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Towards Development of Equivalent Model of Hybrid Renewable Energy Source Plant for Small Disturbance Stability Studies

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***Abstract*—Over the past years, the focus of the research on hybrid renewable energy source (HRES) plants has been on the economic advantages of their integration into power systems. This paper investigates the contribution of the HRES plant to system small disturbance stability and proposes dynamic equivalent model (DEM) of HRES plant for small disturbance stability studies. The analysis takes into consideration typical annual HRES plant compositions identified by applying a clustering method to historical plant production data. Damping and frequency of the least damped electromechanical mode are used for assessing the similarity in the impact of HRES plant compositions on system stability. A transfer function-based DEM of the whole HRES plant is then proposed for each group of plant compositions resulting in similar system stability performance. The results have shown that a small number of low-order DEMs can represent the whole plant in small disturbance stability studies during the year.**

***Index Terms*--data clustering; dynamic equivalent model; hybrid renewable energy source plant; small disturbance stability**

I. Introduction

Over the past years there has been a considerable growth in the installation capacity of renewable energy sources (RESs) in power systems all over the world [1]. Unlike conventional power plants, RES plants are mostly characterized by intermittent production, large number of individual units and power electronics-interface [2]. Integration of different technologies into a single power plant has been recognized as a potential option for improving dispatchability of RESs, and thus enabling the control of RES production by system operators. Hybrid renewable energy source (HRES) plants rely on combining various RES (both dispatchable and non-dispatchable) and storage technologies to obtain more stable power output at the point of common coupling (PCC). So far, the research has been focused on designing economically cost effective HRES plants capable of following pre-specified production profile [3]. However, the alterations in static and dynamic system performance due to integration of HRES plants have been commonly neglected [3]. Different power flows in network due to power being produced at different geographical locations, reduced inertia level, different dynamic characteristics of generation units in service are some of the changes in system structure and operation associated with the installation of HRES plants and decommissioning of conventional power plants.

The need for analyzing the influence of large RES plants on system dynamics has pointed out at the problem of their representation in system stability studies. Namely, detailed dynamic modelling of all individual units in RES plants results in unnecessary complex network models and consequently high computational time required for performing system stability simulations [4]. In order to overcome the issue, dynamic equivalent models (DEMs) have been recommended for representing RES-based plants and networks in system stability studies [4]. The two main types of DEMs are modal analysis and system identification-based models [4]. The former is based on calculating all eigenvalues of the system and eliminating those associated with fast system dynamics. System identification-based approach utilizes system responses to derive DEM parameter values. It can be divided into black-box and grey-box modelling technique depending on the needed amount of information about the system. Unlike grey-box equivalents, black-box models do not require any physical insight into the investigated system and measurements at system boundary buses are the only prerequisite for the application of the method. Most of the DEMs described in the literature are suitable for a specific technology mix in a power plant/distribution network, adequate for a limited number of operating conditions and/or require detailed information about network topology, which limit their application in practice [4].

In this research, the aggregate contribution of various generation and storage technologies to transmission network (TN) stability was assessed. The paper investigates the impact of a HRES plant on small disturbance stability of a TN and provides guidelines for equivalent modelling of the whole

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HRES plant in small disturbance stability studies. The methodology for assessing the influence of HRES plant on system stability is based on typical HRES plant operating scenarios (i.e., HRES plant compositions) during the year. A set of characteristic plant compositions is identified by applying the fuzzy c-means clustering algorithm to historical HRES plant production data. A probabilistic Monte Carlo (MC) approach is used for taking into consideration uncertainties in production and location of individual technologies in HRES plant. Small disturbance HRES plant behavior is assessed on the basis of damping and frequency of the least damped electromechanical mode. A black-box DEM in the form of a transfer function (TF) is proposed for each group of HRES plant compositions resulting in similar small disturbance stability performance. In this way, the annual performance of the HRES plant in small disturbance stability studies is represented by a small set of low order DEMs. In addition, to the best of authors' knowledge, DEM development on the basis of the least damped electromechanical modes has not been reported in the literature. The test HRES plant consists of six RES and storage technologies having the same point of connection to the TN.

II. Methodology

The methodology applied in this study is graphically illustrated in Fig. 1. Inputs and outputs of stages within the procedure are represented by dashed rectangles. The first stage in the study is identifying typical HRES plant compositions during the year (block labelled with (2) in Fig. 1). Performing the study with characteristic HRES plant compositions solves the problem of high computational time associated with investigating all possible HRES plant operating points. Typical HRES plant compositions are determined by applying a clustering method to historical data about the active power outputs of the HRES plant's individual components. A single clustering object consists of individual plants' production at the same time instance, while the number of clustering objects corresponds to the number of time steps in the analyzed historical period.

The fuzzy c-means clustering method, a partitioning clustering algorithm, is chosen to perform data clustering as the historical production data set is expected to be large. One of the main advantages of the algorithm is its low computational complexity, $O(N)$, where N is the number of clustering objects [5]. In addition, the fuzzy c-means clustering method has been used for similar clustering tasks [6]-[8]. The data set is separated into clusters through an iterative process, with the number of clusters defined prior to clustering process [5]. At each iteration, all clustering objects are allocated to all clusters with a certain membership degree, which makes the algorithm suitable for clusters not being well separated [5]. Each cluster is described by a cluster representative (i.e., fuzzy centroid), which corresponds to characteristic HRES plant composition in this study. The fuzzy centroid is defined as follows [5]:

$$w_j = \frac{\sum_{i=1}^{N}(u_{ij})^m x_i}{\sum_{i=1}^{N}(u_{ij})^m}, \tag{1}$$

$$u_{ij} = \frac{1}{\sum_{l=1}^{k}\left(\frac{d(x_i,w_j)}{d(x_i,w_l)}\right)^{1/(m-1)}}, \tag{2}$$

$$\sum_{j=1}^{k} u_{ij} = 1, \forall i = 1, \ldots, N, \tag{3}$$

where w_j is the centroid of the j-th cluster, x_i is the i-th clustering object, u_{ij} is a membership degree of the i-th clustering object in the j-th cluster, $d(x_i,w_j)$ is the Euclidean distance between the i-th clustering object and the j-th fuzzy centroid, k is the number of clusters and m is the fuzziness level (m is usually equal to 2). Internal clustering evaluation indices have been commonly used for addressing the problem of specifying the number of clusters in advance [9]. The clustering procedure is repeated for a range of the number of clusters and the selected index is calculated for each reiteration taking into account inter-cluster and intra-cluster similarity. The number of clusters corresponding to the optimal value of the clustering index represents the optimal number of clusters for the analyzed clustering data set. In order to obtain more reliable estimation of the number of clusters in the production data set, a combination of the three widely applied clustering indicators, mean square error (MSE), clustering dispersion index (CDI), and mean index adequacy (MIA), is used in this study [9]. The optimal number of clusters according to any of these indicators is determined by plotting the indicator against the number of clusters and identifying the knee of the curve using the two-tangent method described in [9]. The final number of clusters, i.e., the number of typical annual HRES plant compositions, is defined as a median value of the numbers recommended by the afore-mentioned indices.

The next stage of the methodology involves probabilistic MC procedure (block labelled with (4) in Fig. 1), which takes into account uncertainties in active power outputs of individual plants and the lengths of connecting lines. Uniform probability distribution is adopted for sampling these uncertainties from the pre-specified ranges. Uncertainties in plant production are varied within the ranges centered around typical annual HRES plant compositions. Small signal stability analysis of the TN is performed for each MC case study by conducting modal analysis in DIgSILENT PowerFactory software environment (block labeled with (6) in Fig. 1). Modal analysis requires computing all system eigenvalues using the classical QR transformation [10]. The influence of different HRES plant compositions on small signal stability is distinguished on the basis of damping and frequency of the critical (least damped) electromechanical oscillation mode (block labeled with (7) in Fig. 1). Electromechanical modes are used for identifying the patterns in HRES plant stability performance as these modes persist longest after a system disturbance and thus determine the overall system dynamic behavior [10]. Grouping of MC case studies according to the similarity in the impact on small disturbance system stability is carried out by applying the fuzzy c-means clustering algorithm to the results of small signal stability studies (block labelled with (8) in Fig. 1). The optimal number of clusters is estimated in the same way as in the case of production data clustering. Each cluster of critical electromechanical modes is represented by a fuzzy centroid, so-called representative critical electromechanical mode.

Furthermore, a representative HRES plant composition is defined for each cluster as one of the simulated plant compositions characterized by the critical electromechanical mode corresponding to cluster medoid (cluster medoid is one of the simulated electromechanical modes being the most similar to the representative critical mode). The number of clusters of electromechanical modes corresponds to the number of DEMs required to represent the HRES plant in small signal stability studies during the year.

The final step in the study involves proposing DEM structure (block labelled with (10) in Fig. 1). Firstly, a time domain electromechanical simulation is carried out for each representative HRES plant composition defined in the previous step of the methodology. The electromechanical simulations are carried out in DIgSILENT PowerFactory software using the full-scale dynamic model of the HRES plant. An increase in TN load is chosen as a system disturbance. The lengths of all connecting lines are set at the average of line lengths simulated in the MC procedure. Voltage and power responses at the PCC are recorded in the simulations and these responses represent a basis for DEM development.

The DEM is developed in the form of a TF for each of the clusters of small signal stability results. The input and output signal of the TF is the deviation of voltage and power at the PCC from their pre-disturbance values, respectively. The full DEM structure is as follows:

$$P_{DEM}(t) = \begin{cases} P_{ss}, t < t_{start} \\ P_{ss} + \mathcal{L}^{-1}\big(TF(s)\big)\big(u_{PCC}(t) - u_{SS}\big), t \geq t_{start} \end{cases}, \quad (4)$$

where P_{DEM} (t) is the active power output of the DEM, P_{ss} is the total HRES plant production in pre-disturbance state, $\mathcal{L}^{-1}$ stands for the inverse Laplace transform, $TF(s)$ is the TF in s-domain, u_{PCC} (t) is voltage at the PCC, u_{SS} (t) is voltage at the PCC in pre-disturbance state and t_{start} is the moment of occurrence of the system disturbance.

The estimation of TF parameters is carried out through an iterative optimization process using System Identification Toolbox in MATLAB [11]. In this process, voltage and active power responses at the PCC that are obtained in the time domain electromechanical simulations are used as TF input and output, respectively. TF numerator and denominator order are gradually increased starting from TF structure corresponding to the representative critical electromechanical mode. For each TF order, TF parameters are initialized using the simplified refined instrumental variable method first and then updated through the optimization process using the Levenberg-Marquardt algorithm [4], [11]. The objective of the optimization procedure is to minimize the difference between TF output and small signal active power response of the detailed HRES plant model:

$$\min_{\theta} RMSE = \min_{\theta} \sqrt{\frac{1}{n}\sum_{i=1}^{n}(P_{ORG,i} - P_{DEM,i})^2}, \quad (5)$$

where $RMSE$ is root mean squared error, θ is a set of TF parameters, n is the number of samples, $P_{ORG,i}$ is the active power response obtained in the electromechanical simulation at the i-th time step, and $P_{DEM,i}$ is DEM output at the i-th time step. The optimization terminates when there is no considerable improvement in $RMSE$ value between two consecutive iterations. Following parameter estimation, the Best Fit Value (BFV) is calculated using (6) [4]:

$$BFV(\%) = 100 \cdot \left(1 - \left|\frac{\sum_{i=1}^{n}(P_{ORG,i} - P_{DEM,i})}{\sum_{i=1}^{n}(P_{ORG,i} - \overline{P}_{ORG})}\right|\right), \quad (6)$$

where $\overline{P}_{ORG}$ is the average of small signal active power response of the detailed HRES plant model. The optimal TF parameters correspond to the lowest TF order with the BFV above a pre-defined threshold (80% is adopted in the study [4]).

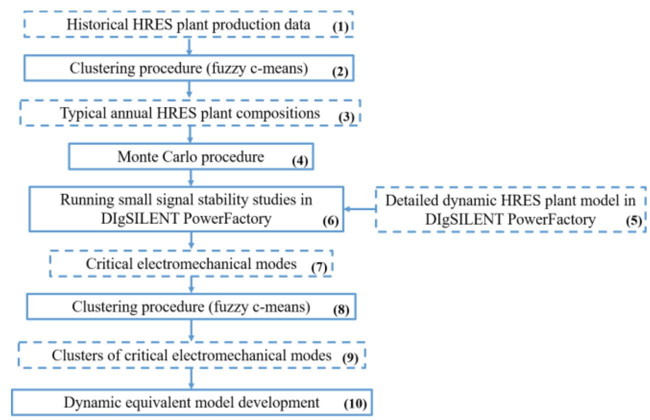

Figure 1. The flow chart of the methodology.

III. TEST SYSTEM

The test HRES plant, along with the test TN, is shown in Fig. 2. The whole test system is developed in DIgSILENT PowerFactory software package 2019 [12]. The analyzed HRES plant contains 6 individual plants: 3 dispatchable RES plants (a pumped hydro storage (PHS), biomass and biogas power plant), 2 non dispatchable RES plants (a photovoltaic (PV) plant and wind farm (WF)) and a battery energy storage system (BESS). The HRES plant design is adopted from [13] and corresponds to an optimal techno-economic HRES plant configuration for the southern part of Greece. Individual plants in the HRES plant are connected to a common 110 kV bus, i.e., the PCC (Bus 17 in Fig. 2), which is further connected to a 230 kV external TN through a transformer and two parallel lines. System load (connected to Bus 17 in Fig. 2) is represented by static exponential load model without frequency dependent components.

The rated capacities and model order of all individual plants in the HRES plant are given in Table I. The model order specified in Table I includes the order of the dynamic model of generation/storage technology and its control system. Nominal power factor of 0.85 is assumed for all SMs in the HRES plant, while the PV plant, WF and BESS do not produce or generate reactive power. The PV plant and WF consist of a certain number of individual, identical, units connected in parallel and are represented by aggregate models obtained by scaling up the models of individual generators [12]. The number of parallel units in service is defined by the plant power production as it is assumed that units in service produce nominal power output of 2 MW.

A generic type 3 model, suitable for large system stability studies, is used for representing WF individual units (doubly-fed induction generators (DFIGs)). The model is developed on the basis of the recommendations given by WECC [14] and IEC [15] and is available in DIgSILENT PowerFactory [12]. PV plant individual units are modelled by a type 4 wind generator model, adequate for full-converter connected wind generators. Given that PV plants and type 4 wind generators are connected to the grid through a full-connected converter and converter can be considered to decouple dynamics of the source on the DC part from the rest of the power system, both technologies can be represented by the same model in system stability studies [16]. The structure of the PV dynamic model used in the paper is similar to the one presented in [17] and is also available in DIgSILENT PowerFactory environment [12]. More details on WF and PV plant modelling can be found in [16]. The hydro generator is represented by the standard fifth order SM model, whereas the sixth order model is used for the biomass and biogas power plant [10]. The control systems of all three SM-based power plants contain the standard IEEE DC1A exciter, while IEEEG3, IEEEG1 and GAST governors are used in the hydro, biomass and biogas plant control system, respectively [10]. The BESS is modelled as a static voltage source with a control system containing a frequency controller, active power-voltage controller, charge controller and relevant protection mechanisms [18]. The voltage source model takes into account the battery state of charge and battery internal losses.

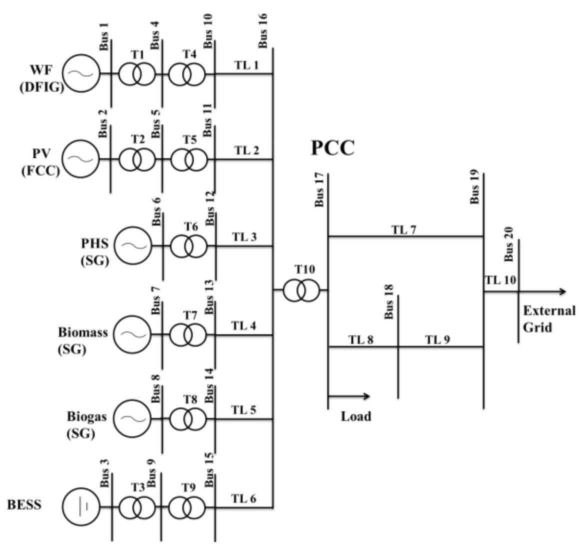

Figure 2. The schematic diagram of the test system.

IV. Results and Discussion

The study is based on optimal economic HRES plant production profiles during one year [13]. The data set was generated through an optimization process with the aim of satisfying system operator requirements in terms of total plant production while maximizing total annual plant revenues. The sampling rate of the data set is one hour. The same system load operating point is adopted for all analyzed HRES plant operating scenarios - system load corresponds to a quarter of the average annual HRES plant production.

The application of the fuzzy c-means clustering algorithm to the historical production data set results in nine clusters of HRES plant compositions, which are given in Table II. Nine clusters are selected based on the values recommended by the MSE, CDI and MIA indices – 9, 5 and 11, respectively. The change of the values of the clustering indicators with the number of clusters is presented in Fig. 3. Probabilistic MC procedure involves generating a thousand MC simulations per characteristic annual HRES plant composition. Uncertainty in the location of individual technologies in the HRES plant is taken into account by varying the lengths of connecting lines (lines TL 1 – TL 6 in Fig. 2) uniformly between 0.5 km and 5 km. As for uncertainties in production forecast, in each set of 1,000 MC simulations, the power output of each individual plant is sampled uniformly in the range of ±5% around the corresponding value in the typical HRES plant composition.

TABLE I. Nominal Capacites and Model Order of Individual Plants in the Test HRES Plant

Technology	WF	PV plant	PHS	Biomass plant	Biogas plant	BESS
Nominal capacity (MVA)	170	265	295	76.5	76.5	125
Model order	17	14	13	14	11	9
Overall model order	78					

TABLE II. Characteristic Annual HRES Plant Compositions

No.	WF (MW)	PV plant (MW)	PHS (MW)	Biomass plant (MW)	Biogas plant (MW)	BESS (MW)
1	18	4	0	64	58	0
2	152	16	0	0	0	2
3	132	112	0	0	0	-89
4	34	4	119	0	0	0
5	56	28	0	58	10	0
6	20	200	0	0	0	-68
7	148	176	-139	0	0	0
8	36	26	0	0	0	92
9	24	148	0	0	0	0

As mentioned in Section II, the focus of small signal stability analysis is on electromechanical modes. Therefore, the least damped electromechanical mode is defined for each MC simulation and shown in Fig. 4. Given that the external network is modelled as a single large SM and only four out of nine typical annual HRES plant compositions (i.e., compositions 1, 4, 5 and 7) have at least one SM-based power plant in service, only these four HRES plant compositions can produce electromechanical modes. Given that all three clustering indicators suggest three as the optimal number of clusters, the results of small signal stability analysis of the above-mentioned four HRES plant compositions can be divided into three groups. Cluster 1 contains the results of the MC case studies based on compositions 1 and 5 that are characterized by two SMs (the biomass and biogas power plant) in operation. These two compositions result in the least damped and fastest electromechanical mode (on average, -0.7 and 1.34 Hz, respectively) among the recorded electromechanical modes. The second cluster includes composition 7, i.e., the composition with the PHS in pumping mode as a single SM in service. Finally, MC cases based on HRES plant composition 4 with the PHS in power generation mode are allocated to cluster 3. Electromechanical modes produced by clusters 2 and 3 have similar frequency (about 1.17 Hz), but slightly different damping: -1.01 and -1.18 respectively.

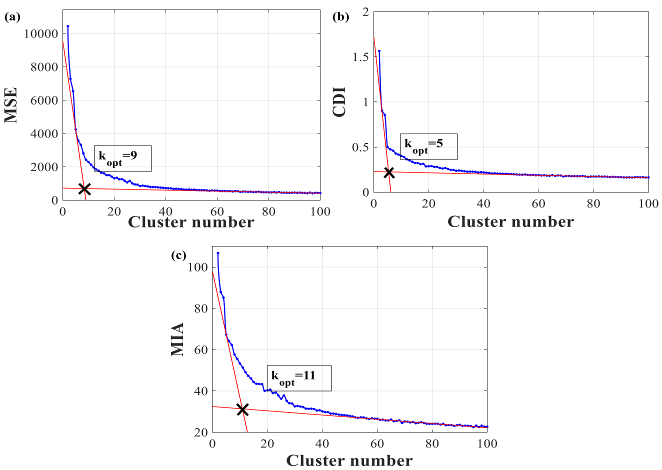

Figure 3. The change of the MSE (a), CDI (b) and MIA (c) with the number of clusters in the historical production data clustering procedure.

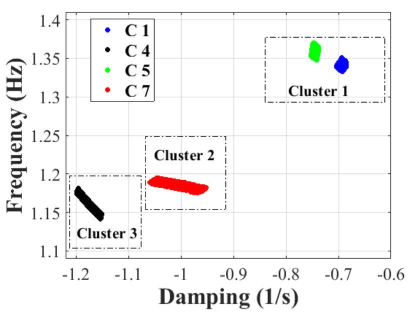

Figure 4. Critical electromechanical modes produced by MC case studies (C: characteristic annual HRES plant composition).

Therefore, all analyzed MC case studies can be divided into 4 groups (3 groups of cases producing electromechanical modes and a group of cases without a SM in service) based on their impact on small signal system stability. The data about the fuzzy centroid (i.e., representative critical electromechanical mode) and the output of the representative HRES plant composition are given in Table III for each of the four clusters. HRES plant compositions associated with each of the DEMs are shown in Fig. 5 in the form of boxplots. Outliers are marked by red asterisks, whereas whiskers cover 99.3% of data in the case of normal distribution. Four clusters of MC cases indicate that four DEMs are required for representing all considered HRES plant operating points in small signal stability studies. Cluster/DEM 4 and 1 cover 50% and 30% of the historical data set, respectively, while the two remaining DEMs represent only around 10% of the data each. Furthermore, the selection of the DEM is determined by HRES plant composition only as all MC cases generated on the basis of a single characteristic HRES plant composition belong to the same cluster.

As described in Section II, in order to derive DEMs time domain electromechanical simulations are performed for representative HRES plant compositions of the four clusters. An increase in system load (represented by load connected to Bus 17 in Fig. 2) corresponding to approximately 5% of the HRES plant output is chosen as a system disturbance. The simulations last 10 seconds and the disturbance occurs at 1 second. The lengths of all connecting lines are set at 2.75 km as it corresponds to the average of the line lengths simulated in the MC procedure. Deviation of active power responses from HRES plant output in pre-disturbance state is shown in Fig. 6 (a) for all electromechanical simulations. The parameters of the representative critical electromechanical mode given in Table III are used for specifying initial TF complex poles prior to the optimization process. In the case of DEM 4, that is, HRES plant compositions without SMs in service, TF poles cannot be initialized in advance (TF can contain only real poles). TF parameter estimation process terminates when the improvement in RMSE value between two consecutive iterations becomes smaller than 1%.

TABLE III. REPRESENTATIVES OF CLUSTERS OF SMALL SIGNAL STABILITY RESULTS

Cluster number	Damping (1/s)	Frequency (Hz)	HRES plant output (MW)
1	-0.72	1.35	149.5
2	-1.01	1.18	184.8
3	-1.18	1.16	157.3
4	-	-	161.4

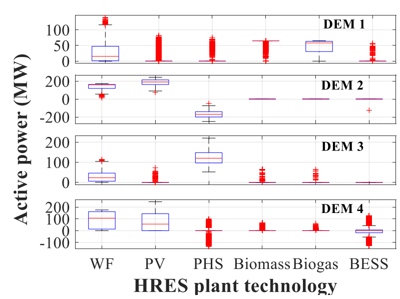

Figure 5. Historical HRES plant compositions corresponding to the DEMs.

As an example, a final form of the TF determined for DEM 1 is given by (7):

$$TF(s) = -10^4 \frac{0.38s^3+10s^2+3.86s+2.02}{(s^2+1.32s+67.2)(s+37.82)}. \tag{7}$$

All four TFs are characterized by one highly damped real pole. While TF for DEM 4 has only one pole, TFs for DEM 1-3 contain a conjugate complex pole as well. Thus, dynamic equivalencing provides a significant reduction in HRES plant model order: the detailed dynamic model requires 78 differential equations, whereas the highest DEM order is three. All DEMs are characterized by high match with the corresponding active power responses obtained in DIgSILENT time domain simulations – *RMSE* index (given by (5)) is below

0.005 MW for all DEMs as well as high match of the corresponding eigenvalues. The active power responses produced by the detailed HRES plant model and DEM 1 are compared in Fig. 6 (b) and the eigenvalues of the critical modes for DEM 1-3 and those obtained from the corresponding detailed HRES plant model in DIgSILENT for the representative HRES plant compositions are shown in Table IV.

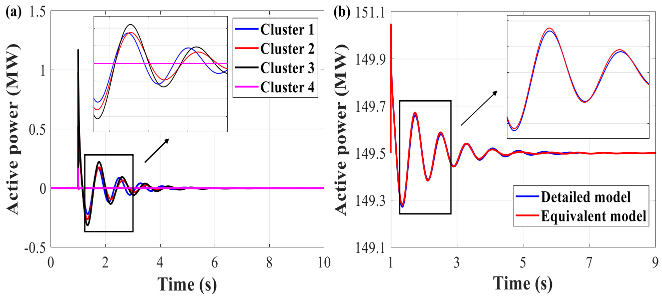

Figure 6. Deviation of small signal active power responses at the PCC from total HRES plant production in pre-disturbance state for all clusters (a); Small signal active power responses at the PCC produced by the detailed HRES plant model (blue) and DEM 1(red) (b).

TABLE IV. CRITICAL MODES OF DEMS AND DETAILED HRES PLANT MODEL

	DEM		**Detailed HRES plant model**	
	Damping (1/s)	**Frequency (Hz)**	**Damping (1/s)**	**Frequency (Hz)**
Cluster 1	-0.66	1.30	-0.70	1.34
Cluster 2	-0.99	1.19	-1.01	1.18
Cluster 3	-1.13	1.16	-1.18	1.16

V. CONCLUSION

The paper provided a detailed analysis of the impact of the HRES plant on small disturbance stability of the network and guidelines for developing DEM of the HRES plant for small signal system stability studies. The test system contains the HRES plant that consists of a range of RES and storage technologies and is connected to the TN through a single PCC.

The presented study is based on analyzing the annual small disturbance performance of the HRES plant considering variable plant compositions. Unsupervised fuzzy c-means clustering method is applied to the historical HRES plant production data set to determine the most probable HRES plant compositions during the year. In this way, the problem of high computational time associated with investigating all possible HRES plant operating conditions is avoided. The influence of characteristic HRES plant compositions on small signal system stability has been established in terms of the damping and frequency of their least damped electromechanical mode. A DEM of the HRES plant is proposed in the form of a TF to model the plant in system wide small disturbance stability studies. Voltage and active power at the PCC are used as the TF input and output signal, respectively. Results have shown that the considered HRES plant compositions can be represented by four low-order DEMs. In addition, only the information about HRES plant composition is needed when selecting the most suitable DEM at any time during the year. Equivalent modelling can provide considerable reduction in the order of the mathematical model of the HRES plant and consequently time required for conducting small disturbance stability studies of large systems.

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