancement traditional SVMs and has high precision and fast convergence as compared to traditional SVMs [13].

In the view of above discussion, a new non-linear LS-SVM based AGC regulator is proposed for large interconnected and non-linear power system with dynamic participation of DFIG based wind turbines along with conventional generators. The proposed regulator can handle uncertainties due to changes in system parameters, error in modelling and load changes. The proposed AGC regulator is trained using an off-line data set consisting of wide range of operating conditions and area load changes generated by robust control technique. The motivation of using the robust control technique for training of the proposed AGC regulators is to consider modelling error and large parametric uncertainties into consideration. To improve the dynamic stability, the LS-SVM based AGC regulator has been reconstructed with applying the robust control technique to power system at different operating point under different load disturbances by using the learning capability of LS-SVM network. This newly developed AGC regulator combines the advantages of the robust control and LS-SVM technique to achieve the desired level of performance for all uncertainties, load disturbances and wide operating conditions and can be quite useful for real world complex power systems. The LS-SVM based AGC regulators have been investigated for a two-area power system with dynamic participation from DFIG and the results obtained are compared with that obtained using MLP NNs and conventional PI based AGC regulators in presence of governor dead band non-linearity for different cases of the plant parameter changes under various area load disturbances.

2 Power system model under investigation

It is a two-area interconnected power system consisting of identical plants with non-reheat thermal turbines and DFIG based wind turbines in each area. The transfer function model of the power system is shown in Figure 1. The structures of state, control and disturbance vectors are given as follows:

$$[X_1]^T = \begin{bmatrix} \int ACE_1 dt \Delta P_{h1} \Delta P_{g1} \Delta F_1 \Delta P_{tie12} \Delta X_{1-1} \Delta X_{2-1} \\ \Delta X_{3-1} \Delta P_{NC1} \Delta \omega_1 \int ACE_2 dt \Delta P_{h2} \Delta P_{g2} \Delta F_2 \\ \Delta X_{1-2} \Delta X_{2-2} \Delta X_{3-2} \Delta P_{NC2} \Delta \omega_2 \end{bmatrix},$$

$$[U_1] = \begin{bmatrix} \Delta P_{C1} \\ \Delta P_{C2} \end{bmatrix},$$

$$[P_{d1}] = \begin{bmatrix} \Delta P_{d1} \\ \Delta P_{d2} \end{bmatrix}.$$

2.1 Design of robust controller

Design of robust controller is available in [9]. However, 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 changing of T_P , T_{12} by 50% and all other parameters by 20% of their original values.

	Lower bound parameters	Nominal parameters	Upper bound parameters
$1/T_{Pi}$	0.025	0.05	0.075
K_{Pi}/T_{Pi}	4.8	6	7.2
$1/T_{ti}$	1.6	2	2.4
$1/R_i T_{hi}$	0.8333	1.0417	1.25
$1/T_{hi}$	2	2.5	3.0
T_{12}	0.2725	0.545	0.8175
b_i	0.34	0.425	0.51
$1/T_{ri}$	8	10	12
$1/T_{wi}$	0.13328	0.1666	0.1999
$1/T_{ai}$	4	5	6
$1/2H_{ei}$	0.11428	0.14285	0.1714

Table 1: Parametric uncertainties of the system

2.2 Design of LS-SVM based AGC regulators

Recently, computational intelligence systems and among them SVMs which in fact are model free dynamics has been used for approximation functions and mappings. The main features of SVMs are their ability to learn from samples and their ability to adapt themselves to the changes in the new environment and are very suitable for problems of real world complex power systems. SVMs are a class of supervised learning model with associated learning algorithm that analyzes data and recognizes patterns. It has excellent pattern recognition and function estimation capability. The salient feature of this technique is that they provide a model-free description of control systems and does not require the perfect model of the plant and are very suitable for control of highly non-linear plants that their accurate models are unknown or have uncertainty such as power system.

The problem of regression is the finding of the function which approximates the mapping from an input domain to the real number based on the training samples. In LS-SVM regression, the training data are mapping from the input space into the higher dimensional feature space via kernel function in which the problem can be implemented in the linear form. The LS-SVM uses a least square loss function to construct the optimization problem based on equality constraints. The least squares loss function requires only the solution of linear

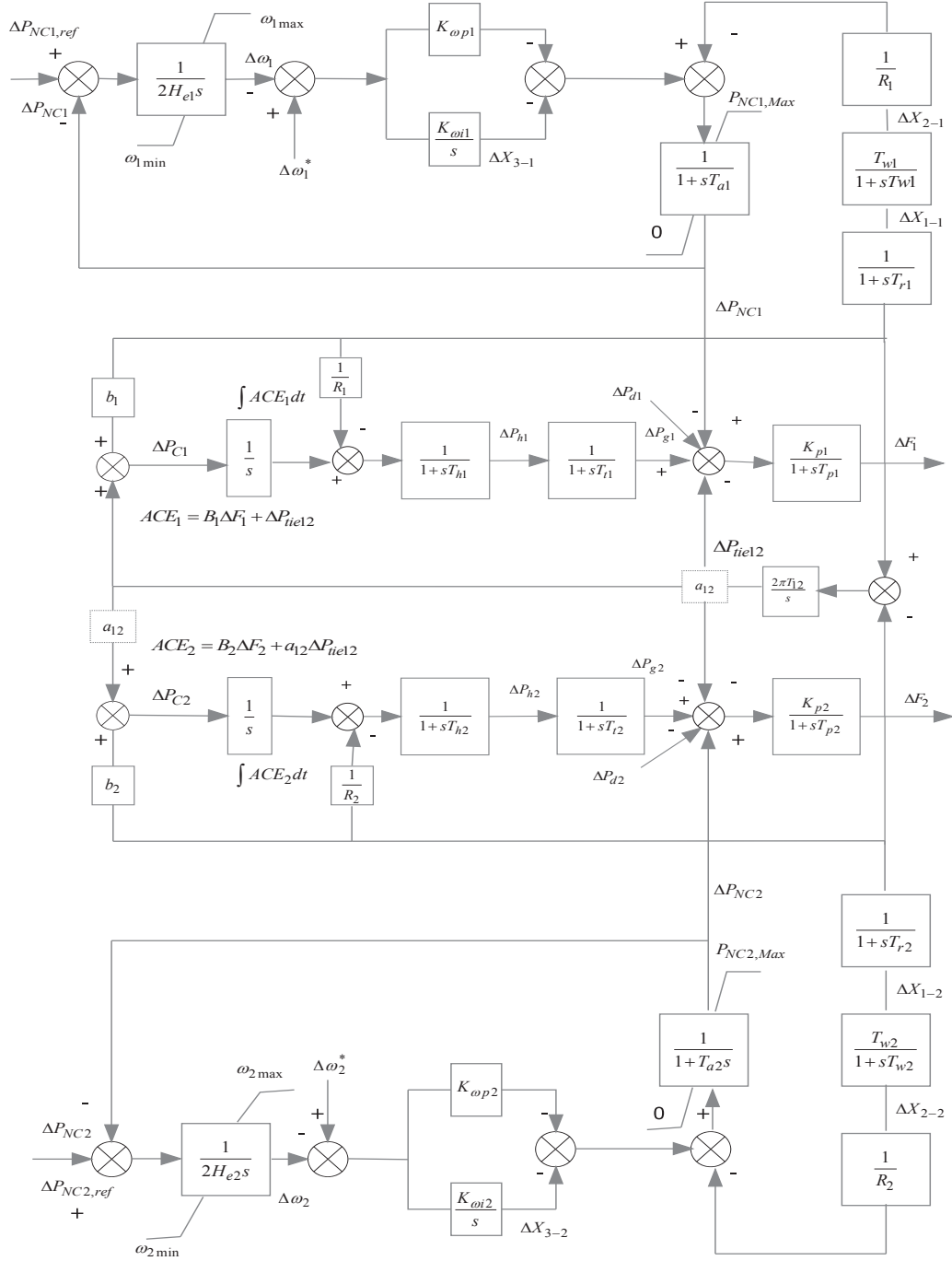


Figure 1: Transfer function model of a two-area interconnected power system with DFIG based wind turbines in each area

equation set instead of long and computationally hard quadratic programming as in case of original SVMs [13]. The LS-SVM equation for function estimation can be written as

$$y(x) = \sum_{k=1}^N \alpha_i K(x, x_i) + b \quad (1)$$

where α_i are the weigh factor, $K(x, x_i)$ are the kernel mapping function between the training sample x and support vector x_i , b represent bias and N represent the total number of training samples. The architecture of LS-SVM network is

shown in Figure 2. The RBF kernel is used for SVMs and can be written as [13]:

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

In this 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. 4000 training samples) which is generated using robust control technique in which the uncertainties are directly introduced in the model and provides the values of vector

α and bias b as given in Equation (1). These values can be used to estimate the function using Equation (1). LS-SVM was trained using the RBF kernel. By proper selecting the two parameters, the kernel function variable σ and an adjustable constant γ , the desired level of the robust performance can be achieved.

2.3 DFIG modelling

The development of transfer function model of DFIG based wind turbines when participating in AGC in the wake of load disturbance is described in [14].

3 Simulation results and discussion

In the present study, the LS-SVM based AGC regulators are designed for a two-area interconnected power system with DFIG based wind turbines in each area. The frequency deviations, tie-line power deviation and load disturbance of each area are chosen as inputs to LS-SVM based AGC regulators. However, all system states were given as inputs to conventional PI and MLP NNs based AGC regulators also. The output of LS-SVM AGC regulators are the control signals, which are applied to the governor in each area. The governor in each area of power system has dead-bands, which are important for speed control under small disturbances [8]. It is known that governor dead-band has destabilization effect on transient response. Therefore, it is important to consider the governor dead-band non-linearity in the study. The designed LS-SVM based AGC regulators are trained from an off-line data set generated by designing and implementing the robust controller for power system in different operating points under various area load disturbances to achieve the desired level of performance by using the learning capability of LS-SVM. The proposed 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 MLP NNs and conventional PI based AGC regulators.

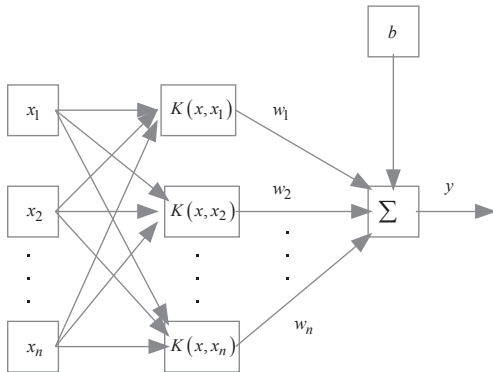


Figure 2: Architecture of LS-SVM network

Case 1: We will test the dynamic performance of power system with nominal parameters as reported 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 Figures 3-4 reveal that the frequency and the tie-line power deviations are settling to

zero steady state value within few seconds. The trends of settling of dynamic responses are not very fast but also very smooth as compared to that obtained with other AGC regulators. The MLP NNs based AGC regulators are trained several times to obtain the desired performance. However, the LS-SVM based AGC regulators do not require efficient training algorithm and there is no need to determine the hidden layer in the design of AGC regulators which is a series drawback of MLP NNs.

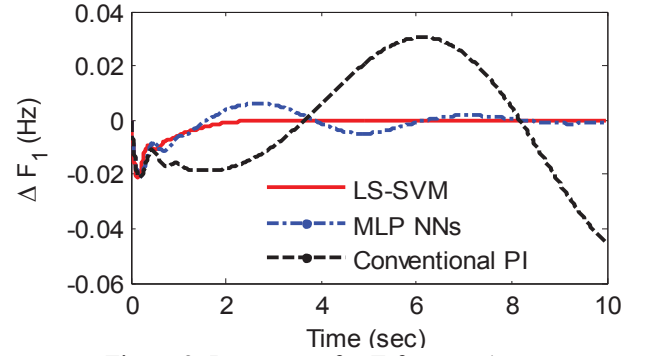


Figure 3: Response of ΔF_1 for case 1

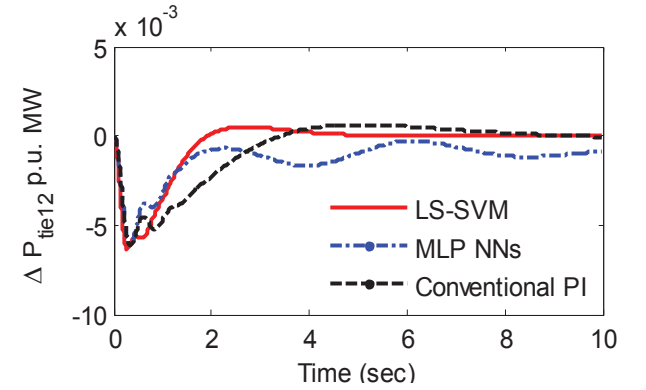


Figure 4: Response of ΔP_{tie12} for case 1

Case 2: The performance of the designed AGC regulator is evaluated by applying the lower bound parameters as given in Table 1 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. An inspection of time response plots of Figures 5-6 reveal that the proposed AGC regulator has better performance as compared to MLP NNs and conventional PI based AGC regulators.

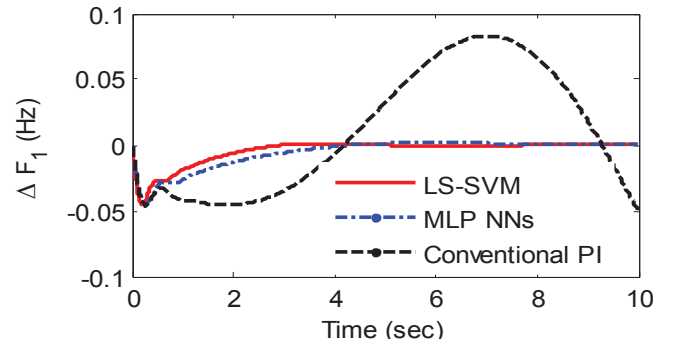


Figure 5: Response of ΔF_1 for case 2

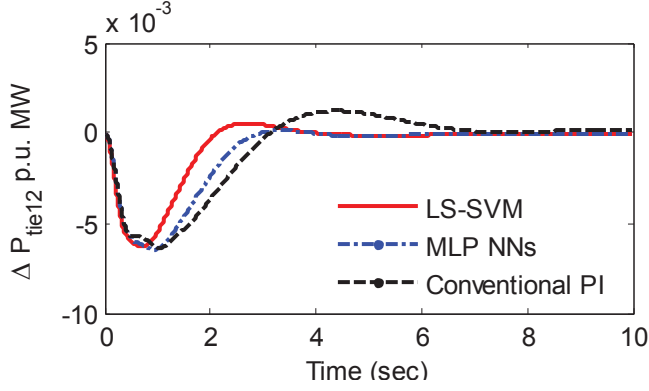


Figure 6: Response of ΔP_{tie12} for case 2

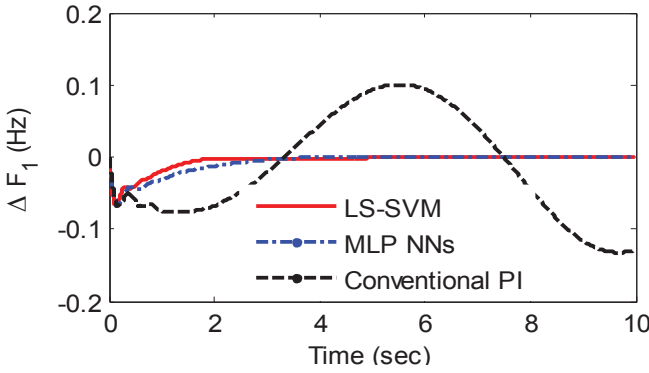


Figure 7: Response of ΔF_1 for case 3

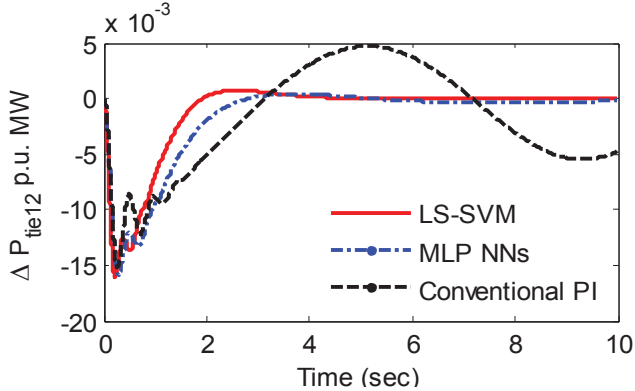


Figure 8: Response of ΔP_{tie12} for case 3

Case 3: We choose the upper bound parameters as given in Table 1 and apply load changes of $\Delta P_{d1} = 0.03$ p. u. MW to area-1 and $\Delta P_{d2} = 0.008$ p. u. MW to area-2 respectively. The dynamic performance of the proposed AGC regulator is evaluated and the system dynamic responses are shown in Figures 7-8. The simulation results indicate that the proposed AGC regulator is showing promising performance in terms of least overshoot and settling time as compared to that obtained with conventional PI and MLP NNs based AGC regulators. At this stage, it can be said that the LS-SVM based AGC regulators are quite robust in its operation for a wide range of

operating conditions and area load changes and can be quite useful for real world complex power system.

4 Conclusion

In this paper, a new non-linear LS-SVM based AGC regulator is proposed for modern power system which are large and interconnected having DFIG. The proposed AGC regulator is trained from an off-line data set obtained from designing and implementing the robust controller to power system under diverse operating conditions and area load changes. The advantage of using the robust control technique for training of proposed AGC regulator is to take large parametric uncertainties and modelling error into account. The RBF kernel is used for support vector machines. An investigation of time response plots reveal that the designed LS-SVM based AGC regulator is showing promising performance for power system with governor dead-band non-linearity as compared to that obtained with MLP NNs 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. However, the MLP NNs based AGC regulators are trained several times with different hidden layers and different combination of neurons per hidden layer to obtain the desired dynamic performance. On the other hand, the LS-SVM AGC regulators do not require efficient training algorithm and there is no need to determine the hidden layer in the design of regulators.

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Nomenclature

a_{12}	area size ratio coefficient
ACE_i	area control error
b_i	frequency bias constant of area i
K_{pi}	power system gain of area i
M_i	effective rotary inertia of area i
R_i	speed regulation parameter of area i
T_{12}	synchronizing coefficient of AC tie-line
T_{hi}	speed governor time constant of area i (sec)
T_{pi}	power system time constant of area i (sec)
T_{ti}	turbine time constant of area i (sec)
ΔF_i	incremental change in frequency of area i
ΔP_{Ci}	incremental change in speed-changer position of area i
ΔP_{di}	incremental change in load demand of area i
ΔP_{tie12}	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
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
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

ΔP^*_ω

reference of area i

$\Delta \omega_i$

incremental wind turbine power set point (reference) based on speed change

ΔX_{1-1}

incremental wind turbine speed of area i
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_{gi}

incremental change in power generation of area i

H_{ei}

wind turbine inertia of area i