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PMU-Based Power System Stabilizer Design: Optimal Signal Selection and Controller Design

Maryam Dehghani, *Senior Member, IEEE*, Mahsa Rezaei, Bita Shayanfard, Navid Vafamand, Mohammad Javadi, *Senior Member, IEEE*, and João P. S. Catalão, *Senior Member, IEEE*

***Abstract*—Phasor measurement unit (PMU) provides beneficial information for dynamic power system stability, analysis and control. One main application of such useful information is data-driven analysis and control. This paper presents an approach for optimal signal selection and controller structure determination in PMU-based power system stabilizer (PSS) design. An algorithm is suggested for selecting the optimal input and output signals for PSS, in which a combination of system clustering, modal analysis and principal component analysis (PCA) techniques is used. The solution for the optimal PSS input-output selection is determined to increase the observability and damping of the power system. The approach can efficiently reduce the number of input-output signals, while the overall performance is not deteriorated. Then, a Linear Matrix Inequality-based technique is elaborated to design the PMU-based PSS parameters. The stabilizer design approach is formulated as a convex optimization problem and the appropriate stabilizer for pole allocation of the closed-loop model is designed. This method is simulated on two sample power systems. Also, to compare the results with the previous methods, the system is simulated and the results of two previously-developed algorithms are compared with the proposed approach. The results show the benefit of the suggested method in reducing the required signals, which decreases the number of required PMUs, while the system damping is not affected.**

***Index Terms*—System Clustering, Modal Analysis, Principal Component Analysis, Phasor Measurement Unit, Linear Matrix Inequalities, Power System Stabilizer.**

NOMENCLATURE

A, B, C	Power system state-space matrices.
A_c, B_c, C_c, D_c	Controller parameters.
A_{cl}	Closed-loop state matrix.
C_j	*j*th cluster center.
$C_{m\times n}$	Covariance of normalized feature matrix.
$C(S)$	Gain of PSS with a lead-lag form.
c	Number of clusters.
D	Feedforward matrix.
d	Number of data.
d_i	Distance of x_i from the nearest cluster center.
F	Transferred modal of state matrix.
$f_{c_i}(k)$	Modal controllability factors of *i*th mode.
$f_{o_i}(l)$	Modal observability factors of *i*th mode.
G	Transferred modal of input matrix.
H	Transferred modal of output matrix.
k	Number of principal components.
K	PSS gain.
l_i, l_o	Input and output signals.
L, M	Matrices of the complex region.
m	Number of patterns.
m_i	Number of inputs.
n	Number of dimension of features vector.
P_j	Principal component of raw features vectors.
p	Number of outputs.
Q	Real symmetrical positive definite matrix.
r	Radius of the composite region.
s	A point in the complex plane.
T_i	Time constants of the PSS model.
u	Input or control vector.
$V_{n\times k}$	Raw features vectors.
v_i	Eigenvectors of the covariance matrix.
$X_{m\times n}$	Data set or features matrix.
$X'_{m\times n}$	Normalized feature matrix.
x	Power system state vector.
x_c	Controller state vector
x_i	*i*th element of data.
x_j	*j*th element of features' vector.
x_{ij}	*ij*th element of features' matrix.
x'_{ij}	Average of *ij*th element of features' matrix.
y	Output vector.
z	Transferred modal of state vector
α	Minimum threshold value as the accuracy approximation.
θ	Angle of the composite region.
λ_i	Eigenvalues of the covariance matrix.
σ	Relative stability margin.
Φ	Right modal matrices of the system.
Ψ	Left modal matrices of the system.

M. Dehghani, M. Rezaei and N. Vafamand are with the School of Electrical and Computer Engineering, Shiraz University, Shiraz, Iran (e-mails: mdehghani@shirazu.ac.ir, mahsarezaei931@gmail.com, n.vafamand@shirazu.ac.ir).

B. Shayanfard is with the Fars Regional Electric Company, Shiraz, Iran (e-mail: shayanfarb@frec.co.ir).

M. Javadi is with the Institute for Systems and Computer Engineering Technology and Science (INESC TEC), Porto, Portugal (e-mail: msjavadi@gmail.com).

J.P.S. Catalão is with the Faculty of Engineering of the University of Porto (FEUP) and INESC TEC, Porto 4200-465, Portugal (e-mail: catalao@fe.up.pt).

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I. Introduction

THIS introduction consists of four parts that present the motivation of the topic, the literature review, the paper contribution and the paper structure.

A. Motivation

With the advent of phasor measurement units (PMUs) in the last decades, extensive approaches in power system monitoring, state estimation, stability and control has been developed [1]. One interesting application of PMU signals is in Wide-Area Damping Controller (WADC) [2]-[5]. In the past, the power system stabilizers and controllers used local signals, while PMUs bring this opportunity to use both local and remote signals of a network to the stabilizers and controllers [6]-[7]. According to the high cost of instrument installation, such as the communication platform, the number of remote signals should be selected in an optimal manner [8].

The location of the universal measurement signals (the inputs of the power system stabilizer (PSS)) must be defined in order to have the most observability with a smaller number of PMUs. Similarly, the location of the universal control signals (the outputs of the PSS) is defined so that maximum controllability is ensured [9]. The smaller number of measurement signals in the network results in less communication links, while a smaller number of control loops leads to less system complexity.

B. Relevant Literature

The recent technology in PSS design is devoted to using appropriate PMU signals for controlling purposes [10]. The methods discussed in the literature for choosing the PSS inputs can be divided in two categories: (i) geometric criteria of observability and controllability based on modal analysis [11]-[13]; (ii) exploiting heuristic optimization methods for finding optimal criteria based on residuals [14]-[15].

Reviewing the state-of-the-art methods show that the final number of the signals is still high and therefore the implementation of all PMU signals is not cost effective. For instance, in [16], modal analysis is used for selecting both the input and output signals, resulting in a large number of selected signals, which increases the complexity of calculations.

In [8], the online wide-area signal selection based on the residue method is exploited for Wide Area Controller (WAC) signal selection. Although much research has been done in this regard, there are still more efforts needed to optimally reduce the number of signals while maintaining the overall performance.

On the other hand, after the wide-area signals are selected, the wide-area controller can be designed based on the measurements received from the PMUs. In recent years, some papers present approaches in this regard. For instance, in [17]-[20], a distributed networked wide-area system is designed. In [21] the controller structure is assumed unknown and the particle swarm optimization method is used to find the optimum controller parameters. In [22]-[23], the reinforcement learning is exploited for wide-area controller design, where the approach is able to update the controller parameters due to possible load changes. This area needs much more effective researches to provide an appropriate controller design approach.

C. Contribution

To determine the optimal input-output signals of PSS from PMU signals, this paper presents an algorithm to find the optimum signals and minimize the number of required signals. First, the buses of the system are clustered optimally with the Imperialist Competitive Algorithm (ICA) as an optimization problem.

Next, for each bus cluster, the generators are clustered. As the number of the received data is very high, it is necessary to use the Principal Component Analysis (PCA) technique in each clustering process to decrease the computation time. Finally, a limited number of generators is selected as a representation of the whole system, which are the candidates for input and output signals. Finally, by applying modal analysis, the optimal number of signals are obtained. Compared to the state-of-the-art approaches, the method results in the least number of input-output signals, while the overall performance is still very much satisfactory.

The other major contribution and the main advantage over [1] is in designing the controller using the determined signals. This paper exploits the Linear Matrix Inequality (LMI) technique to design the controller. The approach is based on allocating the poles of the overall closed-loop model in an appropriate region, which assures damping of oscillations. To achieve this goal, the controller structure is determined according to the optimal input-output signals found in the first part. Then, the LMI technique is exploited to allocate system poles, appropriately. It is important to mention that the problem is inherently in the form of Bilinear Matrix Inequality (BMI). However, we can use convexification approaches to overcome the bilinear terms and solve the problem by convex optimization.

D. Paper Structure

The structure of this paper is as follows. In Section II, the problem definition is presented. The proposed approach for input-output signal selection is described in section III, which consists of four sections: (i) PCA technique; (ii) formulation of optimal clustering; (iii) modal analysis; (iv) algorithm for selecting the optimal input and output signals of the PSS based on PMU data. In Section IV, the algorithm for designing the PSS using the LMI technique is described. The suggested approach is applied on two test systems in section V, followed by the discussion and conclusion in sections VI and VII.

II. Problem definition

In traditional power systems, the PSS inputs and outputs were local signals of the power plant, while by the usage of PMUs in nowadays power systems, the PSS signals can be selected from both local and non-local signals.

Fig. 1 presents a schematic of the power system equipped with universal PSSs that receive signals from different parts of the power system. This paper considers a similar structure, where the inputs and outputs of the PSS can be selected from local or non-local signals. The main objective is to present an optimal approach for designing such universal PSSs.

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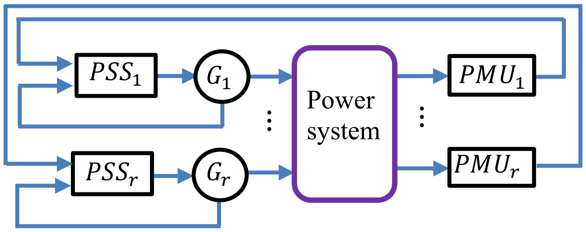

Fig. 1. A sample structure of universal PSS with data of PMUs.

Here, PSS design by using PMU data in a large-scale power system is performed in two steps, as shown in Fig.2.

1- Selecting inputs and outputs of PSS.
2- Designing the selected PSSs.

In the first step, PMUs gather information from the buses and generators. It is important to determine which PMU information should be sent to a PSS, and vice versa. It means that the input and output signals of PSSs should be designed. In the second step, the internal structure of the PSS is designed.

Assume that the linearized model of a power system is defined as below:

$$\dot{x} = Ax + Bu \tag{1}$$

$$y = Cx \tag{2}$$

where x, u, and y are the system states, inputs and outputs, respectively.

Each PSS is installed on one generator and its input is received, both from its generator and the PMUs. Assuming n PSSs in a universal structure as Fig. 1, its transfer function and state-space models can be written as follows:

$$\dot{x}_c = A_c x_c + B_c y \tag{3}$$

$$u = C_c x_c + D_c y \tag{4}$$

$$k(s) = C_c(SI - A_c)^{-1}B_c + D_c \tag{5}$$

$$k(s) = \begin{bmatrix} k_{11}(s) & k_{12}(s) & \dots & k_{1n}(s) \\ k_{21}(s) & k_{22}(s) & \dots & k_{2n}(s) \\ \vdots & \vdots & \vdots & \vdots \\ k_{n1}(s) & k_{n2}(s) & \dots & k_{nn}(s) \end{bmatrix} \tag{6}$$

Consequently, the power system closed-loop model is given as follows:

$$\begin{bmatrix} \dot{x} \\ \dot{x}_c \end{bmatrix} = \begin{bmatrix} A + BD_cC & BC_c \\ B_cC & A_c \end{bmatrix} \begin{bmatrix} x \\ x_c \end{bmatrix} \tag{7}$$

The above structure demonstrates the wide-area control structure. The unknown matrices in (7) are A_c, B_c, C_c, D_c. In Section III, a method for the best input-output PSS selection is elaborated, which determines the elements of (6) that should assuredly be non-zero. Then, in Section IV, the controller unknown parameters (A_c, B_c, C_c, D_c) are designed.

III. PSS Signal Selection Preliminaries

In this paper, an algorithm based on candidate input and output signals is suggested. The information of the buses and generators of a power system is extracted to find the best input and output signals of the PSS. By applying modal analysis, the optimal number of signals is obtained. The overall design procedure of the proposed approach for the PSS input-output selection is illustrated in Fig. 3.

In the proposed approach, first, the buses of the system are optimally clustered with the ICA. Next, in each bus cluster, generators are optimally clustered.

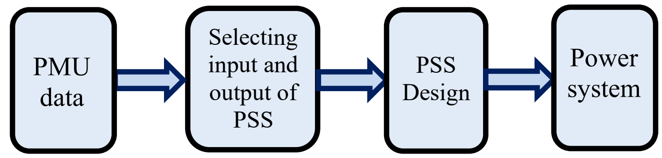

Fig. 2. PSS design by using PMU data in a large-scale system.

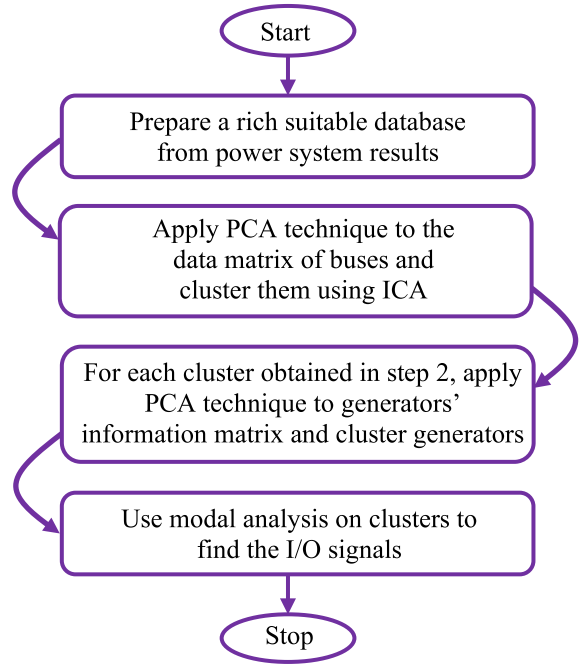

Fig. 3. The overall schematic of the PSS input-output selection approach.

Please note that according to the huge amount of data, clustering is done in two steps such that the optimum number of generators for PSS allocation is determined. To reduce the number of received data, the PCA technique is proposed in both clustering steps. Finally, a limited number of generators is selected for PSS allocation. In the end, the Modal analysis is applied on the system to determine the input/output pairs of the signal. Successive usage of the clustering technique on the reduced data results in a smaller number of required controllers compared to the previous technique.

The calculated (input) output signals are devoted to those generators that are selected in the steps of the proposed algorithm in Fig. 3. To clarify the methodology, the theory is elaborated in the following subsections.

A. Principal Component Analysis

Principal component analysis (PCA) is a known method for reducing the dimension of data or feature without loss of information. This method aims to convert the main features to a smaller number with a linear combination of the main features. Usually, the subset of k principal components contains the information similar to the main data set. The algorithm is described as follows [24]:

Assume a set of n-dimension features' vector x_j ($j = 1,2, \dots, n$), in which, each feature has m patterns. Therefore, the data set is a $m \times n$ matrix ($X_{m \times n}$). Then, the steps of PCA technique are as follows:

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1- The average of each dimension is calculated.

$$x'_{ij} = x_{ij} - \frac{1}{m}\sum_{i=1}^{m} x_{ij} \tag{8}$$

2- Each feature is subtracted from its mean and the normalized feature matrix $X'_{m\times n}$ is created.

3- The covariance of normalized feature matrix is given as:

$$C_{m\times n} = \frac{1}{n-1} X'X'^{T} \tag{9}$$

4- The eigenvalues and eigenvectors of the covariance matrix are calculated.

$$Cv_i = \lambda_i v_i \,, i = 1,2,\dots,n \tag{10}$$

5- The principal components are the eigenvectors of the largest eigenvalues. The first k eigenvectors $(k \le n)$ related to the k largest eigenvalues are selected to represent the raw feature vectors with low dimension.

$$V_{n\times k} = [v_1, v_2, \dots, v_k] \tag{11}$$

The amount of k is defined by a minimum threshold value, having α as the accuracy of approximation of the k largest eigenvectors:

$$\frac{\sum_{i=1}^{k} \lambda_i}{\sum_{i=1}^{n} \lambda_i} \ge \alpha \tag{12}$$

6- According to $V_{n\times k}$, the low dimensional feature vectors are computed as principal components:

$$P_j = V^T {x_j}^T \;\;, j = 1,2,\dots,k \tag{13}$$

B. Formulation of the Clustering as an Optimization Problem

Clustering means identifying the homogeneous groups of data, which are called clusters. Data of each cluster must be alike and be different from the other clusters. The concept of distance is used as a basis of data similarity. Euclidean distance is the most usable similarity criterion. As the distance is inversely proportional to the similarity, for clustering, it is needed to minimize the distance of the data.

Assuming d data , x_i $(i = 1,2,\dots,d)$ will be sectionalized to c clusters. Consider C_j $(j = 1,2,\dots,c)$ as the cluster center and d_i as the distance of x_i from the nearest cluster center. The goal is to minimize the total of these distances. The clustering problem can be defined as an optimization problem, given by:

$$\min \sum_{i=1}^{d} \min_{j} \left\| x_i - C_j \right\|_2 \tag{14}$$

$$i = 1,2,\dots,d \quad j = 1,2,\dots,c$$

In the literature, there are several algorithms for solving the above problem. In this paper, this minimization problem is solved by ICA [25]. ICA starts with an initial population called country. Some of the countries are selected as imperialist. The others named colony are divided among the imperialists. The number of colonies of each imperialist depends on how much powerful it is. Then, the colonies start to move toward the related imperialist and the imperialistic competition begins. Along with the competition, if a colony gains more power than its imperialist, the position of them is exchanged and the colony becomes an imperialist. If an imperialist releases all its colonies, it becomes a powerless country and it will be eliminated. The competition is continued until all the colonies are assigned to the only one imperialist that is the most powerful.

C. Modal Transformation

Based on the Modal transform, the power system model is given as follows:

$$\dot{x} = Ax + Bu \;\rightarrow\; \dot{z} = Fz + Gu \tag{15}$$

$$y = Cx \;\rightarrow\; y = Hz \tag{16}$$

where,

$$F = \Phi^{-1} A\Phi \tag{17}$$

$$G = \Phi^{-1} B = \Psi B \tag{18}$$

$$H = C\Phi \tag{19}$$

where Φ and Ψ are right and left modal matrices, respectively.

If the row ith of G equals to zero, it means that the inputs do not affect the ith mode. Therefore, the elements of G are defined as modal controllability factors. Similarly, if the ith column of H equals to zero, it means that the ith mode of outputs is not observable. Thus, its elements are defined as modal observability factors. The controllability and observability factors are defined below:

$$f_{c_i}(l_i) = \psi_i b_{l_i} \;\;, l_i = 1,2,\dots,m_i \tag{20}$$

$$f_{o_i}(l_o) = c_{l_o}\phi_i \;\;, l_o = 1,2,\dots,p_o \tag{21}$$

where l_i, l_o and i are inputs, outputs and their modes of system and m_i and p_o are the number of inputs and outputs.

According to the modal analysis, the best selection for inputs and outputs are the signals that have the maximum observability and controllability modal factors (according to the elements in G and H matrices).

The signal with the highest observability factor is the best candidate for being selected as an input, and similarly the signal with the highest controllability factor is the most appropriate one as an output. Briefly, the PSS inputs and outputs are selected based on the signals with the highest observability and controllability, respectively.

D. Suggested Algorithm for Selecting Optimal Input and Output Signals of PSS Based on PMU Data

The flowchart of the proposed algorithm is shown in Fig. 4. First, a suitable database is prepared. For this purpose, the different faults are applied to the power system and all data that are received directly from PMUs, such as the angle of bus voltage and the generators' rotor angles, are saved. Then, the data matrix of buses is constructed.

To reduce the number of received data, the PCA technique (as described in section A) is applied to the data matrix of buses. According to B, the optimal clustering is done with ICA on the reduced data matrix.

After bus clustering, the data matrix of generators is constructed for each cluster of buses, and similarly the PCA technique is applied to each data matrix of generators. Then, the generators of each bus cluster are optimally clustered. Finally, by using modal analysis on every cluster of generators, the optimal input and output signals are found. The number of inputs and outputs equals to the number of final generators' clusters because, in each cluster, one generator is selected as a location for installing PSS (input) and one generator is selected as a location for applying the control signal of PSS (output) with modal analysis. It is assumed that each PSS has a lead-lag form as follows [26]:

$$C(S) = 1.4\, K \frac{(T_1 s+1)(T_3 s+1)}{(T_2 s+1)(T_4 s+1)} \tag{22}$$

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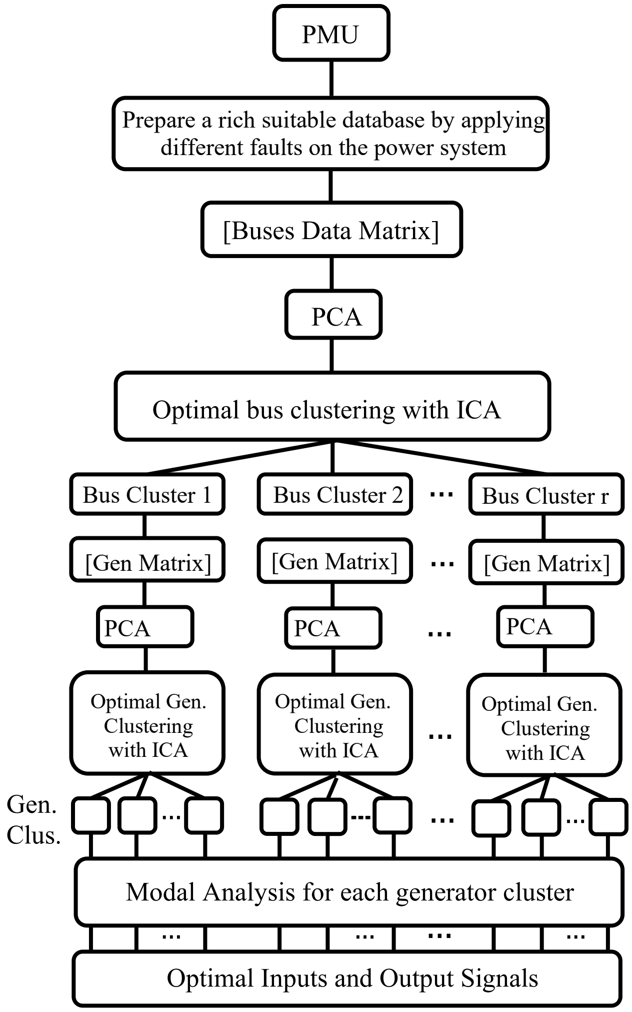

Fig. 4. The flowchart of the proposed algorithm

IV. Formulating PSS Design Method Using Matrix Inequalities

In Section III, the procedure for selecting the inputs and outputs of PSS was explained. The aim of this section is to design the PSSs using the LMI technique. The theory is to place the closed-loop poles of the system in a desired region that assures an appropriate performance of the system.

In this technique, pole placement is achieved via LMIs such that the PSS gain is limited. In other words, the theory of matrix inequalities is used to place the poles in the desired region and at the same time, the static gain of the controller is limited, which results in a system with low gain and high damping.

The LMI region D is a subset of a complex plane, which is defined as below [27]:

$$D = \{s \in C | L + s.M + \bar{s}.M^T < 0\} \tag{23}$$

where L and M are symmetric real matrices.

To locate all eigenvalues of A_{cl} (The closed-loop system model defined in (7)) in the LMI region, there should be a real symmetrical positive definite matrix Q that is satisfied in the following inequality:

$$L \otimes Q + M \otimes (A_{cl}.Q) + M^T \otimes \left(Q.A_{cl}{}^T\right) < 0 \tag{24}$$

To have a desirable control performance, the composite LMI region is used, which is an intersection of three regions as shown in Fig. 5.

1- A half-plane ($Re(s) < -\sigma$), to have a minimum settling time and satisfy a relative stability margin. The matrices in (24) are $L = 2\sigma, M = 1$.

2- A disk which is centered in origin with radius r to avoid large control input. The matrices in (24) are, $L = \begin{bmatrix} -r & 0 \\ 0 & -r \end{bmatrix}, M = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix}$.

3- A sector with the vertex in the origin and the interior angle θ, to have maximum damping $\xi = cos^{-1}\theta$, and minimum overshoot. The matrices in (24) are $L = 0, M = \begin{bmatrix} sin\,\theta & cos\,\theta \\ -cos\,\theta & sin\,\theta \end{bmatrix}$.

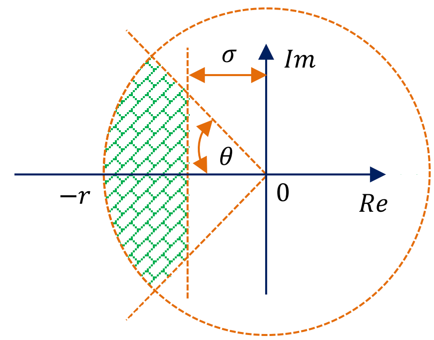

Fig. 5. Composite LMI region [27].

According to (24), the matrix inequalities for three regions is defined respectively as:

$$2\sigma \otimes Q + A_{cl}.Q + Q.A_{cl}{}^T < 0 \tag{25}$$

$$\begin{bmatrix} -r.Q & A_{cl}.Q \\ Q.A_{cl}{}^T & -r.Q \end{bmatrix} < 0 \tag{26}$$

$$\begin{bmatrix} a.A_{cl}.Q + a.Q.A_{cl}{}^T & b.A_{cl}.Q - b.Q.A_{cl}{}^T \\ b.Q.A_{cl}{}^T - b.A_{cl}.Q & a.A_{cl}.Q + a.Q.A_{cl}{}^T \end{bmatrix} < 0 \tag{27}$$

in which $a = \sin\theta$ and $b = \cos\theta$.

To locate the poles in the composite LMI region, there must be a common matrix Q that is satisfied in (25)-(27). Therefore, three matrix inequalities must be solved, simultaneously. However, a challenge in solving the matrix inequalities arises. $A_{cl}.Q$ is not convex because in A_{cl} there are unknown matrices A_c, B_c, C_c, D_c. Therefore, in the $A_{cl}.Q$, there are some bilinear terms due to the multiplication of matrix Q and the controller matrices. Overall, the matrix inequalities in (25)-(27) are Bilinear Matrix Inequalities (BMIs) and the method in [28] can be used to convexify the inequalities.

A. Robust Performance in Various Operating Points

It is necessary for the power system to have a proper performance in different operating points. In this paper, we used the polytopic model of the power system [29]. The idea is to derive a linear model for the power system in various operating points. Then, the overall model is a convex combination of the linear models.

Assume an ith model of a power system in an operating point with matrices (A_i, B_i and C_i). For m different operating points, the polytopic model of the system is defined as follows:

$$A = \sum_{i=1}^{m} \lambda_i A_i, \quad \lambda_i \geq 0, \quad \sum_{i=1}^{m} \lambda_i = 1 \tag{28}$$

In the above definition, A_i is called the side of the polytope, which is an n dimensional matrix. A is the polytopic model.

To guarantee that the poles of the closed-loop system are placed in the composite LMI region, the LMIs according to each operating point in (25)-(27) must be derived and the m sets of LMIs must be solved, simultaneously.

V. Simulation Results

The suggested algorithm is simulated on two test systems: a 13-bus system and a 68-bus system. The systems are simulated in the power system toolbox (PST) [30]. The detailed results are also shared via https://doi.org/10.6084/m9.figshare.14994882

A. 13-Bus System

In Fig. 6, the single line diagram of a two-region, four-machine system is shown. The first step in applying the proposed approach of this paper is to gather the rich and suitable data from buses, transmission lines and generators through the installed PMUs.

To find the location of PSSs and select the optimal inputs and outputs of them, the observability and controllability modal factors are computed for each generator. The results are shown in Table I.

According to the result of the clustering, it has two generator clusters, (G1-G2) and (G3-G4). Thus, it needs two controllers. The location of the measurement signals (input of PSS) and control signals (output of PSS) are shown in Table II.

The modes of the 13-bus system are shown in Figs. 7 and 8 for both open-loop and suggested control strategies, respectively.

The generators' voltage deviation to a 10% step disturbance in the first generator's field voltage are displayed in Figs. 9 and 10. The results demonstrate appropriate damping performance when the proposed controller is applied.

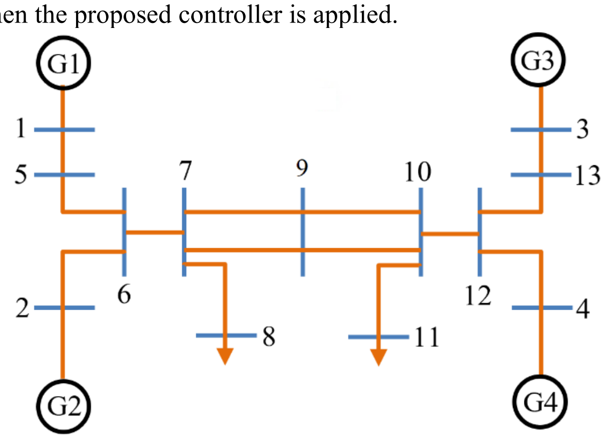

Fig. 6. The single line diagram of the 13-bus (4-machine) system.

TABLE I
THE RESULTS OF MODAL ANALYSIS

Generator	Observability Modal Factor	Controllability Modal Factor
1	2.3364	2.3211
2	2.2283	2.5578
3	2.4388	2.3756
4	2.5070	2.5541

TABLE II
SELECTED INPUT AND OUTPUT SIGNALS WITH THE PROPOSED ALGORITHM FOR THE 13-BUS TEST SYSTEM

Control signal location (output of PSS)	Measurement signal location (input of PSS)
G1-G2	G3-G4

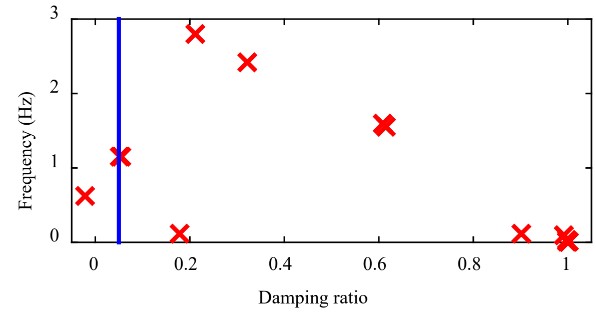

Fig. 7. Modes of the 13-bus system (Open-loop system).

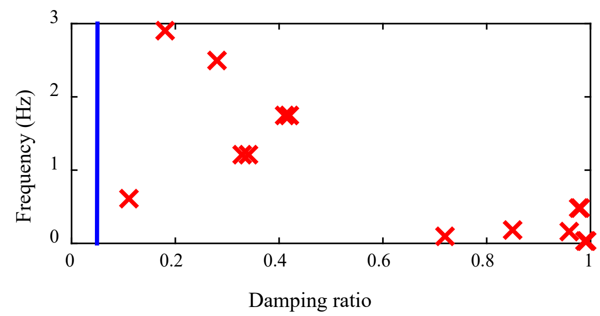

Fig. 8. Modes of the 13-bus system in case of the suggested control.

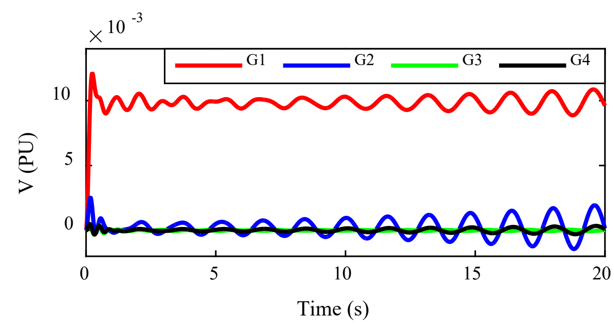

Fig. 9. The response of the 13-bus system to a disturbance in case of the Open-loop control.

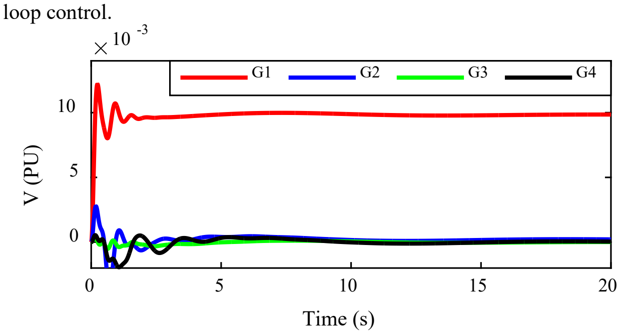

Fig. 10. The response of the 13-bus system to a disturbance in case of the suggested control.

B. 68-Bus Test System

In this sub-section, the approach is simulated on the 68

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buses system with 16 machines [31], shown in Fig. 11. The first step is to gather the rich and suitable data from buses and generators through installed PMUs.

For this system, 391 different faults such as three-phase fault, single/double/triple phase to ground fault, short circuit, loss of load and line outage are applied to most buses and lines. Then, the voltage angle of each bus in all 391 cases constructs a column of the data matrix of buses, leading to a 6120×68 matrix that requires the PCA technique. The final reduced matrix is a 34×68 matrix, which helps to decrease the complexity of the calculation. The results of bus clustering are shown in Table III. For generator clustering, the data matrix is generated by saving the rotor angle of 391 cases. It is a 7480×16 matrix, which is reduced to a 15×16 matrix with the PCA technique.

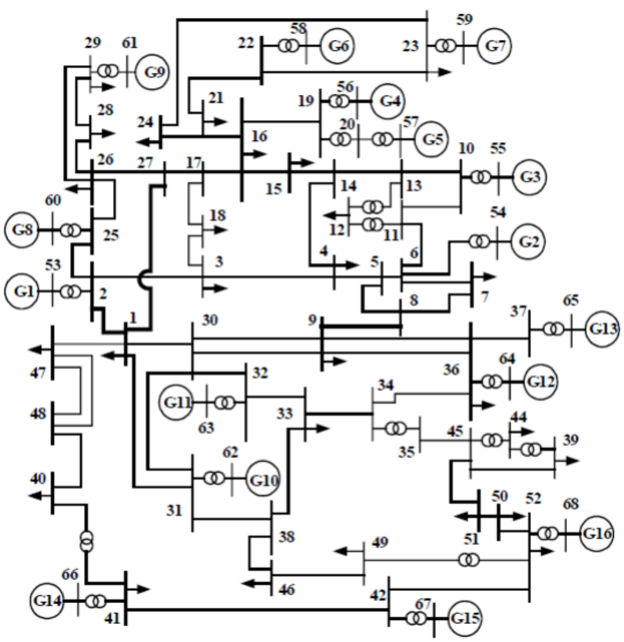

Fig. 11. The single line of the 68-bus test system.

The results of the generators clustering in each bus cluster are shown in Table IV. Finally, the generators are divided into 9 clusters. Therefore, there are 9 pairs of inputs and outputs.

To find the optimal input and output signals, the modal observability and controllability criteria are applied on each cluster. The results of Table V show that there are 3 universal control PSSs on generators 1, 2 and 4 that their output signals are applied to generators 12, 5 and 7, while the other 6 controllers are locally on generators 13, 14, 15, 16, 11 and 9.

To show the effectiveness of the proposed approach, it is compared with the conventional modal approach [11] and the sequential orthogonal (SO) [13] approach. Table VI shows the selected input and output signals of the above three approaches. It reveals that there are 15 input and output pairs selected by modal analysis, while the proposed approach results in 9 pairs.

In the second step, the inputs and outputs selected by the proposed approach, as given in Table VI, are considered for the PSSs and the internal structure of the PSS according to the proposed approach in Section IV is designed.

TABLE III
THE RESULTS OF BUS CLUSTERING OF TEST SYSTEM 2

Cluster	Buses	Generators' numbers
1	41-42-52-66-67-68	14-15-16
2	19-22-23-29-40-49-50-54-55-56-57-58-59-60-61-62-63	2-3-4-5-6-7-8-9-10-11
3	36-37-39-43-44-65	13
4	1-2-3-4-5-6-7-8-9-10-11-12-13-14-15-16-17-18-19-20-21-22-23-24-25-26-27-28-29-30-31-32-33-34-35-38-45-46-47-48-51-53-64	1-12

TABLE IV
THE RESULTS OF GENERATOR CLUSTERING OF TEST SYSTEM 2

Bus Cluster	Generators of each bus cluster	Clustered generators
1	14-15-16	(16), (15-14)
2	2-3-4-5-6-7-8-9-10-11	(2-5-10), (3-4-6-7-8), (9), (11)
3	13	(13)
4	1-12	(1), (12)

TABLE V
SELECTED INPUT AND OUTPUT SIGNALS WITH THE SUGGESTED ALGORITHM FOR TEST SYSTEM 2

Control signal location (output of PSS)	measurement signal location (input of PSS)
13-1-14-15-16-11-9-2-4	13-12-14-15-16-11-9-5-7

TABLE VI
COMPARISON OF SELECTED INPUT AND OUTPUT SIGNALS IN DIFFERENT ALGORITHMS FOR TEST SYSTEM 2

Approach	Control signal location (output of PSS)	measurement signal location (input of PSS)
The proposed approach	13-12-14-15-16-11-9-5-7	13-1-14-15-16-11-9-2-4
Modal approach [11]	5-16-3-12-8-10-5-2-9-7-8-14-7-5-15	5-2-3-12-11-10-13-11-16-7-9-16-13-13-14
SO Approach [13]	16-10-8-3-9-2-12-5-7-10-11-4-13-14	16-4-12-11-2-6-8-5-10-7-3-1-14-13

The modes of the system are shown in Figs. 12 and 13. The voltage deviations of all generators to a 10% step disturbance in the first generator's field voltage are displayed in Figs. 14 and 15. The results show the effectiveness of the proposed approach in determining the optimal selection for the PSS signal, which effectively controls the system behavior in response to disturbances.

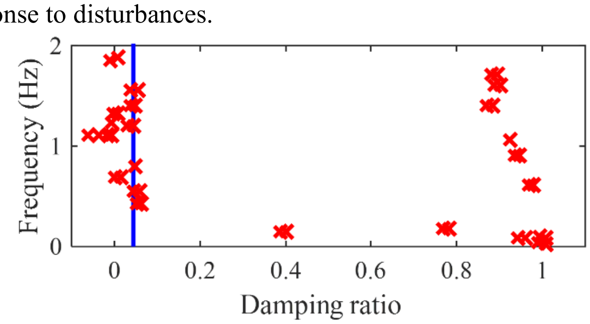

Fig. 12. System modes (Open-loop system).

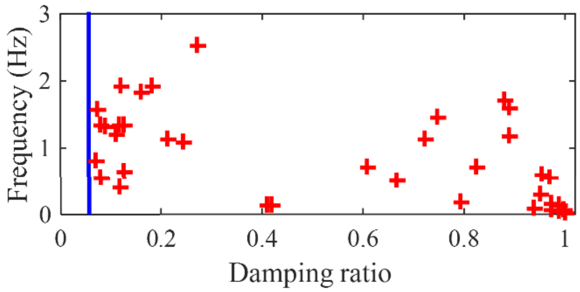

Fig. 13. System modes in case of the suggested control.

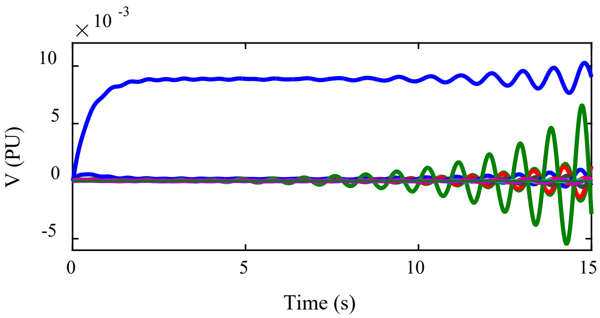

Fig. 14. The response of the Open-loop system to a disturbance.

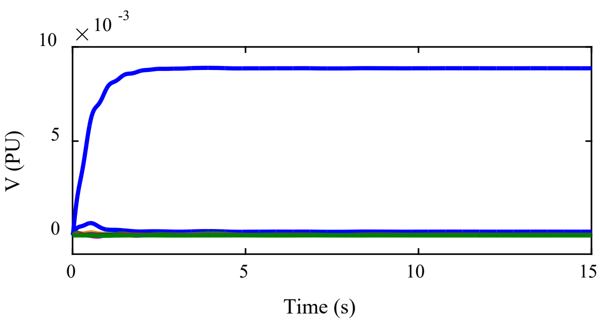

Fig. 15. The response of the system to a disturbance in case of the suggested control.

VI. Discussion

This paper presents a method for optimal input and output PSS signal selection. The optimality of input/output selection is proved by two main concepts. a) The number of PMU signals is optimum b) The result of the closed loop system exploiting WAC is not deteriorated. Considering the 68-bus system, Table VI shows that the number of required inputs/outputs in the proposed approach is less than the Modal and SO approaches. Additionally, the simulation results of the closed loop system in Fig. 13 and Fig. 15 admits the controller capability in damping the power system oscillations.

The proposed approach of this paper can be used for WADC design. Previously, some electric companies in different countries applied PMU-based PSSs or Wide Area Measurement System (WAMS)-based PSSs [32]-[33]. The approach of this paper can be used as an idea to improve the designed PSSs in real power systems that implement PMU/WADC structure. To implement the method completely, it is needed to simulate the power system under study in an appropriate software and use dynamical tests to gather required information from installed PMUs. Then, the power system model (1)-(2) can be identified using the gathered input-output information and the control design approach of Section IV can be exploited.

Obviously, in reality, the WADC may encounter some problems which need to be handled by engineers. A challenge is the time delay in data transmission via the WADC which is approximately 110 ms. Two different strategies regarding this problem are proposed in the literature. One is to design time delay compensators to refine the impacts of time delay [32]. The other, is to design the controller such that the varying time delay with the bound of 110 ms does not affect the WADC. In the literature, Lyapunov Krasovski Functional (LKF) approach is suggested for this design procedure [34]. The research can be continued for considering the time delay impact in designing the WADC in presence of the probable delay in data transmission.

The other problem is the packet loss or packet dropout [34]. When the PMU data is missed, the control centre is not able to make any decisions unless appropriate programs are implemented that can overcome the packet loss or dropout, mathematically.

VII. Conclusion

In this paper, a method for optimal input and output PSS signal selection and their related controller design based on the data of PMU was proposed. First, the PSS input-output selection was carried out based on the modal analysis technique, and by clustering buses and generators in the system, an appropriate optimal strategy for signals' selection was reached. The combination of generator clustering and bus clustering using modal analysis and PCA techniques resulted in the desirable damping with the least number of input and output signals. Then, the selected input-output signals were used in the PSS structure and exploiting the LMI techniques, the PSS parameters were designed. The developed algorithm has several computations that are completely offline and, after the design procedure, they can be implemented in practice with a low computational burden. Therefore, it is an appropriate algorithm for being implemented in power systems. The method was applied on two standard benchmarks. Compared to the previous approaches in this area, the suggested algorithm reduced the cost and complexity of the monitoring system while the control performance was not deteriorated.

Briefly, the paper concludes the following points:

- The overall damping of signals can be improved by a WAMS PSS (PMU-based PSS), instead of conventional PSSs.
- By optimal selection of input/output signals in a WAMS PSS, we can avoid too complicated structure with a reasonable damping of signals.
- After selecting the input/output signals of the WAMS PSS, the control design techniques such as pole-placement can be used to find the PSS parameters.

The research can be continued in the future by considering the communication channel problems, such as time delay and packet dropout. Also, the real-time implementation of the approach is suggested.

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