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Original Article

Prediction of Available Transfer Capability with the Penetration of DG using ANN Techniques

Manjula S Sureban[1], S.G. Ankaliki[2]

[1,2]*Department of Electrical and Electronics Engineering,*
Shri Dharmasthala, Manjunatheshwara College of Engineering and Technology, Dharwad,
Affiliated to Visvesvaraya Technological University, Belagavi, India.

[1]*Corresponding Author : smanjula845@gmail.com*

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Abstract *- The modern power system is subject to transformation from centralized to a distributed one because of the rapid advancements in Distributed Generation (DG) technology. At the same time, the increased demand for electricity is resulting in transmission network congestion, and the transmission lines are pushed to operate closer to their limit. This raises a need for power system operators to evaluate and enhance the Available Transfer Capability (ATC) of existing transmission lines to relieve the congestion in transmission networks and improve the power system reliability and security. Several methods, viz. Sensitivity factors-based methods and repeated power flow methods are used to estimate ATC by performing power flow studies. This paper demonstrates the development of Artificial Neural Networks (ANN) to predict the day ahead ATC of power system with the penetration of DGs by using its past performance.*

Keywords *- PTDF method, ANN, Solar SG, Regression, Loss sensitivity factor.*

1. Introduction

The increased penetration of DGs in existing power systems has led to numerous challenges in efficient operation and power network control. Recently, the transmission system has become highly congested because of the growing need for electricity and the insufficient capacity of transmission infrastructure. The operational and planning issues to relieve network congestion initiate certain challenges for the power system operator. In such situations, the prediction of ATC becomes an important subject. ATC of the system is the capability of the transmission network to allow power transfer between two areas, zones or buses for additional commercial trading. The inaccurate estimation of ATC leads to the inefficient utilization of the transmission network. To address this problem, accurate and efficient ATC prediction methods are needed. According to the framework provided by "North American Electric Reliability Council (NERC)", the "Total Transfer Capability (TTC) of transmission line is the maximum amount of power that can be transferred between two areas or zones or buses without causing the overload of transmission lines, violations in voltage limits at system buses and/or any other system security problems"[1].

Mathematically, ATC is written [2] as per Equation (1).

$$ATC = TTC - TRM - CBM - ETC \tag{1}$$

Here, "Transmission Reliability Margin (TRM) is the transfer ability of the system required to ensure that the power system is secure during any kind of uncertainties". Also, "Capacity Benefit Margin (CBM) is the transfer capability reserved for load serving agencies to access generation reliability requirements". "ETC is the Existing Transfer Commitment".

The researchers have proposed various techniques for the evaluation of ATC, such as sensitivity factors-based methods, which evaluate ATC by evaluating Power Transfer Distribution Factors (PTDF) for a particular transaction [3]. Even though these methods are simple to handle, they are less accurate, especially for large systems. Few researchers have discussed about Continuous Power Flow (CPF) methods, which are more accurate but do not address the issue of convergence in power flow solution; however, a few researchers have proposed repeated power flow methods for evaluation of ATC that are mathematically less complex, and more efficient to carry out power flow with improved convergence [4]. Probabilistic methods are also used to evaluate ATC with better accuracy, whereas statistical approaches are used to model load and generation uncertainties [5]. As AI techniques are proven tools for real-time predictions in many applications, a few authors have used ANN-based algorithms to evaluate ATC by making use of historical data. In paper [6], researchers have employed a multi-layer feed-forward neural network to evaluate the power transfer capability between two areas. Along with evaluation, enhancing the ATC of transmission lines is also an important issue to address in power system planning since the transmission lines operate near their limits. The enhancement of their power transfer capability to accommodate the additional power without violating the system limits is another challenge addressed in the literature. Various FACTS devices, viz. Thyristor Controlled Series Capacitor (TCSC) and Static Var Compensator (SVC) are used to enhance the ATC by modifying the transmission line reactance [7]. Various optimization techniques such as "Hybrid Grey Wolf Flower Pollination Algorithm", TLBO [8], Gravitational search [9] and Adaptive Moth Flame optimization [10] are various optimization algorithms applied to determine and improve ATC of transmission lines with the aid of TCSC.

Determination of ATC is a crucial task to be performed by the power system operator, especially in the scenario of an integrated complex power system with renewable penetration. To relieve network congestion and to carry out the power transaction economically, the determination of ATC becomes the primary objective. Also, the enhancement of ATC is another issue to be addressed when operating transmission systems securely and within safe limits. It is observed that many studies are carried out on ATC evaluation by considering the conditions in the system to be static.

The variation in load, generation, system conditions, and contingency conditions must be considered for real-time monitoring. Also, the methods such as CPF and RPF are more time-consuming. With the aid of AI techniques, the computational speed and accuracy can be increased. This paper addresses the use of Artificial Neural Networks (ANN) to predict the values of ATC between pairs of buses for different percentage penetration of solar DG using the "Levenberg-Marquardt Algorithm" and "Scaled Conjugate Algorithm". The results are compared with the DC-PTDF method.

2. Methods

The determination of ATC plays a vital role in assisting the power system operator in making decisions about economic transactions and relieving network congestion without disturbing the security and reliability of the system. Various approaches are discussed to evaluate ATC. There are four categories of ATC evaluation methods. (a) Optimal power flow-based methods (b) Sensitivity Factors Based Method (c) Repeated Power Flow (RPF) method (d) methods using probabilistic approach. All these methods evaluate ATC of transmission lines based upon the existing system conditions. But artificial intelligence techniques such as regression models, fuzzy inference systems, expert systems, and Artificial Neural Networks (ANN) can be employed to evaluate ATC based upon the existing conditions and predict the ATC for future conditions. The important features of ANN, such generalization, learning from nonlinear data for future prediction, are used in this paper for the prediction of ATC in the presence of DGs by using forecasted load demand and forecasted generation from DG.

2.1. Sensitivity Factors based Methods

The sensitivity factors-based methods use the sensitivity factors of a system for a given topology to evaluate ATC. The "Power Transfer Distribution Factor" (PTDF) indicates "the incremental distribution of power flows corresponding to transactions between two areas/buses/regions" [11]. There are two ways of defining PTDF while evaluating ATC: AC-PTDF and DC-PTDF.

The DC-PTDF use only active power flows during ATC computation, whereas the in-PTDF method considers both the active and reactive power flows. AC- The PTDF method is more accurate than DC PTDF; however, most researchers have used the DC-PTDF method as it involves simple computations and takes less time to implement. In this study, the DC-PTDF method is used.

PTDF is "a fraction of the power from seller to buyer flowing through a given transmission line" [12]. Symbolically, $PTDF_{ij,\ mn}$ represents the fraction of overall transactions from source bus 'm' to sink bus 'n' which transfer through a transmission line connecting buses 'ii and'j'. The $PTDF_{ij,\ mn,\ was}$ evaluated using Equation (2).

$$\mathrm{PTDF_{ij,mn}} = \frac{\mathrm{x_{im}-x_{jm}-x_{in}+x_{jn}}}{\mathrm{x_{ij}}} \tag{2}$$

In Equation (2), x_{ij} indicates the transmission line's reactance connecting the buses i and j. Xi_m, X_{jm}, X_{in} and Xjn are the elements present in the bus sensitivity matrix or reactance matrix derived by taking the inverse of the bus admittance matrix. The Transfer Capability (TC) of a line connecting i-j by making use of PTDFs is evaluated from Equation (3)

$$T_{ij,mn} = \begin{cases} \frac{\mathrm{P_{ij}}^{\max}-\mathrm{P_{ij}}^{0}}{\mathrm{PTDF_{ij,mn}}} & ; \quad \mathrm{PTDF_{ij,mn}} > 0 \\ \frac{-\mathrm{P_{ij}}^{\max}-\mathrm{P_{ij}}^{0}}{\mathrm{PTDF_{ij,mn}}} & ; \ \mathrm{PTDF_{ij,mn}} < 0 \\ \infty & ; \quad \mathrm{PTDF_{ij,mn}} < 0 \end{cases} \tag{3}$$

In Equation (3), $\mathrm{P_{ij}}^{\max}$ is the maximum power limit of the line connecting bus i and j, $\mathrm{P_{ij}}^{0}$ is the real power that flows through a line between bus i and j for base case analysis. The line with minimum transfer capability is noted as the constraining branch, which decides the ATC of the system. Finally, the system's ATC is computed using Equation (4).

$$\mathrm{ATC} = \min\{\mathrm{T}_{\mathrm{ij,mn}}\} \tag{4}$$

2.2. ANN Models for Evaluation of ATC

Artificial Neural Networks are "the systems consisting of a huge number of simple and highly integrated data processing elements". The neural network's architecture is defined based on Biological Neural Networks (BNN) [12]. ANNs are arranged in 'layers' and comprise a huge number of interconnected 'nodes' with an 'activation function'. The training data, called 'inputs are provided via the 'input layer'. The input layer interacts with one or more 'hidden layers' where the real data processing takes place using 'weighted' connections. The hidden layer then interacts with the 'output layer' from which the outputs are derived. The fundamental configuration of an ANN is shown in Figure 1.

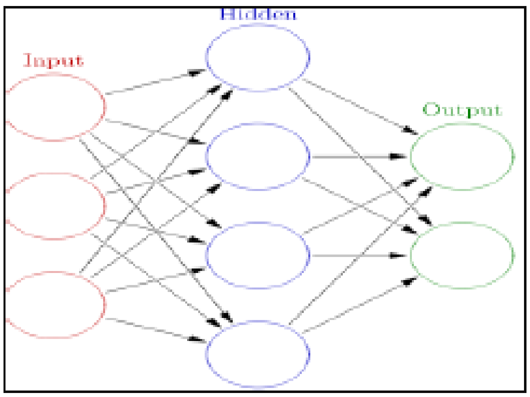

Fig. 1 Fundamental configuration of Neural Network

When input data along with the target pattern is provided to a neural network, it starts iteration with a random guess about the output, known as 'predictions'. Then checks how far the predictions are from the actual one provided as 'targets' and accordingly makes adjustments in its connection weights [13]. This type of learning in ANN is called as supervised learning. Several supervised learning algorithms are proposed for weight adjustment based on the given training data. The Levenberg–Marquardt (LM) algorithm is one such efficient iterative supervised learning algorithm used for solving nonlinear least square problems. It is the most commonly used algorithm to choose a local minimum, which need not be a global minimum. This method finds the solution even if the initial solution is very far from the final minimum [14]. In the SCG algorithm, the weights and biases of the NNs are updated based on the calculated gradient and the scaled conjugate direction. SCG does not carry out a line search every iteration to find the optimal step size like LM algorithm [15].

3. Case Study

The IEEE 14 bus system is used as the test system in this study to predict ATC. This system consists of three PV buses, nine load buses, two transformers, and one shunt capacitor. To prepare a data set for training an ANN to predict ATC of said system for various loading conditions over a period of 24 hours, a sample load profile shown in Figure 2 is considered. Here, the base load is 259MW, and for a period of 24 hours, the system's load varies from 220MW to 280MW, which is approximately 70% to 108% of the base case. 105% of the base load is considered the peak load for analysis, which occurs at the 12th hour. In this study, solar DG is modelled as a real power generator [16] located at the optimal load bus. The MW generation from solar DG depends upon the solar irradiation. The MW power obtained from the photovoltaic system is given by Equation (5)

$$P_{pv} = \begin{cases} P_{pvr} \times \left(\frac{G}{G_0}\right) & 0 \leq G \leq G_0 \\ P_{pvr} & G_0 \leq G \end{cases} \tag{5}$$

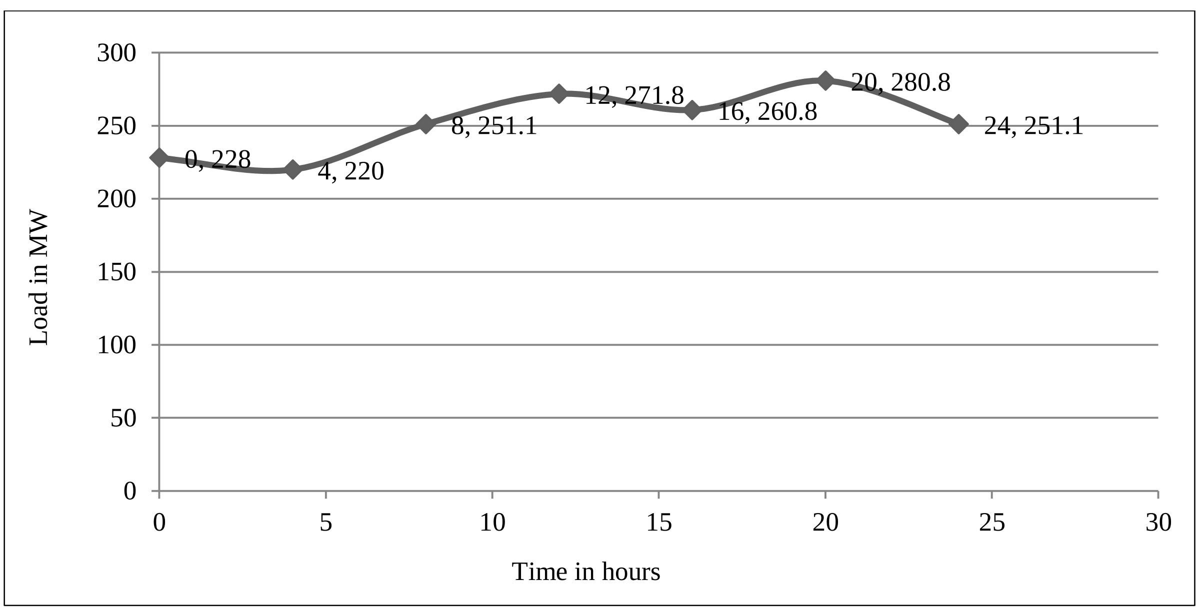

Fig. 2 Sample load profile

The solar DG power rating is considered to be 20MW, which is nearly 10% of the total generation in the system. The solar irradiance rating is 1000 W/m^2. The variation of solar irradiation in W/m^2 for a period of 24 hours is shown in Figure 3. The power output in MW from PV DG for 24 hours by considering the irradiance pattern as per Figure. 2 for different penetration levels is calculated using Equation (5) and tabulated in Table 1.

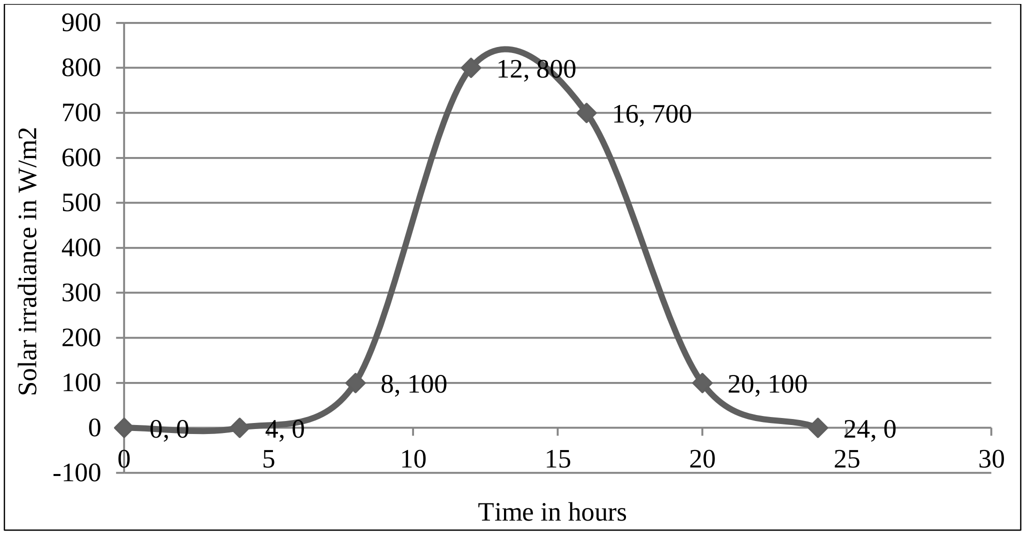

Fig. 3 The variation of solar irradiation over a period of 24 hours

Table 1. PV DG output for 24 hours

Time in hours	Solar irradiation in W/m^2	Power output in MW for different penetration level in %			
		10% DG rating = 20MW	20% DG Rating = 40 MW	30% DG rating = 60 MW	40% DG rating = 80MW
0	0	0	0	0	0
4	0	0	0	0	0
8	100	2	4	6	12
12	800	16	32	48	64
16	700	14	28	42	56
20	100	2	4	6	8
24	0	0	0	0	0

The suitable location for placement of DG resulting in reduced losses is obtained by calculating the "Real Power Loss Reduction Sensitivity Factor (PLRSF)" shown in Equation (6).

$$\mathrm{PLRSF} = \frac{P_{\text{loss with DG}} - P_{\text{loss base}}}{P_{\text{DGi}}} \tag{6}$$

Here, P_{DGi} is the real power rating of DG located at load bus i, $P_{\text{loss base}}$ is the power losses in the system for the base case without DG, and $P_{\text{loss with DG}}$ is the real power loss in the system after placing DG. The PLRSF value should always be negative as the real power losses in the system are to be reduced after placement of DG; otherwise, the DG integration into the system is not suggested. Therefore, the bus with the maximum negative PLRSF value among all other buses is chosen as a suitable location for DG placement. To find a suitable location of the DG, the PLRSF is calculated by inserting the DG in load buses one after the other during peak load conditions and at a unity power factor. The PLRSF are tabulated in Table 2. It is clear from the table that the 14^{th} bus is the optimal location for the insertion of DG, as it results in the least power losses with the largest PLRSF

Table 2. PLRSF with DG at load buses

Load Bus	For a 20MW-rated solar DG at the load bus		
	Power loss in MW	PLRSF	Rank
4	13.324	-0.1215	5
5	13.613	-0.1034	8
9	13.299	-0.1231	3
10	13.288	-0.1238	2

11	13.478	-0.1119	6
12	13.499	-0.1106	7
13	13.319	-0.1218	4
14	13.033	-0.1397	1

4. Results

Data set preparation is the first and most important step for training neural networks. The accuracy of the result obtained from the trained model depends on the quality and size of the data set used for training. In this work, having obtained the forecasted solar DG output in MW and load demand for a test system the available transfer capability is predicted by preparing data set using previous data by considering five input parameters viz. time in a day, load demand in MW, forecasted power generation from DG at optimal location in MW, source bus, and sink bus. The target set is prepared by evaluating ATC for all these input conditions using the PTDF method. The data is collected every five minutes for a duration of 24 hours with bus 2 as a source bus and 5 as a sink bus. This resulted in an input data set of 289X5 and a target data set of 289X1. The same shall be created for any combination of source and sink bus. Diagrammatic representation of a trained neural network by considering 10 neurons in the hidden layer is shown in Figure 4. Out of 289 data samples, 203 are used for training, 43 for validation, and 43 for testing. The neural network is trained using the LM and SCG algorithms to obtain the desired performance. The regression plots for both the algorithms are depicted in Figure 5 (a) and 5 (b). It is observed that the training performance is satisfactory for both the algorithms, as the regression values are very close to the expected regression value of 1. The training performances for both the algorithms are shown in Figure 6(a) and 6(b). It is observed that the LM algorithm takes 20 iterations and the SCG takes 38 iterations for processing. Processing time for the LM algorithm is almost equal to zero, as SCG takes 30 seconds.

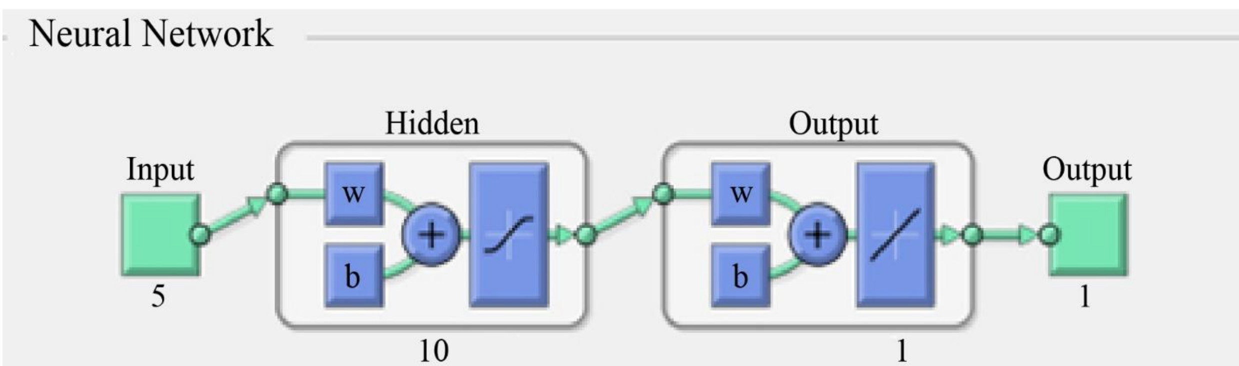

Fig. 4 Schematic of trained Neural Network

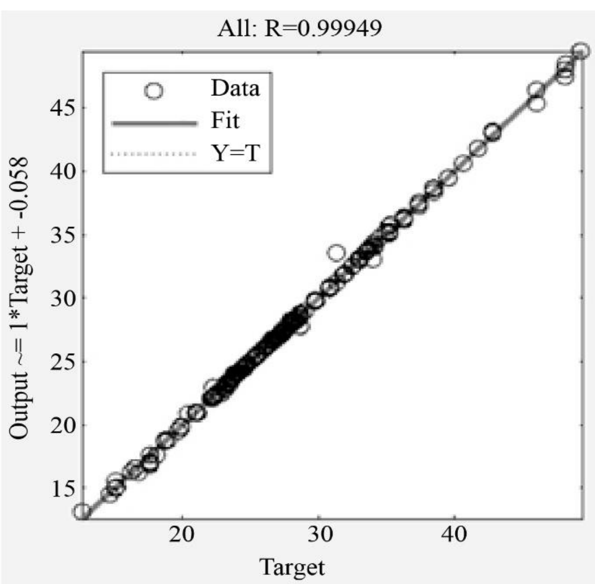

Fig. 5(a) Regression plot for ANN using Levenberg–Marquardt algorithm

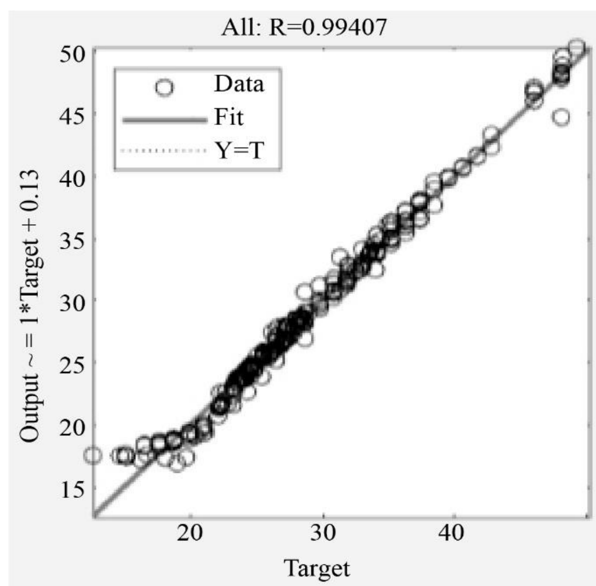

Fig. 5(b) Regression plot for ANN using the scaled gradient conjugate algorithm

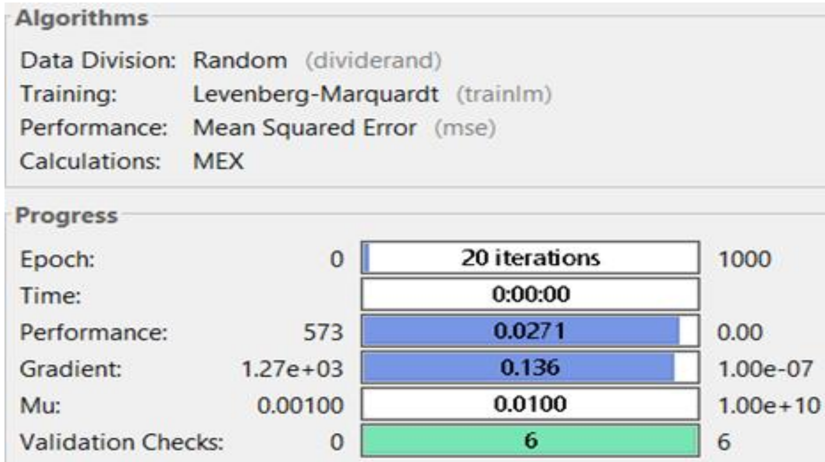

Fig. 6(a)Training Performance for the LM algorithm

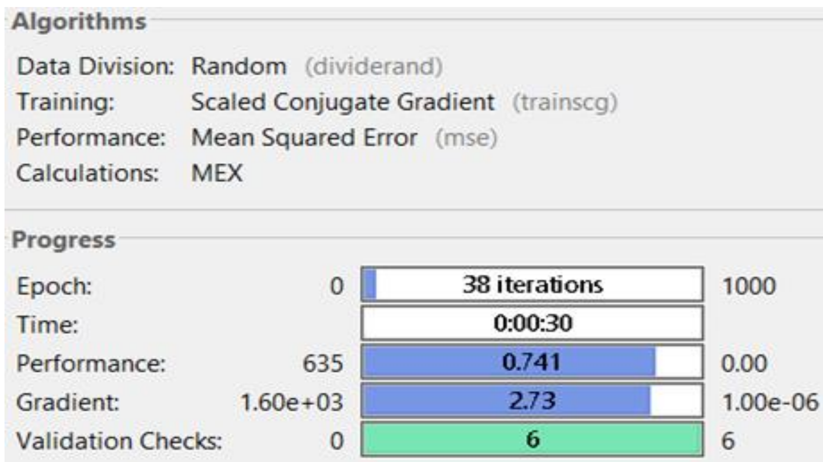

Fig. 6(b) Training performance for SCG algorithm

The error histograms displayed in Figure 7 (a) and 7 (b) show that errors are very much closer to the zero error line for training, validation, and testing using the LM algorithm compared to that of SCG. The regression values and Mean Squared Errors (MSE) during training, validation and testing for both the algorithms are tabulated in Table 3.

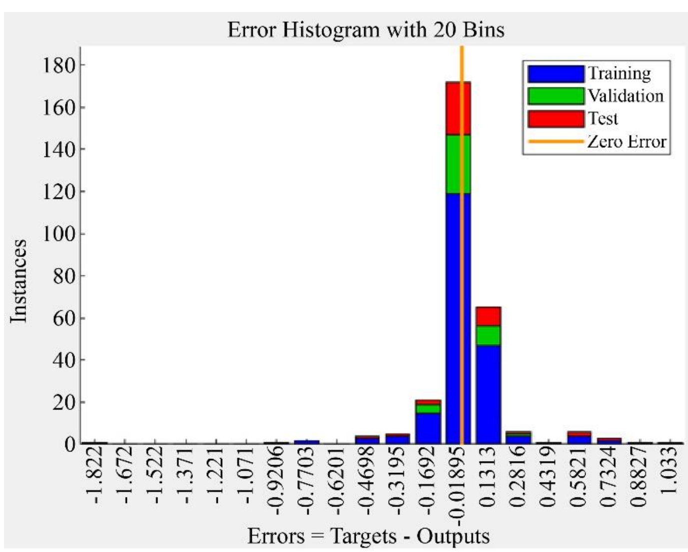

Fig. 7(a) Error histogram for the LM algorithm

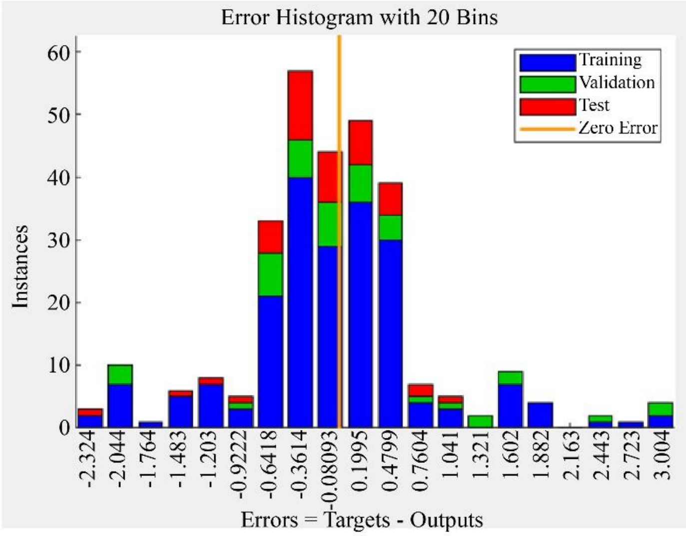

Fig. 7(b) Error histogram for SCG algorithm

Table 3. Metrics of LM and SCG algorithms

Algorithm	LM Algorithm		SCG Algorithm	
Process/Metric	**Regression**	**MSE**	**Regression**	**MSE**
Training	0.99479	0.0576161	0.993073	0.7802096
Validation	0.99521	0.0358506	0.985163	1.29465
Testing	0.99971	0.0444589	0.996674	4.119995

After ensuring that the performance of the trained neural network is satisfactory, the model is deployed to predict ATC in MW from bus number 2 to bus number 5 for any other conditions. Here, two cases are considered to demonstrate the efficiency of the trained model.

Case 1: 11:04 hours, Loading = 0.98.

Solar DG in MW (Penetration level): 15MW (10%), 30MW (20%), 45MW (30%), 60MW(40%).

Case 2: 16:18 hours, Loading = 1.01%.

Solar DG in MW (Penetration level): 13MW (10%), 26MW (20%), 39MW (30%), 52MW(40%).

Table 4 shows the predicted ATC values using the LM and SCG algorithms for case 1 and case 2. It is ensured that these data are not used for training. The results are also compared with the PTDF method. It is noted that the predicted ATC values using the LM algorithm are more accurate than those using SCG. It is also observed that DG penetration enhances ATC values. Here, the two algorithms, viz. LM and SCG used for training the neural network have resulted in good performance in terms of regression nearer to one and MSE nearer to zero. The evaluated ATC using these algorithms is accurate when compared with the PTDF method.

The trained models can be further used to predict ATC during any other load conditions and with any other DG penetration level.

Table 4. Predicted ATC values using LM and SCG algorithms

Method	ATC in MW for Case 1 for the DG penetration of				ATC in MW for Case 2 for the DG penetration of			
	10%	**20%**	**30%**	**40%**	**10%**	**20%**	**30%**	**40%**
ANN-LM algorithm	28.67	33.16	48.57	60.1	24.06	34.56	41.28	50.25
ANN- SCG algorithm	27.67	41.46	49.54	52.57	24.06	35.81	38.2	43.73
PTDF method	28.344	37.635	46.668	55.461	24.053	32.414	40.5637	48.5157

5. Conclusion

The ATC prediction and interpretation are important to ensure network reliability and manage congestion problems in the presence of distributed generation at different penetration levels. This paper uses ANN techniques to predict ATC for varying load and DG penetration conditions. The two algorithms, viz. LM and SCG used for training the neural network have resulted in better performance in terms of regression nearer to one and MSE nearer to zero. The trained models can be used to predict ATC for any other load conditions and DG penetration level. The proposed models can be further used in deciding the economic transaction at a given operating condition to improve the reliability and security of the power system by ensuring economic operation. Conventional methods to evaluate ATC can estimate only static values. The static ATC does not reflect the time-varying generation patterns and grid dynamics. The need for a dynamic ATC evaluation framework using time series approaches and the use of AI techniques for the evaluation of dynamic ATC would be the future scope of this work.

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