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

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***Abstract*—The paper studies the influence of the hybrid renewable energy source (HRES) plant on system voltage stability. System stability analysis is carried out for a set of the most probable annual HRES plant compositions. These compositions are obtained from the historical HRES plant production data set using an unsupervised clustering method. Identification of patterns in the results of voltage stability studies enables the development of equivalent models (EMs) of the whole plant. The EMs are derived in the form of a synchronous machine with adequate reactive power support capability and connected to the grid at the same bus as the HRES plant. The results obtained with the test system have shown that a few EMs are sufficient to represent the whole HRES plant in voltage stability studies throughout the year.**

***Index Terms*--data clustering; equivalent model; hybrid renewable energy source plant; voltage stability**

I. Introduction

With the ever-increasing awareness of environmental issues, renewable energy sources (RESs) have become an attractive option for contributing to environmental protection and sustainable development. The total installation capacity of RESs reached more than 2,500 GW at the end of 2019 [1]. Still, the increased penetration of RESs in the grid has caused numerous challenges in power system planning and operation, with intermittent production from RESs being recognized as the major problem [2]. Hybrid renewable energy source (HRES) plants have been seen as a promising solution for the issue of stochastic power output from RESs [3]. HRES plant concept relies on the ability of different generation and storage technologies to compensate each other deficiencies to a certain extent [3]. It combines non-dispatchable RESs with dispatchable renewable generation and storage technologies in order to obtain stable and flexible power output of the whole plant. In this way, reliability of meeting operator requirements in terms of following the specified production profile is increased and chances for participating in energy and ancillary service markets are higher in comparison with single-technology RES power plants [4]. So far, the focus of the research has been on the optimal design and dispatch of individual technologies in HRES plants from the economic point of view, without taking into consideration the influence of optimal economic HRES plant production profile on the overall system performance [4].

Unlike traditional synchronous machine (SM)-based power plants, RES power plants comprise a large number of individual units spread across a considerable geographical area. Detailed modelling of every component in these plants in large system stability studies is becoming highly impractical [5], [6]. Detailed models of RES plants are often impossible to be developed due to lack of data and confidentiality issues that sometimes prevent the exchange of detailed network models between different network operators [5]-[7]. Thus, equivalent models (EMs), that is, simplified representations, of RES power plants have been recommended for their modelling in system stability studies [6]. Aggregation-based, modal analysis and system identification-based techniques have been widely used in equivalent modelling of RES plants, as well as the whole distribution networks (DNs) and microgrids (MGs) [6] – [9]. The first approach identifies coherent groups of generators and represent them by equivalent generators having the same structure as individual generation units. Modal analysis-based method is based on full-eigenvalue analysis of the system, while the second one uses measured/simulated system responses to estimate model parameters. Depending on the model structure, system identification-based models can be divided into black-box and grey-box models. Black-box models are focused on achieving high match between the responses of the detailed model and EM, without taking into account system physical structure. On the other hand, the structure of grey-box models corresponds to the combination of physical models of the most important devices in the system. Most of the EMs reported in the literature are suitable for a specific technology mix in a power plant/DN/MG, require model redevelopment whenever operating condition changes and/or need detailed

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information about network topology, which limit their practical applicability [6] – [9].

This paper investigates the impact of a HRES plant on voltage stability of a transmission network (TN) and proposes the structure of EM of the whole HRES plant suitable for voltage system stability studies. The proposed modelling procedure is applicable to any technology mix in the HRES plant as well as for a range of operating points. The assessment of the influence of the HRES plant on voltage system stability is performed on the basis of characteristic annual HRES plant compositions. These compositions are defined by applying a data mining technique to the historical production profiles of the considered HRES plant. HRES plant compositions that result in similar voltage system stability performance are grouped together and these groups represent a basis for development of grey-box EMs of the whole HRES plant. Equivalent modelling methodology provides a set of EMs for representing the HRES plant in voltage stability studies during the year. EM is developed in the form of a single SM with adequate reactive power support capability. The methodology is tested on the HRES plant consisting of a range of non-dispatchable and dispatchable RES and storage technologies.

II. METHODOLOGY

The flow chart of the methodology adopted in this study is illustrated in Fig. 1 (dashed rectangles in Fig. 1 mark inputs and outputs of different stages within the procedure). The study begins with the identification of typical plant compositions during the year using an unsupervised data mining method (block labelled with (2) in Fig. 1). The use of the most probable annual HRES plant compositions instead of all possible HRES plant operating points provides a computationally efficient analysis. The patterns in HRES plant compositions are determined by applying a clustering method to historical HRES plant production data. Power outputs of individual plants are grouped into a vector at each time step in the analyzed historical period and these vectors are used as inputs to the clustering procedure.

Given that the historical data set is expected to be large, the fuzzy c-means clustering algorithm is chosen to perform data clustering due to its low computational complexity ($O(N)$, where N is the number of clustering objects) [10]. Furthermore, the algorithm has already been used for clustering similar data sets [11]-[13]. Characteristic annual HRES plant compositions correspond to cluster representatives. The algorithm belongs to a group of partitioning clustering methods, meaning it divides the data set into a pre-defined k number of clusters through an iterative procedure. However, unlike the rest of partitioning clustering algorithms that allocate each clustering object to a single cluster, the fuzzy c-means algorithm assigns all clustering objects to all clusters with a certain membership degree [14]. This feature of fuzzy clustering is especially useful in case of clusters not being well separated [14]. A cluster representative (so-called fuzzy centroid) is defined as follows [14]:

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

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

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

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 and m is the fuzziness level (m is usually equal to 2).

Internal clustering evaluation indices, based on assessing inter-cluster and intra-cluster similarity, are usually used for estimating the optimal number of clusters [15]. In this study three common clustering indicators, mean square error (MSE), clustering dispersion index (CDI), and mean index adequacy (MIA) are used [15]. The fuzzy c-means clustering process is repeated for a range of the number of clusters and the chosen clustering indices are calculated for each clustering result. The values of these indices decrease with an increase in the number of clusters, resulting in an L-shaped curve. The optimal value of the index is located at the knee of the curve, which is estimated using the two-tangent method described in [15]. The final number of clusters, i.e., the number of characteristic annual HRES plant compositions, is determined as the median value of the optimal number of clusters identified by the afore-mentioned indicators.

Uncertainties in production and location of individual plants in the HRES plant are accounted for using a probabilistic Monte Carlo (MC) approach (block labelled with (4) in Fig. 1). In each MC case study (CS), the lengths of lines connecting individual plants to the point of common coupling (PCC) and active power of individual plants are sampled uniformly from the pre-specified ranges. Typical annual HRES plant compositions represent a basis for generating uncertainties in HRES plant production. Voltage system stability is analyzed for each MC CS. Voltage stability studies are performed in DIgSILENT PowerFactory software by computing active power – voltage (P-V) curves at the selected buses in the system (block labelled with (6) in Fig. 1). Voltage stability limit is determined by increasing the selected system loads (by the same percentage value) gradually until the load flow calculation stops converging. The increase in the selected system loads in the first iteration is 0.5% of their initial values, while the change of the system demand in the following iterations varies between 0.01% and 2% (recommended values by DIgSILENT PowerFactory [16]). Step size reduces as the system approaches the voltage stability limit. Active power outputs of individual plants in the HRES plant remain constant in voltage stability study, while the external grid covers the mismatch between the analyzed demand and HRES plant output. The critical points of P-V curves, i.e., load margin (the difference between the system demand at which voltage collapse occurs and the initial system demand) and the voltage of the bus that collapses first, are used to analyze the contribution of the HRES plant to voltage stability (block labelled with (7) in Fig. 1). MC CSs are grouped on the basis of the similarity in the impact on voltage system stability by applying the fuzzy c-means clustering method to the values of load margin and critical bus voltage (block labelled with (8) in Fig. 1). The number of clusters is defined as in the case of the production data clustering. In order to represent load margin and critical bus voltage on a common scale, both clustering variables have to be normalized prior to clustering process. In this study, the normalization is carried out using the maximum recorded value so that both clustering variables have values within the same range [0–1]. Each cluster of critical points of P-V curves is described by a fuzzy centroid, so-called a representative critical point. In addition, a representative HRES plant output is assigned to each cluster. The representative HRES plant output is defined as a "fuzzy" average (see (1)) of HRES plant power outputs in MC cases associated with the relevant cluster.

The number of clusters of voltage stability results corresponds to the number of EMs necessary to represent the HRES plant in voltage system stability studies during the year. EM is developed for each cluster in the form of a SM (PV type) connected to the PCC through a step-up transformer and a line. EM parameters are: the maximum reactive power production of the SM for the analyzed SM active power output (Q_{max}), the rated capacity of the SM and step-up transformer, the short-circuit ratio of the step-up transformer (u_k) and the length of the connecting line. SM active power output corresponds to the analyzed total HRES plant production. The rated capacities of the SM and step-up transformer are the same and calculated based on the SM active power output and the Q_{max} value. It is assumed that the step-up transformer has no copper loses and the length of the connecting line is equal to the average of the line lengths simulated in the MC procedure. The parameters Q_{max} and u_k are estimated through an optimization process (block labelled with (10) in Fig. 1). The values of these parameters are varied within the pre-specified ranges and voltage stability study is performed for each combination of the parameters. In this stage of the methodology, SM active power output is equal to the representative HRES plant output for the considered cluster. For each combination of EM parameters, EM accuracy, i.e., the difference between the critical point of the P-V curve produced by the EM and the representative critical point of the relevant cluster, is calculated as follows:

$$Err(\%) = 100 \cdot \sqrt{\left(\frac{P_{crit}^{EM,i} - P_{crit}^{REP,i}}{P_{crit}^{REP,i}}\right)^2 + \left(\frac{u_{crit}^{EM,i} - u_{crit}^{REP,i}}{u_{crit}^{REP,i}}\right)^2}, \quad (4)$$

where $P_{crit}^{EM,i}$ and $u_{crit}^{EM,i}$ are load margin and critical bus voltage produced by the EM for the i-th cluster, $P_{crit}^{REP,i}$ and $u_{crit}^{REP,i}$ are the representative load margin and critical bus voltage for the i-th cluster.

The combination of Q_{max} and u_k resulting in the smallest value of the *Err* index is selected as the optimal. The next step involves implementing a set of EMs in DIgSILENT PowerFactory software and storing it in the software library (block labelled with (11) in Fig. 1). EM evaluation is carried out by comparing voltage stability results produced by the detailed and equivalent HRES plant model in previously defined MC simulations (block labelled with (12) in Fig. 1). EM performance is assessed using the *Err* index as well as the indicators corresponding to the addends in the sum in (4):

$$\Delta_Y(\%) = \frac{Y_{EM} - Y_{ORG}}{Y_{ORG}} \cdot 100, \quad (5)$$

where Y_{ORG} and Y_{EM} are load margin or critical bus voltage obtained using the detailed model and EM, respectively.

III. Test System

As already mentioned in Section II, the test system used in this paper (presented in Fig. 2) is modelled in DIgSILENT PowerFactory software package [16]. The HRES plant consists of 6 technologies: 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 analysed HRES plant corresponds to the HRES plant design defined in [17] as an optimal techno-economic solution for the southern part of Greece. All the considered technologies are connected to a common 110 kV bus, i.e., the PCC (Bus 17 in Fig. 2). The HRES plant is 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 constant power load model.

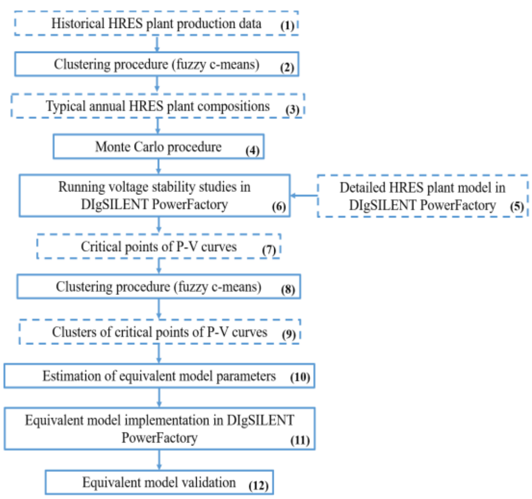

Figure 1. The flow chart of the methodology.

The rated capacities of all individual plants in the HRES plant are given in Table I. Nominal power factor of 0.85 is adopted for all SMs in the HRES plant. A typical capability curve, given in [18], is assigned to each SM-based power plant in the HRES plant. Unlike SM-based power plants, the PV plant, WF and BESS do not provide reactive power support. The PV plant and WF are modelled by a certain number of individual, identical, units connected in parallel. The number of parallel units in service depends on the power production of the plant as it is assumed that active units produce nominal power output. The nominal power of individual generators is the same for both types of plants, 2 MW. A generic type 3 wind generator model is used for representing the WF as it consists of doubly-fed induction generators (DFIGs). The model structure is in line with the guidelines given by WECC [19] and IEC [20] and is available in DIgSILENT PowerFactory [16]. As for the PV plant, a type 4 wind generator model is used. This model is appropriate for full-converter connected generators. As both the PV plants and type 4 WFs are connected to the grid through a converter, the same model can be used for representing these plants in system stability studies [21]. The model is also available in DIgSILENT PowerFactory [16] and its structure is similar to the one described in [19], [22]. The standard fifth order SM model is used for representing the PHS, while the biomass and biogas power plant are represented by the sixth order model [23]. The BESS is modelled as a static voltage source that takes into account the battery state of charge and battery internal losses [24].

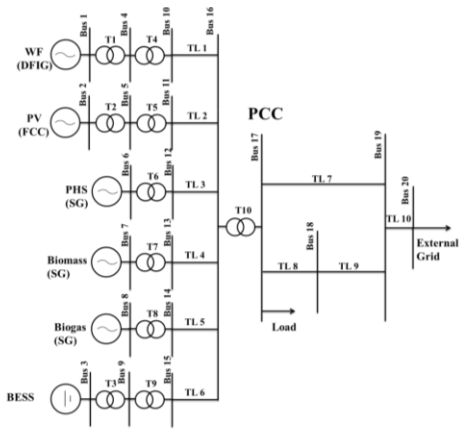

Figure 2. The schematic diagram of the test system.

TABLE I. NOMINAL CAPACITIES 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

IV. RESULTS AND DISCUSSION

An artificial one-year HRES plant production data set with a one-hour sampling rate is used in the analysis [17]. The data set was generated based on weather patterns, electricity price and demand profiles in the analyzed geographical area. At each hour, the production levels of the HRES plant's individual components were determined through an optimization procedure with the objective of satisfying the required production profile while minimizing total plant costs. The impact of the HRES plant on voltage system stability is investigated for a single system load value corresponding to a half of the average annual HRES plant power production. All simulations are performed on a PC with Intel® Core™ i7 processor at 3.4 GHz and 16 GB of RAM.

The fuzzy c-means clustering algorithm is applied to the HRES plant production data set. The change of the clustering indicators with the number of clusters is shown in Fig. 3. The MSE, CDI and MIA indices suggest 9, 5 and 11, respectively, as the optimal number of clusters. As the median value of the estimated optimal number of clusters is equal to nine, the production data set was divided into nine clusters. Nine characteristic annual HRES plant compositions are given in Table II. MC probabilistic CSs are generated on the basis of methodology described in Section II. A thousand MC simulations are conducted per typical annual HRES plant composition. In each MC simulation, lengths of connecting lines (lines TL 1 – TL 6 in Fig. 2) are sampled uniformly between 0.5 km and 5 km. When it comes to HRES plant composition, in each set of 1,000 MC simulations, the production of each individual plant is chosen uniformly from 10% range centered at the value corresponding to the typical annual HRES plant composition (shown in Table II).

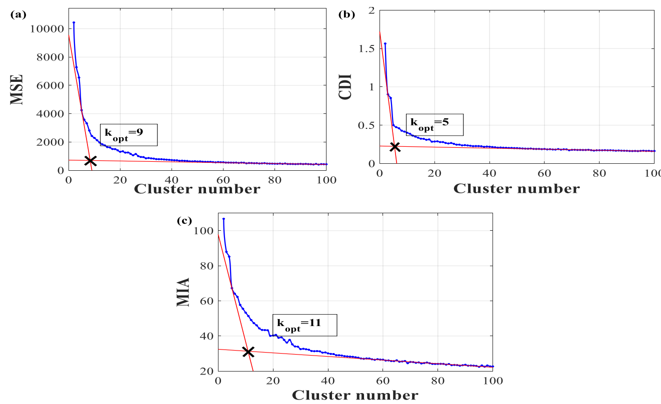

Figure 3. The change of the MSE (a), CDI (b) and MIA (c) with the number of clusters in the case of the production data set clustering procedure.

TABLE II. TYPICAL 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

The results of voltage stability analysis for 9,000 MC CSs, along with marked clusters, are presented in Fig. 4. The fuzzy c-means clustering method is applied to clustering objects consisting of the normalized load margin and critical bus voltage of the simulated cases. The CDI and MSE indices suggest 5 clusters, while 6 is the optimal number of clusters according to the MIA indicator, which means the median value is 5. Thus, the results of voltage stability studies are divided into 5 groups, which consequently implies that 5 EMs are required for representing the considered HRES plant operating conditions in voltage stability studies. All 1,000 MC cases produced on the basis of a single characteristic HRES plant composition are assigned to the same cluster. Therefore, the uncertainties in the production of individual plants and the location of these plants within the HRES plant have no considerable impact on voltage stability and the selection of the most suitable EM at any time during the year depends on HRES plant composition only. The data about cluster representatives are given in Table III.

The first 2 groups of voltage stability results are produced by the same HRES plant technology mix: the WF, PV plant and

PHS. The difference in voltage stability performance comes from the operation mode of the PHS. Namely, the PHS is in generation mode in the case of cluster 1, while it operates in pumping mode in the case of cluster 2. Load margin and critical bus voltage are higher and lower, respectively, for cases in cluster 1 compared to cases allocated to cluster 2. The third cluster describes the remaining HRES plant compositions with SMs in service - compositions 1 and 5 (the biomass and biogas power plants are in operation). Clusters 4 and 5 are generated by typical HRES plant compositions having only converter-connected technologies in service: cluster 4 contains compositions 8 and 9, while compositions 2, 3 and 6 belong to cluster 5. Compositions belonging to cluster 4 are characterized by the BESS being in discharging mode (composition 8) and the dominant production from the PV plant when the WF and PV plant are the only active sources in the HRES plant (composition 9). On the other hand, compositions 3 and 6 are characterized by the BESS being in charging mode, whereas composition 2 has almost zero power coming from the BESS and is dominated by WF production.

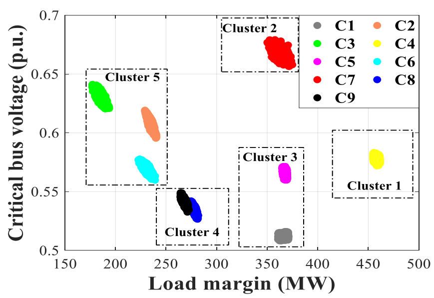

Figure 4. Voltage system stability results (C: characteristic HRES plant composition).

Duration of clusters per month, that is, the expected time of use of the EMs, is defined based on the historical production data set and shown in Fig. 5. EM 3 – 5 are the most dominant models in every month during the year, except during the winter period when EM 4 has small duration. EM 5 and EM 3 cover about 35% and 30% of the data, respectively, while around a fifth of the historical production data set is assigned to EM 4. The remaining two EMs represent 10% of the data each. The final step in the study involves EM development for each of the five previously defined clusters. The parameter Q_{max} is estimated from the range of (-300 - 300) Mvar in the optimization process, while the parameter u_k is varied from 5% to 30%. The length of the line connecting the equivalent SM to the PCC is set at 2.75 km as it corresponds to the average of the line lengths simulated in the MC procedure. In EM parameter estimation process, SM power output is equal to the representative HRES plant output for the particular cluster (given in Table III). The parameters of all five EMs as well as the deviation of EM results from the representative voltage stability results are given in Table IV. Lack of reactive power support in the case of converter-connected plants is reflected in the low value of parameter Q_{max}. The difference between load margin value obtained using the EM and the representative value is on average 1.1% (the maximum is 2.21% for EM 5) for the five equivalents. On the other hand, the accuracy of the developed EMs in terms of critical bus voltage is slightly lower, on average 5% with the maximum difference between the EM and representative result of 10% in the case of EM 5. EM 5 is characterized by the lowest accuracy, which is expected as cluster 5 is the most dispersed cluster. It can be seen from Table IV that the errors in voltage stability results obtained with different EMs are to a very large extent driven by the clustering error (4) shown in column 4.

Model accuracy is further assessed using all MC CSs from voltage stability analysis. All 9,000 previously defined MC CSs are simulated using the EMs instead of the original full-scale HRES plant model. The errors in the values of load margin and critical bus voltage are computed for each MC simulation. The $\Delta_{Load\ margin}$ and $\Delta_{Critical\ bus\ voltage}$ indicators given by (5) are shown in Fig. 6 in the form of boxplots. Outliers are marked by red asterisks, whereas whiskers cover 99.3% of data in the case of normal distribution. Fig. 6 indicates that the developed EMs are sufficiently accurate. The deviation of load margin values produced by EMs from the accurate values is below 3% for the majority of the analyzed cases. EM 1 and EM 3 are characterized by the highest accuracy in terms of load margin – the error is below 0.5% for 99% of the MC cases assigned to them. When it comes to critical bus voltage, the median error of the value of critical bus voltage is below 10% for all models except EM 2 whose median error is slightly above 14%.

TABLE III. CLUSTER REPRESENTATIVES OF VOLTAGE STABILITY RESULTS

No.	Load margin (MW)	Critical bus voltage (p.u.)	HRES plant output (MW)
1	458.2	0.58	155
2	362.6	0.67	182.6
3	367.1	0.54	147.5
4	272.7	0.54	161.3
5	216.8	0.6	158

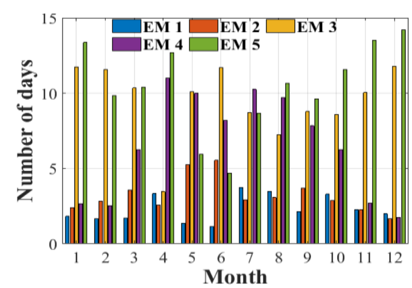

Figure 5. The expected time of use of EMs during the year.

TABLE IV. EM PARAMETERS

EM	Q_{max} (Mvar)	u_k (%)	*Err* (%)	$\Delta_{Load\ margin}$ (%)	$\Delta_{Critical\ bus\ voltage}$ (%)
1	180	5	3	0	3
2	115	25	4.6	-1.05	14.48
3	45	3.5	5.56	0.08	5.56
4	-50	5	2.79	-2.09	1.85
5	-65	8	10.24	2.21	-10

In addition, the process is highly computationally efficient as it can be performed in less than six hours. Identifying the number of typical plant compositions and EMs takes 56 minutes and 5 minutes, respectively. The time required for these tasks depends linearly on the analyzed number of clusters, size of clustering data set, time for performing a single fuzzy c-means clustering and time for calculating clustering indices. When it comes to EM parameter estimation, the computational time is 125 minutes, and determined by the number of EM parameter combinations and time required for running a single P-V curve simulation in DIgSILENT PowerFactory (around 0.5 seconds for the test system). Finally, all P-V curves in the 6th and 12th stage of the process are computed in 75 minutes each.

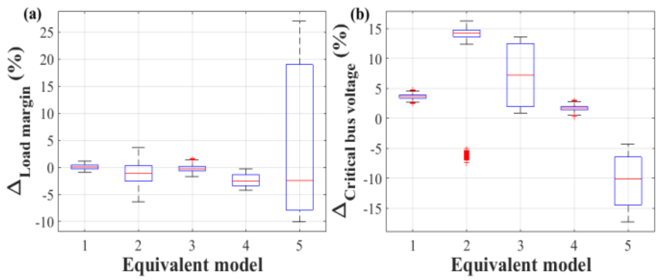

Figure 6. EM accuracy in terms of load margin (a) and critical bus voltage (b).

V. Conclusion

The paper has investigated the influence of the HRES plant composition on voltage stability of the TN. The initial study towards developing EM of the whole HRES plant for voltage system stability studies is presented as well. The analysis is based on historical data about the production of HRES plant's individual components, which eliminates the issue of high computational time required for investigating all possible HRES plant operating scenarios. Unsupervised clustering technique is used for identifying typical annual HRES plant compositions from the historical data set. HRES plant compositions are divided into groups according to similarity in voltage stability behavior (i.e., the values of load margin and critical bus voltage) and these groups represent a basis for deriving EMs of the whole HRES plant. Methodology for EM development provides a set of EMs suitable for representing the HRES plant in voltage stability studies during the whole year. The EM structure is in the form of a single SM with adequate reactive power support capability. The SM is connected to the same bus in the network as the considered HRES plant. Results obtained with the test system have demonstrated that the behavior of the whole HRES plant can be represented by a few models throughout the year. It is shown that the choice of the most suitable EM for a particular time period depends on HRES plant composition only. The presented results pave the way towards development of robust EMs of HRES plants for voltage stability studies in TNs.

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