Topological and structural analysis of the electric power grid of Southeast Europe

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Abstract – *The analysis of the electric power grid of Southeast Europe using modularity function hierarchical clustering reveals the important network characteristics which can help finding the critical points and links of the network. Further, this analysis shows the influence and impact of each country in the power transmission network as well as their grouping in strongly connected modules. We found the connected clusters of transformers and generating nodes and analyzed how these clusters are distributed among the countries involving in this network. Additionally, this analysis showed the impact of the countries in the cluster formation and by looking into two levels of hierarchical clustering we identified the main nodes of the network that are crucial for network connection.*

Keywords: power transmission network, clustering, Girvan-Newman modularity

1. INTRODUCTION

Today we are surrounded with systems whose structure includes elements of interaction. These systems properties and behavior can be explored using networks representation. Important examples include the Internet, telephonenetworks, collaboration networks, airline routes, power networks, different biological networks. The mathematical and empirical study ofnetworks has emerged in the last decade resulting in different analysis algorithms helping to reveal the complex system characteristics independent of its nature. [1]

A major part of the complex networks analysis science includes the analysis of emergence of clusters, modules or also referred as communities in the network. The modular analysis of a system can show the organizational structure and emphasize the groups of nodes in the network that are more similar and highly inter-connected. The process of grouping similar nodes into clusters or modules is called clustering. [2] These modules are locally dense even when the analyzed network is sparse. The presence of modules atdifferent scales reveals the network evolution and accelerates the emergence of complexsystems by detecting stable intermediate building blocks.

Today there exist many clustering algorithms based on different approaches. Modularity function algorithms are addressing the strength of the module compared to a null model, multi-resolution algorithms are exploring the clusters of different levels of modularity, links clustering instead assigning communities to the nodes uses assigns community to each link, andrandom walks on graph combinedwith compressed decomposition in maps are being usedfor accurate and fast network clustering. [3]

Power transmission networks are man-made networks which are of crucial importance to our society, motivating the research and practice on analyzing the structural and organizational properties that contribute to higher reliability and robustness of these networks.The elements and modules of these networks perform individual and collective tasks such as generating and consuming electrical load, transmitting data, or executing parallelized computations. One can study the robustness of these systems to the failure of random elements. When modularorganization is critical to overall functionality, networks may be far more vulnerablethan expected. The properties of the electric power networks are analyzed in many papers that exist in the literature. We review several abstract and power system analyses that are used to understand the structural characteristics of the networks. [4][5][6]

According to the agreements that are already signed as the Energy Community Treaty [7] and Southeast Europe Regional Electricity Market (SEE REM) [8] and South-East Europe Cooperative Initiative [9], the Southeast Europe should have a single trade for electricity in the future. In order to accomplish this, it is necessary to have adequate power transmission network. In this paper we use a clustering algorithm to analyze the topology and the structure of the power grid of the Southeast Europe, by exploring the distribution of the clusters in the networkin terms of the states in this region and the capability of the transmission network in the region to meet these requirements.

This paper is organized as follows. Section II describes the methods used for data analysis and Section III and IV are the results and the conclusion.

2. METHOD

Data – Southeast Europe power transmission network

The power transmission network of the Southeast Europe, analyzed in this work, includes the following countries: Macedonia, Serbia, Bulgaria, Albania, Kosovo, Croatia, Bosnia and Herzegovina, Montenegro, Slovenia, Greece and Romania. We are considering power transmission lines of 440kV and upper voltage levels. The power network of European network of transmission system operators for electricity (ENTSO) is used (https://www.entsoe.eu/).Figure 1 shows the power network of Southeast Europe.

The Southeast European power grid consists of about 240 nodes (which represent the transformers and the generation capacities) and 280 lines. Each node represents a transformer in the power grid. It is assumed that the electricity generators are connected to the nearest node, i.e. to the nearest transformer in network.

Figure1. Electric power grid of Southeast Europe

Graph Representation

We represent the power transmission network with a graph where a transformers are represented with a vertices of a graph (nodes) and the connecting power transmission lines are represented with graph edges (links).The basic mapping of the network is an undirected, unweighedgraph $G= (V, E)$.$V$is the set of vertices, hererepresented as nodes, and $E$is the set of edges, theinteractions between them.
Graph is represented by an adjacency matrix showing which vertices of a graph areadjacent to which other vertices. The adjacencymatrix of a graph with$n$ vertices is an $n\times n$ matrix wherethe non-diagonal entry $m_{ij}$is the number of edges from vertex$i$ to vertex j, and the diagonal entrym_{ij}number of edges (loops)from vertex i to itself. Adjacency matrix for undirected graph is symmetric and can be represented as follows:

$$A_{ij} = \begin{cases} 1, & if\ i\ is\ connected\ to\ j \\ 0, & otherwise \end{cases}$$

Modularity function

In this work we focus on the effective fast community detection algorithm based on the Girvan-Newman Modularity Function [10]. This modularity function presents one of the biggest breakthroughs in cluster detection. Theequation proposedcompares the quality of agiven cluster, with the quality of a randomgraph by finding the difference of the fractionof edges that fall into the cluster, and the expectednumber of edges distributed at random, Equation (1). A positivenumber less than 1, meansthat the number of edges in the group is greater thanthe number at random i.e. the cluster is well defined.Number between zero and -1 means that the analyzededges don't form a good cluster. The randomization ofthe evaluated edges is done with preserving each vertexdegree. The Girvan-Newman modularity measure is defined as follows:

$$Q = \frac{1}{2m}\sum_{ij}\left[Aij - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j), \qquad (1)$$

where$A_{ij}$is the weight of the edge between vertices$i$and j, k_i=sum$_j$(A_{ij}) is the sum of the weights of theedges attached to node i, $c_i$is the community to whichnode i is attached, $\delta(c_i, c_j)$ is the Kronecker delta symbolwhere $\delta(u, v) = 1$ if u = v and 0 otherwise, and m =1/2 sum$_{ij}A_{ij}$.The matrix A represents the adjacency matrixof the graph.

The algorithm developed by Blondel et al. [11] uses a hierarchical agglomerativemethod, where at the beginning each node representsone cluster. Nodes, and later clusters are merged tryingto maximize the modularity, exploring the full topologyof the graph. This algorithm uses a greedy technique, where communities are represented with supervertices. At the start all nodes are in a different community, but as each node chooses a new community, the communities are replaced with supervertices. Two supervertices are connected if an edge exists between any two nodes from the two supervertices. Again, at each step the modularity is calculated from the initial topology. These steps are repeated iteratively until a maximum of modularity is reached.Therefore the hierarchical clustering results in several partitions. After the first step the partition found consists of many communities of small sizes. At subsequent steps, larger and larger communities are generated due to the aggregation in supervertices, Figure 2.

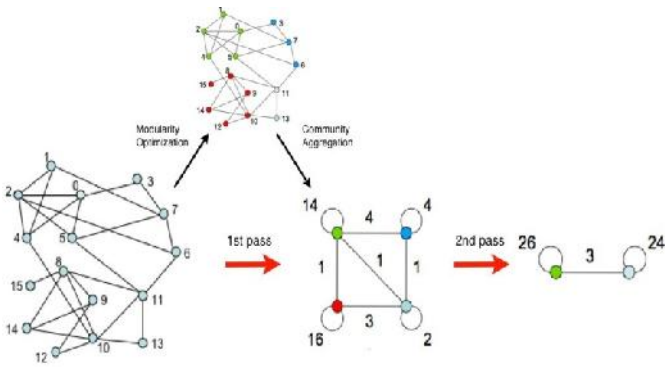

Figure 2.Visualization of the clustering steps. Each iterationhas two phases: one where modularity is optimized by allowing only local changes of communities; one where the found communities are aggregated in order to build a new network of communities. [11]

4. RESULTS

Thehierarchicalnetwork analysis resulted in four levels of partitioning, but only two of them make sense. The first level has 20 clusters(Figure 3) and the second10 clusters (Figure 4). On each level we explored the characteristics of the transmission network of the Electric power system of Southeast Europe.

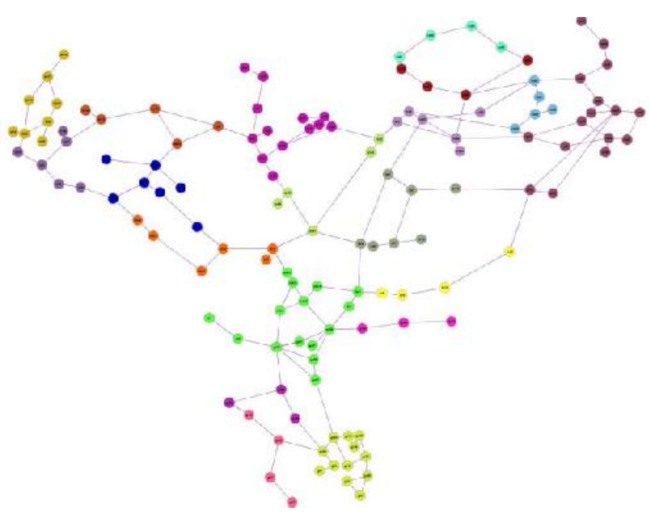

Figure 3. First level of clustering of the power transmission network of Southeast Europe

It is interesting to analyze how the clusters are distributed in terms of the states in this region.Given that in the future there will be a common electricity market that does not recognize boundaries between countries,it is interesting to examine the capability of the transmission network in the region to meet this requirement.Thereby in this paper, using a clustering algorithm,we explore the topology and structure of the network in terms of the countries. For this purpose, as a measure of how the network is clustered according to the countries we use the data for the number of countries per cluster, and the number of clusters per country.

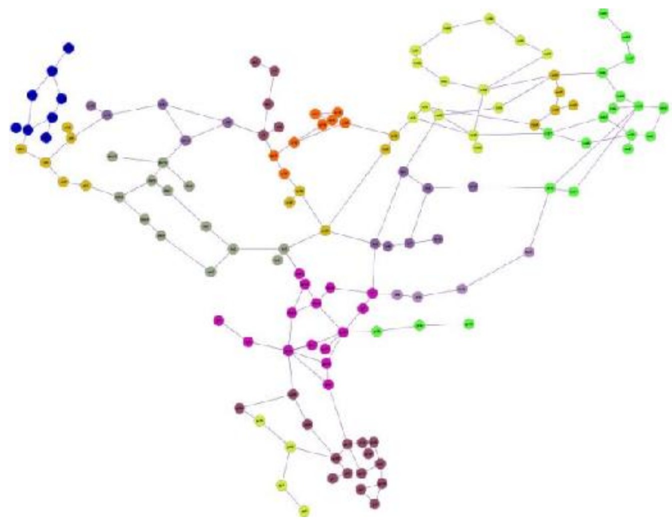

Figure 4. Second level of clustering of the power transmission network of Southeast Europe

On Figure 5 the number of countries per cluster is presented for the two levels of partitioning. It can be noticed that most of the clusters are located into only one country. This is especially case for the first level of clustering, where 70% of the clusters belong to one country. For the second level of clustering 40% of the clusters belong to one country.

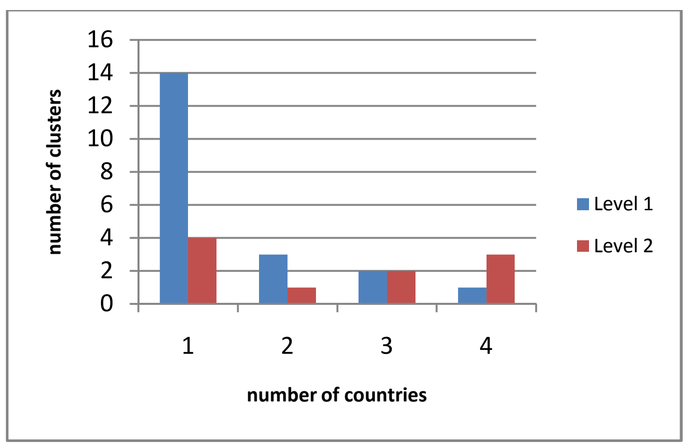

Figure 5. Number of clusters per country

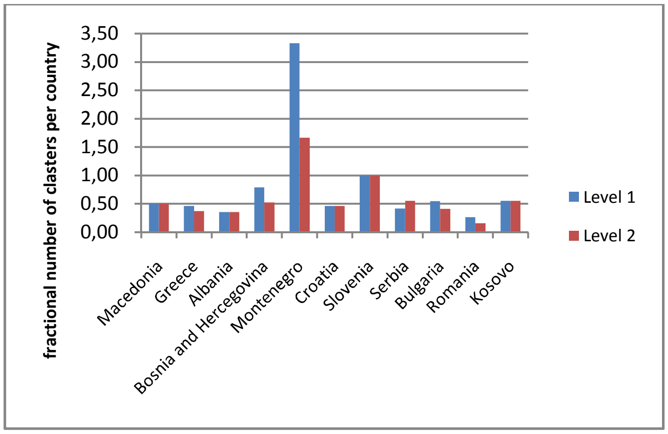

Figure 6. Fractional number of clusters per country

Figure 6 shows the fractional number of clusters per country, which for a certain country is calculated by dividing the number of clusters in that country by the population. Smaller countries such as Montenegro, Slovenia and Bosnia and Herzegovina are more clustered compared to Romania and Greece, which shows that the clusters of those countries are not bounded by the country borders. This may be a legacy of the development of the network from the time when a lot of these small countries were integrated into one country- the Yugoslav Republic.

Another interesting property of the network can be drawn from the data about how many of the lines which connect two clusters, also connect two different countries. This data shows which of the border transmission lines should be upgraded in the future in order to have integrated network. For the first level of clustering 20% of the lines between two clusters are also border lines. This percentage is a little higher for the second level of clustering, i.e. it is about 22%. It is interesting that although the level of clustering was changed the lines between clusters which are also border lines remained the same. There are six such lines which connect Serbia with Bulgaria, Romania and Kosovo, Macedonia with Kosovo and Romania with Bulgaria.

The crucial nodes in the network are detached in Figure 7. This are the nodes that connect more than three different clusters, or nodes that have links to nodes that belong to more than three different clusters. Two of these nodes belong to Serbia, three to Bulgaria, four to Romania, one to Kosovo and one to Bosnia and Herzegovina.

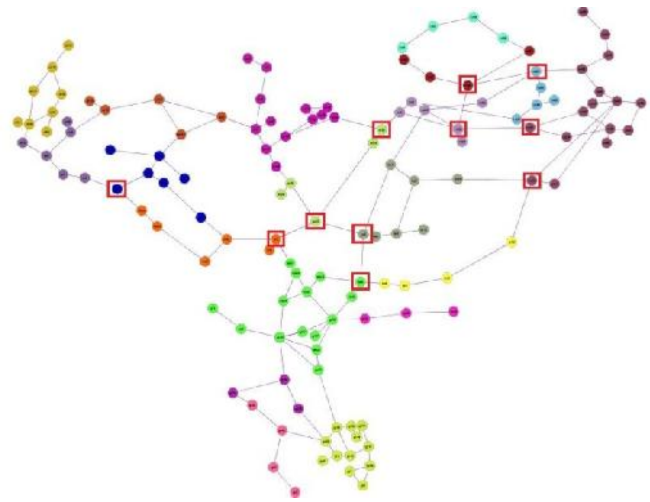

Figure 7. Nodes that connect more than three clusters

5. CONCLUSION

The clustering analysis of the power transmission network of South East Europe helps identifying the grouping clusters of the network and the links and nodes that connect them. This can help to assess the critical points of the network and the isolated islands. In this work we analyzed two levels resulted from the hierarchical clustering of the network using the Girvan – Newman modularity function. From these results we can see the structure of the network by analyzing the belongings of clusters by country showing that each country presents a major cluster or belongs to several connected clusters which is the case with the small countries where the power nodes have main function of connecting neighboring countries i.e. clusters, or were part of former bigger country and thus part of one cluster. The separate analysis of the both levels showed that we can uniquely identify the power generators and transmission links that are connecting several different clusters and mark them as critical points of the network.

Further analysis of this network can include identification of the isolated islands for preventing cascading events and analysis of the network vulnerability by removing the detected connecting links.

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