Evaluation of the Applicability and Advantages of Application of Artificial Neural Network Based Scanning System for Grid Networks

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Abstract. This chapter presents the application of an artificial neural network-based monitoring system power grid network. Neural net modules used for this study are of two kinds, a distributed separate artificial neural net (ANN) module to monitor all lines individually from separate points in the network and central common multiple-input, multiple-layer ANN to monitor all lines together. Only the active power flowing on all the lines of the utility network were monitored using the ANN's. This work elaborates and evaluates the technical repercussions of both the modules. The ANN model employed was a feed-forward net with backpropagation of error. The aspiration of the task is to deliberate on the opportunities and obstacles of the various configurations of ANN models employed.

Keywords: Artificial neural network · Grid system · Power system computing · Power system control · Power system security

1 Introduction

The radical and astonishing novel progress in the field of computation during the previous four decades have inspired engineers and researchers to consider machine intelligence and pattern recognition with revived vitality, as deduced from Refs. [1–5] and many similar articles available in many pioneer journals [6–10]. Utilization of pattern recognition in any area alleviates such intricate complications that are difficult to identify otherwise [11, 12]. And the speed of response is also comparatively much faster for a machine learning unit when compared to other modes [13, 14]. ANN is the building block of pattern recognition and machine intelligence and its utilization to obtain any objective is very difficult unless it is properly trained [15]. Application of ANN methodologies to any field has its own intrinsic complexities for which an engineer has to be properly educated [16].

Pal et al. have shown in [16, 17], how the ANN models were used for identifying the critical contingency cases after the security assessment cycle was completed, but it serves no practical purpose and the time consumption is still too much for the ANN

C. R. Panigrahi et al. (eds.), *Progress in Advanced Computing and Intelligent Engineering*, Advances in Intelligent Systems and Computing 1198, https://doi.org/10.1007/978-981-15-6584-7_23

to be considered as a viable alternative to the currently practiced methods. In [18] the authors have gone one step ahead and have developed a monitoring method for the crucial power system parameters such as active power (MW) and reactive power (MVAR) using designated ANN for each line separately, which can be used to identify the contingencies of any line or any disturbance in the power system, immediately. Similarly, in [19], the authors have used a common ANN to monitor all the similar parameters using a common ANN, which can be useful for the Load Dispatch Centers to identify the stability of the power network as a whole.

In this chapter, neural net models have been applied to track the MW power circulating on the transmission lines of Damodar Valley Corporations' (DVC) power grid [41–44], and to identify the insecure or secure state of the active power flowing [16, 17]. As elaborated [18, 19] in two modes of ANN monitoring modules, "distributed, single-input small neural net to monitor each line separately, from different points in the power system, and multiple-input, multiple-layer neural net, to monitor all lines together from a common point", had been examined. In this work, the opportunities and obstacles of both the modules have been discussed and then some conclusions were derived from the work and the advantage and disadvantage of the methods are discussed.

This chapter is standardized as follows. Section 1 proposes the work, Sect. 2 elaborates the network under study, Sect. 3 describes the neural network model and its architecture, Sect. 4 explains the software used for simulation and the models developed, Sect. 5 deliberates the outputs of simulation and ANN monitoring and Sect. 6 concludes the chapter, followed by acknowledgements and references.

2 DVC Grid Network

The diagram for the DVC's grid network is as shown in Fig. 1.

For a given loading condition, based on day-ahead load forecast, the unit commitment, and scheduling, a load flow program is run to calculate the loading conditions of the transmission lines [20, 21]. After the line-loadings are calculated, it is given a differential calculative-error margin of $\pm 10\%$, to generate the apt amount of data for training the artificial neural network that will be used for monitoring the lines of the network [20–25]. The contingency analysis is also performed for the event of an outage of any of the lines in the above-mentioned load forecast scenario, to identify the critical flow gates which may get overloaded causing a cascade event, which may then lead to the blackout of a large part of the power grid [26–30].

The predominant hitch in the traditional process of load flow methods-based security monitoring procedures is that it is prevalently iterative and computation-intensive in nature, which exhausts most of the time allotted to the power system operator for protective and control actions [31–40].

3 Types and Description of ANN

As explained previously, two different modes ANN modules, dispersed, individual input simple neural net for observing each line individually, from distinct places in the power network, and a multiple-input, multiple-layer complex neural net, for tracking all lines

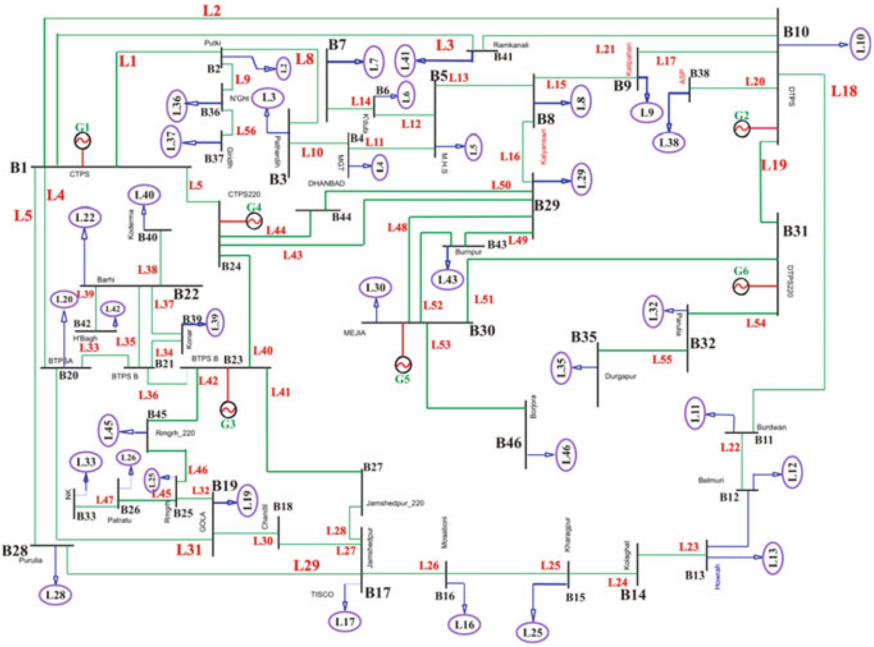

Fig. 1. Damodar valley corporation's DVC-46 bus network

collectively from a central point, have been performed [16–19]. They are elucidated below.

3.1 Multiple-Input Multiple-Layer Common ANN

As mentioned in Sect. 2, taking into consideration the differential calculative-error margin of $\pm 10\%$, the secure range training datasets for the ANN's are developed, based on load forecasting, unit commitment, scheduling, and transmission line limits. The power flows beyond the aforementioned range is assumed to be insecure for ANN training purposes. It is presumed that the MW power flow beyond the calculated range will provoke instability and insecurity in the power grid [19].

After taking into consideration the previously mentioned prerequisites, a training data set is established for ANN development of each line. All these datasets are then tabulated into a single datafile, which is used to develop the supervised ANN model. The input nodes in this ANN will be equal to line parameters to be monitored and to preclude any confusion, one multiple-input-multiple-layer ANN will be used to monitor only one type of data. For this case, we develop one ANN for the purpose of monitoring MW power flow on all the network lines. This way the overall trend of MW power flow deviation on the whole power network can be monitored. The common ANN monitor is as shown in Fig. 2.

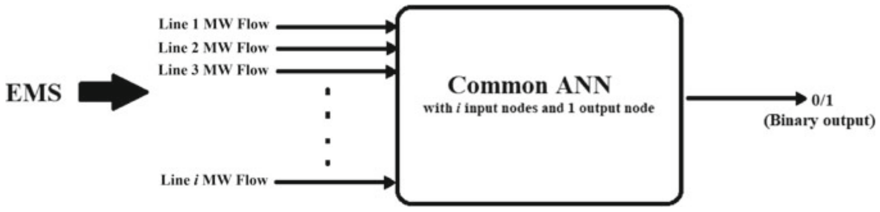

Fig. 2. Common-ANN monitor for DVC-46 bus network

3.2 Distributed Single-Input Small ANN

In this case, every line is monitored by dedicated specifically trained ANN [18]. The procedure for the training and development for the separate ANN is similar to the previous method, with the only difference that there is separate datafile containing training data for each line to be monitored. After the training converges, we have separate ANN monitors for each line. It is as shown in Fig. 3.

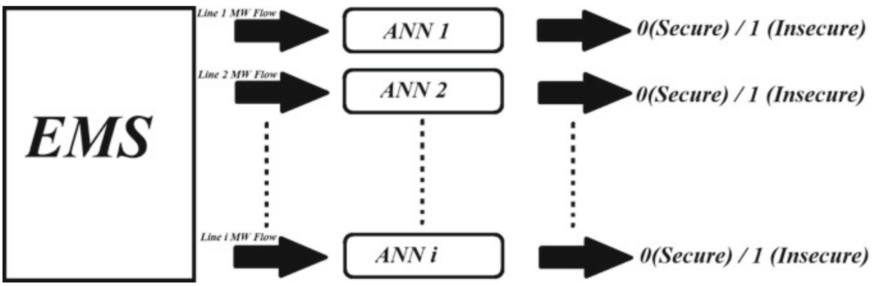

Fig. 3. Separate ANN monitor for DVC-46 bus network

Thereafter, the ANN monitor is simulated in both the scenarios, and the results are discussed in the subsequent section [45–51].

4 Simulation

The simulation was performed with the help of the Neural Network Toolbox on Simulink and MATLAB (R2015a) using the OPAL RT's OP-5600 simulator. The device had the frequency step-size of 50 μs [18, 19], and the simulation was run in real-time with hardware in the loop for a duration of 30 min. Three major faults were brought about on crucial lines of the network, in the duration of the test. They were, a two-line fault on line-3 at 10 min, a three-line-to-ground fault on line-9 at 18 min, and a three-line fault on line-21 at 25 min, respectively. The Simulink model is similar to the one as shown in Fig. 4.

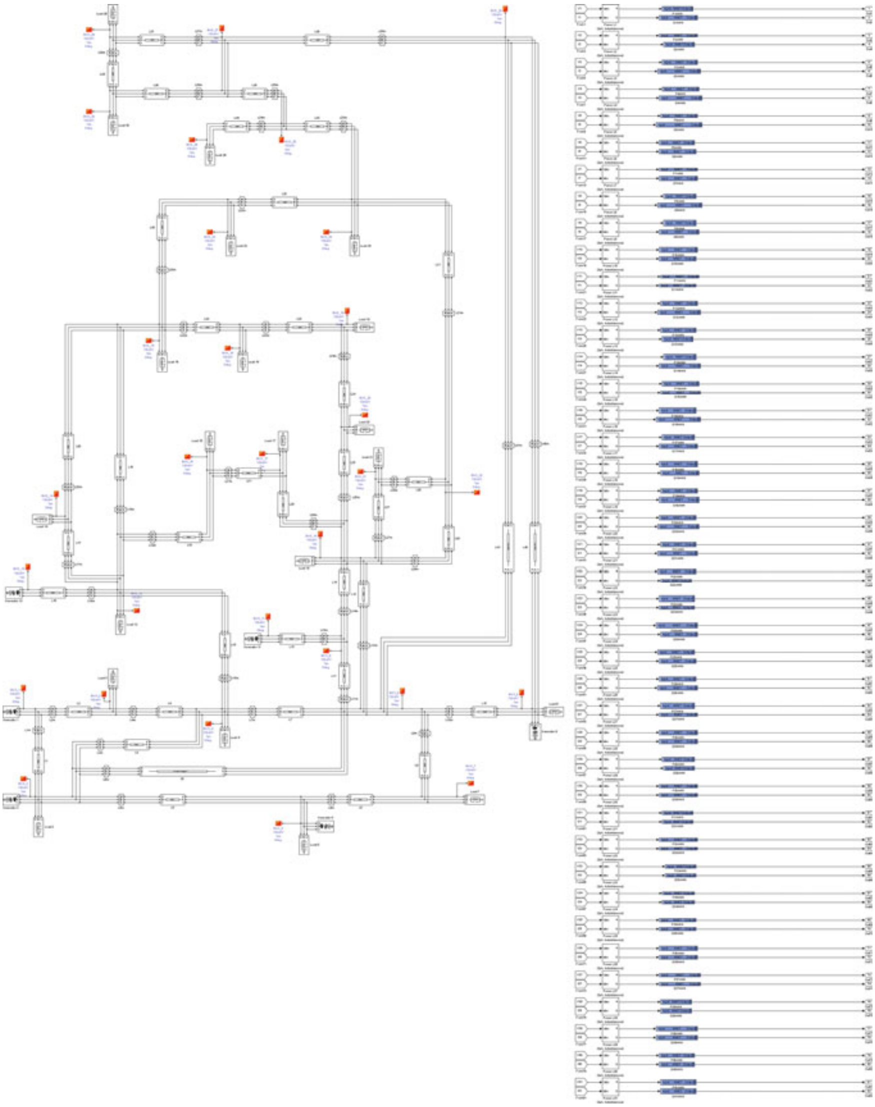

Fig. 4. Simulink model of power network with one ANN monitoring each line's MW power. In common ANN the network model is the same but there is only one ANN monitoring all lines

5 Results of Monitoring

The developed network was simulated for a period of 30 min using both ANN modules separately and their responses were recorded in memory. Thereafter, to observe and analyze the performance of the ANN modules, the recorded data was mapped out in a graph. The details of the ANN's recorded outputs have been elucidated in the following segments.

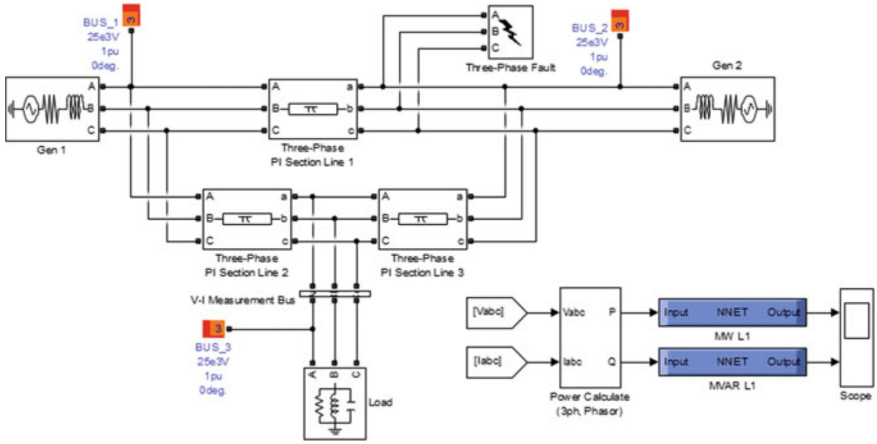

Fig. 4. (*continued*)

5.1 Multiple-Input-Multiple-Layer Common ANN

The output plot of the central common ANN tracking and monitoring model has been shown in Fig. 5 [19].

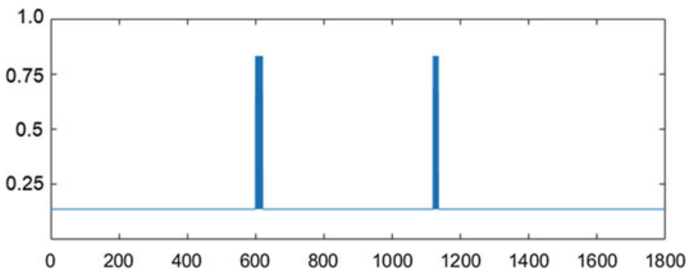

Fig. 5. Common ANN monitoring response

As shown in Fig. 4, the plot of the common ANN monitoring response, it is evident that the two-line fault on line-3 at 10 min and line-9's, three-line-to-ground fault at 18 min affect the stability and the security of the whole power network for several seconds, but then the power flows rebound to stable state. The three-phase fault on line-21 at 25 min does not affect the power network as a whole, albeit there are some localized effects that die down promptly. The meticulous performance of these lines during the fault events can be seen more distinctly by the separate ANN monitor as discussed in the succeeding sections. In the plot diagrams, "the X-axis shows time in seconds and the Y-axis shows the magnitude of ANN output, between 0 (Secure) and 1 (Insecure)", as shown in [19].

5.2 Distributed Single-Input Small Individual ANN

The response of the separate ANN is more detailed and the output of the ANN monitor gives an intricate insight into the behavior of the power flows on each line. The response of the distributed single-input small ANN monitoring modules, tracking the MW power flowing on each of the lines is elucidated below [18]. Since there are 56 lines in the DVC-46 bus system, to preserve page-space, here the similar types of responses have been represented under the same figure as elaborated below [18]. Figure 6, shows ANN response of lines affected by all faults.

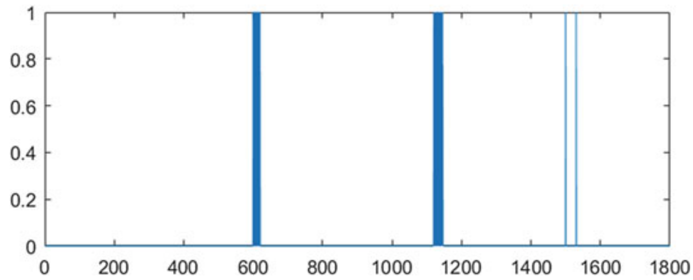

Fig. 6. Separate ANN monitoring response for lines affected by all faults

From Fig. 6, the ANN monitoring response of the lines getting affected by all three faults is shown. Here, lines 1, 2, 3, 4, 5, 21, and 29 are affected by all three faults and the response of the ANN is more or less similar to the one shown in Fig. 6. The ANN response of the lines affected by only the first two faults is as shown in Fig. 7. These lines are lines 6, 8, 10, and 56.

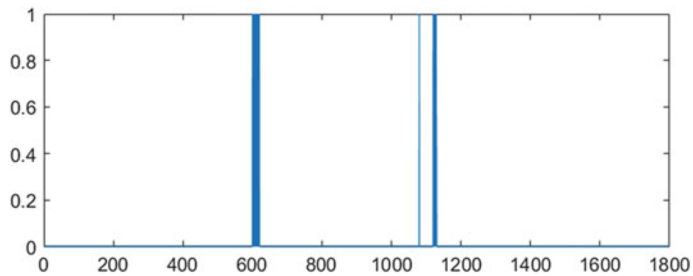

Fig. 7. Separate ANN monitoring response for lines affected by the first two faults

The ANN response of the lines affected by the last two faults are as shown in Fig. 8. These lines are lines 17, 18, 19, and 20.

The ANN response of the lines affected by the first and the last faults are as shown in Fig. 9. These are lines 38, 40, 43, and 44.

The ANN response of the lines affected by only the first fault is as shown in Fig. 10. These lines are lines 11, 12, 13, and 14.

The ANN response of the lines affected by only the second fault is as shown in Fig. 11. Only line 16 is affected by the second fault.

The ANN response of the lines affected by only the last fault is as shown in Fig. 12. Only line 15 is affected by the last fault.

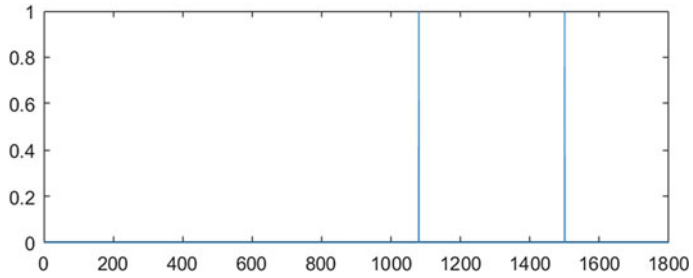

Fig. 8. Separate ANN monitoring response for lines affected by the last two faults

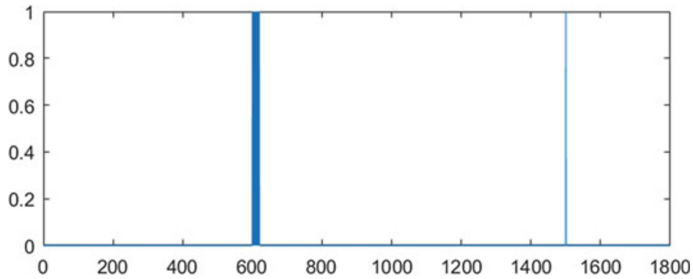

Fig. 9. Separate ANN monitoring response for lines affected by first and last faults

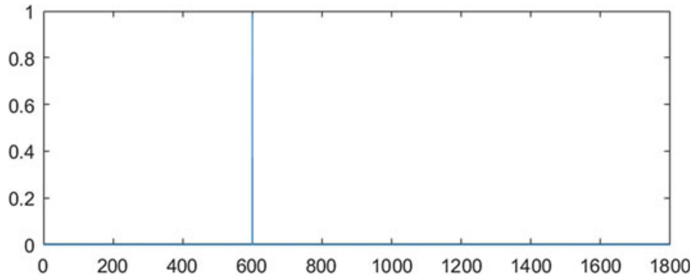

Fig. 10. Separate ANN monitoring response for lines affected by only the first fault

The ANN response of the lines not affected by any fault is as shown in Fig. 13. Here, we can see that the ANN response stays at 0, which signifies that the active (MW) power flow on such lines remains in a secure state. They are lines 7, 9, 22, 23, 24, 25, 26, 27, 28, 30, 31, 32, 33, 34, 35, 36, 37, 39, 41, 42, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, and 55.

From all of the above responses, it can be seen that the ANN's monitoring each line gives the response of the effect of the line faults, immediately. These kinds of prompt forewarn can allow the Power System Operator (PSO) to take corrective actions punctually, thereby reducing the risk and dangers of uncontrolled equipment outage and by keeping the power system in a stable operational state [52].

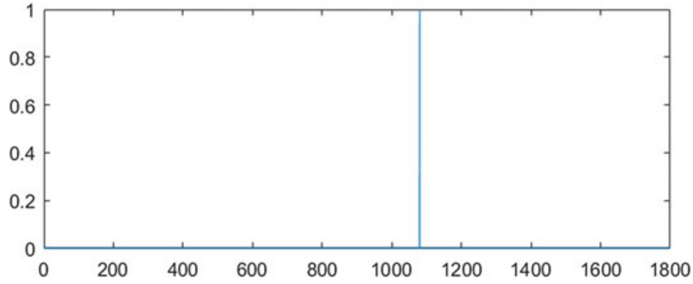

Fig. 11. Separate ANN monitoring response for lines affected by only the second fault

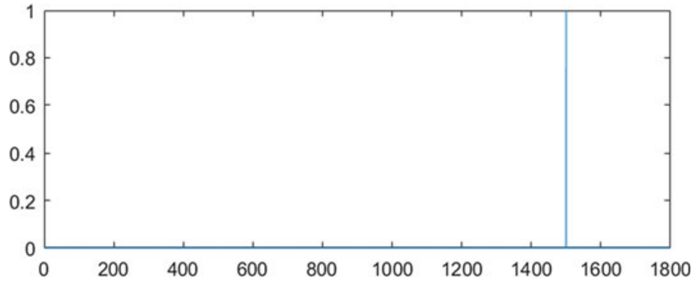

Fig. 12. Separate ANN monitoring response for lines affected by only the last fault

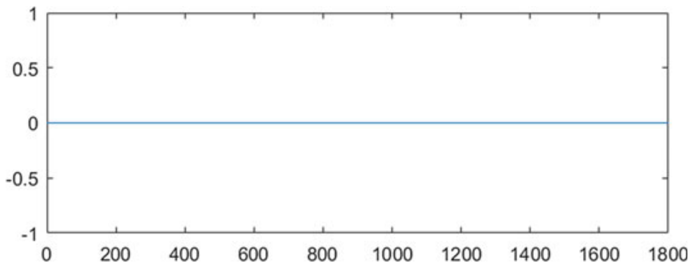

Fig. 13. Separate ANN monitoring response for lines not affected by any fault

6 Conclusion

The above analysis has emphasized the subsequent points:

(a) *ANN Model Development and its Time Consumption*: It takes more time to develop separate ANN monitoring modules to observe each line individually in comparison to developing a common ANN monitoring module. For example, assuming a power network has ‘n’ transmission lines and ‘t’ is the time consumption of each module generation, then the gross time expenditure for generating separate neural net models will be $(n * t)$ but the time taken for the development of a common neural net model is only ‘t’.

(b) *Labor Involved*: It is burdensome and time-consuming for generating disperse numerous ANN monitor modules to observe every line individually, but it's simpler, quick, and less complex for generating the common ANN for observing all lines collectively.
(c) *ANN Output Observation Contrast*: It may be swift and simpler to generate a common ANN model, but, while in practice it's very arduous to single out the network lines where a fault had happened. Even the response of the multiple-input multiple-layer common ANN's may not be factual enough. Whereas, while utilizing a separate ANN mode of observing the network, the ANN's monitoring each line individually provide response corresponding to the state of their respective lines power flow immediately. Also, the separate ANN's provide better summarization and extra awareness on their respective lines (faulty and otherwise) compared to the common ANN.
(d) *ANN Application Suitability*: The denouement of this study demonstrates the economical suitability of the common ANN monitoring mode for a central, power network monitoring facility or a center for load despatch (CLD) but the separate ANN monitoring mode for each line individually could be more economical and better suited for the distinct sub-stations of network understudy or the various Grid Operation and Administration Divisions (GOAD) while applying it.
(e) *Contingency Analysis*: It has been observed from this work that performing contingency studies on a power network while utilizing separate ANN mode of monitoring is much easier and less time-consuming compared to the application of a common ANN monitoring mode for the same purpose.

This work provides an elaborate analysis of the relevance of the two configurations of supervised learning feed-forward ANN's to monitor a power network. The results could be reproduced by utilizing other numerous types of ANN models for a better understanding and judgement of the endeavor. The training algorithms for ANN's may also be altered to obtain a fine-tuning of the results. The end results are very inspiring and demonstrate the practicability of the ANN's for real-time. This scheme of ANN application may also help machine learning trainees to grasp an understanding of the application of ANN for power network security. For future scope, automatic learning, decision trees, and joint ensemble of ANN's may be used to reduce the errors incurred due to human interaction during training.

Acknowledgements. This project was technically supported by the professors and staff at the Electrical Engineering Department at Jadavpur University, Kolkata, since February 2017. The financial support was arranged by the Ministry of Human Resource Development under the Indian Government and the Technical-Education-Quality-Improvement-Programme, Phase-2, under grant to registration number R/2016/0010, from February 2015.

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