Wide-area measurement signal-based stabiliser for large-scale photovoltaic plants with high variability and uncertainty

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Abstract: In this study, norm bounded linear quadratic Gaussian controller synthesis method is utilised to design a wide-area measurement signal (WAMS)-based power oscillation damping controller at photovoltaics (PV) plants. The uncertainties associated with the system are confined by the system matrices which are the affine functions of parameters belong to a convex polytopic region. A hybrid method based on Hankel singular value (HSV) and right-half-plane zeros (RHP-zeros) is utilised to assess and select the optimal feedback signal for the PV wide-area damping controller. First, the HSVs of the delayed subsystems are employed to preselect the candidate signals for damping the target mode. Then, the RHP-zeros and the modal interaction measures of the candidate signals are evaluated. Finally, the signal with minimum variance in HSV and modal interaction over the wide range of operating conditions is selected as the optimal feedback signal for the controller design. The wide range of operating conditions is obtained by the probabilistic distribution of loads, synchronous generators and PVs. The approach has been tested on a large 16 machine, 68 bus test system as compared to geometric measures of controllability/observability method and has shown improved performance.

1 Introduction

Worldwide capacity of grid connected photovoltaic (PV) power plants has increased significantly over the last ten years [1, 2]. Even the current installation is nearly 1%, the present growth suggest that a 15–20% level might be seen in foreseeable future [3]. Furthermore, among these installed capacity, 33% are centralised grid-connected PV system [4]. A significant number of large-scale PV plants are already in operation around many utilities, such as plants in Ontario (100 MW) in Canada, Bressi (91 MW) in Germany, Montalto di Castro (84.2 MW) in Italy, Lopburi (73 MW) in Thailand, and so on. Moreover, PV plants over 100 MW size are recently being commissioned around the globe, such as plants in Sonoran Desert, AZ (150 MW) in USA, Golmud (200 MW) in China, Yuma County, AZ (250 MW) in USA, and so on [2].

Low frequency electromechanical oscillations of 0.1–2 Hz frequency range have adversely affected many power grids worldwide [5]. The increased penetration of stochastic generators like PV units leads to a long distance power transfer and the maximum use of the existing network, resulting in smaller stability margin [6–8]. In [6, 7, 9] advocate that because of the integration of large-scale PVs, the inter-area mode of the system could adversely be affected. Therefore the proliferation of such generations on power systems has imposed the requirement that they should also contribute to the network support through damping control of inter-area oscillations, which could add additional technical value of the PV to the power system. The research effort in [10] proposed a damping controller based on robust control technique in the PV plant. However, the controller was designed on a naıve system without considering signal latency (time delay) and the stochastic nature of the power grid.

Rapid development of phasor measurement units (PMUs) and data communication techniques enable utilities to employ remote/wide-area measurement signals for effective power oscillation damping (POD) [11]. So far numerous feedback signal selection methods have been reported in literatures. The most frequently used one is the residue technique based on modal analysis [12]. Other feedback signal selection methods are also proposed based on geometric measures of modal controllability/observability (GMCO), the minimum singular value (MSV), and the Hankel singular value (HSV) in [13–15]. Nguyen-Duc et al. [16] have proposed a hybrid method of wide-area signal selection based on GMCO, loop to mode measures and phase compensation conflict. However, all these control signal selection methods are based on the nominal operating condition and the controller is intended to obtain the required damping performance under the worst case operating scenario.

High variability and uncertainty in power system is inevitable in future power grid because of the proliferation of stochastic generations and changing nature of consumer
demands, which could result in large variations of ‘modal observability’ of the signal considered for damping control. In some operating conditions modal observability of the selected signal could be poor for the target mode, whereas for other modes are good, resulting in poor controller performance or even destabilisation of some modes. Thus, a control signal has been sought that has minimum variation performance or even destabilisation of some modes. Therefore along with the MC/observability, it is vitally important to consider other aspects of signal selection for wide-area damping control to perform in an unpredictable manner. Therefore along with the MC/observability, it is vitally important to consider other aspects of signal selection for wide-area damping control.

In this paper, a systematic design procedure of PV wide-area damping controller (PV-WADC) is presented by combining a stabilising signal selection procedure and robust controller design based on the norm bounded linear quadratic Gaussian (LQG) criterion, with particular attention to robust performance evaluation of the controller on multiple operating conditions. The paper is organised as follows: following this section, mathematical background on signal selection methods and the generation of probabilistic operating conditions are illustrated in Section 2. Section 3 briefly illustrates the theoretical background of norm bounded LQG control synthesis. In Section 4, optimal signal selection procedure is described in 16 machine 68 test system. Application example of the proposed controller along with performance evaluation is depicted in Section 5. Finally, conclusions are drawn in Section 6.

2 Mathematical background

2.1 Delayed power system model

The general form of the power system linearised model for oscillation study is as follows

\[ \dot{x} = Ax + Bu \]  

(1)

\[ y = Cx + Du \]  

(2)

where \( \Delta x, \Delta y \) and \( \Delta u \) are the state, output and input deviations of the system, whereas \( A, B, C \) and \( D \) are the linearised matrices.

Often the remote/wide-area measurement signals provide greater observability to the inter-area oscillation mode [11]. Hence, PV-POD is synthesised here by utilising such signal. However, time delays are involved in wide-area signals which could deteriorate the performance of the closed-loop system [20]. Therefore the delays corresponding to such signal need to be considered for controller synthesis. The time delay operator \( e^{-sT} \) can be transformed into a rational transfer function by Padé approximation [21].

The \( m \)th order approximation of \( e^{-sT} \) can be expressed as

\[ e^{-sT} \approx N(s) = \frac{N_m(s)}{N_m(-s)} \]  

(3)

\[ N_m(s) = \sum_{j=0}^{m} \frac{(2m-j)!(-sT)^j}{j!(m-j)!} \]

where \( T \) is the delay time. A better match between the given function \( e^{-sT} \) and its approximation \( N(s) \) is guaranteed by increasing the order \( m \). The order to choose for the Padé approximation depends on the system dynamics, and found that the second-order approximation satisfies the demands of inter-area oscillations quite well. The rational transfer function of second-order Padé approximation can be transformed to the state-space representation as follows

\[ \Delta x_d = A_d\Delta x_d + B_d\Delta u_d \]  

(4)

\[ \Delta y_d = C_d\Delta x_d + D_d\Delta u_d \]  

(5)

where \( \Delta x_d \) is the state vector, \( \Delta u_d \) input vector and \( \Delta y_d \) is the output vector of delay state-space model, whereas \( A_d, B_d, C_d \) and \( D_d \) are the state-space realisation of the Padé approximation. By connecting (4) and (5) in cascade with the delay-free system (1) and (2), the time-delayed model is obtained with the following system matrices

\[ A_D = \begin{bmatrix} A & 0 \\ B_d C & A_J \end{bmatrix}, \quad B_D = \begin{bmatrix} B \\ B_d D \end{bmatrix} \]

(6)

\[ C_D = [D_d C \quad C_d] \]

The delay of 80–100 ms (delay between measurement unit and controller) [22] is considered in this research for obtaining delayed power system model.

2.2 Modal controllability (MC)

Suppose a modal analysis of a system matrix \( A \) produces the eigenvalues \( \lambda_i \) (assumed distinct for \( i = 1, \ldots, n \)) and the corresponding matrix of left eigenvectors, \( F = [f_1, f_2, \ldots, f_n] \). The MC associated with mode \( i \) and \( k \)th input \( (B_k) \) is [5, 12]

\[ MC_i = f_k B_k \]  

(7)

If \( MC_i = 0 \), then the mode \( i \) is uncontrollable from the selected input \( k \). The higher the value of the MC is, the better the controller to control the target mode.

2.3 HSV and modal interaction measures

The system shown in (6) can be transformed to a balanced realisation [23]. Let \( (A_h, B_h, C_h, D_h) \) be a minimal realisation of a transfer function \( G(s) \), then \( (A_h, B_h, C_h, D_h) \) is called ‘balanced’ if the solution of the following Lyapunov equations

\[ A_h P + P A_h^T + B_h B_h^T = 0 \]  

(8)

\[ A_h Q + Q A_h^T + C_h^T C_h = 0 \]  

(9)

are such that \( P = Q = \text{diag}(\sigma_1, \sigma_2, \ldots, \sigma_n) \), where \( \sigma_i \) are the HSV such that, \( \sigma_1 \geq \sigma_2 \geq \ldots, \sigma_n \), and \( P \) and \( Q \) are,
respectively, controllability and observability Gramians. Once the HSV are found for a single input/output pair, the ‘total contribution’ of a mode ($\lambda_k$) to the candidate input/output pair is [16]

$$C_k = \sum_{i=1}^{n} \sigma_i^2 p_i(\lambda_k)$$  \hspace{1cm} (10)

where $p_i(\lambda_k)$ is the participation factor of the $i$th state variable to mode $\lambda_k$ [12]. Ideally, $C_k$ need to be high in order to obtain the best signal for controller design. The ‘modal interaction’ for the particular mode $\lambda_k$ can be obtained by dividing its contribution and the total contribution of all other modes [16]

$$I_k = \frac{C_k}{\sum_{j \in \Lambda} C_j}$$  \hspace{1cm} (11)

where $C_j = \sum_{i=1}^{n} \sigma_i^2 p_i(\lambda_j)$. From (11), it is evident that $I_k$ resolves how the other modes would be affected if one tries to control mode $\lambda_k$ from the selected input/output pair. Thus, $I_k$ is defined as the interaction measure between controller and the modes. For a wide-area controller, an input/output pair with $I_k$ close to 1 is better for the controller design [16].

### 2.4 Generation of probabilistic operating condition

With the proliferation of intermittent renewable energy and change in demand patterns, power system has encountered increasing uncertainty and variability in operating conditions [18]. This section depicts a method of obtaining various operating conditions for the purpose of assessing the variations of modal observability and the interaction of the feedback signals as well as the robust performance evaluation of the controller.

#### 2.4.1 Variability of demand and conventional generator output: The uncertainty of generators and loads are modeled by Gaussian distribution functions. The output and demand of the generators and loads at nominal operating condition are considered as the mean ($\mu$) for the distribution. The standard deviation of the corresponding load and generator are obtained by considering certain percentage of coefficient of variation (CV) around $\mu$. A $\pm 3\sigma$ variations around the mean is employed to cover 99.73% area of the Gaussian distribution curve, and the standard deviation of the distribution can be obtained as

$$\sigma = \frac{\mu \times CV(\%)}{3 \times 100}$$  \hspace{1cm} (12)

#### 2.4.2 Variation of PV output: The output power of PV can be expressed as [24]

$$P_{PV} = A_x \eta I_{PV} = A_x \eta (k_i T - k_i T^2)$$  \hspace{1cm} (13)

where $A_x$ is the array surface area ($m^2$), $\eta$ is the efficiency of the PV panel, $T$ and $T'$ are the parameters that depend on inclination, declination, reflection of ground, latitude, hour angle, sunset hour angle, and $k_i$ is the hourly clearness index. If the probability density function (PDF) of the hourly clearness index is known, one can obtain the PDF of $P_{PV}$. PDF of $P_{PV}$ depends on the sign $T$ and $T'$, can be expressed as [24] (see (14))

- For $T > 0$ and $T' < 0$, and (see (15))
- For $T > 0$ and $T' > 0$

Where $k_u$ represents the upper bound of $k$, $C$ is the parameter of the PDF, and

$$\alpha = \frac{T}{T'}, \quad \alpha' = \sqrt{\alpha^2 - 4 \frac{P_{PV}}{\eta T A_c}}$$  \hspace{1cm} (16)

Line contingency is also considered in generating multiple operating conditions. Transmission lines are selected by the contingency ranking index based on Hopf-bifurcation (HB) [25], and feasible operating conditions for each line contingency are generated.

### 3 Norm bounded LQG control

To facilitate the norm bounded LQG controller design the performance function $J$ expressed in (17) needs to be minimised

$$J = \lim_{T \to \infty} \frac{1}{T} E \left[ \int_0^T (x^T Q x + u^T R u) dt \right]$$  \hspace{1cm} (17)

where $Q = Q^T \geq 0$, $R = R^T > 0$ and $E$ is the expectation operator. The controller which minimised performance function $J$ can be expressed as [26]

$$A_c = A - B R_{T'}^{-1} B^T P_T - P_T C^T R_{T'}^{-1} C$$  \hspace{1cm} (18)

$$B_c = P_T C^T R_{T'}^{-1} C; \quad C_c = R_{T'}^{-1} B^T P_T$$  \hspace{1cm} (19)

Here, $P_T$ and $P_t$ are symmetric positive definite solutions of the following control algebraic Riccati equation and filter algebraic Riccati equation

$$P_T A + A^T P_T + P_T B R_{T'}^{-1} B^T P_T + Q_T = 0$$  \hspace{1cm} (20)

$$P_T A + A^T P_T - P_T C^T R_{T'}^{-1} C P_T + Q_T = 0$$  \hspace{1cm} (21)

If there is $\varsigma (\rho)$ uncertain system with a matrix $P$ (symmetric}
positive definite) and a scalar $\alpha > 0$ such that [26]

$$\begin{bmatrix} A(p)^T P + PA(p) + C(p)^T C(p) \& PB(p) \\ B(p)^T P \end{bmatrix} \leq 0$$ (22)

To minimise $\alpha$, one must find $P = P^T > 0$ such that $\alpha$ is minimised subject to above LMI constraint. If (22) is satisfied for all $\zeta(p)$ system, then

$$\|G(p)\|_\infty \leq \gamma := \sqrt{\alpha}$$

Now, for the nominal system $|G(s)| \leq \gamma$, if there is a matrix $P$ (symmetric positive-definite) such that the following LMI is satisfied

$$\begin{bmatrix} A^T P + PA + C^T C \& PB \\ B^T P \end{bmatrix} \leq \gamma I$$ (23)

Let, the infinity norm of the LQG controller is bounded by $\mu$ where $0 < \mu < 1/\gamma$ [26], and

$$\|G_c(s)\|_\infty \leq \mu$$

Assumed that $\Gamma \in \mathbb{R}^{n \times n}$ is a square root of $P$, and $P = \Gamma^T \Gamma$. By using coordinate transform ($\xi = \Gamma x$), the system becomes

$$\dot{\xi} = \hat{A} \xi + \hat{B} u$$

$$y = \hat{C} \xi$$

where $\hat{A} = \Gamma A \Gamma^{-1}$, $\hat{B} = \Gamma B$ and $\hat{C} = \Gamma C^{-1}$. Pre-multiplying (23) by $\text{diag}(T^{-1}, I)$ and post-multiplying by its transpose, the following expression can be obtained

$$\begin{bmatrix} A^T + \hat{A} + \hat{C}^T \hat{C} \& \hat{B} \\ \hat{B}^T \& -\gamma I \end{bmatrix} \leq 0$$ (24)

Hence, from (24) it is evident that without losing the generalisation, (23) is satisfied with $P = I$ which reveals that the LQG controller is also gain bounded. The designed LQG controller is said to be norm bounded by $\mu$ ($0 < \mu < 1/\gamma$) if it satisfies

$$R \geq I$$

$$Q \geq -\mu^2 P \hat{C}^T \hat{R}^{-1} \hat{C} P - \hat{C}^T \hat{R}^{-1} \hat{C} P \hat{C}^T \hat{R}^{-1} \hat{C}$$ (25)

$$Q = -(A + A^T) + \hat{C}^T \hat{R}^{-1} \hat{C}$$

4 Optimal signal selection

The test system used in the paper is 16 machine 68 bus network shown in Fig. 1 [27]. It is an interconnected test system of New England (NEST) and New York power system (NYPS) with five areas, where $G_1$-$G_{13}$ represent the generators of NEST and NYPS whereas $G_{14}$-$G_{16}$ are the dynamic equivalents of the three neighboring areas connected to NYPS. The sixth-order synchronous generator model is considered for all the 16 generators. The generators $G_1$-$G_3$ are equipped with slow excitation system (IEEE-DC1A), whereas $G_9$ is equipped with fast acting static excitation system (IEEE-ST11) [27]. The aggregated system load is $P_L = 17,620.65 \text{ MW}$, $Q_L = 1,971.76 \text{ MVAr}$, and generation $P_{CG} = 18,408.00 \text{ MW}$. The system and generator data are given in [27]. PVs are considered at bus 16, 30, 38 and 48. The instantaneous penetration of 6% is considered for the analysis. The load sharing of the conventional generators is changed in the same proportion to accommodate the PV generator to the system. It is assumed that PV plants are operating at 60% of their rated capacity in the nominal system operating condition. For the analysis generic model of the PV is used [28]. The detail about this generic model can be found in [28, 29].

Modal analysis has been performed to assess the low frequency oscillatory stability of the system with the large-scale PV plants. Table 1 shows the two lightly damped inter-area modes of the system. Between the two modes, mode 1 is more critical as the damping of the mode

![Fig. 1 Sixteen machine 68 bus test system](www.ietdl.org)
is very low (% $\zeta = 2.34$), suggesting a remedial measure needs to be taken to enhance the damping of the mode. Damping of the other mode is greater than 5%, settling in 12 s. From the table, it can be seen that mode 1 represents the inter-area oscillation of Areas 4 and 5 against Areas 1–3.

Before selecting the feedback signals, suitable location for POD in the PV needs to be selected. MC measure is used to select the location. MC results reveal that the PV-1 is the best location for plugging in a POD to damp out the critical inter-area mode. In this study, the real power through transmission lines is considered as an initial set of feedback signals. A prescreening of this set is carried out based on $C_k$ (10) under nominal operating condition. As the location of the controller is fixed at PV-1 (invariant B), $C_k$ depends on the output matrix $C$. The real power signals having normalised magnitude of $C_k \geq 70\%$ are chosen as the set of potential feedback signals. Then the modal interaction measures $I_k$ (11) for the set of potential feedback signals are evaluated. For the clarity of presentation, the potential signals with $C_k$ and $I_k$ are listed in Table 2. It is evident from Table 2 that the candidate signal 6 which has high $C_k$ value has an adverse effect on other modes of the system. The candidate signals 3 and 4 seem to be the best signals as they have fairly good modal observability and low interaction to other modes of the system at nominal operating condition. However, analysis of RHP-zeros reveals that the system with candidate signals 3, 4 and 6 has RHP-zeros. Hence, these signals have been discarded from further analysis.

The final signal selection is done by evaluating $C_k$ and $I_k$ for various operating conditions. Wide range of operating scenarios is obtained by the probability distribution of loads, conventional generators, and PV plants as described in Section 2. The histograms of the system load, PV plants, and synchronous generator outputs for all scenarios are shown in appendix (Figs. 9i and ii). Total of 250 feasible operating conditions are generated to evaluate the variations of the $C_k$ and $I_k$ under multi-operating conditions. Signals with minimum mean absolute error (MAE) of $C_k$ and $I_k$ is the optimal choice for the control signal.

### Table 1 Dominant inter-area modes with large-scale PV penetration

<table>
<thead>
<tr>
<th>Mode no.</th>
<th>Eigenvalue $f$, Hz</th>
<th>% $\zeta$</th>
<th>Generator participation</th>
</tr>
</thead>
<tbody>
<tr>
<td>mode 1</td>
<td>$-0.0824 \pm j3.5165$</td>
<td>0.589 2.34</td>
<td>G1–G13, G14–G16 (areas 4 and 5 against areas 1–3)</td>
</tr>
<tr>
<td>mode 2</td>
<td>$-0.3672 \pm j4.502$</td>
<td>0.716 8.129</td>
<td>G15 against G14, G16 (area 2 against areas 1 and 3)</td>
</tr>
</tbody>
</table>

### Table 2 Wide-area signal candidates to the dominant inter-area mode

<table>
<thead>
<tr>
<th>Candidate signal no.</th>
<th>Line between buses</th>
<th>Line no.</th>
<th>$C_k$</th>
<th>$I_k$</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1–2</td>
<td>1</td>
<td>0.835</td>
<td>0.6282</td>
</tr>
<tr>
<td>2</td>
<td>8–9</td>
<td>16</td>
<td>0.863</td>
<td>0.7990</td>
</tr>
<tr>
<td>3</td>
<td>9–36</td>
<td>48</td>
<td>0.856</td>
<td>0.8307</td>
</tr>
<tr>
<td>4</td>
<td>9–36</td>
<td>49</td>
<td>0.856</td>
<td>0.8307</td>
</tr>
<tr>
<td>5</td>
<td>36–57</td>
<td>50</td>
<td>0.889</td>
<td>0.8046</td>
</tr>
<tr>
<td>6</td>
<td>37–65</td>
<td>62</td>
<td>1.000</td>
<td>0.7652</td>
</tr>
</tbody>
</table>

Table 3 depicts the MAE of $C_k$ and $I_k$ for candidate signals. The results in Table 3 reveal that the candidate signal 5 has the minimum MAE of $C_k$, whereas signal 1 has the minimum MAE of $I_k$. The MAE of $I_k$ for candidate signals 1 and 5 is very close. Hence, the candidate signal 5 is selected as the optimal control signal for the PV-WADC.

### Controller design and performance evaluation

#### 5.1 Controller design

The norm bounded LQG design scheme has been used in this paper as described in Section 3. Two PODs have been designed; namely, Controller 1 (with signal selected by the proposed method), and Controller 2 (with signal selected by the GMCO) for comparison. Ruan et al. [30] shown that power system damping can be achieved through the modulations of either real and/or reactive power of voltage source converters. Reactive power modulation at the
converter of the PV is used here for the oscillation damping. Fig. 2 shows the control overview of the 16 machine 68 bus test system. Step-by-step controller design procedure is described below:

Step 1. Obtain the region of interest for the variation of system loads and PV generations as depicted in Fig. 3.
Step 2. Find $\gamma$ of the uncertain system such that (22) is satisfied.
Step 3. Obtain $P$ to the LMI of (23) for the nominal system and get the transformed system matrices.
Step 4. Chose LQR weighting matrices based on the performance requirement and obtain $P_r$ and $P_f$.
Step 5. Solve (18) and (19) to obtain the required controller.

The ‘Balanced Reduction Method’ available in Robust Control Toolbox [31] has been used to reduce the order of the power system to design the PV-WADC effectively. The open-loop system is reduced from 172 to 11 orders. The LMI associated with the control design method has been solved in YALMIP [32]. The order of the designed controllers is equal to the reduced order model of the power system which is relatively high for the implementation. Hence, the model reduction has been executed again to reduce the order of the design controllers without losing the effectiveness on the frequency of interest. Fig. 4 shows the frequency response of full- and reduced order controllers. From the results in Fig. 4 it is clear that the sixth order controllers have the indistinguishable control characteristics for the frequency range of interest (0.1–2 Hz). Electromechanical (EM) modes are shown in Fig. 5 for the system with and without controllers. Fig. 5 depicts that both controllers move the target mode (mode 1) further left in the s-plane. It is also noticeable from the figure that the Controller 2 has an adverse effect on inter-area mode 4 of the system since it has shifted the mode 4 to the right.

Transient response has been analysed to verify the linear analysis results. Three phase self-clearing fault are simulated at bus 36 for 100 ms. The nonlinear simulation...
has been carried out for 20 s. The results concerning the dynamic response of the power flow in tie-line between buses 1 and 27 is shown in Fig. 6. It can be seen from this that the POD performance of Controllers 1 and 2 is almost the same for the nominal operating condition as described in Section 4, but Controller 1 has slightly better response.

5.2 Controller performance evaluation

The uncertainties in power system encompass not only the variation of operating conditions because of load demands, generation outputs and network topologies, but also uncertainties in the load characteristics and variations in time delays of the wide-area signals. This section depicts the robust performance assessment of the designed controllers under different operating conditions, load characteristics and time delays. Fig. 7 shows the percentage of the damping factor for the target inter-area mode of oscillation under different operating conditions, whereas Fig. 8 shows the percentage of damping of other inter-area modes under the same operating conditions. Robust performance assessment results in Fig. 7 depict that the performance of Controller 1 is better than that of the Controller 2 under the wide range of operating conditions and contingencies tested. For the vast majority of cases investigated (including outage contingencies) for both controllers, there are some operating regions in which damping performance of the controllers is reduced significantly. However, the variations in damping performance are less for Controller 1 than for Controller 2. From the results in Fig. 8 it can be seen that the damping of other inter-area modes varies less with Controller 1 as compared to Controller 2.

The robust performance of the damping controller is further evaluated under different load characteristics since the change of load characteristics is quite common, and difficult to predict [33]. Table 4 shows the damping of the target inter-area mode for different load characteristics. From the table, it can be seen that the damping performance of the Controller 1 is more robust as compared to Controller 2 for different load characteristics. It is worthwhile to note that the system with Controller 2 will experience more variations in oscillation frequency on the target inter-area mode.

The effect of time-delay variations of feedback signal on controller performance is demonstrated in Table 5. From the table it is evident that the damping performance of the both controllers is gradually declined as the time delay of the feedback signal is increased. However, the deterioration of Controller 2 damping performance is more significant as compared to Controller 1.

### Table 4 Damping of inter-area mode for different load characteristics

<table>
<thead>
<tr>
<th>Type of load</th>
<th>Controller 1</th>
<th>Controller 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>ZIP</td>
<td>12.83, 0.598</td>
<td>12.14, 0.6063</td>
</tr>
<tr>
<td>Z</td>
<td>13.15, 0.5908</td>
<td>12.56, 0.613</td>
</tr>
<tr>
<td>P</td>
<td>12.81, 0.598</td>
<td>11.89, 0.614</td>
</tr>
<tr>
<td>real P; reactive Z</td>
<td>11.02, 0.598</td>
<td>11.05, 0.598</td>
</tr>
<tr>
<td>real Z, reactive P</td>
<td>11.91, 0.592</td>
<td>8.02, 0.623</td>
</tr>
<tr>
<td>real P, reactive I</td>
<td>9.84, 0.592</td>
<td>7.56, 0.593</td>
</tr>
<tr>
<td>dynamic</td>
<td>12.64, 0.584</td>
<td>12.20, 0.527</td>
</tr>
</tbody>
</table>

*ZIP, polynomial; I, constant current; P, constant power; Z, constant impedance

### Table 5 Damping of critical inter-area mode for time-delay variation

<table>
<thead>
<tr>
<th>Time-delay, ms</th>
<th>Controller 1</th>
<th>Controller 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>150</td>
<td>13.0, 0.5840</td>
<td>11.58, 0.610</td>
</tr>
<tr>
<td>200</td>
<td>12.09, 0.5872</td>
<td>9.67, 0.604</td>
</tr>
<tr>
<td>250</td>
<td>10.80, 0.5900</td>
<td>8.74, 0.615</td>
</tr>
<tr>
<td>300</td>
<td>9.08, 0.6094</td>
<td>7.34, 0.589</td>
</tr>
<tr>
<td>350</td>
<td>8.13, 0.5904</td>
<td>6.30, 0.6127</td>
</tr>
<tr>
<td>400</td>
<td>7.30, 0.5852</td>
<td>5.25, 0.59</td>
</tr>
</tbody>
</table>
This paper presents a reactive-power modulation-based WADC at utility scale PV plants for stabilising the inter-area oscillation mode in an interconnected power system. High variability and uncertainties related to generations and loads have been considered in designing such controller. A norm bounded LQG controller has been designed for the class of uncertain systems with system matrices which are the affine functions of parameters belong to convex polytopic region. An appropriate polytopic region for the test network is formed based on the uncertainty range of the system loads and PV outputs. Hybrid signal selection method for delayed system is proposed utilising the concepts of HSV-based MC/observability, RHP zeros, and mode to loop interactions. The final selection of the signal is achieved by checking the minimum variances of modal observability and interaction to ensure the robust performance of the controller for a wide range of system operating conditions. A detailed robust performance assessment has been carried out over a wide range of operating conditions obtained from the probabilistic distribution of loads, generators and PV plants. From the analyses it is apparent that the designed controller based on the proposed method provides better robust performance than the controller designed by the geometric measures of MC/observability.

7 References


8 Appendix

See Fig. 9.
Fig. 9 Histograms of system load, synchronous generator outputs and PV plants

i Histogram: (a) system load (GW), (b) synchronous generator outputs (GW)

ii Histogram of PV generator outputs (pu)