UTILIZING OBSERVABILITY ANALYSIS TO CLUSTER SMART INVERTERS ON SECONDARY CIRCUITS FOR RESIDENTIAL DEPLOYMENT

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ABSTRACT

As residential customers continue to connect Distributed Energy Resources (DERs) with smart inverters unto distribution systems, distribution engineers face new challenges of accurately modelling residential smart inverters for distribution system optimization. Depending on the coordination strategy, the impact of these DERs can represent a positive contribution to the system operation. However, if the coordination strategy does not consider the interaction between DERs and the distribution system for clustering them, the distribution system integrity can be compromised. This paper describes an approach to group smart inverter Photovoltaics (PVs) deployed within a secondary circuit (low voltage system) to enable the correct monitoring and control of these smart inverters. It further explains the process used to coordinate clustered smart inverter PVs to enhance distribution operation optimization.

INTRODUCTION

Several utilities in the United States have seen an increased interest in residential Solar PV connection. Lately, the grid connected PVs utilize smart inverter technologies. The smart inverters allow a wide range of functionalities. In order to optimize the benefits offered by the smart inverters and also ease the operations of distribution systems with high PV penetration, distribution operators will like to monitor and control smart inverters. However, monitoring and controlling several inverters may not be practical due to several complexities. Instead of monitoring and controlling individual inverters across the distribution system, the inverters can be clustered.

The work herein summarized mainly focuses on clustering smart inverters connected directly on secondary systems. The use case explained in this paper will describe the technique to cluster PV inverters where several smart inverters were deployed at residential customers' sites.

The layout of the paper is to initially describe the methodology to cluster the smart inverters; lastly the paper will explain the results of the two test cases with the clustered inverters.

WHY CLUSTER DISTRIBUTED ENERGY RESOURCES?

The interconnection between the elements within a network can be classified using a connectivity level. This level can be obtained by considering the systems topology, the electrical proximity between the interconnected elements, their geographical proximity, among other criteria. In the case of PVs, the feature to be evaluated will be the active power contribution from the smart inverters connected to a secondary distribution system. In some instances, the rated sizes of the smart inverters connected to secondary distribution systems ranges from 3 to 10 kVA. Depending on the total number of smart inverters deployed on the secondary system, the numbers may range from a few hundreds to thousands. The easiest way to determine the active power contribution of all the smart inverters connected to a secondary system is to group them. Once the PVs are grouped, each set of PVs within the same group can be coordinated for monitoring and control purposes.

Clustering of the PVs can be performed manually based on the geographical distances and physical location of each PV, and then overlaid onto the secondary distribution system. The manual approach isn't accurate as the electrical distances of the PVs might not be taken into consideration.

This paper proposes a combined method that utilizes graph theory and observability analysis for clustering PVs in order to monitor and control the clustered PVs. The methodology is described in the next section.

METHODOLOGY

Concept of defining the functional clusters

As described in the section above, depending on the number of PVs within a distribution system there may be a need to group the PVs. The functional clusters are the groups of PVs created as a first pass in the approach. These clusters are formed considering the connectivity strength between PVs. This index is determined by considering the distribution network topology and the connection point of the PVs. The network modeling was done using OpenDSS [1]. To illustrate this concept, the

IEEE 8500 node distribution system was used. Normally it is possible to obtain the incidence branch-to-node matrix representation (B2N) of the system as shown in Figure 1.

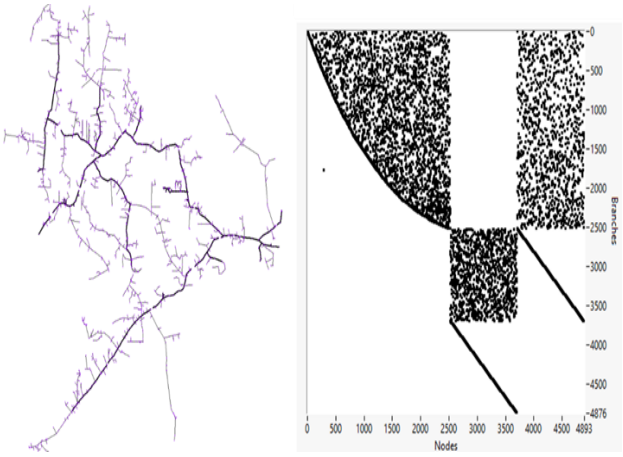

Figure 1. IEEE 8500 nodes test system and its B2N representation [2]. The black dots are values different from 0 (1 or -1)

In Figure 1, the nodes correspond to the circuit's buses. The branch to node representation is generated as it is given by the network model generated by the user. This means that the order of the nodes is not hierarchical, leading to an additional challenge. For clustering the PVs according to its connectivity, it is simpler to know the nodes around the PV point of connection. However, the nodes might be randomized, because one node might not necessarily be connected to another.

For reorganizing the nodes within the distribution system, another representation derived from the B2N matrix is used. This representation is the Laplacian matrix described as follows [3]:

$$L = I^T I = D - Ad \qquad (1)$$

In (1) I is the incidence B2N matrix, Ad is the admittance matrix and D is the degree matrix. The Laplacian matrix (L) is symmetrical and describes how the nodes of the network are interconnected. Since the columns and rows represent the nodes of the system, the diagonal of the Laplacian matrix corresponds to the number of edges attached to each vertex [4], while the other cells have a value equal to -1 if they are adjacent to the vertex in the diagonal as follows [5]:

$$L_{i,j} = \begin{cases} \deg(v_{i,j}) & if\ i = j \\ -1 & if\ i \neq j\ and\ adj\ to\ diag \\ 0 & otherwise \end{cases} \qquad (2)$$

By using this representation and part of the algorithm for reorganizing sparse matrixes proposed in [6], the incidence matrix is reorganized to define a diagonal patter within the Laplacian matrix. The diagonal pattern will reveal the set of diagonal blocks coupled together through its linking diagonals and as a consequence, hierarchically organized [7].

The previous statement means that with the new distribution it is possible to see the buses connected around a selected point of connection. An example of this distribution is shown in Figure 2.

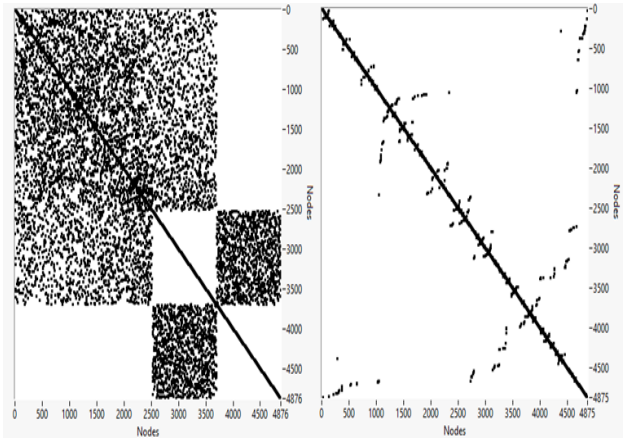

Figure 2. At the left the initial Laplacian matrix, at the right the same matrix reorganized for highlighting interconnected buses.

As can be seen in Figure 2, the initial pattern which describes the location of the non-zero elements of the Laplacian matrix looks fuzzy. On the other hand, after the reorganizing the non-zero elements that are directly tied to another, it makes it easier to link and connect the buses together.

After organizing the buses, it is possible to cluster the proposed PVs by setting a maximum distance between them to define an area. The distance will be defined in terms of the number of buses between the PV connection points.

Since the buses of the circuit have been organized, the interconnection degree between 2 buses will be defined by the number of buses between them. If there are no buses between 2 buses, it means that these buses have the highest interconnection degree. This degree will decrease when the number of buses between the observed points increases.

Identifying the monitoring location

After the clusters of PVs are defined, it is necessary to define the measurement point within the cluster for monitoring. This monitoring point is crucial since it will be the gateway that will be used by the Distribution Management System (DMS) for controlling the set point of each clustered set of PVs.

The location of the measurement point will depend on the needs of the application. For example, if the control strategy is focused on the power delivered to the grid by the clustered PVs, then the location of the monitor may seem obvious. However, in some other cases such as voltage control, the location of the meter can be complicated to define.

To support this type of scenario, the monitoring location is determined by using observability analysis and the variable measured at the PV point of connection [8, 9]. The first analysis will work as a filter revealing the needed measurement points considering the distribution of the PVs within the cluster. The second process will reveal the better monitoring location considering the best candidates and the levels of the variable to measure within the group.

The observability analysis is performed by using a direct numerical method proposed in [10]. This method proposes a linearized method that considers the topology of the network and a measurements matrix called the Gain matrix (G). G can be decomposed into its triangular factors using the *square root free Cholesky* factorization to be operated with the B2N matrix of the system [11]. As a result, using the sub-network defined by the cluster of PVs and proposing an initial random measurement point within the cluster, it is possible to propose new measuring locations and evaluate the observability of the cluster automatically. This analysis is performed by checking the linear dependency of the elements delivered by the measurement matrix, revealing that only the elements linearly independent are the necessary measurements. Finally, with the set of measurements an extra analysis is performed to determine the best location for monitoring the cluster. Sometimes, it can be tricky depending on the cluster's size and distance between the buses of the cluster. Nevertheless, in this approach and covering the voltage monitoring case, we propose the use of an average measurement point to represent the best location. This is to check the voltage levels at the filtered list of possible locations and then, to select the best location where the voltage has a value within a range representing the majority of the measurement points. This concept is illustrated in Figure 3.

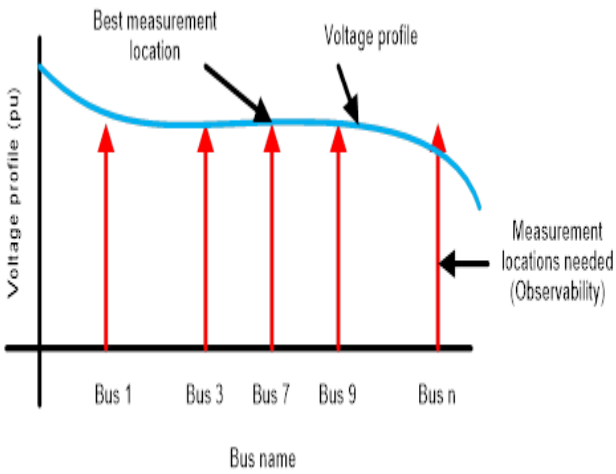

Figure 3. Measurement location methodology

This approach is based on the assumption that the voltage will not change drastically if the buses within the cluster are electrically close. This assumption is supported by the fact that in previous analysis, the cluster was formed by checking the proximity of the buses in terms of connectivity. As a result, a particular bus within the cluster should report a voltage value closer to the other buses in the same cluster.

However, it is important to highlight that the criteria may change depending on the variable to be measured and the analysis that will be performed with the clusters. As mentioned above, the location may seem obvious in some cases.

CASE STUDIES

This methodology described above has been developed into an algorithm and coded for implementation within OpenDSS. This was applied to 2 different distribution systems, named systems A and B respectively. The parameters of each system are described in Table 1.

Table 1: Parameters of the modelled distribution system

System	A	B
Number of buses	4746	4321
Lines	4128	3854
Existing PVs	912	496

These circuits are also shown in Figure 4 and Figure 5.

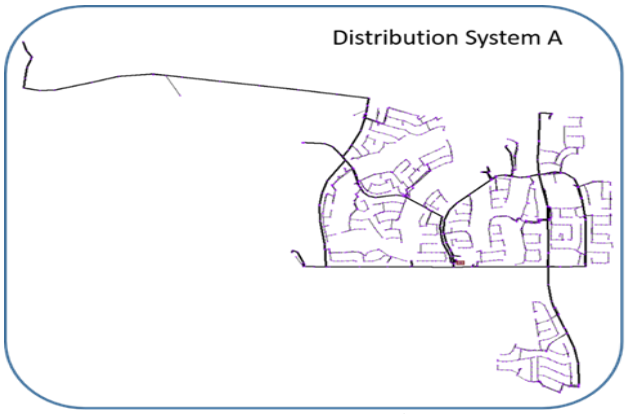

Figure 4. Geographical layout of use case A

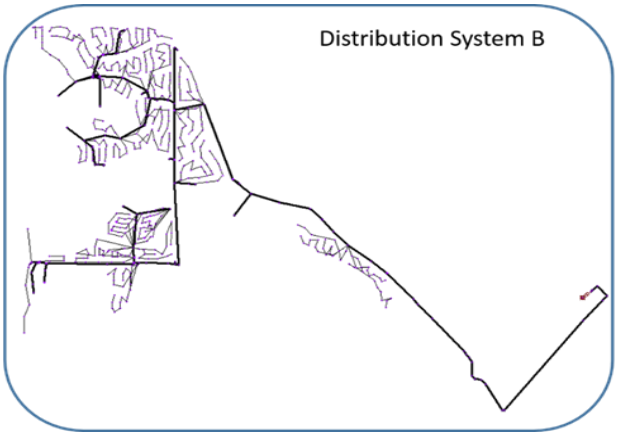

Figure 5. Geographical layout of use case B

In order to apply the proposed methodology, the following parameters have been proposed as boundary conditions in the algorithm developed.

1. For creating the clusters, a maximum distance between PVs is equivalent to 250 buses.
2. Additionally, the variable to be observed is the voltage of the cluster.

After running the algorithm (using the defined parameters), 3 clusters were formed per circuit with their monitoring location. This results are shown in Figure 6 and Figure 7.

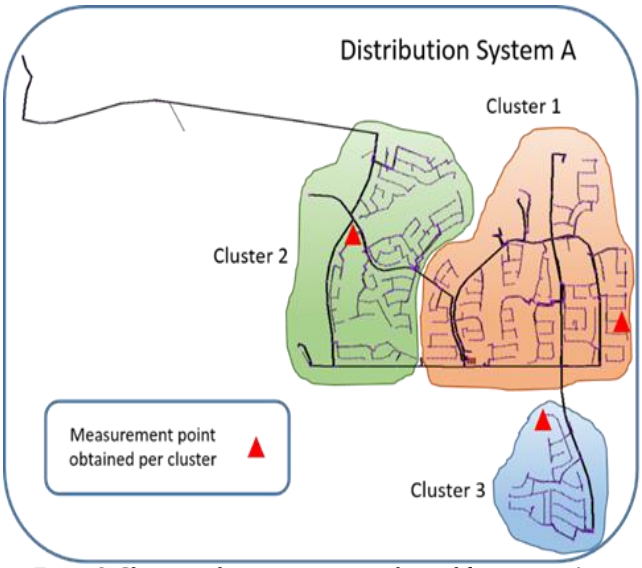

Figure 6. Clusters and monitoring points obtained for use case A.

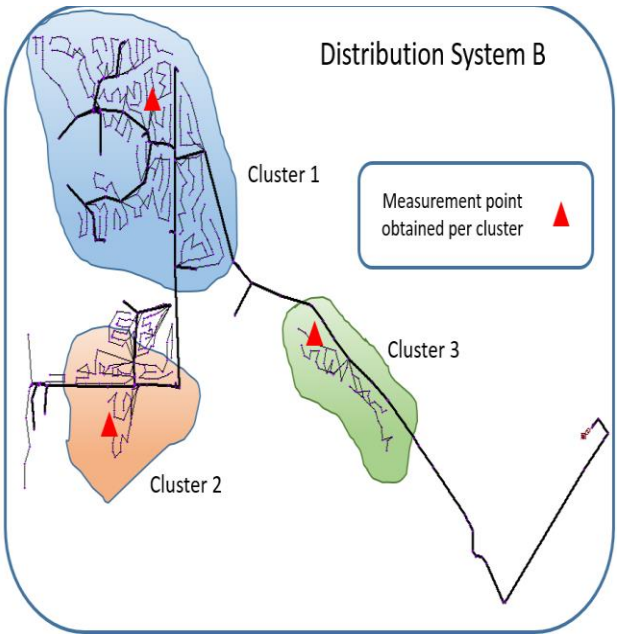

Figure 7. Clusters and monitoring points obtained for use case B.

As can be seen in Figure 6 and Figure 7 that the location of the measurement point is not necessarily obvious within the cluster. The location of the measurement point corresponds to the most logical location within the cluster considering the voltage difference between all the possible locations within the cluster.

The distance between the buses allows the clustering of the PVs into more groups, in case it would be required. The monitoring location will depend on the size of the cluster and the proximity of its elements. This concept is shown in Figure 8 where the proximity of the buses defines if they belong or not to a certain cluster.

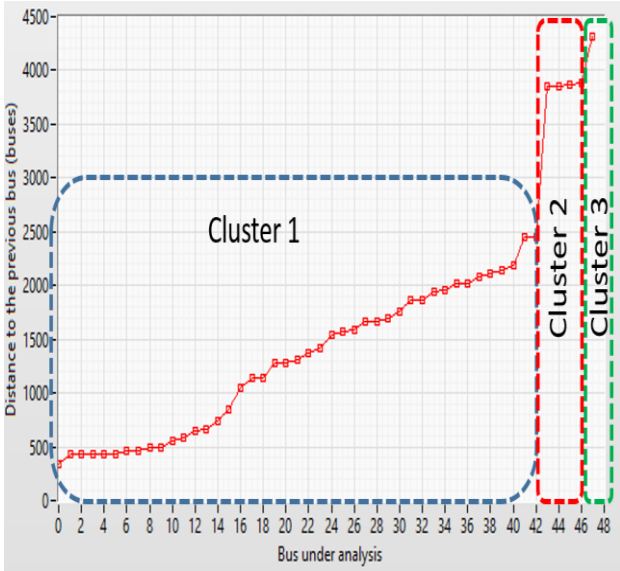

Figure 8. Connectivity indexes for creating clusters in Case B

To confirm this results, the clustering is made manually by using the geographical distance and physical location of the PVs to group the PVs. After the clustering was manually made, the order suggested by this activity is analyzed using the analysis shown in Figure 8. The results of the analysis are shown in Figure 9.

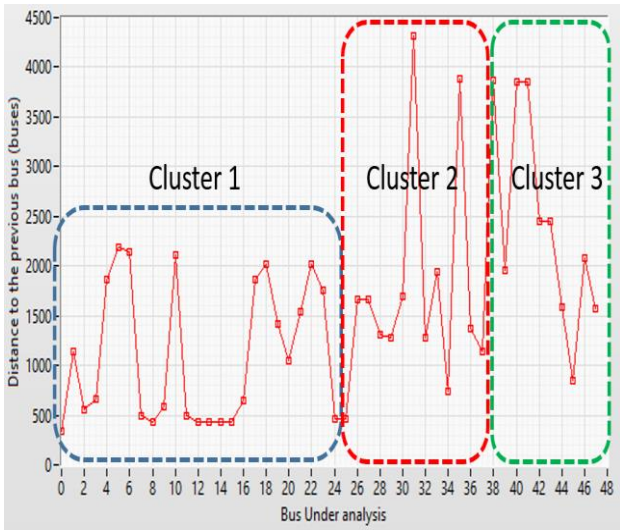

Figure 9. Clusters created manually for Case B

As can be seen in Figure 9, there is no defined pattern for the clusters. The only pattern that was observed is that the PVs are closer geographically and as such, they should be closer electrically. But as Figure 9 reveals, the PVs within a cluster could be pretty far away from each other.
In the case where an element within a distribution system needs to be removed or added, or elements within a cluster is resized, there is no clear criteria for this to be done systematically. This is a major disadvantage when creating the clusters manually. In addition, the location of the measuring point will be performed randomly or heuristically made when the clusters are built manually. The criteria for selecting a measurement point is not clear when working manually, an issue that is covered by the algorithm proposed in this paper.

CONCLUSION

This paper proposed a systemic clustering methodology for grouping smart inverters connected to secondary systems. Two case studies were analyzed to demonstrate the effectiveness of the proposed methodology.

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