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Resilience Neural-Network-Based Methodology Applied on Optimized Transmission Systems Restoration

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Abstract: This paper presents an advanced methodology for restoration of the electric power transmission system after its partial or complete failure. This load-optimized restoration is dependent on sectioning of the transmission system based on artificial neural networks. The proposed methodology and the underlying algorithm consider the transmission system operation state just before the fallout and, based on this state, calculate the power grid parameters and suggest the methodology for system restoration for each individual interconnection area. The novel methodology proposes an optimization objective function as a maximum load recovery under a set of constraints. The grid is analyzed using a large amount of data, which results in an adequate number of training data for artificial neural networks. Once the artificial neural network is trained, it provides an almost instantaneous network recovery plan scheme by defining the direct switching order.

Keywords: transmission power system optimization; transmission system restoration; artificial intelligence; artificial neural networks; power system analysis

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1. Introduction

The transmission system is considered stable when it is capable of returning into a steady state after a disturbance. The steady-state operating point is the state of the electric power system (EPS) in which all its variables are within the limits that assure the full system integrity, i.e., the state into which the system will return after "small" disturbances.

In practice, EPS stability will be preserved if unstable and faulty parts of the system are disconnected from its healthy parts promptly. Specifically, the stability of a system generation unit is the ability of a generation unit to remain synchronized with the system despite the disturbances. On the other hand, the loss of generator synchronism, e.g., because of the overload, can cause generator disconnection from the system. This can produce greater loading of other generators and can cause a loss of their synchronism as well. This situation can lead to complete outage of the whole system. As the worst possible failure that can happen to an EPS, such situation should be avoided whenever possible.

Depending on the nature of the failure and the extent of the produced damage to the EPS, such situations can last from minutes to hours and even dozens of hours.

Renewable energy resources are increasingly implemented in the power systems. Wind and solar power plants are stochastic and intermittent power sources that are sometimes difficult to predict. Since the power systems are becoming more complex, it is important that all faults and failures are well managed. Otherwise, the power system can have cascading failures, which might lead to a blackout eventually. In recent years, there have been a great number of widespread blackouts and severe disturbances of power systems around the world, such as: the January 2015 blackout in Pakistan, the March 2016 blackout in Turkey, the June 2019 Argentina, Paraguay and Uruguay blackout, and the August 2019

Java blackout [1,2]. Furthermore, the European power systems are facing faster and more frequent severe disturbances followed by constantly reducing inertia of the grid [3–5].

Different power systems use different solutions for optimal system operations. All of them try to implement some kind of a defense scheme to keep the system safe from blackout. This does not eliminate the possibility of a blackout to occur; however, it is very important that the EPS recovers as quickly as possible.

Presently, the detailed EPS restoration plans are created in advance, based on the power flow calculations, dynamic simulation of the operation states [6–8] and the transient electromagnetic phenomena [9] that occurred in the previous system contingencies. That is, the human experts heuristically gather knowledge in non-real time and prepare directions and whole scenarios on how to restore the system in certain types of situations. The dispatchers will follow these directions and scenarios when encountering a similar situation in their real-time operation.

Using mathematical optimization and computer science in EPS has become standard practice. Heuristic algorithms, such as genetic algorithms [10], artificial neutral networks [7,11] and graph theory [12], are applied in system restoration. The strategies for EPS restoration are highly dependent on the specific features of the system [13,14], primarily regarding the characteristics of the load and the generating units. In practice, the features of the EPSs and their parts differ greatly from each other, so the restoration plans cannot be fully generalized.

The required computing time and the capability of finding restoration plans under unexpected fault conditions are critical issues in power system restoration estimation. In this paper, an alternative of using artificial neural networks in power system restoration is investigated. The use of artificial neural network (ANN) in system restoration has already been a subject of research in distribution and transmission systems [7,11,13–15]. However, this paper presents a new approach using a different set of constraints, implementing ANN to find the optimal system topology for maximum load recovery. After training the ANN with enough data, the method is able to provide almost instantaneous network recovery plan scheme by defining the direct switching order of the affected breakers. Most of the analyzed papers use restoration time for the optimization goal. The most important novelty of this paper is that it introduces optimal topology of the grid for the optimization goal, that is, the input for the beginning of the transmission system restoration process. In this paper, a model of a part of real transmission network is used to simulate different fault conditions. The paper introduces the methodology and algorithm based on the artificial neural network approach using the multi-layer perceptron (MLP) to ensure optimal restoration based on maximum stable load recovery.

2. System Restoration Plans

To avoid a power system cascading breakdown, the system operator proposes the system defense plan (SDP), i.e., a real-time analysis and communication between the main subjects of the power system, system breakdown analysis, system vulnerability assessment and system possibility of going through emergency operating conditions (e.g., self-healing).

Furthermore, the system restoration process includes the current system condition assessment, generation optimization and connections of loads at the transformer substation level. There are two basic issues in the planning of system restoration. The first challenge concerns the generality of restoration plans. Plans should be uniform and transferable from system to system regarding the basic procedures, usually according to the system restoration plan (SRP). However, a review of the available literature and interviews with dispatchers from different system operators reveal that differences in "strategies" of restoration plans are closely related to differences in the characteristics of individual power systems.

Another challenge to establishing effective plans is a common unavailability of effective optimization tools. The problem of system restoration needs to be considered through a number of variables (post-mortem analysis of various disturbances), and therefore, it cannot be formulated as a single-objective optimization problem. Moreover, these optimization problems belong to the class of combinatorial optimization problems.

2.1. General Procedure

The general procedure of system restoration [6,16] has three phases:

- Preparation,
- System restoration,
- Load restoration.

In these phases, the main difference between the preparation phase and the next phase is that during the preparation phase, it is necessary to take urgent actions. In the preparation and system restoration phases, the primary goal is to control the load restoration to keep the system stable, while in the load restoration phase, the primary goal is to energize the loads as soon as possible [16,17].

According to the general procedures of system restoration above and the available literature, the restoration strategies can be classified into five general types [17]: "bottom–up", "top–down", "outside–inside", "inside–outside" and "joint restoration", each described in the following paragraphs.

Bottom–Up: This strategy is based on predefined islands within the power system with the possibility of a black start (BS) of production units within the island. The islands are synchronized into a single power system after power restoration of each individual island. The main operations involved in this process are the start-up of production units that have the possibility of a black start, the start-up of production units that do not have the possibility of a black start (non-black-start—NBS), power restoration of islands and the synchronization of all islands into a single power system.

Top–Down: This strategy restores the transmission network by activating the black-start generating units and afterward engaging other non-black-start generating units. The main steps include starting the black-start generation units, restoring the power supply of the transmission network and starting the non-black-start generating units.

Build-Inward: This strategy can be applied to power systems with additional (reserve) connection to other available interconnections. By switching on the auxiliary transmission lines, connections are established with an external system to restart the production units with the possibility of a black start. It then moves from this basic system and power source into the process of system restoration. This strategy is implemented through several operations and steps, such as switching on the transmission lines, restoration of transmission networks and the start of production units that do not have the possibility of a black start.

Build-Outward: To re-establish supply of an outer ring of the transmission network without using the interconnections, the system restoration must go from the ring to the external network. The main tasks of this strategy are activating the black-start generating units, establishing the power supply of the outer ring of the transmission network and activating non-black-start generating units.

Build-Together: In this strategy, the transmission network is restored in stages to provide sufficient power to fit the load. After that, the generating units without the possibility of a black start located close to the load are activated.

Each power plant, including the distributed sources, can be classified as a generation unit that has the possibility of a black start or does not have that option. An NBS unit must be supplied with an external power source to start the auxiliary devices before restoration, while a BS unit can be activated without an external power source. In the initial process of restoring a power system without external connections, and thus the power supply, the primary task is to activate the BS units to provide power to start the NBS units. During the process of activation, the BS units, such as hydropower plants, are used to regulate the frequency and voltage due to their fast response time. Under normal operating conditions, activating NBS units can take the most time to establish the power system, since the NBS units' activation time is much longer than the BS units. It is important to determine NBS units' start-up order, since this affects the power system restoration time. After NBS units' order is determined, the main transmission lines are supplied with voltage to create a foundation for activation of significant loads.

The main task of the load restoration process is to determine the order and amount of load that can be activated in a single step. At each step, the load active power must be limited and aligned to the generator active power; otherwise, the frequency stability limitations cannot be met. In order to ensure voltage stability, the main generators' reactive power must be in balance with the reactive power of the activated loads. In addition to generator control systems, such as excitation control systems and turbine speed control systems, static and dynamic load behavior has a large influence on the frequency and voltage deviations during system restoration [18].

2.2. Technical Conditions for Power Supply Restoration

To implement system restoration plans, it is necessary to check their technical feasibility both under the normal operating condition and under the disturbed operating conditions [19]. Technical feasibility of system restoration plans includes the following:

2.2.1. Active Power and Frequency Regulation Balancing

During the system restoration process, it is necessary to maintain the system frequency within the allowed limits using the inertia of the generating units (especially turbines) and protection settings [20]. This is achieved by restoring (or activating) loads in steps that can be adjusted to the inertia of the entire system and the response of the synchronized system [21].

2.2.2. Reactive Power and Voltage Regulation Balancing

To keep the system voltages within the permitted limits, the following operations are performed during the system reset procedure: restoration of power supply of high-voltage lines to a voltage lower than nominal, operation of the generator at the minimum allowed voltage levels, disconnection of static capacitors, switching on shunt reactors, setting up regulation transformers and activating loads with inductive power factors [1].

2.2.3. Transient Overvoltages

During a black start, overvoltages can occur in certain parts of the system. Transient overvoltages can also occur as a result of circuit breakers switching, so care should be taken to establish a large part of the system relatively quickly to avoid the risk of damaging the loads' insulation [7].

2.2.4. Self-Excitation

There is a possibility of self-excitation of the generation units if the excitation current is relatively large in relation to the power of the generation unit. This can result in an uncontrolled increase in voltage and can result in damage to the primary equipment within the generation unit. Self-excitation can also occur on the load side due to a sudden loss of power supply, by switching off the circuit breaker at the beginning of the transmission line and by switching off the circuit breaker located at the beginning of the line, which is connected to a large motor (or a group of motors).

2.2.5. Switching on the Load in Cold State

If the load power supply is switched off for several hours or longer, the current when restoring the power supply to the consumer can be 8 to 10 times higher than the nominal value. This group of loads include light, high-voltage motors and thermostatically controlled devices (such as air conditioners, refrigerators, freezers, stoves and electric heaters).

2.2.6. System Stability

During the system restoration procedure, voltage and angle must maintain stability. In general, angular stability is checked when multiple generation units are used in the system restoration phases, while frequency stability is a major issue in assessing the feasibility of a system restoration plan.

2.2.7. Relay Protection Setting and Load Monitoring

During the system restoration, a constant change in the power system configuration and operating conditions can lead to an unwanted tripping of the relay protection. In cases where there is a rapid drop in frequency, it is necessary to start load shedding in the system or activate underfrequency load shedding plans to avoid another collapse of the system [22].

2.2.8. Organizing Power System into Islands

In order for the entire interconnection to restore power as quickly as possible, it is necessary to divide the system into islands, but the following criteria must be met [12]:

- each island should have enough power for a black start;
- each island should have sufficient connections between generation units, with the possibility of a black start of generation units that are not able to do so in order to be able to restore them;
- each island should be able to regulate frequency of generation units and loads within the prescribed limits;
- each island should have adequate real-time voltage monitoring and regulation in order to maintain an appropriate voltage profile;
- all nods in the island bordering with "neighboring" islands should be equipped with synchronization devices;
- all islands should exchange information with each other.

3. Resilience Neural-Network-Based Methodology for System Restoration

Optimal system restoration after complete or partial collapse implies fast and reliable load power supply restoration, in a way that is also economically acceptable.

The development of plans/scenarios for system restoration is based on the criteria described in the previous chapters where specific, most probable scenarios are also analyzed, which are divided into subsystems according to the transmission. However, there is no general scenario that includes a specification of all elements of the transmission system, which is assumed to be used regardless of the nature of the disturbance that caused the system to collapse.

Each partial or complete system breakdown is specific, considering the cause of its occurrence, the state of elements in the transmission system at the time of breakdown and after breakdown, as well as loads (power flows) in the system itself, which will directly affect the definition of a restoration plan. It should be noted that it is extremely important, when defining the restoration plan, to identify the available generating units with the possibility of a black start, the generating units that can be started with external power supply, the shortest route to the generating units and loads (from a geographical and electrical perspective) and the time of their restoration.

With optimal system restoration, it is possible to consider scenarios that include restoration not only of individual elements of the system but also the restoration of larger parts of the system—entire sections of transmission lines and associated loads. In this case, it is necessary to balance between the produced active and reactive power in relation to the load and ultimately to maintain system frequency and voltage stability in the process of system restoration.

3.1. Algorithm for Opimal Pre-Restoration Topology

It is imperative that system restoration takes place in a way that restores a series of subsystems that are eventually synchronized into a single interconnection, with criteria as mentioned in Section 2.2.8.

Generally, it is necessary to conduct an analysis and define the activation of priority loads with a continuous calculation of power flows (balance between generation and load). Additionally, the maximum power of each priority load for each geographic area and power system area must be predefined, which will meet the criterion of active power and generation, as well as reactive power and voltage regulation capacity. Furthermore, when defining the plan for activating loads in steps, priority must be given to lower power loads and loads at the end of the energized unloaded transmission line.

During restoration, due to the danger of increase in voltage, it is necessary to:

- block automatic transformer regulators,
- keep the system voltage (subsystem/island) lower than the rated voltage (recommended 0.9–1.0 Un) to compensate for the generation of reactive power of the energized but unloaded lines or lightly loaded lines.

Optimal system restoration refers to the system reconfiguration after collapse or partial collapse, considering the switching status of individual switchgear before the start of the system restoration process. This avoids the lengthy process of switching off all circuit breakers after a collapse, and in the process of restoration, switching off the circuit breakers according to the "step by step" principle. In Figure 1, a flow chart is shown, which is part of the procedures for system restoration with the goal of procedure optimization, which means determining the switching status of all switchgears before the start of restoration.

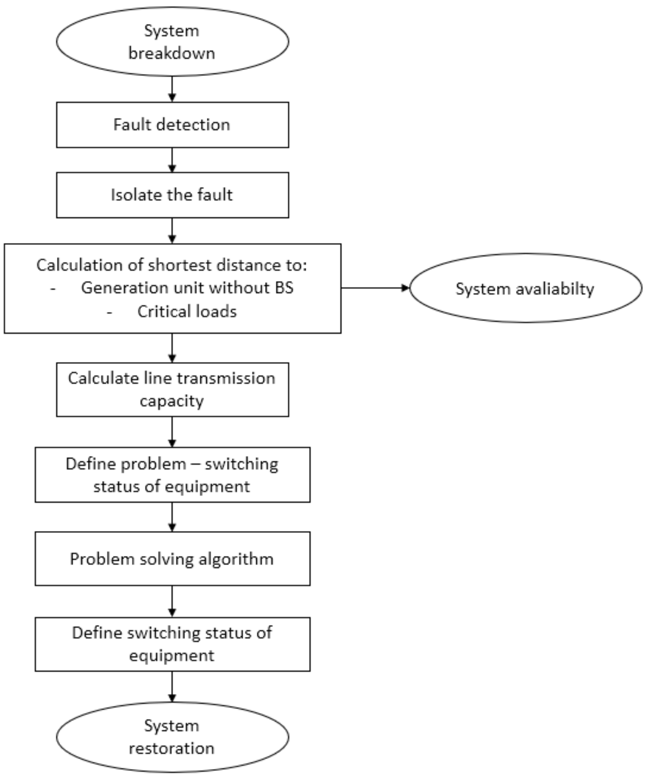

Figure 1. Optimal pre-restoration topology algorithm.

A key part of the flow chart of the optimal system restoration procedure is:

- Problem definition, relating to switchgear settings,
- Problem-solving algorithm.

3.2. Problem-Solving Algorithm—OSRA

The algorithm for solving the problem of optimal switching states of switching devices can be based on various optimization methods, from iterative procedures to artificial intelligence. In any case, it is necessary to satisfy the limitations and the objective function. An algorithm's objective function is not uniquely defined and is usually taken as the time required to restore the system or as the percentage value of the total connected load.

In this paper, the objective function is maximizing the value of the total connected load for re-energization. For that purpose, it is assumed that u marks the current configuration of a selected part of the transmission system whose operating state is determined with x. The objective function can be described as $f(x,u)$, which gives a relative measure of the operating costs of the power system in configuration u for operating state x. For configuration u to be viewed as a solution to the problem, certain constraints must be satisfied. The objective function is to find the optimal network configuration u, which will maximize $f(x, u)$ under a set of certain constraints:

$$\max_{u \in Z} f(x,u) \tag{1}$$

subject to

$$\begin{aligned} F(x,u) = 0 \\ G(x,u) = 0 \end{aligned} \tag{2}$$

where Z is a set of all possible network configurations, and F and G are nonlinear functions, which represent all constraints. The total number of opened and closed breakers in the power system is marked as n_s, the current configuration can be displayed as a vector $u = [u_{1,}\ u_{2,\ \ldots\ ,}\ u_{n\_s}]^T$ where each element represents the status of each breaker $u_i = \{0,1\}$, $1 \leq i \leq n_s$ where $u_1 = 1$ marks the breaker i that is closed, and $u_1 = 0$ marks the breaker i that is opened. Therefore, all possible configurations u can be displayed as $Z = \{0,1\}^{n_s}$. To check the constraints, it is necessary to have complete information about the voltage magnitudes and voltage angles at each bus. This information is included in the stated variable x [23].

The main limitations are bus voltages, transmission grid capacity and power balance. Busbar voltage limitations can be described as

$$V_i^{min} < V_i < V_i^{max} \tag{3}$$

where V_i is the voltage of busbar no. i, between the minimum allowed voltage V_i^{min} and maximum allowed voltage V_i^{max}, i is the number of busbars in the subsystem. Limitations of the transmission line capacity can be described as

$$P_i^2 + Q_i^2 \leq S_{i,max}^2 \tag{4}$$

where P_i is the active power contribution of the line connected to the node, Q_i is the reactive power contribution of the line connected to the node, S_{imax} is the highest apparent power, which can be supplied by the line to the node no. i. Power balance limitations can be described as

$$\sum S_{Generation} = \sum S_{Load} + \sum S_{Losses} \tag{5}$$

where $S_{Generation}$ is the total generation of the subsystem, S_{Load} is the total load power, S_{Losses} is the total losses. The above instructions represent guidelines for optimal system restoration where planned restoration of larger parts of the subsystem (like islands) is used.

The optimal system restoration algorithm (OSRA) is based on artificial neural networks. In this case, the multi-layer perceptron is used to determine the optimal system restoration operations, by determination of the circuit breaker closing order, given the necessary conditions in the transmission network.

The MLP structure is organized in a way such that each of the 96 neurons in the ANN input layer is assigned to one value of the input vector, representing bus voltages, voltage angle, active and reactive power values of the connected lines and loads obtained from the measurement blocks. The hidden layer has 50 neurons and a sigmoid transfer function. The output layer has 10 neurons and a linear transfer function. The 10 neurons in the output layer represent the status of all breakers and their respective switching order, ranging from 1 to 10; if the switching status remains unchanged, it is considered as 0. The complete algorithm consists of two stages. In the first stage, the network input matrix is created. The network input matrix contains bus voltages, voltage angle, active and reactive power values of the connected lines and loads, resulting in an input vector size of 96 values per snapshot.

The load flow calculations in the first stage result in two sets of input–output data: the switching states matrix $M_{swtichstates}$, containing the breaker status values, and the input matrix M_{input} with bus voltages, voltage angle, active and reactive power values of the connected lines and loads. A total of 5120 simulations for obtaining the input-output vectors are performed for different initial load values and breaker positions, resulting in the switching states matrix $M_{switchstates}$ and the network input matrix M_{input} containing 5120 input–output vectors in total.

The bus voltage U is defined as $|U_{n_b}| = \left[\left|U^a_{n_b}\right|, \left|U^b_{n_b}\right|, \left|U^c_{n_b}\right|\right]^T$, the voltage angle θ is defined as $\theta_{n_b} = \left[\theta^a_{n_b}, \theta^b_{n_b}, \theta^c_{n_b}\right]^T$, the active power is defined as P_{n_b}, and the reactive power is defined as Q_{n_b}, where n_b marks the bus number and *a, b* and *c* mark the phases. Therefore, the input matrix M_{input} can be shown as

$$M_{input} = \left[|U_1|, \ldots, |U_{n_b}|, \theta_1, \ldots, \theta_{n_b},\ P_1, \ldots, P_{n_b}, Q_1, \ldots, Q_{n_b}\right]^T \tag{6}$$

The switching states matrix $M_{switchstates}$, containing the breaker status values, can be shown as

$$M_{swtichstates} = [x_1, x_2, \ldots, x_{n_s}]^T \tag{7}$$

where $x_n = \{0,1\},\ 1 \leq n \leq n_s$, where $x_n = 1$ marks the breaker n that is closed, and $x_n = 0$ marks the breaker n that is opened, and n_s is the number of total analyzed circuit breakers.

The OSRA algorithm flow chart is shown in Figure 2. The second stage of the OSRA algorithm uses the switching states matrix and changes the switching states of open switches and compares them with the corresponding input matrix while performing condition checks, considering which switching order restores the largest load back to the system with each switching operation. If the condition is met, the switching order value in the switching order matrix is increased; otherwise, the next switching state is inspected. After all iterations are performed, a full switching order matrix $M_{switchorder}$ is created.

$$M_{switchorder} = [x_{s,1}, x_{s,2}, \ldots, x_{s,n_s}]^T \tag{8}$$

where $x_{s,i} = \{0,k\},\ 1 \leq i \leq n_s,\ 1 \leq k \leq n_s$, where n_s is the number of total analyzed circuit breakers, $x_{s,i} = 0$ marks the circuit breaker I that remains closed, $x_{s,i} = k$ marks the circuit breaker i that will close, and k marks the switching order of the circuit breaker i. The full switching order matrix is used as an output matrix for the training of ANN.

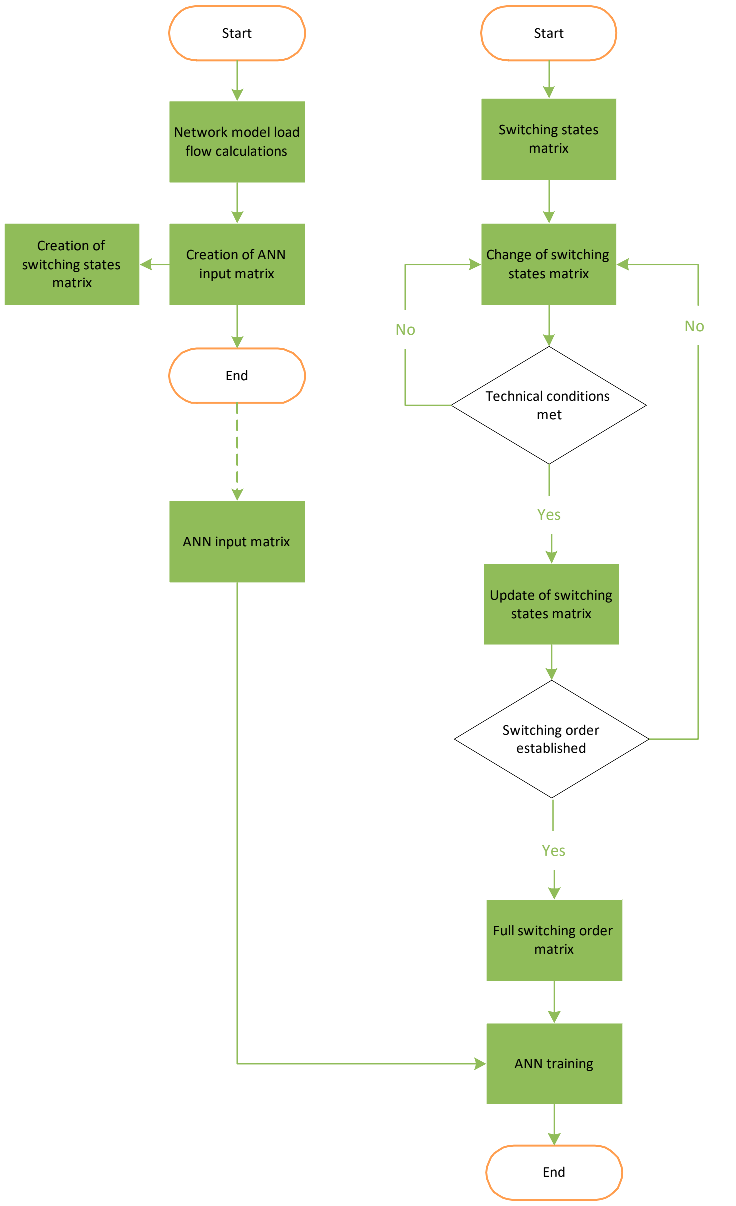

Figure 2. System restoration optimization algorithm OSRA flow chart.

Figure 3 shows the applied structure on neural network, which consists of input, hidden layer, output layer and output with the indicated number of neurons used in each layer, as already described in the MLP structure above.

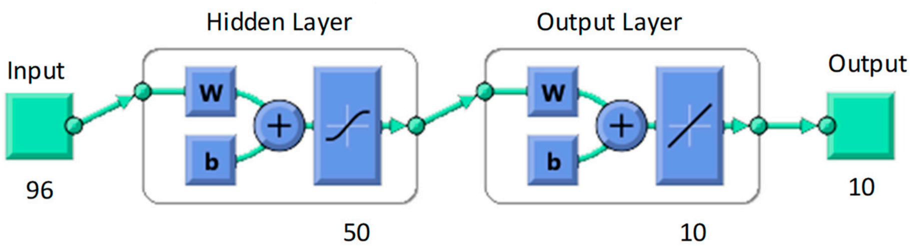

Figure 3. Artificial neural network structure in OSRA algorithm.

3.3. Comparison with Existing Methods

A comparison of the proposed OSRA methodology with existing and similar methodologies for power system restoration is presented in Table 1. This comparison shows the novelty of the research work. In the available literature, there are multiple research papers describing the problem of optimal system restoration, but each paper has certain differences, either in the optimization technique or the objective function or the constraints.

Table 1. Comparison of OSRA with existing methods.

Reference Paper	Application of ANN	Max Recovered Load	Constraints and Power Flow	Switching Sequence Matrix
[7]	Y	Y	N	N
[10]	N	Y	Y	N
[11]	Y	N	Y	N
[12]	N	N	Y	Y
[13]	Y	N	Y	N
[14]	Y	N	Y	N
[15]	Y	N	Y	N
OSRA	Y	Y	Y	Y

Y = Yes, N = No.

According to Table 1, OSRA is a unique algorithm compared to the other referenced methodologies and enables an adaptive technique based on deep learning applicable to a variety of transmission power system topologies.

4. Case Study

4.1. Test Transmission System Model

The proposed methodology does not include running the restoration of the grid. Instead, it gives optimal grid topology as an input for the restoration process. This paper proposes using ANN in order to establish optimal topology based on the detected faults that caused system blackout. Therefore, comparing the restoration times is not an issue. Defense plans anticipate that after a blackout, all the load circuit breakers should be disconnected, and this paper proposes a novel approach, which keeps part of the loads connected. Accordingly, a case study is presented in the following chapters.

The test network used in this paper represents a part of a real transmission network in the Croatian transmission system, containing 23 buses and 22 lines at 220 kV and 110 kV voltage levels. The network with all its elements was modeled in MATLAB Simulink [24]. The measurement blocks were placed at 10 buses, and network operation was controlled by 10 circuit breakers. The network's single-line diagram with indicated relevant elements in the network is shown in Figure 4. Elements B1–B10 represent 10 circuit breakers in the model, SS1 through SS16 represent the busbars, the G1C swing generator is connected at the SS16 bus bar. There are a total of 10 loads connected in the network to the bus bars, SS1, SS2, SS5, SS6, SS7, SS8, SS9_2, SS12, SS13, SS14. Part of the Simulink model of the same network showing SS1, SS2 and SS3 is shown in Figure 5, representing the section of the above diagram marked in the blue rectangle in Figure 4.

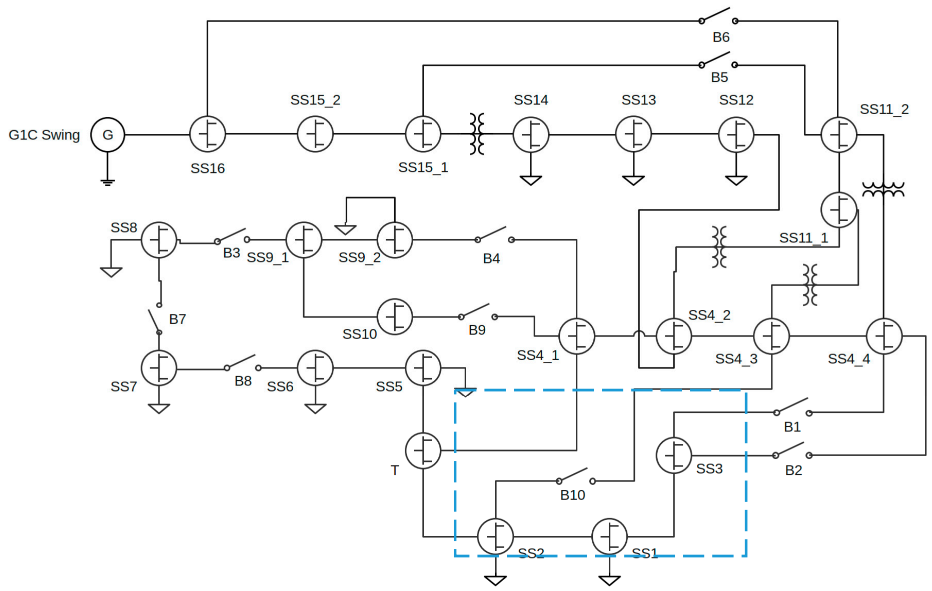

Figure 4. Section of case study network SLD.

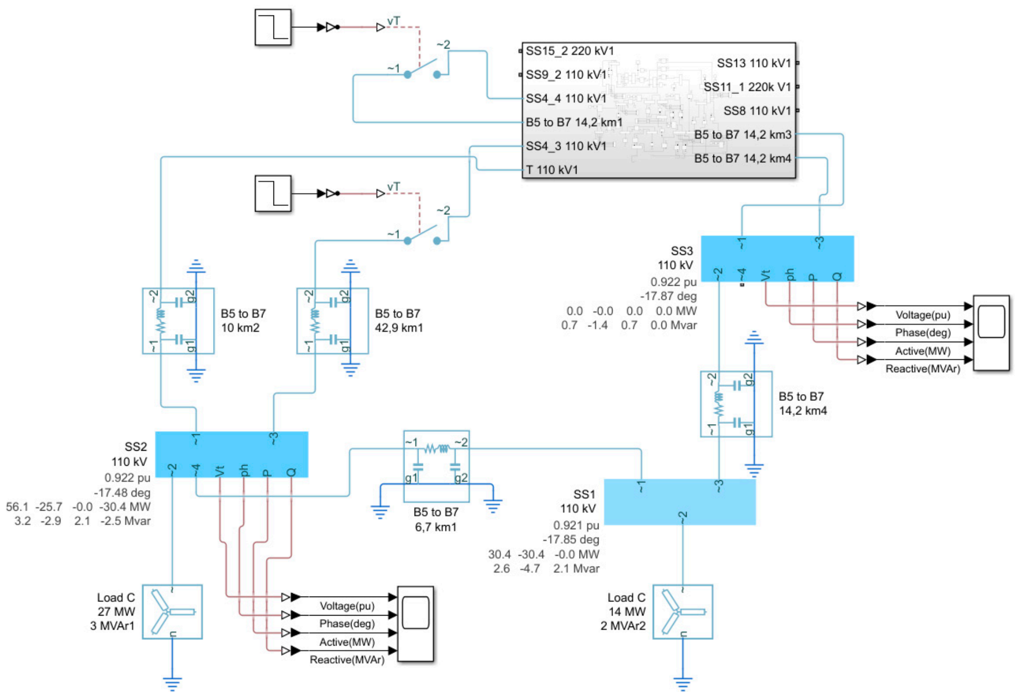

Figure 5. Section of case study network Simulink model.

4.2. Simulation Using OSRA Algorithm

In the OSRA algorithm, the input data matrix used to train the neural network consists of 5120 input vectors, including all circuit breaker configurations, bus voltages, transmission grid capacity and power balance limitations, as described in Section 4. The input data is initially divided into 4096 vectors for network learning, 512 vectors for validation and 512 vectors for testing. In all ANNs used in this paper, a distribution of 80% learning, 10% validation, 10% testing was used, while the input data themselves were randomly assigned to a particular group.

The neural network training was conducted for different numbers of neurons in the hidden layer. Networks with 30, 50, 75 and 100 neurons were trained and compared. The best network training performance was achieved for a 50-neuron artificial neural network, as shown in Figure 6 after 308 epochs.

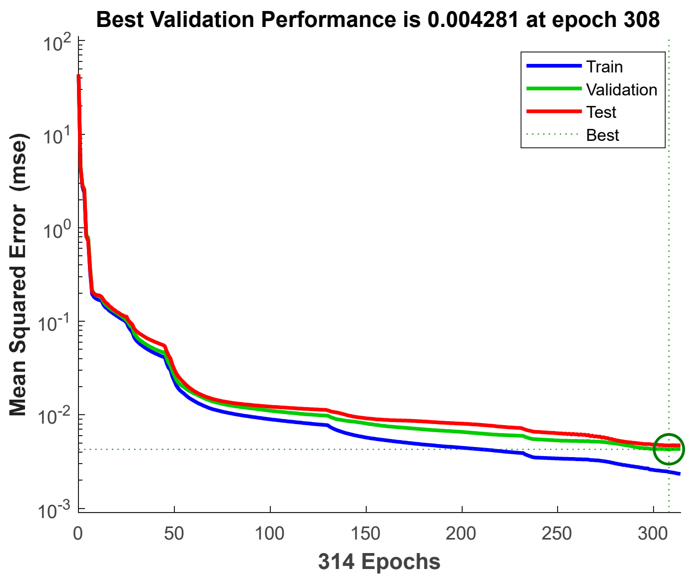

Figure 6. Artificial neural network training performance.

Figures 6 and 7 show the ANN learning parameters, which show the success of ANN formation and accuracy based on randomly selected input vectors used for validation and learning. Figure 7 shows that in the 314th epoch, i.e., iteration, the best data validation was achieved, and the best ANN performance was achieved, which had the smallest square error of 4.281×10^{-3}.

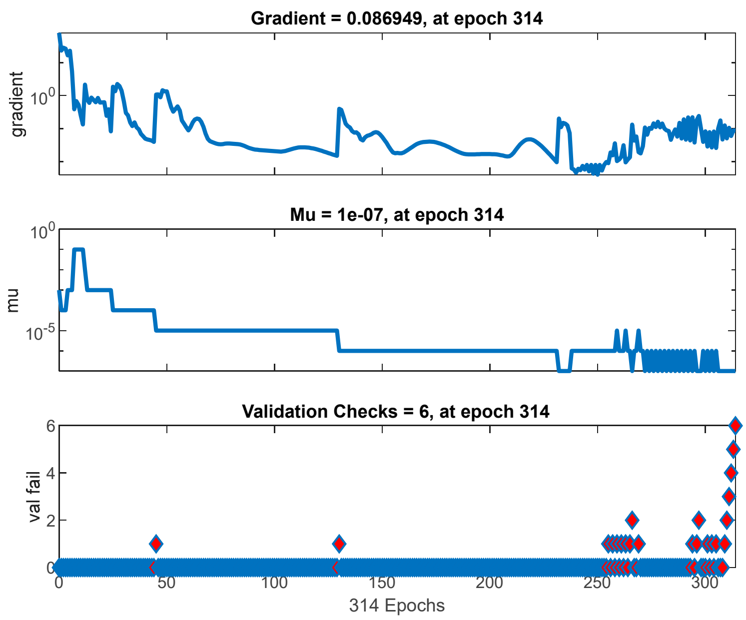

Figure 7. Artificial neural network validation performance (val fail, mu, gradient).

In Figure 7, the first part shows how the value of the gradient changed, i.e., its decrease through individual epochs, while the second part of the picture shows the number of validations per individual epoch. After a number of unsuccessful validations are repeated, ANN training is automatically terminated.

Figure 8 shows the error histogram, which shows how many cases of individual data deviated from the area of zero error, i.e., the deviation of the output data from the target data in the form of a graph with 20 columns. Testing was performed using the input–output vectors with a different load condition than the one used during the training phase. The test input matrix contains 1024 test vectors on which the artificial neural network was tested. The results were compared to the known switching order matrix, and the difference was recognized as a faulty switching order (9). The best results were calculated for the artificial neural network with 50 neurons in the hidden layer, which was able to give a correct switching order in 88.9% of instances. The accuracy of the neural networks for different numbers of neurons is shown in Table 2.

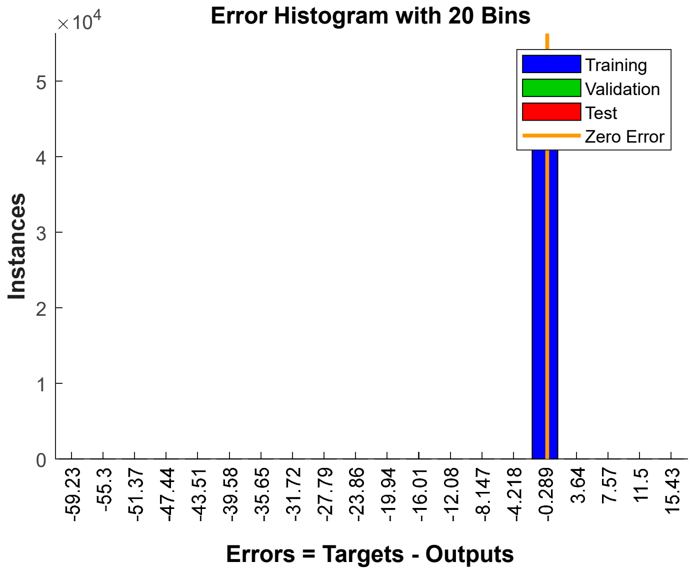

Figure 8. Error histogram.

Table 2. Performance of prediction depending on neuron number.

Number of Neurons	30	50	75	100
Test result [%]	83.7	88.9	78.7	83.8

ANN learning was performed for the whole system. In the following paragraph, two use cases of the OSRA algorithm application within the case study are shown. For the M_{input} vector, which represents the switching status of the transmission network breakers after the fault, the corresponding output matrix was used as the input for the neural network within the restoration algorithm. The result of the neural network calculation is the M_{switch} vector, which represents the optimal switching order of the circuit breakers necessary for the optimal system restoration.

For the tested input vector in the first use case, a total of $n_s = 10$ breakers were analyzed. The switching status of the transmission network breakers after the fault is

$$M_{input} = [0, 0, 0, 1, 1, 0, 0, 0, 0, 1]^T$$

where $m_{in} = 0$ marks the breaker status opened, and $m_{in} = 1$ marks the breaker status closed. Figure 9 shows the switched-on breakers after the fault; closed breakers are marked in red.

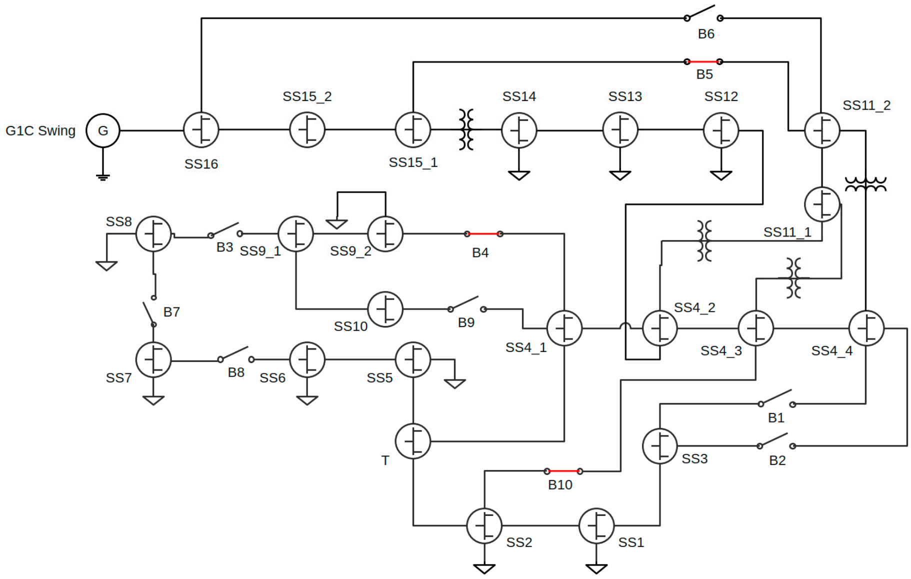

Figure 9. Breaker status after fault for first use case.

After applying the OSRA algorithm, the neural network calculates the corresponding optimal switching order vector with the following values:

$$M_{switch} = [6,7,1,0,0,2,3,4,5,0]^T$$

where $m_{s1} = 6$ marks the switching order for the first breaker n = 1, $m_{s2} = 7$ marks the switching order for the second breaker n = 2, and so on, until all n_s breakers are closed, and the system is fully restored.

In the second use case, the switching status of the transmission network breakers after the fault is

$$M_{input} = [0,0,0,0,0,1,1,0,1,1]^T$$

After applying the OSRA algorithm, the neural network calculates the corresponding optimal switching order vector with the following values:

$$M_{switch} = [5,6,1,2,3,0,0,4,0,0]^T$$

5. Conclusions

The restoration of a transmission system after a partial or complete breakdown is a challenging task, since it is not unambiguous and depends on the operating state of the system, as well as the availability of elements. An optimal system set-up requires the analysis of the most likely scenarios, which are the basis for system adaptation before starting the restoration, high plant automation, reliable communication routes and education of the transmission system operator.

This paper described the problem of transmission system restoration according to the theoretically developed criteria. The general criteria and plans for system restoration, the technical conditions for system restoration and the experiences of the system operators were presented. It should be noted that due to the scope of the topics of load equivalence and distributed sources at the interface of the transmission and distribution network, this paper did not go into the depth of their impact on system restoration, but it is important to conduct a separate analysis of these subjects through a separate project task.

Consequently, an algorithm for optimal system restoration, OSRA, was proposed, which aimed to direct the transmission system operator to optimally and safely perform identical and modified operations listed in the baseline system restoration scenarios. The methodology proposed a combination of optimization constraints along with using a large set of data to train artificial neural networks. The advantage of this approach is that the artificial neural network is trained offline. Training itself is time consuming, but once trained, the artificial neural network can give almost instantaneous results using online data, resulting in high-speed proposal of a restoration solution. Most of the analyzed papers use restoration time for the optimization goal. The most important novelty of this paper is that it introduced optimal topology of the grid for the optimization goal, that is, the input for the beginning of the transmission system restoration process

Further improvement in the development of restoration plans is proposed, which would include an analysis of the impact of the distributed sources and characteristics of individual loads through their equivalents at the interface of the transmission and distribution network; based on this, general and specific sub-scenarios could be developed.

The optimization of the system restoration process should be approached thoroughly, but the dominant problem is the problem of defining individual elements of the system that can be restored in parallel and thus currently form an island. The solution is in the iterative procedures that can be solved using artificial intelligence algorithms with monitoring, measurement and protection supported by an advanced network infrastructure (e.g., devices for synchronized phasor measurement) in transmission but also in distribution power systems, which should be the basis for future activities in the field of system restoration.

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