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Improvement of voltage stability and loadability of power system employing the placement of unified power flow controller using artificial neural network

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ABSTRACT

This paper proposes a voltage stability and loadability improvement model of power systems by incorporating the optimal placement of flexible alternating current transmission systems (FACTS) using an artificial neural network (ANN) called OPFANN. The key aspect of this model is to identify the weakest lines which having the most probability of voltage collapse utilized for placing FACTS devices. As installing a new power system network with rapidly increasing power demand cannot be possible, the operator usually operates the power system close to the stability limit. In this regard, continuous monitoring and improvement of system voltage stability and loadability of the existing system are vital issues for energy management systems nowadays. However, the proposed OPFANN introduces a more straightforward and faster scheme for voltage stability monitoring systems using ANN. Intelligent and reliable data samples have been designed to train the ANN based on two-line voltage stability indices (LVSI) techniques. Compared with other works, OPFANN effectively improves voltage stability and loadability at the load point by installing the unified power flow controller (UPFC) FACTS devices to the weakest lines. OPFANN can provide information on voltage collapse points using ANN and reduce the further computational cost of LVSI. Finally, OPFANN ensures faster and more secure operation of the power system.

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1. INTRODUCTION

Currently, power systems are operating significantly closer to the stability limits because of economic factors, natural changes, dynamic energy requirements, and shortage of installation capacities for the electricity open market. It is known that line voltage collapse may occur at any point in the power systems or, subsystems that may damage the total power system. Therefore, energy management systems (EMSs) concentrate on online voltage stability monitoring [1]. Most of the researchers introduce the line voltage stability indices (LVSI) for monitoring voltage stability are basically two types: i) voltage stability indices based on the Jacobian matrix and ii) voltage stability indices based on system variables [2]. It is noted that the latter is more convenient than the first one because of less computational time [2], [3]. On the other hand, flexible alternating current transmission system (FACTS) devices are also integrated with the power system (PS) for dynamic control of voltage, impedance, and phase angle of high voltage alternating current (AC) transmission lines [4].

Furthermore, FACTS devices can control the network condition quickly by directly affecting system parameters and this feature of FACTS can be exploited to improve the voltage stability, loadability, and steady-state and transient stabilities of a complex PS [5], [6]. This allows increased utilization of the existing network closer to its thermal loading capacity which ultimately avoids the requirement of constructing new transmission lines.

A number of works have been introduced in the literature for voltage stability monitoring using artificial neural network (ANN) and voltage stability control using FACTS devices [4]-[17], among which some models discussed online voltage stability indicators [10], [11] only for monitoring voltage stability but did not give any sorts of solution of instability problem. The rest of the models (e.g., [8], [9]) have introduced power systems (PSs) with the FACTS devices focused on improving the line voltage stability by graphical analysis, and compared to various FACTS devices' performances. It is necessary to identify which lines require FACTS devices in a multi-bus (or, line) PS like IEEE-14 bus system (BS), where 20 lines are available. It is not a better idea to use FACTS devices in each line of the system as per the required basis, which is almost overlooked in the above models. In [7], the above problems have been solved using thyristor controlled series compensator (TCSC) FACTS devices, but unified power flow controller (UPFC) has the best performance according to [4], [5], [14]. It is noted that how much voltage stability of the system is increased after using FACTS devices is not clearly mentioned employing any parameters or, indicators in the above solutions. Only one line voltage stability index is used to detect the weakest buses in [7], which may reduce the model's reliability. According to our view, no model has been introduced to compare the amount of improvement of reactive loadability of the system after using FACTS devices considering LVSI methods as far as we know.

It is important to know that, the calculation of line voltage stability indices is a complex task with huge time costs due to the nonlinearity of line loading conditions. Furthermore, the loading condition of PS lines is constantly changing, therefore the operator needs to monitor the voltage stability condition of the lines continuously. Therefore, the operator requires a straightforward and faster online voltage stability monitoring system. In this regard, ANN has obtained significant attention for online voltage stability monitoring studies. By virtue of the non-linear nature of the line voltage stability monitoring problem, the neural network is being used more than the conventional process of voltage stability monitoring. Lots of works reported in the literature about online voltage stability monitoring based on ANN in [7], [8], [10], [18]–[21], that show the ability of ANN to approximate the functional relations between line voltage stability indicators and PS parameters that are affecting the selected voltage stability index [20], [21]. One of the main causes of using ANN in load line voltage stability monitoring is that the functional relationship of parameters becomes different from one topology to another [7], [22].

According to the above discussions, it is observed that most of the existing models suffer from some limitations: i) how much improvement of system stability and loadability found after installing FACTS devices has not been mentioned yet, ii) optimal selection of FACTS device is not performed, and iii) data generation is not verified by another L-index method. However, to overcome the above-mentioned limitations in PS, this paper proposes a model of optimal placement of FACTS devices using ANN (OPFANN). The key aspects of our proposed model OPFANN are identifying the weakest lines with the most probability of voltage collapse utilized for placing the FACTS devices in PS. The proposed model is simpler because LVSI and ANN can identify the weak lines, FACTS devices install in the line to increase the voltage stability and load lines loadability at the load point and calculate the improvement of system stability and loadability after placing FACTS devices with the help of LVSI. Furthermore, the proposed model addresses which lines require the FACTS devices in a multi-bus (or, line) PS rather than using the FACTS devices in each and every line of the system. After using FACTS devices, the voltage stability and loadability of PS are improved using LVSI in this model. A rigorous comparison is reported in this paper for improving system stability by introducing LSVI based on system variables and other approaches. The idea is implemented here to extend our earlier work [23].

The rest of this paper is organized as follows. Section 2 describes the proposed model according to stepwise discussions. Detailed experimental results of our experimental studies are presented in section 3 including detailed comparisons with the existing works. Finally, section 4 discusses the concluding remarks and future strategies.

2. PROPOSED MODEL OPFANN

In order to overcome the existing limitations of the voltage stability improvement models in PS, in this paper, a model of optimal placement of FACTS devices using ANN has been proposed. The focusing issues of our proposed model OPFANN are to locate the weakest lines that are most probable to be voltage collapses used for placing the FACTS devices in PS. The block diagram of OPFANN model has been mentioned in Figure 1. For better comprehensibility, the stepwise discussion of the proposed OPFANN is as follows:

Step 1: Select suitable two methods of line voltage stability indices (L-index) from the various methods mentioned.

Step 2: Generate the training data samples for ANN training.
Step 3: Construct a feed-forward back propagation artificial neural network (FFBPANN) using MATLAB NNTool. After that, FFBPANN is trained using the constructed data samples according to the training process.
Step 4: Complete the training process of ANN and find out the minimum error.
Step 5: Find out the weakest lines of IEEE-14 BS according to the ranking of L-index values.
Step 6: Select the optimum and faster FACTS device among others of static var compensator (SVC), static synchronous compensator (STATCOM), TCSC and UPFC on basis of the simulation result in MATLAB SIMULINK.
Step 7: Place the selected FACTS device in the weakest lines of the IEEE-14 BS.
Step 8: Compare the enhancement of voltage stability of PS with FACTS and without FACTS devices.
Step 9: Determine the range of maximum reactive power supply from each weakest line with FACTS and without FACTS devices.
Step 10: Repeat the total procedure from step 1 to 9 for IEEE-30 BS.

It is now clear that, the idea behind the proposed model OPFANN is straightforward to be improved PS voltage stability and loadability of the load lines. Only the weakest lines are located in a certain PS network that are most probable to be voltage collapsed. In this case, a number of suitable FACTS devices are attached in those positions for improving PS stability.

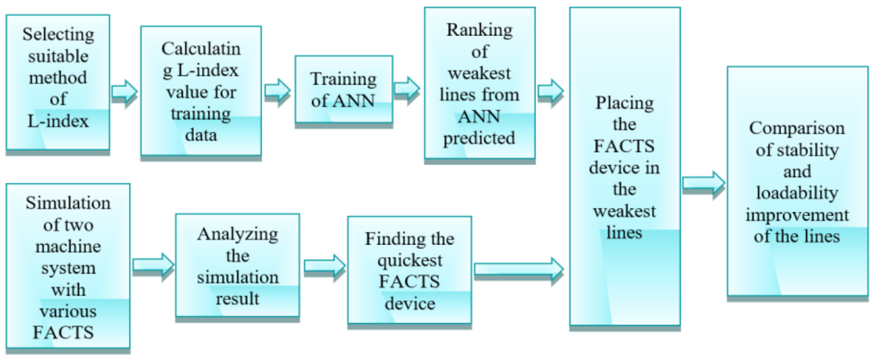

Figure 1. Block diagram of the proposed OPFANN model

3. EXPERIMENTAL STUDIES

In order to evaluate the proposed OPFANN model and how it works, a series of experiments have been conducted using MATLAB simulator. Prior to the experiments, the appropriate generation of training data for ANN and the initialization of ANN is significant. That's why, worldwide recognized two bus systems (BSs), i.e., IEEE-14 and IEEE-30 were introduced here [7].

It is known that an ANN is a vital paradigm with a strong prediction capability in various non-linear applications [24]. However, in PS-related applications, ANN can predict the line voltage conditions very quickly and identifies the weakest lines to the operator in a simple way. Therefore, the operator can take the necessary steps to be installed the FACTS devices. To improve the voltage stability effectively, two factors are significant to be considered: i) accurate data generation for perfect training of ANN and ii) selection of FACTS devices. In this regard, the selection of FACTS devices in the proposed model, the process of training data generation, and analyzing the ANN training performances have been discussed in this context.

3.1. Selection of LVSI method

In order to determine the stability of PS in a particular area, LVSI methods have significant measures. A number of line voltage stability indices methods based on system variables available in the literature [7], [8], [10], [18]–[21], among which Line stability index (L_{mn}) [25] and fast voltage stability index (FVSI) [11] are selected in this proposed model because of their simplicity and popularity. It is noted that both techniques are formulated on basis of power flow through the online system. The formulations of L_{mn} index and FVSI index are given by (1) and (2).

$$L_{mn} = \frac{4XQ_R}{[V_m sin(\theta-\delta)]^2} \tag{1}$$

$$FVSI = \frac{4Z^2 Q_R}{V_S^2 X} \quad (2)$$

Here, V_m is the m^{th} bus voltage in (1), Q_R is the reactive power at n^{th} bus, R is the line resistance between buses m and n, X is the line reactance between buses m and n, δ_m is the voltage phase angle of m^{th} bus, δ_n the voltage phase angle of n^{th} bus, where, $\delta=\delta_m-\delta_n$, and $\theta=tan^{-1}$ (X/R). In the case of (2), V_S is the sending end voltage and other parameters are the same as discussed before.

3.2. Training data generation

In this context, a set of training data samples was generated to be trained the ANN using the L_{mn} method, whereas the FVSI method was used to verify the training data. However, in the case of generating the training data, the reactive loads varied from 0% to 500% from the base values of IEEE-14 BS and IEEE-30 BS in accordance with [7]. The line voltage index (L-index) was calculated for the load variation using two LVSI methods. Finally, it can be summarized that to initialize the ANN, training data is consisted by i) input data and ii) output or, target data. Specifically, input data are the variation of reactive loading condition of the lines (Q_R), whereas target data are the values of LVSI (i.e., L_{mn} and FVSI) according to loading conditions.

In this context, 51 data samples were generated for each BS (i.e., IEEE-14 and IEEE-30) utilizing the computation of the line stability index (L_{mn}) method using (1). As such, computation is so much complex, there is a necessity to be verified either the computation was right or, wrong. That's why, an alternative LVSI method, i.e., FVSI is incorporated here, mentioned in (2). In this regard, similar computations were done for the 51 data samples using the FVSI method.

3.3. ANN setup

The MATLAB ANN tool was considered for conducting the simulation studies in this context. Various hidden layers and functions were considered randomly to initialize the ANN perfectly. On basis of the trial-and-error method, the ANN with one hidden layer including ten hidden neurons and LOGSIN function for neurons of hidden and one output layer was selected. For instance, in the case of IEEE-14 BS, the network of 14 neurons in the input layer and 20 neurons in the output layer was considered. On the other hand, for IEEE-30 BS, 30 neurons and 41 neurons were used in the input and output layers.

3.3.1. Training process of ANN

The total 51 data samples for ANN training were partitioned into three ways: i) training samples, ii) validation samples, and iii) testing samples. The ANN used the training data samples to be trained using the Back-propagation algorithm, whereas the validation data samples were used to terminate the training process. It is noted that the hidden-layer weight and output-layer weight of ANN were updated during the training process based on training data samples. On the other hand, validation data samples are unseen data by which ANN training can be terminated optimally. Finally, the testing data samples are used to justify the performance of ANN upon the unseen data. It should be noted that the performance of ANN is measured during the training processes on basis of mean squared error (MES) technique that can be defined as (3).

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(A_n - P_n)^2 \quad (3)$$

A_n represents the actual value, P_n represents the predicted line voltage stability index, and N represents the total number of samples available.

The training performance of ANN on training data samples for the IEEE-14 BS has been shown in Figure 2(a). It is seen that the training error is decreased while the number of epochs increases. In this case, the minimum error threshold of ANN was set up at 10^{-7}. In Figure 2(b), the training performance on validation data samples is exhibited. The minimum error threshold was found here at 136 numbers of epochs for the IEEE-14 BS, where the ANN training was terminated. After terminating the training, ANN was applied to the testing data samples, and the performance is reflected in Figure 2(c). Similar phenomena are reflected for IEEE-30 BS in Figures 2(d) to 2(f), respectively. Here, the minimum error threshold of ANN was set up to 10^{-7}, and the ANN training was terminated at the epoch of 180.

3.3.2. Performance of trained ANN for prototype data

In order to justify the trained ANN for the IEEE-14 BS and IEEE-30 BS, three prototype data samples each were fed to ANN, whether it worked well or not. In this regard, total six data samples were designed based on L_{mn} method mentioned in (1). After that, these prototype data samples were applied to the trained ANN, and finally, the corresponding prediction results were obtained presented in Figures 3 to 8. It was observed that almost similar values of L_{mn} for actual and predicted data sets were obtained except for line 19 of sample 1 with a small difference shown in Figure 4.

The calculated MES results of the above-mentioned three prototype data samples that were fed to the final trained ANN were presented in Table 1. It can be seen that the minimum MSE value of ANN of the IEEE-30 BS is 1.18E-08 for sample 2. By analyzing and comparing the MES values of these samples with other models of [3], [10], [26], it can be said that the prediction performances of ANN were satisfactory.

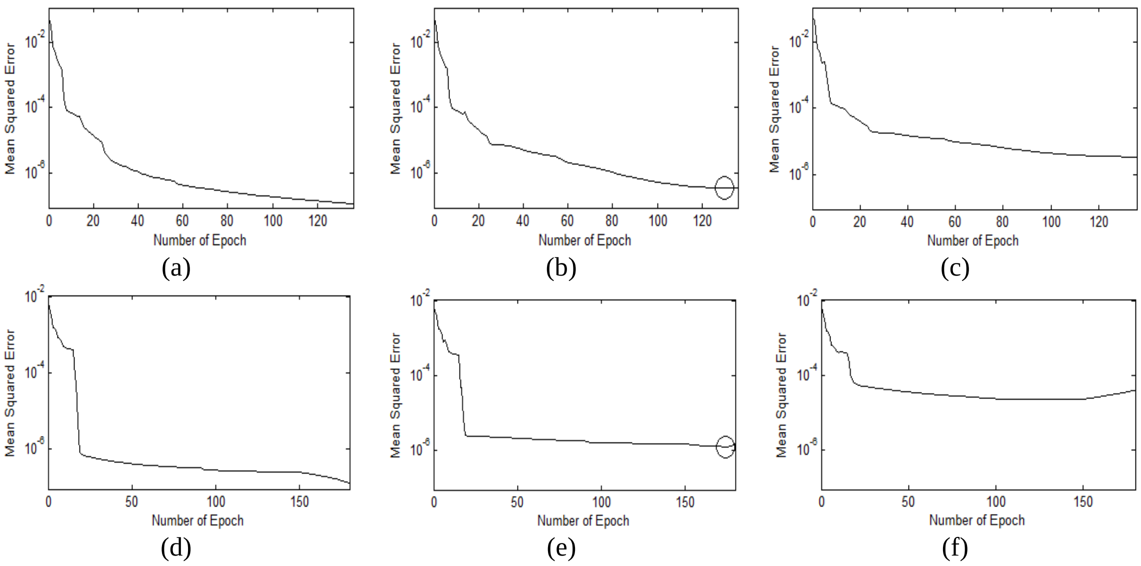

Figure 2. The performance of ANN in (a) training of IEEE-14, (b) Validation of IEEE-14, (c) testing of IEEE-14, (d) training of IEEE-30, (e) validation of IEEE-30, and (f) testing of IEEE-30 BS

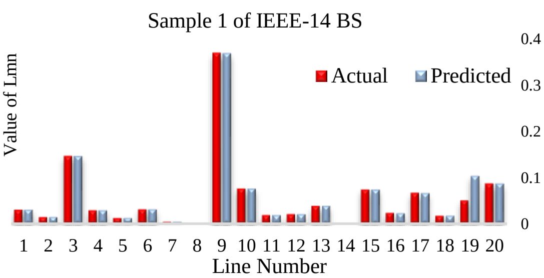

Figure 3. Comparison of actual and predicted L_{mn} for sample 1 for IEEE-14 BS

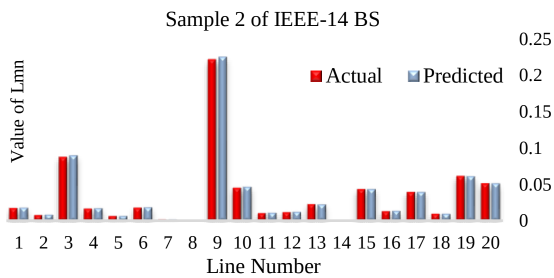

Figure 4. Comparison of actual and predicted L_{mn} of sample 2 for IEEE -14 BS

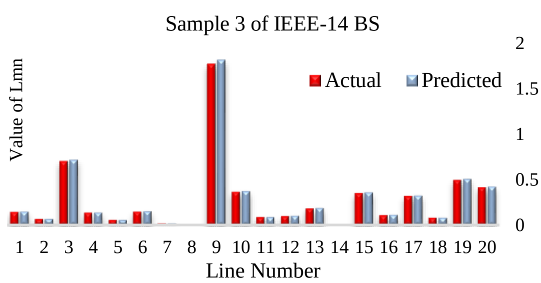

Figure 5. Comparison of actual and predicted L_{mn} of sample 3 for IEEE -14 BS

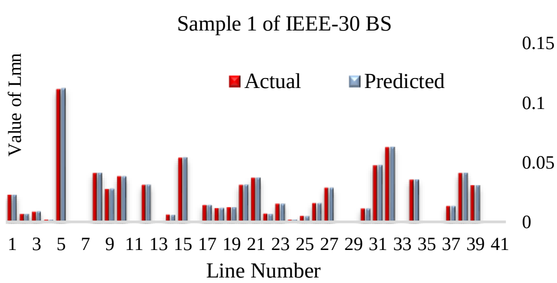

Figure 6. Comparison of actual and predicted L_{mn} of sample 1 for IEEE-30 BS

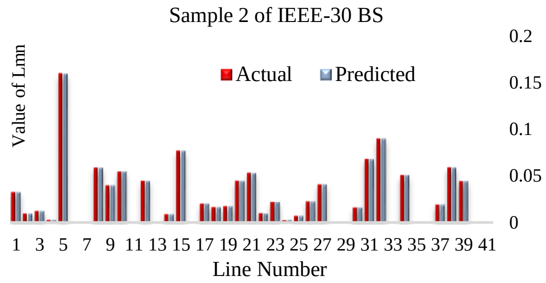

Figure 7. Comparison of actual and predicted L_{mn} of sample 2 for IEEE-30 BS

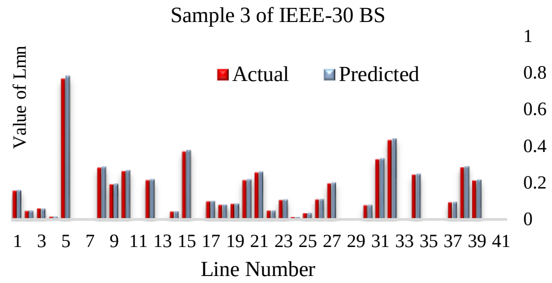

Figure 8. Comparison of actual and predicted L_{mn} of sample 3 for IEEE-30 BS

Table 1. Calculated MES results of ANN for prototype samples of IEEE-14 BS and IEEE-30 BS

MSE of IEEE-14 BS			MSE of IEEE-30 BS		
Sample 1	Sample 2	Sample 3	Sample 1	Sample 2	Sample 3
1.46E-04	9.24E-07	2.38E-04	3.40E-08	1.18E-08	1.74E-05

3.4. Ranking of weakest lines

As discussed before, the value of L_{mn} should not be greater than one for the voltage stability of lines. The smaller value of L_{mn} signifies here the better voltage stability in the lines. Therefore, the line with a larger value of L_{mn} is weaker than the line with a smaller value. According to the values of L_{mn} of the lines, the weakest lines can be ranked. Ranking of the weakest lines of the IEEE-14 BS and IEEE-30 BS was done based on two types of loading conditions: i) base loading condition and ii) variant loading conditions of IEEE-14 BS and IEEE-30 BS. In this context of variant loading, loads of the 14 buses in the IEEE-14 BS were changed randomly instead of considering the base loads. Analyzing the predicted values of L_{mn} of the IEEE-14 BS and IEEE-30 BS at different loading conditions, the five weakest lines were identified shown in Table 2 having the most probability of voltage collapse. It can be concluded that whenever the loads are changed in the various buses of PS, the ranking of the weakest lines is also changed.

Table 2. Ranking of weakest lines of IEEE-14 BS for different loading conditions

Rank	Ranking of weakest lines of IEEE-14 BS						Rank	Ranking of weakest lines of IEEE-30 BS					
	For base loading			For variant loading				For base loading			For variant loading		
	Line No.	From Bus	To Bus	Line No.	From Bus	To Bus		Line No.	From Bus	To Bus	Line No.	From Bus	To Bus
1	9	4	9	3	2	3	1	5	2	5	32	23	24
2	3	2	3	9	4	9	2	32	23	24	31	22	24
3	19	12	13	6	3	4	3	15	4	12	34	25	26
4	20	13	14	4	2	4	4	31	22	24	38	27	30
5	10	5	6	19	12	13	5	38	27	30	21	16	17

3.5. Selection and installation of FACTS devices

In this context, a PS is considered consisted by two machines of 1,000 and 5,000 MVA, 50 Hz, 640 km transmission lines, and three buses that was simulated using various FACTS devices (i.e., UPFC, TCSC, SVC, STATCOM, and static synchronous series compensator (SSSC)) to be found out the effective one. Performance data of PS with SVC, STATCOM, SSSC, TCSC, and UPFC FACT devices according to the time required to stable bus voltages, power flow, and rotor angle have been mentioned in Table 3. On the other hand, Table 3 also shows the peak overshoots of the systems with different kinds of FACTS devices. Analyzing the data of Table 3, it is clear that UPFC is the quickest FACTS device as it took 5,633 s to stable the bus voltages and 6.80 s to stable the power flow. Again, the system with UPFC has a peak overshoot of 0.20 p.u. (upper side distance from reference) and 0.458 p.u. (downside distance from reference) as shown in Table 3, those are comparatively better than other FACTS devices. Unified power flow controller that is able to control concurrently all three network parameters (i.e., voltage, impedance and transmission angle) of the power system [27]. Therefore, UPFC was selected for placement. Here, five UPFC FACTS devices with capacitive reactance X_C=0.05 p.u. and inductive reactance X_l=0.05 p.u. were installed in the weakest lines one by one those were ranked before [4], [7], [17].

Table 3. Performance analysis of SVC, SSSC, TCSC, STATCOM, and UPFC FACTS devices

FACTS devices time requirement for stability	SVC	STATECOM	SSSC	TCSC	UPFC
Voltages	7.50 s	6.133 s	10.133 s	6.80 s	5.633 s
Power	9.50 s	7.40 s	10.50 s	7.20 s	6.80 s
Rotor angle	11.50 s	9.10 s	12.00 s	7.70 s	8.00 s
Peak overshoots in p.u. (upper)	0.20	0.20	0.345	0.184	0.20
Peak overshoots in p.u. (downside)	0.457	0.463	0.464	0.465	0.458

3.5.1. Stability improvement

FACTS devices UPFC having capacitive reactance X_C=0.05 p.u. and inductive reactance X_l=0.05 p.u. were installed in the weakest lines one by one. The voltage stability improvement of the load lines of IEEE-14 PBS and IEEE-30 BS by the optimum placement of FACTS devices has been reported in this context. In case of obtaining stability improvement, we have considered the predicted values of L_{mn} for the base load condition of IEEE-14 BS and IEEE-30 BS. The values of improved stability (L_{mn}) of weakest lines of IEEE-14 BS were calculated as mentioned in Table 4. The average improvement of those lines is more than 35% of IEEE-14 BS. Further considering the similar procedure for those weakest lines in IEEE-30 BS, the calculated stability improvement found is also mentioned in Table 4. The average stability improvement of the weakest lines of IEEE-30 bus is more than 30%.

Table 4. Stability improvement of IEEE-14 BS and IEEE-30 BS after the installation of FACTS devices

Stability improvement of IEEE-14 BS				Stability improvement of IEEE-30 BS			
Line No.	Stability without FACTS	Stability with FACTS	Stability Improvement in %	Line No.	Stability without FACTS	Stability with FACTS	Stability Improvement in %
9	0.3691	0.2127	42.38	5	0.1589	0.1063	33.23
3	0.1463	0.1112	24.00	32	0.0896	0.0569	36.49
19	0.1029	0.0700	32.01	15	0.0768	0.0492	35.96
20	0.0864	0.0528	38.84	31	0.0677	0.0460	32.08
10	0.0756	0.0476	37.00	38	0.0587	0.0377	35.78

3.5.2. Loadability improvement

The loadability improvements of the load lines of IEEE-14 BS and IEEE-30 BS have been reported in this context involving the optimum placement of FACTS devices. To estimate the line loadability, L_{mn} method was used here. It is known that the maximum value of L_{mn} in terms of stability criteria might be one. It means that the highest value of load that can be connected in the line under-voltage stability condition when the L_{mn} value is one [3]. For instance, the line no. 9 of IEEE-14 BS without FACTS devices containing the value of L_{mn} was 0.3691 Table 2 while the reactive load on the line was the base load of 16.6 MVAR connected on Bus 9.

As a result, the value of L_{mn} of line no. 9 depends on the impact of load of Bus 9. Therefore, the L_{mn} value of line no. 9 can be one whenever the load of (16.6/0.3691) 44.954 MVAR is connected in Bus 9. In contrast, in improving the stability of IEEE-14 BS, UPFC FACTS (i.e., X_C=0.05 p.u. and X_l=0.05 p.u.) devices was connected in that particular line no. 9 without changing the load, the value of L_{mn} was being decreased to 0.2127. According to a similar way it is found that, the load in the line no. 9 can be increased to 78 MVAR to be obtained the L_{mn} value of one. Thus, it can be said that the loadability of line no. 9 has been improved due to attaching UPFC FACTS device. In the same way, loadability for line no. 3 was also calculated.

The loadability improvement of the five weakest lines for base loading conditions of IEEE-14 BS is shown in Figure 9. Here, UPFC FACTS devices of X_C=0.05 p.u. and X_l=0.05 p.u. were installed in the lines. It is observed that the average loadability improvement of the weakest lines is more than 37 MVAR (i.e., 48%). In the other hand, the loadability improvement of the five weakest lines for base loading conditions of IEEE-14 BS including installed UPFC FACTS devices of X_C=0.10 p.u. and X_l=0.05 p.u. are reported in Figure 10. Here, the average loadability improvement of the weakest lines is more than 49 MVAR (i.e., 36%).

Similar set of experiments were also conducted in this context for base loading conditions of IEEE-30 BS. The obtained results are reported in Figures 11 and 12, respectively for five weakest lines considering the values of X_C=0.05 p.u. and X_l=0.05 p.u. as well as X_C=0.10 p.u. and X_l=0.05 p.u. in UPFC FACTS devices. Here, the average loadability improvements of the weakest lines are more than 42 MVAR (i.e., 38%) and 34 MVAR (i.e., 33 %), respectively.

3.6. Comparison with other models

The comparison with other modes can be divided into two parts. First is the comparison of ANN performance, and second is a selection of FACTS devices for loadability improvement of the power system.

The comparison of ANN performance according to MSE calculation has been mentioned in Table 5, where Table 6 represents the comparison of loadability improvement. Analyzing Tables 5 and 6, it can be claimed that the performances of the proposed model are far better than those of the existing models.

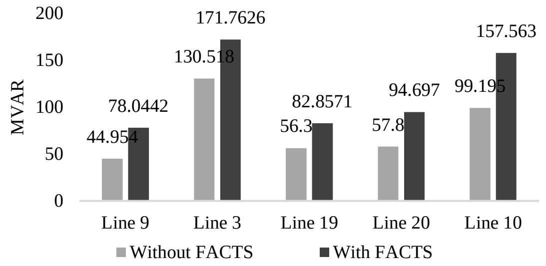

Figure 9. Loadability improvement of 5 weakest lines in IEEE-14 BS for X_C=0.05 p.u., X_1=0.05 p.u.

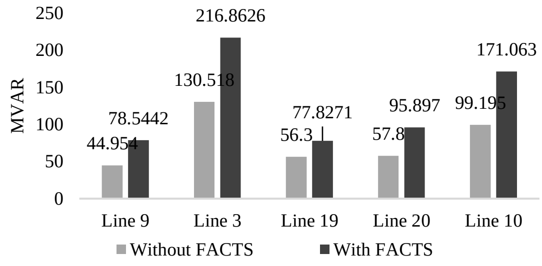

Figure 10. Loadability improvement of 5 weakest lines in IEEE-14 BS for X_C = 0.10 p.u., X_1 = 0.05 p.u.

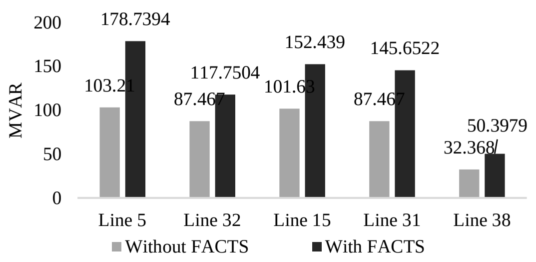

Figure 11. Loadability improvement of 5 weakest lines in IEEE-30 BS for X_C = 0.05 p.u., X_1 = 0.05 p.u.

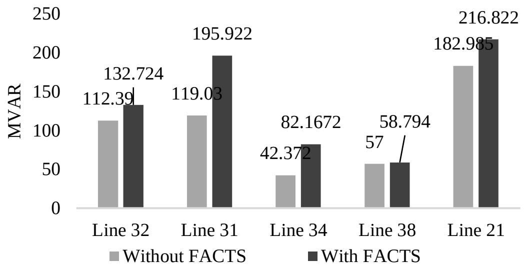

Figure 12. Loadability improvement for variant loading of IEEE-30 BS for X_C = 0.10 p.u., X_1 = 0.05 p.u.

Table 5. Comparison of ANN model's performances with existing models

Models	Method of ANN	Error value (MAPE/MSE)	Comment
Bahmanyar and Karami [10]	Back Propagation	4.1000	The lowest MSE value
Goh *et al.* [2]	Back Propagation	0.0976	has been found in
Nor *et al.* [28]	Back Propagation	2.1875	proposed model that is
Proposed model	Back Propagation	1.18E-08	1.18E-08

Table 6. Comparison of loadability improvement and selection of FACTS devices

Models	Power system and method	FACTS devices types	Loadability Improvement	Comment
Jayasankar *et al.* [7]	IEEE-14 and ANN	TCSC	Not calculated	The quickest FACTS device UPFC has been selected in proposed model and
Rashed *et al.* [15]	IEEE-14 and GA, PSO	TCSC	22% and 29%	highest loadability improvement has been
Proposed model	IEEE-14 and ANN	UPFC	48%	found in proposed model

4. CONCLUSION

This paper proposes a voltage stability and loadability enhancement model of power systems (OPFANN) incorporating optimal placement of UPFC FACTS devices using ANN. The focusing issue of OPFANN is to identify the weakest lines and install FACTS devices to improve voltage stability and loadability of PS. Particularly, OPFANN reduces the complexity and time requirement of voltage stability monitoring of load lines using ANN. The operator can effectively ensure the consumers how much load can be added to the lines before and after installing UPFC FACTS devices.

The effectiveness of this model has been tested on the IEEE-14 BS and IEEE-30 BS. Significant voltage stability and loadability improvement were also obtained in PS after placing FACTS devices in the proposed OPFANN. The maximum obtained stabilities for IEEE-14 BS and IEEE-30 BS after installing FACTS devices were 42.38% and 36.49%, respectively Table 4, whereas, 48% and 38% achievements for maximum loadability of IEEE-14 BS and IEEE-30 BS, respectively Figures 9 to 12. The effectiveness of the ANN model has been verified by calculating MSE. The minimum MSE value of trained ANN for IEEE-30 BS has been found 1.18E-08, which is better than the other existing models. Finally, we can say that our proposed model OPFANN can easily identify the weakest lines with the most probability of voltage collapse utilized for placing the FACTS devices in BS. OPFANN is straightforward because the weak lines of a BS can be identified easily involving LVSI and ANN. Thereby, voltage stability and load lines loadability at the load point are improved rapidly by installing the FACTS devices to those lines.

In future, OPFANN might be clarified for a larger and real-life network following more comprehensive experiments. In that case, it might be beneficial to ensure secure and reliable service to the consumer. Furthermore, it might be more economical as a new load can be added without installing a new PS network. Thus, loadability of the existing lines might be increased after installing FACTS devices.

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