Assessment of Temporary Overvoltages During Network Lines Re-Energization

Rajagopal PEESAPATI[1], *Vinod Kumar YADAV*[2], *Niranjan KUMAR*[1]

[1]Department of Electrical & Electronics Engineering, National Institute of Technology Jamshedpur, Parallel Road, Adityapur, Jamshedpur, Jharkhand, 831014 India
[2]School of Electrical, Electronics and Communication Engineering, Galgotias University, Greater Noida, Uttar Pradesh, 201306 India

gopal.12rsee009@nitjsr.ac.in, v3k5y7@gmail.com, nkumar.ee@nitjsr.ac.in

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Abstract. *Power system blackouts are very infrequent, but they have a Brobdingnagian effect on the system performance and devices. The present research work offers remarkable techniques for the assessment of temporary overvoltages all through the re-energization of network lines. The main goal of this research work is to first-rate and reenergize the network lines for the purpose of restoration. In the later stage, the magnitudes and durations of the Temporary Overvoltages (TOVs) that occurred during the energization of unloaded transformer are estimated. The assortment and re-energization of network lines is done on the basis of Data Envelopment Analysis (DEA) and conceptual method respectively. The assessment of TOVs is done on the basis of MATLAB/Simulink and Feed Forward Neural Networks (FFNNs). The proposed models are verified on IEEE 30 bus test system for the analysis purpose. The Mean Absolute Percentage Error (%MAPE) obtained through various forecasting methods is examined to check the robustness of the proposed approaches. The simulation and FFNN results presented in this research work helps in designing the exact withstand voltage rating for various network components employed at the moment of re-energization.*

Keywords

Data Envelopment Analysis, Feed Forward Neural Networks, power system restoration, temporary over voltages.

1. Introduction

Restoration of the power system after a major or a partial blackout is complex and time consuming in nature. This needs several actions to take place in a very short time and with high accuracy. The power system restoration task is multi-objective and can be solved based on stochastic models. The restoration plan consists of several objectives like total system risk, total served energy in the period of restoration and total restoration time. The proposed approach optimizes the different kinds of objective functions for the generating units. The re-energization process of electric isolated areas can be divided into three different stages, i.e., restoration planning, control actions during system degradation and power system restoration [1]. A computational methodology was proposed to evaluate the re-energization activities during the power system restoration [2].

Different issues in power system restoration are discussed and solution methods are elaborated in the existing literature. A systematic power system restoration planning for Hydro-Quebec is described and suggested in designing the new software that incorporates an optimization algorithm and an advanced user interface [3]. Power system restoration plays a key role in the restructured power industry. The issues related to restoration to power industry and in the electricity market environment are analyzed and compared [4]. The simulation work helps in the best way of loading the power plants and is applied for hydro power plant and steam power plant restoration [5].The PJM and Hydro Quebec systems are restored using a step by step procedure which doesn't involve numerical calculations.

On the other hand, DEA has been utilized in measuring the efficiencies of banks, electrical distribution utilities by providing a score that equals to one for efficient units and less than one for inefficient units [18].

Similarly, DEA is employed to find the efficiencies of Indian Electric Power Distribution Utilities and evaluated the best operating divisions in the state named Uttarakhand [19]. Recently, the DEA technique was also applied to select the transmission lines to be energized after the blackout in the grids [7]. The power system restoration problem involves so many factors like frequency monitoring, black start unit energization, transmission line energization and transformer energization [8] and [9].

The temporary overvoltages, that occur during the energization of transformer in the process of restoration are beneficial in designing the Volt-Ampere ratings of the devices to be used at that instant. The temporary overvoltages are reduced by controlled switching, the evaluations of inrush currents for single phase transformer are done on the basis of automatic procedure [10], [11] and [12]. The experimental set up for prediction of flashover reveals that the relative humidity plays a major role in initiation of partial arc. ANNs with 14 hidden layer neurons, learning rate as 0.01 and with 3500 iterations are found to be best suited for predicting the flashover of 11 kV insulator. Artificial Neural Networks are used for the best estimation in many fields. The limitations encountered by the usage of Artificial Neural Network in the power system restoration problem are discussed, improvement techniques have been developed and the same was analyzed on a 162 bus transmission system [13], [14] and [15].

This paper applies FFNN method to estimate the magnitudes and durations of TOVs during the re-energization of network lines. At first the network lines are selected for the restoration and are restored. Secondly the TOVs are estimated through a forecasting technique which are useful in determining the withstand voltage rating of the devices to be used during the process of re-energization. The proposed models are applied on test system and the results are compared with the MATLAB/Simulink results.

After a brief introduction on re-energization and causes of TOVs, Section 2. describes different methodologies used for selection, energization and estimation. Section 3. presents the various inputs and outputs used for DEA methodology. System configuration and case studies are discussed in the Section 4. Analysis of the simulation results and advantages of this paper over past research are compared in Section 5. Finally, various conclusions drawn from the results are discussed in Section 6.

2. Methodologies

2.1. Selection of Network Lines for Re-Energization

DEA is a linear programming technique which identifies the best practice within a sample and measure efficiency based on differences between observed and the best practice units. It is first introduced by Charles, Cooper and Rhodes [17] (CCR-model) to measure the efficiencies of similar type of Decision Making Units (DMUs). DEA is typically used to measure technical efficiency. The organizations/firms for which the relative efficiency is to be calculated are technically referred to DMUs. So the performance of each DMU measured is relative to the performance of all other DMUs. If the unit with its optimal weights receives the efficiency score of 1 then that particular unit is efficient. If the unit with its optimal weights receives the efficiency score of less than 1 that particular unit is inefficient. Consider there are t DMUs which take m inputs and produces s outputs. Let x_{ij} and y_{rj} be the input and output values of the $DMU_j (j = 1, 2, \ldots, t)$. Then the mathematical form without preassigned weights is given as:

$$\text{Maximize } \eta_p = \frac{\sum_{r=1}^{s} u_r y_{rp}}{\sum_{i=1}^{m} v_i x_{ip}} p = 1, 2, \ldots, t. \quad (1)$$

Subject to:

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} p = 1, 2, \ldots, t \,\&\, j \neq p. \quad (2)$$

$$u_r \geq 0 \; r = 1, 2, \ldots, s. \quad (3)$$

$$v_i \geq 0 \; i = 1, 2, \ldots, m. \quad (4)$$

In above Eq. (3) and Eq. (4) represents the output and input weights obtained in the DMU_p run. The above fractional mathematical form is converted to linear programming model for solution and given as:

$$\text{Maximize } \eta_p = \sum_{r=1}^{s} u_r y_{rp}. \quad (5)$$

Subject to:

$$\sum_{i=1}^{m} v_i x_{ip} = 1. \tag{6}$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0,\ j = 1, 2, \ldots, t \,\&\, j \neq p. \tag{7}$$

The linear programming model represented in Eq. (5), Eq. (6) and Eq. (7) along with Eq. (3) and Eq. (4) is solved for each. The scores obtained this way in each of the run are used for the selection of network lines to be energized. In general DEA technique produces score less than one but by removing self constraints it gives a score more than 1.

2.2. Re-Energization Planning of Network Lines

The concept of Generic Restoration Milestones (GRMs) and Generic Restoration Actions (GRAs) are proposed in [6] for the re-energization of transmission lines. The major tasks for power system restoration is unit start up, network energization and load pick up. The GRMs involved in power system restoration are shown in below algorithm 1) :

1) GRMs Involved for Power System Restoration

```
GRM 1:  formation of the black start
and non black start building block.
GRM 2:  island Creation
GRM 3:  management of Islands
GRM 4:  establishing Transmission grid
GRM 5:  load restoration in each
Islands
```

For the implementation of each GRM a set of GRAs should be optimized. In general GRAs take account of:

2) GRAs Involved for Implementation of GRMs

```
GRA 1:  start black start unit
GRA 2:  find path
GRA 3:  energize line
GRA 4:  restore load
GRA 5:  synchronize
GRA 6:  connect tie line
GRA 7:  crank unit
GRA 8:  energize bus bar
```

For the efficient implementation of GRMs a set of GRAs are to be optimized along with a set of following constraints:

3) GRAs Involved for Implementation of GRMs

```
C1:  limit of each generating unit
C2:  steady state overvoltage
C3:  switching transient overvoltage
C4:  voltage stability
C5:  capacity of each line
```

A combination of GRMs is used for specific restoration plan which depends upon the type of the system to be restored. The type of the system depends on the existence of black start units or non black start units [16]. The various combinations of GRMs and GRAs along with their constraints for different type of systems are given in Tab. 1.

Tab. 1: Represents the implementation of various GRMs through various GRAs and their respective constraints.

Case	Type	Implementation of GRMs	Implementation of GRAs withtheir constraints in small brackets shown at the first instant.
1	With black start unit	Establish Transmission grid	GRA 2 & 3 (C1,C2,C3,C5) and 8 (C3)
		Build Island	GRA 1, 2, 3, 4 (C1,C2,C4,C5), 7 (C1,C2, C5) and 8
		Manage Island	GRA 2, 3, 5(C1,C2,C3,C5), 6 (C1,C2,C3,C5) and 8
		Load restoration in each Island	GRA 2, 3, 4 and 8
2	With non black start unit	Form the non black start building block	GRA 1, 2, 3, 4, 7 and 8
		Establish Transmission grid	GRA 2, 3 and 8
		Build Island	GRA 1, 2, 3, 4, 7 and 8
		Load restoration in each Island	GRA 2, 3, 4 and 8
		Manage Islands	GRA 2, 3, 5, 6 and 8
		Connect with neighboring system	GRA 2, 3, 5, 6 and 8

2.3. Feed Forward Neural Networks (FFNNs)

During the re-energization process the major concern is related to temporary overvoltages caused by transformer energization at lightly loaded condition. The overvoltages occurring in the reenergization process are estimated through MATLAB/simulation and the artificial neural networks. FFNNs are used in many fields like estimation, pattern recognition and control systems. The model proposed in this research work will use Feed Forward Neural Network (FFFN) which is the basic model of Multi Layered Perceptron (MLP). FFNN model is used for the estimation of TOVs during the energization of transformer in the restoration process. The output from a hidden/output layered neuron is shown as below:

$$S = f\left(\sum_{j}^{m}\sum_{i=1}^{n} u_{ij}x_{ij} + b_j\right), \tag{8}$$

where u_{ij} - weight between the i^{th} neuron in input/hidden layer and j^{th} neuron in hidden/output layer, x_{ij} - input of the neurons and b_j - bias of the neurons.

The output from this neuron may be either input to other neuron in adjacent layer or final output at the output layer. In general, the back propagation algorithm is used as training method for the feed forward neural networks. In this particular training process, the weights assigned in the iteration 1 are updated until the goal set was reached or limit of iterations was reached. After the training the obtained outputs are produced with less squared error. The sum of squares is used as the error function for this purpose. It is represented as shown below:

$$\text{error} = \frac{1}{n}\sum_{i=1}^{n}(t_i - S_i)^2, \tag{9}$$

where S - output of the Neural Network and t_i - desired output.

The weight updating is processed based on the equation as shown below:

$$u_{ij(new)} = u_{ij(old)} - \eta\frac{\partial(\text{error})}{du_{ij(old))}}. \tag{10}$$

Large numbers of testing data have been used to check the proposed solution in the most objective way at practically all possible parameter variations. The robustness of the proposed approach is examined according to the expression presented below:

$$MAPE = \sum_{i-1}^{n}\frac{|S_i - Actual_i|}{Actual_i}\cdot 100, \tag{11}$$

where $Actual_i$ are the i^{th} FFNN predicted value and actual value obtained through Simulink respectively.

3. Inputs and Outputs to the DEA

The different inputs and output for the DEA model are selected based on the insight given by [7]. The IEEE 30 bus test system is considered in the evaluation and analysis purpose. The test system comprises of 41 network lines. There is a need of acceptable inputs and output for the selection of network lines to be restored. Each network line is considered as a DMU and the scores of the same are evaluated using the model 2. Brief description of the inputs and output for the model 2 are as follows:

- **Output:** The priority of line to energize is considered as the output in present research work. This parameter reflects the power flow before the instant of major or minor blackout.
- **Input 1:** The per unit (p.u.) reactive power flow in the network line is considered as the primary input.
- **Input 2:** The rank depending upon different climatic conditions is considered as the secondary input. The test bus system is divided into 6 zones depending on the climatic conditions as shown in the Fig. 1. The different climatic conditions considered are hottest, coolest, humid, rainy and iced. These climatic conditions are ranked from 1 to 5 and issued to different zones. The nearby zones are considered with same climatic conditions and ranked equally.
- **Input 3:** The equipment reliability is considered as tertiary input and defined as the chance it will survive in service for a required length of time.
- **Input 4:** The line operation time is considered as fourth input and is calculated from the statistical methods [2].
- **Input 5:** The p.u. real power flow in the network line is considered as fifth output.

4. System Configuration and Case Studies

The test bus system is considered for analysis and implementation purpose in the research work. The test system consists of 41 network lines, 2 generators, 4 synchronous condensers and 2 shunt capacitors. The bus voltage varies from 1.00 p.u. to 1.08 p.u. and the phase angles of each bus are considered as zero degrees. The present research work considers 100 MVA as base MVA and 400 kV as base kV. The networks used for the case studies are designed in the MATLAB/Simulink platform. The generators are designed as voltage sources in series with impedances. The network lines are modelled as PI section lines for every 25 km. The network lines are constituted of lumped resistances and inductances. The capacitances are considered at starting and at the end position of the network line section. The

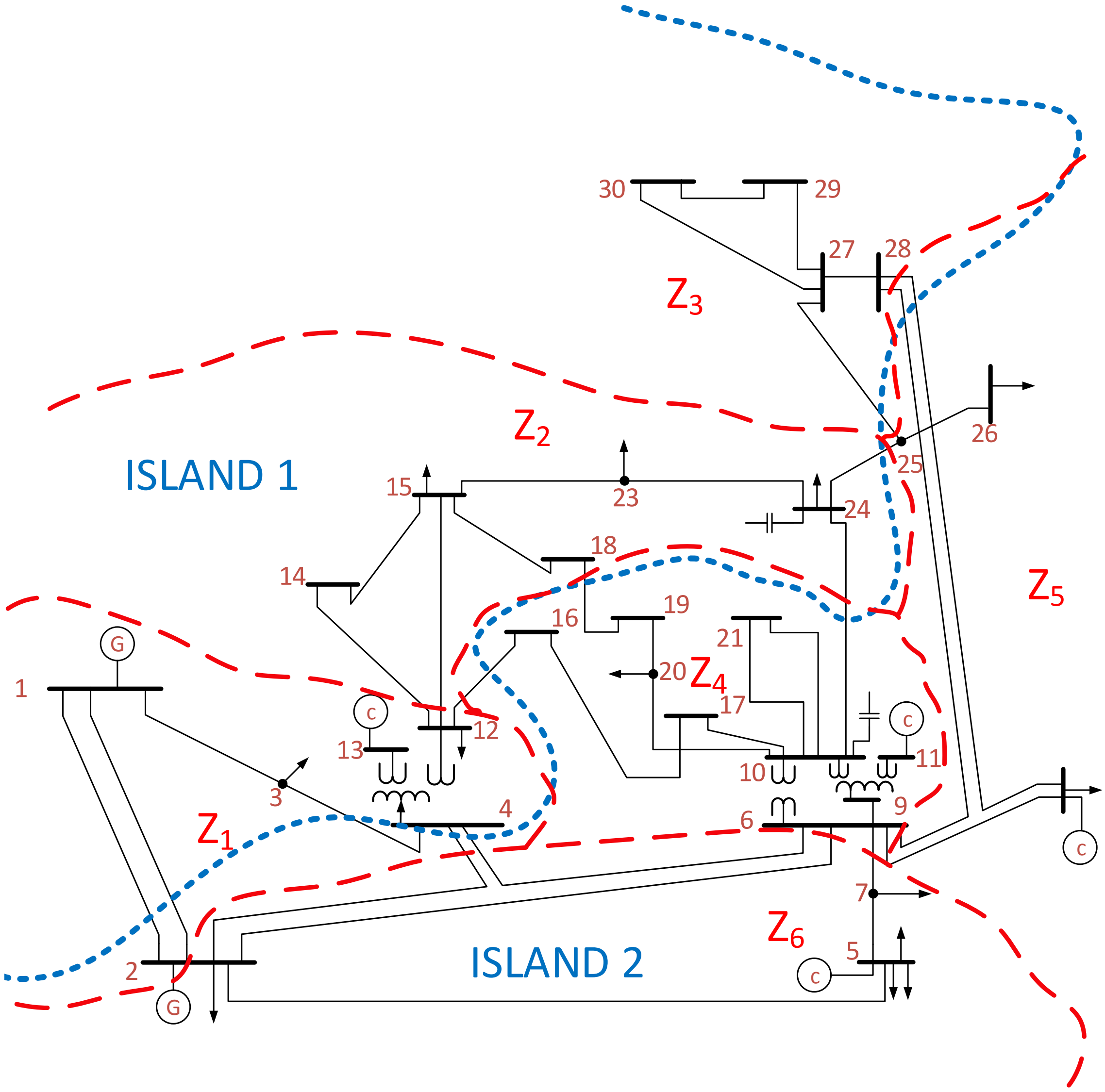

Fig. 1: IEEE 30 bus system divided into different Islands and Zones.

power transformers are designed with leakage inductances, copper loss component, core loss components and magnetizing components. The power transformer rated in this research work is considered as 500 MVA. The loads constitute of constant impedances. Here for the analysis, two loads connected to two different transformers of the network are considered. The single line diagrams of each case study are shown in Fig. 2 and Fig. 3.

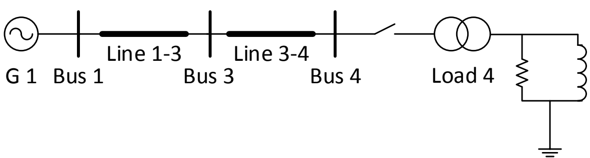

Fig. 2: Single line diagram of power system for case 1.

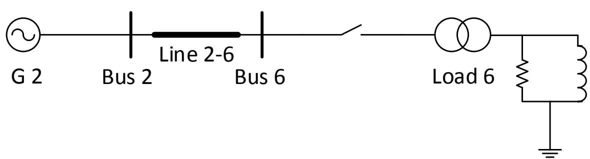

Fig. 3: Single line diagram of power system for case 2.

5. Results and Analysis

The results of various methodologies presented in Section 2. are discussed in this Section. This research work comprises selection of network lines to be restored, restoration planning of selected network lines and estimation of the temporary over voltages, occurred during the process of restoration.

Tab. 2: Results of the network lines scores more than 1.

DMU	From bus	To bus	Input 1	Input 2	Input 3	Input 4	Input 5	Output	Score
1	1	2	0.0480	1	2.9945	8	0.0831	17.73	4.91
2	1	3	0.3353	1	1.5571	9	0.0980	9.240	1.24
3	2	4	0.0962	2	1.8711	9	0.0328	4.56	1.23
4	3	4	1.4161	2	2.6240	1	0.4917	8.30	3.18

5.1. DEA Analysis

DEA model shown in Subsection 2.1. is applied to select the network lines to be reenergized for the restoration purposes. The details of inputs and outputs for this model have been discussed in Section 3. . The model was run for each transmission line separately and entirely 41 times to evaluate the scores which are depicted in Tab. 2. The output is the priority of the line energization which is maximized by keeping the inputs constant. The results of DEA model for each of the transmission lines that score more than 1 are presented in the Tab. 2.

The selected network lines for reenergizing are (1-2), (1-3), (2-4) and (3-4), as these network lines score more than 1. The DEA model that's used in this paper is sensitive to the results, so one has to be very careful in the selection of inputs and outputs. The optimization model takes reactive and real power flow as inputs for reducing the

5.2. Restoration Analysis

The network lines that are selected based on the DEA model are restored based on the concept of GRMs and power transmission after the major or a partial black out. The lines are ranked based on decreasing order of the obtained scores to know the sequence of the transmission lines that are to be energized.

GRAs. The test system is divided into two different Islands based on the view given by [7]. The restoration process of selected network lines requires 6 GRMs, associated GRAs and constraints to be satisfied. The non black start units are started in GRM 1 such that the power for energizing the network lines will draw from these generators. The network lines (1-2), (1-3) and (2-4) are energized during the implementation of GRM 2. Restoring the load 2 at the bus bar 2 in the GRM 1 is meant for maintaining the stability of the power system during the implementation. During the process of GRM 3 the entire test bus system is divided into the Islands. The concept of dividing the entire power system into Islands enables the isolation of the healthy system from faulty one. The test bus system after the dividing into Islands is shown in Fig. 1. Restoring the load at bus bars 3 and 4 is done during the implementation of GRM 4.

The two Islands are synchronized in the GRM 5. Restoration of network lines is completed by connecting the tie line (3-4) during the implementation of GRM 6. The associated GRAs and constraints for implementation of every GRM are described in the Section 2. . The combined analysis of both the methodologies reveals that the need of continuous energized path for restoring the network lines in a systematical way. This depends on the selection of input and output parameters chosen for the DEA model.

5.3. Estimation of Temporary Overvoltages (TOVs) Analysis

The present work estimates the peak and duration of TOVs that have occurred during the process of restoration by both Simulink and Artificial Neural Networks. The Simulation tool is applied to a section of test bus system to measure the values of the voltage peaks and their time duration at the transformer buses as shown in both single line diagrams of Fig. 2 and Fig. 3. The generators in the both single line diagrams are non black start units. The serving of the load is done through the energization of transformers at buses 4 and 6 respectively in further restoration steps. During this process of restoration, the transformer was energized and TOVs occurred due to light loaded condition of the transformer. The parallel resonance peak occurred at 110 Hz and 125 Hz for the networks 1 and 2 respectively. The peak values of TOVs which are measured through Simulink and predicted through FFNNs for the both circuits 1 and 2 are shown in Fig. 4 and Fig. 5 respectively. Similarly, the durations of TOVs for the circuits are shown in Fig. 6 and Fig. 7 respectively. It was revealed that the maximum peaks of the network 1 and 2 were 2.28 p.u. and 1.78 p.u. respectively for the source voltage of 1.125 p.u.

The peaks (>1.4 p.u.) resided for an average of 0.003703 seconds in the first network and for an average of 0.001440 seconds in the second network. The FFNNs were trained with the goal of minimal error and the estimated values of the peaks and duration for the single line diagrams 1 and 2 are shown in Fig. 4, Fig. 5, Fig. 6 and Fig. 7. In this work, network consisting of 12 neurons in one hidden layer is found sufficient for predicting the peaks and duration of the TOVs. The figures reveal that there is a complete agreement of the FFNN result with the

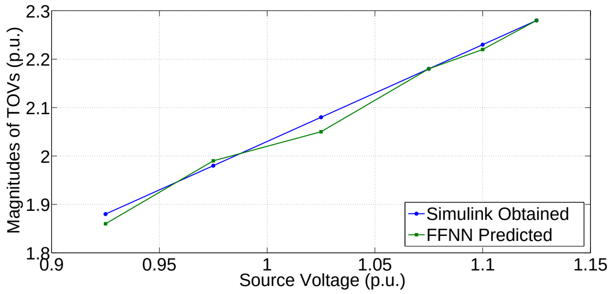

Fig. 4: Comparison of peak of TOVs obtained through FFNN and Simulink for single line diagram in case 1.

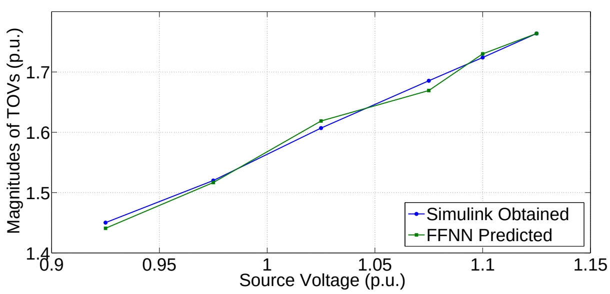

Fig. 5: Comparison of peak of TOVs obtained through FFNN and Simulink for single line diagram in case 2.

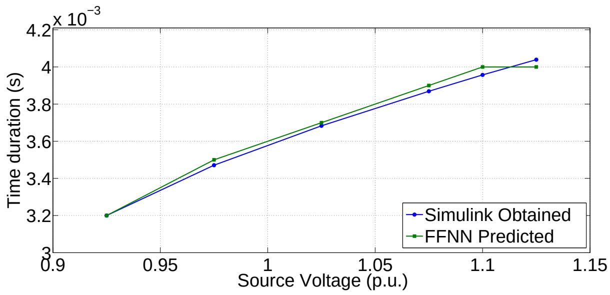

Fig. 6: Comparison of duration of TOVs obtained through FFNN and Simulink for single line diagram in case 1.

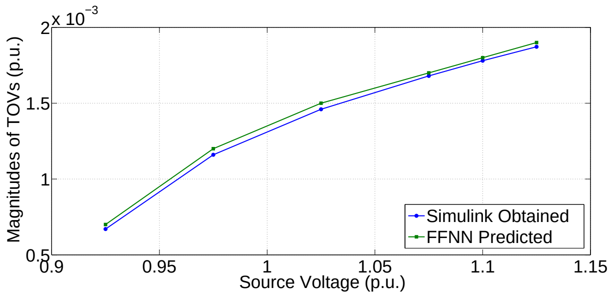

Fig. 7: Comparison of duration of TOVs obtained through FFNN and Simulink for single line diagram in case 2.

MATLAB/Simulink values. The $\%MAPE$ values obtained through proposed approach are presented in the Tab. 3. It can be revealed that the $\%MAPE$ values proposed by FFNNs in this work are low as compared to the methods proposed in [11]. The entire results show that the method used for estimation in this research work is more sensitive and accurate in forecasting the output when compared with the other conventional and Simulink models. The estimation of TOVs are needful in designing the withstand voltage of the devices used during of re-energization of network lines. A comparison of results in terms of $\%MAPE$ is also shown in Tab. 3.

Tab. 3: Comparison of $\%MAPE$ obtained through proposed FFNN and previous researches

	$\%MAPE$ by the proposed FFNN	$\%MAPE$ by previous research works [11]
Voltage	0.4083 (Circuit – 1)	1.0773 (Case – 1)
	0.1250 (Circuit – 2)	1.32884 (Case – 2)
Time duration	0.7125(Circuit – 1)	1.9520 (Case – 1)
	2.1875 (Circuit – 2)	1.1231 (Case – 2)

6. Conclusion

In this research work DEA have been applied on test system for the selection of network lines for the purpose of restoration. Based on the results obtained, 4 network lines were selected for the restoration purpose. The selection process used in this research work is better, more accurate and more appropriate as compared to other conventional methods. The conceptual method has been applied to re-energize selected transmission lines. The new concept "Generic Restoration Milestones" have been implemented in this research work. The conceptual method requires 6 GRMs and associated GRAs to restore the system. The combined analysis of above two methodologies reveals the need of continuous energized path for restoring the network lines in a systematical way. This reveals that choosing of inputs and outputs play a key role in the selection and re-energization of network lines where the conventional methods have not been implemented. A portion of bus test system is considered in the estimation of peak and duration of TOVs through MATLAB/Simulink and FFNNs. The study of level of TOVs in the proposed research work helps in insulation coordination for various network components in order to ensure safety and optimized distribution of electrical power. It can be concluded that the estimation of TOVs helps in operation of surge arrester in order to increase accuracy of protection levels to guarantee insulation coordination to an even high degree. The Simulink results conclude that the magnitude and duration of the TOVs depends on the source voltage, system capacitances and overall rating of the system. The peak and duration of TOVs are estimated through the application of radial basis neural network. This network is adopted for obtaining the minimum error while estimation. The results of FFNN are very near to the results of Simulink and produce very low values of %MAPEs in Voltage and in duration of peaks. The method used for estimating by minimum error is more accurate in approximation and quite easier to implement than the other conventional methods.

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About Authors

Rajagopal PEESAPATI was born in Vizianagaram, India. He received his M.Tech. degree from National Institute of Technology Jamshedpur, India. Presently he is pursuing Ph.D. degree from the same Institute. His research interests include power system planning and optimality.

Vinod Kumar YADAV was born in Varanasi, India. He received his M.Tech. degree from National Institute of Technology Jamshedpur and Ph.D. degree from IIT Roorkee. His research interests include power system restructuring and AC/DC power flow analysis.

Niranjan KUMAR was born in Khagharia, India. He received his M.Tech. degree from National Institute of Technology Jamshedpur and Ph.D. degree from IIT Roorkee. His research interests include power system restructuring and AC/DC power flow analysis.