Increasing resilience of power systems using intentional islanding; a comparison of Binary genetic algorithm and deep learning based method

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Abstract— **Several algorithms combining qualitative and quantitative components are currently used for splitting a large interconnected power grid into islands as a measure to provide the best reconfiguration option when a fault appears. The aim of this article is to compare the clustering results of a binary genetic algorithm and a deep learning based method in order to identify the differences and to find in which cases it is rather better applicable each of the techniques.**

Keywords—intentional islanding; binary genetic algorithm; deep learning; graph convolutional networks; power system;

I. INTRODUCTION

The electrical grid is a critical infrastructure that needs to be resilient, having minimum service disruptions during critical events and ensuring the lowest impact on end users. The integration of microgrid architectural frameworks in electrical grids has urged system operators to design new methods towards preserving the stability and reliability of the grid. Microgrids allow the smooth incorporation of distributed energy resources (DERs) in the system [1], which are usually renewable small-scale sources of energy, that can be coordinated in a decentralized way, offering modular and flexible features [2]. One of the major benefits of microgrids is their ability to operate connected to the grid, but also disconnected, in an autonomous islanded mode [3]. Courtesy of this versatile nature, they have been utilized to enhance energy delivery and stability in power systems [4].

In cases of severe disturbances, caused by unexpected physical phenomena or human faults, a possible loss of generators can often lead to cascading outages in the grid and result in wide area blackouts. Modern electrical grid architectures integrate managing mechanisms, that are activated in cases of such emergency and allow the power system to respond quickly, enabling a rapid restoration back to a secure state. Such an efficient control strategy is described by the process of intentional islanding, which can be implemented in microgrid architectures in order to alleviate the effects of major disruptions and protect the grid from cascading failures [5].

Intentional islanding is a procedure during which the grid is divided into several partitions, called islands, that are self-sustainable and isolated from each other. At the core of the intentional islanding problem lies the decision of which lines to disconnect, so that robust islands are formed, with the objective of having minimum loss of load supply. Towards the goal of minimizing load shedding and potential disruptions, islanding solutions aim to group the available generators in a coherent manner [6] and the formed islands are determined in a way that allows them to maintain voltage and frequency balance through appropriate control strategies. As a result, it has been shown to improve reliability since the continuity of supply is increased for the loads in the islanded areas and is suggested as a mechanism for protection in emergency situations. The problem exhibits a non-deterministic polynomial-time hardness, and most solutions are employing optimization methods to select the optimal scheme [7]. Several techniques rely on graph theory since the grid can be transformed into a graph representation, and the scheme can be obtained by then solving a multi-objective optimization problem [8].

This paper examines how methods of distinct nature perform when solving the problem of intentional islanding. The first proposed technique aims to find the optimal solution that will guarantee the grid stability, relying on a binary genetic algorithm (BGA). Following a contrasting approach, the second method is based on a deep learning architecture that utilizes graph convolutional neural networks (CNN) and addresses large and complex power systems, with an increased efficiency. The investigated approaches are evaluated on several test cases that involve grids of varying size and topology, demonstrating their effectiveness in solving the intentional islanding problem by examining the power imbalance, the response time, the number of clusters and line disconnections that are required.

II. TECHNIQUES FOR POWER GRID CLUSTERIZATION

Common approaches model intentional islanding as a combinatorial optimization problem, with objective functions aiming to minimize the supply and load imbalance, or the power flow disruption [9]. When it comes to the second objective, islanding solutions rely on a technique called spectral clustering, with roots in graph theory. Using this method allows to calculate the isolated segments through the corresponding eigen-values and eigen-vectors of a matrix that represents the graph of the electrical grid [10]. This technique is demonstrated in [11] by introducing a two-step clustering algorithm that groups the generators so that islands with isolated loads are avoided. At the first step the grouping is achieved using a normalized clustering method and the islanding is completed at the second step through constrained spectral clustering. A similar solution is presented in [12] where the algorithm relies on constrained spectral clustering to form the islands, ensuring minimum power flow disruption on the process. The method manages to achieve high efficiency in large grids, by requiring to solve the eigen-problem only once, for any given number of islands.

Using the graph representation of the electrical grid, the islanding method proposed in [13] determines the Laplacian and the weight matrices and solves the generalized eigen-value problem. The islands are determined based on the coherency of the available generators, using a spectral k-embedded clustering algorithm. The final solution is given after the normalization of the corresponding eigen-vectors, by applying the algorithm on the k-1 lowest eigen-values.

The intentional islanding problem is often formulated as a mixed-integer linear programming (MILP) problem. Relying on the graph representation of the electrical grid, the splitting process is transformed into a graph partition problem, aiming to disconnect the minimum number of lines. This approach is described in [14], where the proposed algorithm adds the objective of minimizing the power flow disruption at the formed islands. The complexity of the problem is first reduced through a pre-processing method and afterwards the trees that connect every generator to the minimum quantity of nodes are calculated to provide the final solution.

A. *Deep Learning Based Method for Intentional Islanding*

Traditional methods are often unable to offer a quick solution for intentional islanding that minimizes the load-generation imbalance at the islanded segments. By relying on their strong generalization capacity, deep learning architectures can potentially provide an efficient and reliable solution to this problem. The advent of deep learning has recently led to significant breakthroughs in several areas, and especially in computer vision, targeting various smart applications. However, the structures that are utilized in most use cases rely on Euclidean distance data and cannot be easily applied in graph models. By investigating methods of integrating graph data inside deep architectures, the class of graph convolutional networks (GCNs) has emerged. These networks allow the capture of patterns inside graphs through the encoding of elements as vertices and their correlation as edges.

Our deep learning approach for the intentional islanding problem is thoroughly presented in [15] and relies in a GCN architecture to determine the splitting strategy. The electrical grid is modeled by a graph representation, which allows us to employ GCN layers in our deep learning model. This representation depicts each bus in the grid as a vertex in the graph, and each transmission line and transformer as an edge. The edges have weights attached to them, representing either the active power flow or adjacency information. By running a power flow analysis on this model, we extract the required information, such as angle, voltage magnitude, and power demand for the buses, and active, reactive power flow, as well as adjacency information for the lines.

The graph partitioning strategy is based on the normalized min-cut problem [16], which was formulated as follows:

$$L = -\frac{Tr(S^T \hat{A} S)}{Tr(S^T \hat{D} S)} + || \frac{S^T S}{\left\| S^T S \right\|_F} - \frac{I_K}{\sqrt{K}} ||, \tag{1}$$

where || || is the Frobenius norm, S represents the result regarding which cluster the node should belong to, A and D indicate the adjacency and degree matrices, respectively. IK is the multiplication of S with its transpose matrix and Tr() is the average operation. L represents the total loss function for the minimum cut and Lc is the cut loss term. Lc might result in a local minima solution, meaning that after the optimisation, Lc tends to assign all vertices in a binary cluster result, regardless of how many classes are assigned as the desired outcome. Lo represents the orthogonality penalty term so that nodes from different clusters are orthogonal and the number of nodes is the same in each cluster.

The above method is incorporated in our approach to the problem of intentional islanding, allowing as to offer an and-to-end deep learning solution that ensures minimum load-generation imbalance at the formed islands, with as few line disconnections as possible, while satisfying the requirement for coherent grouping of the generators. In order to minimise the power imbalance, the following loss function is used:

$$L_{load-gen} = \frac{1}{K} \sum_{k=1}^{K} |YB|, \tag{2}$$

where Y is the output matrix from the GCN with dimensions n*g and contains the associations between the nodes and the partitions. B is the n dimensions vector for the load-generation result, as approximated from the state estimation process.

To avoid situations where there is no supply of power after the islanding and enhance the stability of the electrical grid, we set a requirement that each cluster should contain at least one generator. The corresponding loss function is defined as follows:

$$L_{gen} = softmax\_cross\_entropy(p, Y_{gen}), \tag{3}$$

where Ygen represents the matrix that indicates the buses connected to the source generators, p is a vector that ranges from 0 to g, and softmax_cross_entropy represents the classical function for multi-class optimisation loss.

In order to train and evaluate our solution, we used PyTorch as the main deep learning platform, along TensorFlow and Mxnet. This platform allows us to utilise a GPU with cuda cores, to significantly accelerate the whole process, with a GTX-2060 GPU in our case achieving the solution in less than a second. However, the model was also evaluated on a CPU to examine the performance when GPUs are not available.

B. Binary genetic algorithm

Genetic algorithms, a type of evolutionary algorithm (EA), can be very effective at solving non-convex optimization problems, particularly when solutions can be represented as strings of numbers, and the quality of solutions can be represented using a single objective [17]. It uses the clustering quality measure given by a combined fitness function for a genetic algorithm (GA). To implement this GA, we represent a solution to the clustering problem as a string of binary variables, with each bit representing the status of a branch in the network.

The chromosome of this algorithm is a binary array with all the elements that can be connected or disconnected. To create the chromosome, the BGA uses the lines and loads that are present in the grid. This creates a relation between the binary value and the element in the grid to apply the changes to the system.

The cost function is determined using four different criteria to have a consistent solution. Each criterion helps to determine the best solution. The criteria are described in the following list:

C1: Minimum number of disconnected lines. Penalization for each power line disconnected and the quantity of this penalization is the power flow in the disconnected line.

C2: Minimum number of disconnected loads. Similar to the previous criterion but with the electric loads that can be disconnected.

C3: This criterion sets the minimum number of islands that will be formed. This value is set as an input in the configuration. For the evaluation scenarios evaluation, this value is set to 2.

C4: Energy balance on each island. On the evaluation of this criterion is performed a simple power balance, generation less consumption, if there is not enough power to maintain the island then it penalizes the solution.

Finally, the four criteria are summed together with a configured weight for each criteria.

The network-partitioning problem is turned into a graph – cut problem, related to the graph theory. A system with n buses corresponds to a graph model G (V, E). The node set V and the edge set E correspond to the buses and the lines of the network respectively. The edge weight matrix W = (Wij), i,j=1,2,…n, can also be defined. In case Wij=0, then the nodes i and j are not connected. Otherwise, they are connected.

The BGA represents variables as an encoded binary string and uses the binary strings to minimize the cost. It begins by defining the optimization variables, the cost function, and the cost. Then it ends by testing for convergence [17, 18].

III. SCENARIO DEFINITION

Both clustering techniques use the same grid model input using pandapower [19] library, as well as the same output format.

The grid model uses the pandapower data format to describe the topology and the elements on the grid. This format contains the electric elements that can be found in the electric infrastructure, such as buses, lines, loads, generation, load switches or shunts.

The results obtained from both techniques are represented in a diagram with the proposed islands, a summary of the KPI proposed and a pandapower format with the results.

To compare the results, a set of grid models had been used:
- Scenario 1: simple case including 9 buses, IEEE9 [20].

- Scenario 2: A distributed and quite mesh grid including 15 buses MV CIGRE [21].

- Scenario 3: and a large grid 179 buses: MV Oberrhein [19]. These cases represent various scenarios from small to large power grids.

In each scenario has been created a fault in a bus that should be isolated. The fault could come from different natures, for example a device malfunction or an intrusion.

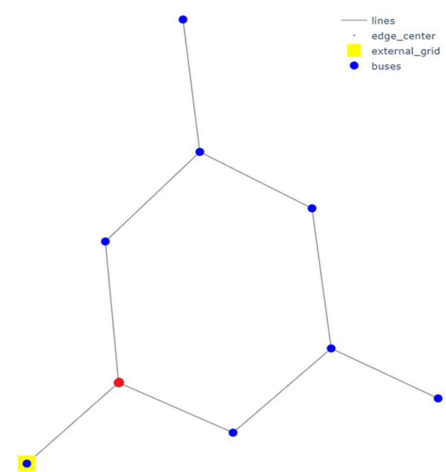

Figure 1: First scenario IEEE9, fault located at bus 4.

The first scenario, depicted in Figure 1 has been chosen for the low number of buses and the islanding possibilities with the three available generation points. This electric grid is a standard case provided by several electric calculation tools. It has one external connection and two generators, each one connected at the end edges of the grid. On the other side, the loads are in the middle busses, this allows different possibilities to supply the consumptions. The fault in the first scenario is located in bus 4, this bus connects the external grid with the rest of the buses. This fault provides a solution in case of the main grid failure.

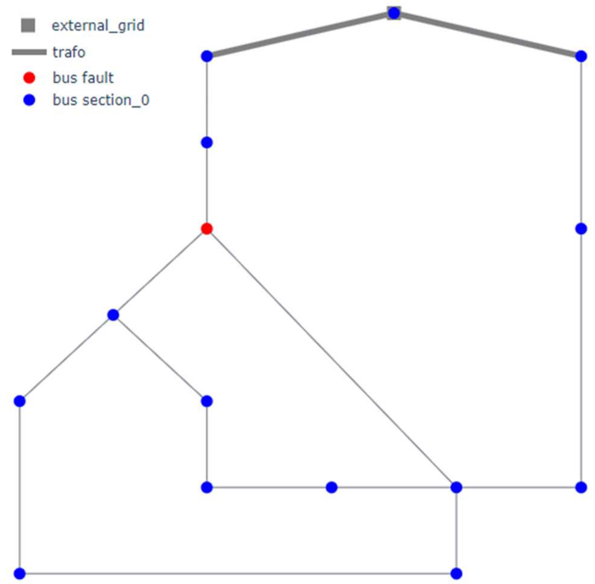

Figure 2: Second scenario MV CIGRE with all DERs, fault located at Bus 3.

The second scenario, depicted in Figure 2, has a medium size, some distributed generation and several possibilities to supply all the consumptions. Into this electric grid, there is only one external connection and 15 generations distributed overall the grid. This distribution of resources allows the creation of new electric islands sectorising the electric grid in small parts. In this scenario, the fault is located at Bus 3. On this bus, there are two loads connected that cannot be supplied due to the isolation of this bus. Also, the faulty bus is considered a transmission bus that supplies the downstream buses, the proposed methods must find another way to maintain the supply.

The third scenario, depicted in Figure 3 is a big grid composed of 179 buses, 2 transformers, 149 loads and 153 generators distributed overall the grid. This scenario has slight modifications from the original to have enough distributed power, with these modifications allows supplying most of the consumptions close with the distributed resources. In this scenario, the fault is located at bus_84. On this bus, there is connected a generator that should be isolated due to the fault. Also, this bus connects two parts of the grid forcing the proposed methods to find another way to supply all the consumptions.

The key performance indicators to compare the techniques presented are the following:

- Number of **disconnected lines**: the lines that have to be disconnected to perform the new topology. This value means changes to do on the grid to create the new topology. Depending on the infrastructure, these changes can be done automatically or manually.

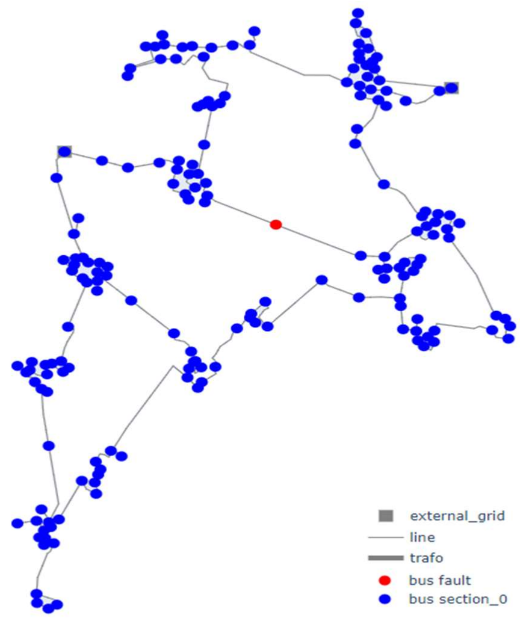

Figure 3: Third scenario MV Oberrhein, fault located at bus_84.

- The **number of islands** generated: the number of generated islands. For one side, if this indicator is high means that there are small clusters, which can be translated to an increase of resilience of the entire system, but on the contrary, this system is more complex to maintain each island.
- **Power imbalance** in all the islands: this value is the sum of the imbalance on each island. Imbalance means the power that cannot be supplied using the generators located on each island. The intention is to have this value as closes to zero as possible.
- Algorithm **time**: The sent time for each method to find a solution. Time is important when an incident appears on the grid and needs to be solved as soon as possible.

To be able to compare the described techniques the scenarios have been performed using similar machines. This allows comparing the time needed for the calculations. The machine characteristics where the tests have been performed are Intel i5 8th Gen of CPU and 8 GB of RAM.

IV. Results

The solution offered by the GCN deep learning method follows the principles of recent intentional islanding approaches as proposed by [12] and [22]. The goal of the splitting strategy is therefore to group the affected bus in a suitable cluster, so that the created islands are as stable and reliable as possible and are connected to at least one generator. As a result, it defines the island margins in a way that cascading failures are avoided in smaller islands and alleviates the impact of the disturbance this way. The visual results of this solution are depicted in Figure 4: Aggregeted results of the GCN deep learning method. and Table 1: Results of the two methods on the considered KPIs. shows the numerical results for each KPI.

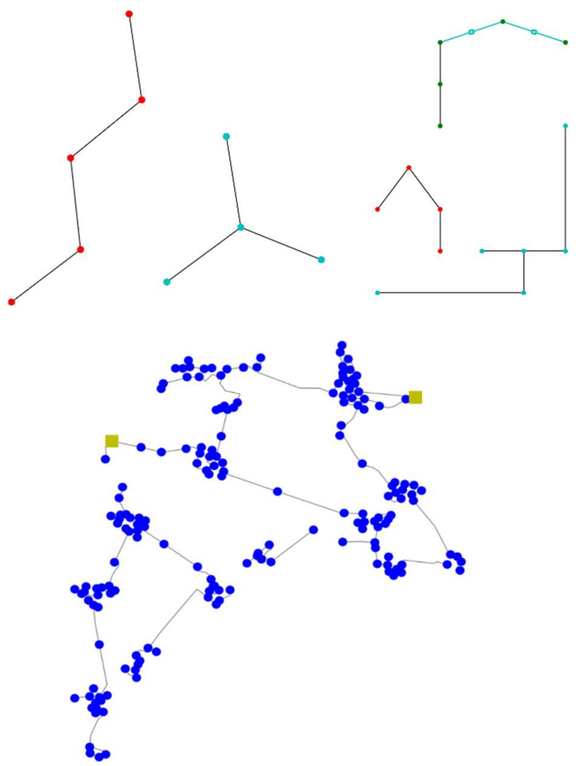

Figure 4: Aggregeted results of the GCN deep learning method.

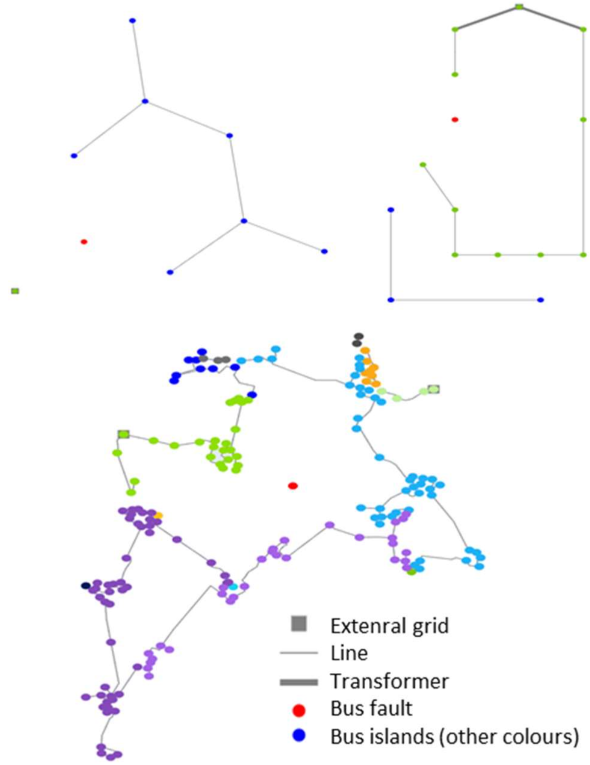

Figure 5: Aggregated results of BGA method.

The result of the binary generic algorithm are depicted in the Figure 5, also the KPI are shown in the Table 1.

The proposed islanding scheme for the first scenario isolates bus 4. Due to the fault, all the lines related to the bus have to be disconnected. As a result of these changes, the bus linked with the external grid is isolated from the rest because the connection has been broken due to the bus isolated. The rest of the buses remain connected with two generators that have enough power to maintain the supply to the loads.

The solution of the second scenario creates two islands section_0 and section_1. Section_0 connects the external grid with most of the buses that have consumptions, maintaining the electric supply. Section_1 is an island of three buses self-sustainable thanks to the energy resources located there. The imbalance result is negative because the isolated bus has some consumptions that cannot be supplied due to the isolated bus.

The last scenario creates 13 islands, due to the grid size and to achieve the power supply to all the islands. All the created islands have enough power supply to maintain to all unless one, the section_9. The surrounding buses cannot supply this section because there is no enough power to sustain its consumption.

Table 1: Results of the two methods on the considered KPIs.

KPIs	***CNN***	***BGA***
Scenario 1		
Disconnected lines	2	3
Number of Islands	2	2
Total powe imbalance [MW]	-4.9547	0
Time [s]	5.9	8.654
Scenario 2		
Disconnected lines	5	5
Number of Islands	3	2
Total powe imbalance [MW]	-3.5565	-0.482
Time [s]	6.4	13.758
Scenario 3		
Disconnected lines	19	17
Number of Islands	8	13
Total powe imbalance [MW]	-3.901	-0.128
Time [s]	10.3	174.607

V. CONCLUSIONS

The electric grid is a critical system, and for that reason is important to find methods to increase its resilience. When an issue appears on the grid, the system operator needs a fast solution to know how to react, but also important, how to maintain the power supply to all the consumptions. The proposed solution is to use an intentional islanding process to sectorize the grid in small portions. This article presents two methods of intentional islanding using different calculation methods where each one has advantages and disadvantages.

Both methods present a new exploitation scenario improving the reliability of the entire system in case of an issue. The GCN deep learning method creates clusters, in a way that groups the affected bus in an appropriate island, aiming to maintain supply throughout the system, and in case of potential instability, avoid cascading failures to the rest of the grid. On the other hand, the BGA method isolates completely the affected bus from the rest of the system and sectorize the rest of the grid to improve its resilience for new situations.

The binary genetic algorithm needs more time to find a solution, but it always tries to find the best solution for the islanding according to its criterion. This method has a strong connection between the size of the grid and the needed time. With the GCN deep learning method, the solution is faster, and can also be significantly improved using a GPU. However, the power imbalance on the islands is higher than the BGA method, which means that not all the consumptions can be supplied after the islanding.

In conclusion, there are two methods: one that is fast but less sensitive to the possible effects, and the other that is slower and takes into account all the possibilities by avoiding power supply issues.

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