A Data-driven Approach to Grid Impedance Identification for Impedance-based Stability Analysis under Different Frequency Ranges

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***Abstract*— The instability caused by inappropriate damping design of grid-connected converters under specific grid impedance makes the grid impedance estimation a crucial issue. To guide the system controller design toward a stable and adaptive system under various operating conditions, a three-stage data-driven approach for grid impedance identification with three different frequency ranges is proposed by taking advantage of massive data coming from measurement and/or simulation. In the case study, Monte-Carlo simulation is adopted for obtaining the grid impedance data under different operating conditions. K-means clustering is used to partition the processed impedance data, and a high order grid impedance model is generated for each frequency range, in accordance with the practice of resonance mitigation design. The estimation results show that with this approach, the grid model in different frequency ranges can be reduced without losing accuracy while having the potential of being more accurate for impedance-based stability analysis.**

Keywords—data-driven, grid impedance data, Monte-Carlo simulation, identification, K-means clustering, transfer function model, impedance-based stability

I. Introduction

Grid impedance has always been an important topic ever since the first distributed generation with grid-connected converters connected to the point of common coupling (PCC) for its impact on islanding detection and stability of the whole system [1]-[3]. Especially recently, with more and more power electronics interfaces from renewable energy and modern loads rendering the traditional power system into a complex high order power-electronics-based system. Such systems contain several resonant points due to the interaction of the grid-connected converters and the grid, more evidently when the connection is at the PCC of the “weak grid” which is either due to long transmission line or widespread adoption of converter-interfaced distributed generation within this grid. This fact is receiving increasing attention for its impact on system stability and reliability [1]-[12]

The relationship between the grid-connected converters and the grid in terms of impedance-based stability is determined by both the converter output impedance (which concerns both the converter’s control dynamics and its passive filters) and grid impedance seen from the converters. Without appropriate damping design of the grid-connected converters (output impedance shaping), resonance at different frequencies might occur and this will result in poor power quality caused by the harmonics in certain frequencies and even instability of the system due to the resonance [2], [4], [5], [7]-[12]. A recent study on system resonances for the doubly fed induction generator (DFIG) system shows that resonance might occur with inadequate damping of the controller for different frequency ranges, namely under high, medium and low frequencies [6].

Most of the previous studies focus on how to shape the output impedance of grid-connected converters to make it compatible with the grid. However, there is no sufficient effort made on the grid side. Most of the studies that deal with output impedance design of the converters take the grid as the combination of passive elements, in the form of the connection of resistances and inductances in series. Practically, the grid impedance is very complex—it is frequency dependent and variant throughout the whole measurement spectrum [12]. Studies investigating the grid frequency-dependent impedance identification can be generally divided into two groups. One group considers the non-intrusive methods and the other intrusive methods.

Both methods mainly consider the grid models that are still in the passive mode [3], [13] and [14]. These passive models are not suitable for impedance-based stability analysis simply because it is far too simplified to represent the reality.

Until recently, people started to look at the grid impedance with active model. In [3], the authors proposed an online method for identifying the active nonlinear model of the grid. However, it only gives the online identification algorithm, and not the guidance with respect to how to use it to handle multiple operating conditions which should be addressed in the designing stage of the grid-connected converters.

In this paper, to aid the design towards a more stable controller, by taking the advantage of data analysis, a data-driven approach for grid impedance identification is proposed to derive a grid model covering different frequency ranges. To test this proposed approach, a case study is carried out on a modified IEEE 13-bus test feeder. The improved estimation results will shed light on the further application of grid impedance modelling for the stability assessment and compatibility design.

II. Proposed Data-Driven Approach for Grid Impedance Identification

A. General Procedure of the Proposed Method

The general procedure of the proposed new approach is outlined in Fig. 1, which involves three typical stages for a data-driven application, from data collection, data processing to data analysis. In the first stage of this particular study, the impedance data need firstly to be obtained by physical measurements through either non-intrusive or intrusive methods [13], [14]. For an adaptive controller design, the physical measurements need to be conducted through an adequate duration of time to capture all the concerned scenarios. The data can also be obtained through simulation which covers enough operating conditions of interest.

In the following second stage, the data is further processed to derive the grid models. Generally, before we design the system to make it adaptive to various operating conditions, scenarios (or use cases) as many as possible need to be comprised and considered. This is why long measurement periods and intensive simulations are desired. It requires processing of massive data without generality, which poses challenges for the controller design. The numerous operating conditions of the grid result in different grid impedances. These impedance sets are subsequently explicitly broken down into several groups [12]. It is feasible to reduce the size of the dataset via clustering technique and pick up the reduced number of impedance patterns as representatives for the entire operating conditions [15].

In the final stage of this approach, a system identification method is applied to the reduced sets of the grid impedance data. The entire operating condition is now represented by the several patterns and the representative vector is chosen as the centroid of each pattern group. The identification algorithm is based on a transfer function model as detailed in [16].

The following subsections introduce the key points and main technologies in more details concerning data collection, data processing and data analysis for the grid modelling. The data collection in this research is achieved through Monte-Carlo simulation. In practice, invasive methods to measure the grid impedance will be more suitable for the proposed method since more data will more properly represent the operating conditions. The noninvasive method relies only on accidental external disturbances and thus has the difficulties in collecting enough data.

B. Grid Impedance Data Collection

Study [12] reveals that the grid impedance from multiple samples, i.e., obtained from the frequency sweeping at the point of the connection, can be explicitly classified into several different groups in which there are small deviations in the values of the impedance within each group. Based on this observation, it can be hypothesized that the grid impedance in a certain connection point might have a few different patterns which provide possibilities for the reduction of the scenarios which needs to be considered for designing an adaptive controller. Various scenarios are generated using Monte-Carlo simulation with different load and generation profiles, as well as changed topologies through switching of the breakers. It is worth noting here that in the simulation, there are some limitations by using the impedance measurement block. By adding the impedance measurement block in the Simulink, some non-linear components are disconnected from the network, which include machines and power electronic devices except breakers, three-phase fault, ideal switch, and distributed parameter line blocks. Therefore, it might limit the scope of the research by using this method.

By using the impedance measurement blocks, the grid

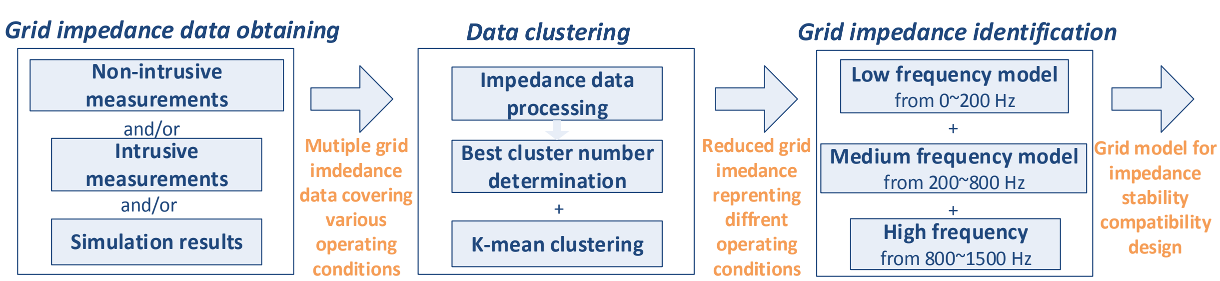

Figure 1. Flowchart of proposed data-driven approach for grid impedance identification

impedance can be measured from the three-phase system. The measured grid impedance data is in the form of impedance (magnitude and angle) under predefined frequencies and can then be recorded for further processing. The specific design of Monte-Carlo simulation to generate different operating conditions of the grid will be introduced in the case study.

C. Grid Impedance Data Preprocessing and Clustering

The data preprocessing part is to prepare the dataset of the raw data to make it suitable for the following processing and calculation in the data clustering.

The harmonic impedance measured from a certain point of connection in an electric network by the impedance measurement block in the Simulink, can be written as the relationship between voltage and current under different frequencies, i.e., the transfer function concerning these two variables, as follows

$$Z_{POC}(f) = \frac{V_{POC}(f)}{I_{POC}(f)} \tag{1}$$

The raw grid impedance data from one measurement 'i' is in the form of a vector of complex values associated with different frequencies, denoted as z_i, which can be written as

$$z_i = \begin{bmatrix} z_{i1} & z_{i2} & \cdots & z_{im} \end{bmatrix}^T \tag{2}$$

where $z_{ik} = R_{ik} + X_{ik} j$, R_{ik} and X_{ik} are the real part and the imaginary part of the grid impedance in the kth frequency of the vector z_i, respectively, and m is the number of the distinct frequencies.

As the general data clustering algorithm is only able to process real numbers instead of complex numbers, the complex vectors need to be transformed into real vectors, denoted as $x_i (i = 1, 2, \cdots, m)$ in (3)

$$x_i = \begin{bmatrix} R_{i1} & R_{i2} & \cdots & R_{im} & X_{i1} & X_{i2} & \cdots & X_{im} \end{bmatrix}^T \tag{3}$$

For simplicity, the vector is not normalized as the real part and imaginary part are not much different in magnitude. For a more general procedure, the real part and the imaginary part can be normalized respectively.

For the whole dataset, it can be denoted as a matrix $X \in \mathbb{R}^{2m \times n}$

where $X = [x_1 \quad x_2 \quad \cdots \quad x_n]$,

At this point, the dataset is ready for further processing. For the clustering algorithm here, we chose the K-means clustering to partition the dataset due to the following reasons:

- The purpose of using cluster algorithm is to reduce the scenarios as guidelines for controllers' design into fewer patterns. Since no labeled data is available, an unsupervised learning algorithm is chosen for the classification.
- K-means algorithm is one of the simplest unsupervised learning algorithms which follows an easy and simple procedure to classify a certain dataset.

A brief description of the K-means algorithm employed assuming the number of clusters as k, is shown in the following steps:

1. Select a vector randomly from X and take this vector as the first centroid denoted as c_1.
2. Compute distances from each vector to c_1 and denote the distance between the centroid c_1 and the vector x_m as $d(\mathrm{x}_{m,}\mathrm{c}_j)$.
3. Select the next centroid c_2 randomly from X with probability $\dfrac{d^2(x_m, c_1)}{\sum_{j=1}^{n} d^2(x_{j,} c_1)}$
4. To choose the centroid j:
   a. Calculate the distance from each vector to each existing centroid and assign each vector to its closest centroid.
   b. Select the new centroid with a probability proportional to the distance from itself to the closest centroid already chosen, i.e., For $m = 1, \cdots, n$ and $p = 1, \cdots, j-1$, select centroid j randomly from X with the probability

$$\frac{d^2(\mathrm{x}_m, \mathrm{c}_p)}{\sum_{\{\mathrm{h}:\mathrm{x}_h \in C_p\}} d^2(\mathrm{x}_{h,} \mathrm{c}_p)} \tag{4}$$

where C_p is the set of all vectors closest to centroid c_p and x_m belongs to C_p.

5. Repeat the last step until k^{th} centroid is chosen.
   For the choice of cluster number k, a certain metric can used to determine whether the value of k is proper or not. In this research, we use the silhouette value of the vectors. The silhouette value of each vector is a measure of how similar that vector is to other vectors in the same cluster, compared with the vectors in other clusters. The silhouette value for the i^{th} vector, $s_i \in [-1, 1]$ is defined as

$$s_i = \frac{b_i - a_i}{\max(a_i, b_i)} \tag{5}$$

where a_i is the average distance from the i^{th} vector to the other vectors in the same cluster as i, and b_i is the minimum average distance from the i^{th} vector to vectors in a different cluster, minimized over clusters.

The higher the average silhouette $s_{avg} = \frac{1}{n}\sum s_i$, the better the choice of the number of the clusters is.

D. The Identification Algorithm to Derive Transfer Function Model of the Grid Impedance

With the reduced sets of grid impedance data, the identification algorithm is employed on these representative grid impedance datasets which are reverted from the representative vector of each cluster obtained from the last processing stage. The algorithm used for the identification fits the discrete frequency sweeping grid impedance data into a model that can be used in the design of converters' controllers. The grid impedance data is essentially the discrete frequency response of the dynamic system and the transfer function model is chosen as it is easily combined with the dynamic models of the controllers. To increase the fidelity and computational efficiency, the model can be estimated under a certain frequency range of interest which can be taken as dominant in the specific problem studied, i.e., the resonance under different frequencies.

As the representative grid impedance data is discrete frequency response data, it could be directly estimated into a discrete transfer function or indirectly into continuous a time transfer function by converting the discrete model estimated into a continuous one. In either model, the critical part is the estimation algorithm, and these are identical for both models. Basically, it consists in solving an optimization problem which finds a transfer function G_r^* with order r which minimizes the least square deviations between the data calculated from the estimated model and that from the actual sampled data:

$$Mininize\sum_{i=1}^{m} W(\omega_i)\left|G_r^*(\omega_i) - G(\omega_i)\right|^2 \qquad (6)$$

$W(\omega_i)$ is frequency-dependent weight, m is the number of the measured impedance data as aforementioned, and $G(\omega_i)$ is the magnitude of the sampled grid impedance. The detailed algorithm can be found in [17].

To evaluate the accuracy of the estimated model, the following metric is defined to measure the fit:

$$FIT = (1 - \frac{norm(\mathrm{G}_r^*(\omega) - \mathrm{G}(\omega))}{\mathrm{norm}(\mathrm{G}(\omega) - \mathrm{mean}(\mathrm{G}(\omega))})*100\% \qquad (7)$$

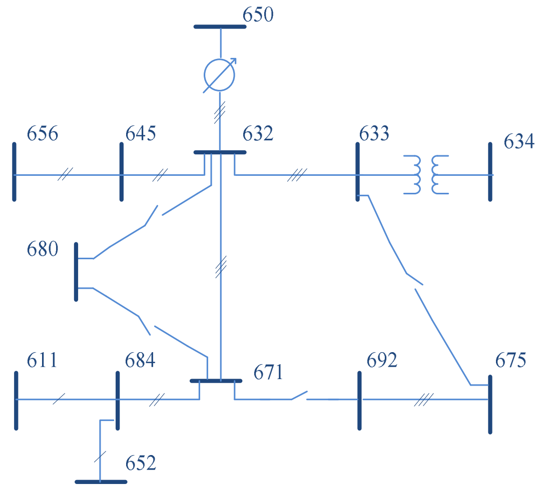

Figure 2. IEEE 13-bus test feeder with two added transmission lines

III. Case Study and Verification

In this work, a case study is conducted on the modified IEEE 13-bus test feeder as shown in Fig. 2. Two additional transmission lines are added to make the case study more suitable to the emerging meshed network topology. One of these lines is added between Bus 680 and 632 and the other between Bus 633 and 675. The type of these two lines is similar as the line between Bus 632 and 671 and the length of each line is 3200ft. The remaining information of this network data can be found in [18].

In this case study, the grid impedance data under different frequencies in multiple operating conditions are obtained through Monte-Carlo simulation. The accuracy in the representation of the real system is highly dependent on the number of simulations as it is a tradeoff between computational efficiency and accuracy. It typically requires that the number of simulation samples to be much larger than the number of cases studied. The number of simulations is chosen as 1000 in view of the above considerations which is reasonable with the particular cluster number for the dataset in this case study.

These 1000 different scenarios are generated by changing the states of all the four breakers and the load conditions in Bus 634, 646, 692 and 632, respectively. Specifically, the status of each breaker is randomly set as on or off in each Monte-Carlo simulation. At the same time, the value of the reactive and the active power (of each phase) at the four load buses is sampled from a uniform distribution on the interval [0,1] with the given value from the test feeder as the base. The observed grid impedance is measured between Phase C and the ground at Bus 671 with the impedance measurement block.

After collecting the data, the next step is to cluster the measured data. The optimal cluster number of K-means clustering is determined by visual observation in the trial-and-error process. The selection criteria are illustrated by Fig. 3. The cluster number is chosen based on (5) in a trial-and-error process. The larger the s_i, the better the choice

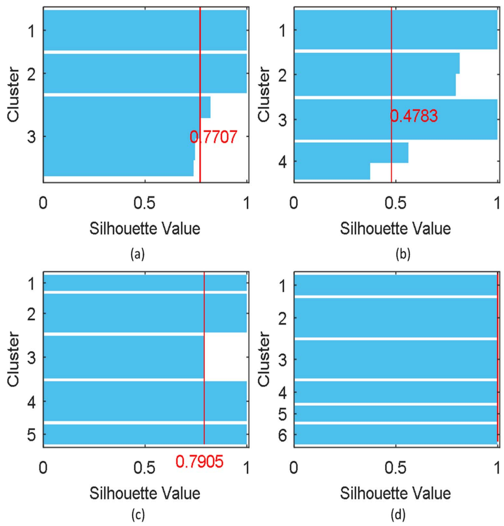

Figure 3. Silhouette plots with different number k of clusters: (a) with $k=3$, (b) $k=4$, (c) $k=5$, (d) $k=6$

of the cluster number for the following data clustering. As observed from Fig. 3, when k is chosen as 6 s_i is the largest and thus the data will be partitioned into 6 groups.

The partitioning results of the impedance data by using the algorithm introduced before are shown Fig. 4. Fig. 5 shows the estimation results using the centroid vector in one cluster with k chosen as 6. With the separated model for each frequency range in Fig. 5 (a)-(c), fewer identification parameters are required and the individual accuracy in each range is higher in most cases than those taking the grid behavior at the whole frequency spectrum as in Fig. 5 (d).

IV. Discussion

The application of this method is promising in light of the rapid progress of smart grid development regionally and nationally [19], [20]. In the visionary smart distribution system with microgrids as the building blocks, the interaction of the subsystems will become even more significant [21], [22]. The modeling of the grid will thus be the mandate since considering the worst case might be misleading in the stability analysis [23].

The proposed grid modelling method still has the limitation due to the use of the specific simulation software. The dynamic of the power electronics system inside the grid cannot be represented at this stage. Since the values of the representative grid impedance data within a pattern group still have slight deviations compared to that of other sets in the same group, the conservative stability margin needs to be considered when using the estimated grid model.

V. Conclusion

In this paper, we presented a method to apply data analysis for the grid impedance identification. The proposed method is based on massive data from advanced measurement and/or simulation technology. It provides improved performances in terms of model simplicity and

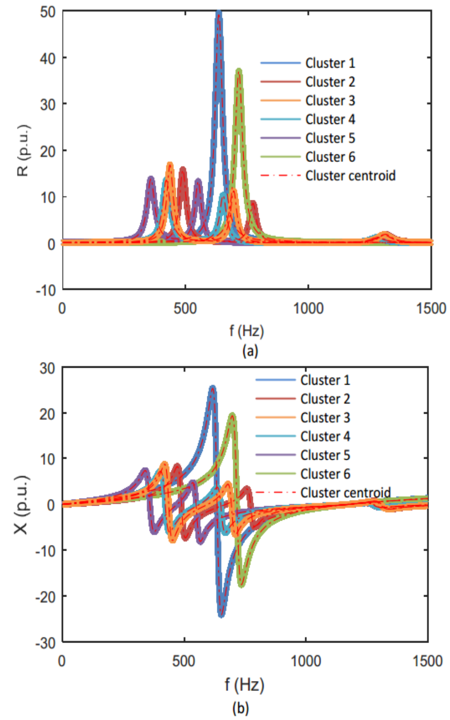

Figure 4. Grid impedance data partition results

accuracy. This is suitable for stability analysis covering different frequency ranges and will be instrumental in guiding the design of adaptive controllers for grid compatibility of power electronics dominated power systems that can shape their output impedances. This attempt will shed light on how data technology is applied to the modern power system with high penetration of power electronics and will foster the fusion of these two disciplines. The future work of this research includes expanding this approach in terms of detailed algorithm implementations. The application for stability assessments applying this approach will be further studied.

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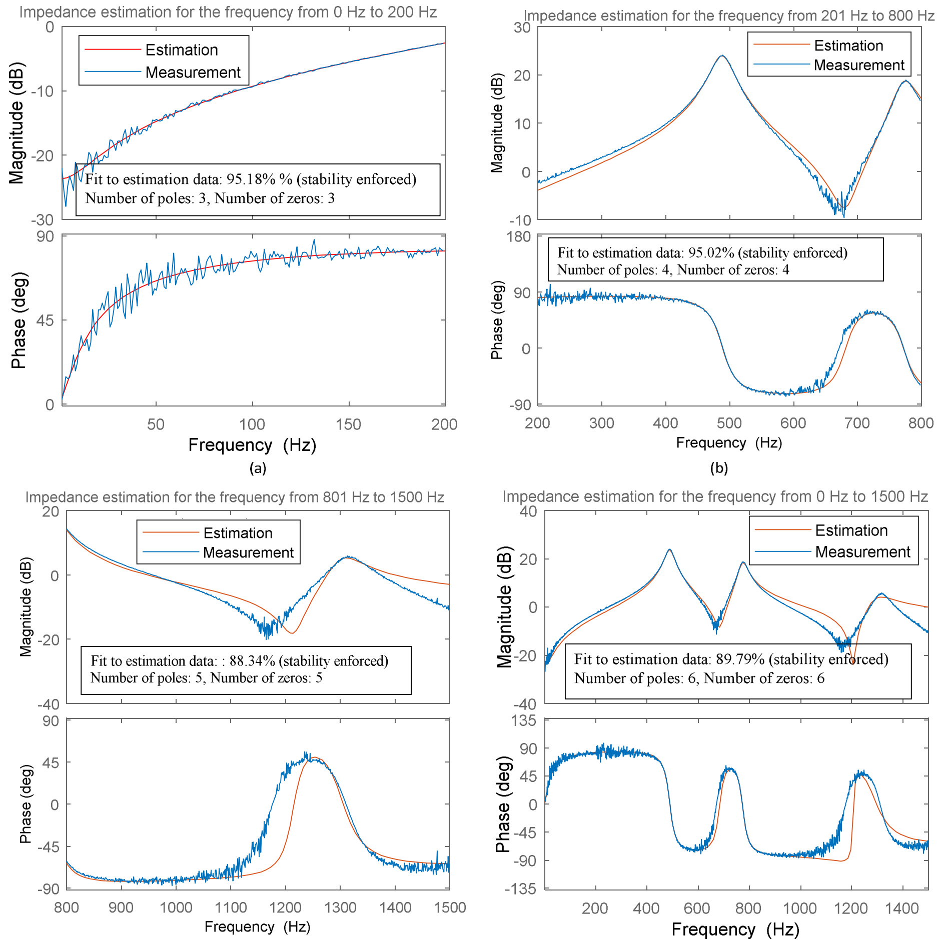

Figure 5. Grid impedance identification results

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