Performance Assessment of Steady-State Voltage Stability Indices for Parameter Validation Using ANFIS

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Abstract—**Precision and consistency in monitoring the voltage stability conditions of power system networks remain vital aspects of modern power system operation. Thus, this study presents a machine learning approach for comparative performance evaluation of some voltage stability indices (VSIs). Six essential power system parameters from the transmission line data and load flow solution at different real and reactive load levels are used as input information for implementing adaptive neuro-fuzzy inference system (ANFIS) models based on the subtractive clustering rules. The performance of the considered VSIs is evaluated using the mean absolute percentage error (*MAPE*), the Percentage Relative Root-Mean-Square Error (*RRMSEp*), and the linear regression based on correlation coefficient *R*. The IEEE 30-bus system is used as a test, and the predictive analysis results are obtained for several simulation runs for parameter tuning and model regularity. Considering the *MAPE* analysis, *FVSI* with average *MAPE* = 4.7429% and maximum *MAPE* = 6.6574% outperformed the other VSIs; average *MAPE* values are 5.6165% for *LMN*, 12.4684% for *NLSI* and 14.7167% for *LQP*. The consistency of *FVSI* for precise monitoring of power system voltage stability condition, compared to the other VSIs, is verified by the *RRMSEp* and *R* analysis results.**

Keywords— Power system security; voltage stability indices; predictive analytics; Machine learning; neuro-fuzzy expert systems

I. Introduction

Almost all power systems, especially in developing countries, are prone to either partial or total voltage collapse, and this is due to the insufficient grid capacity to meet the excessive load demand requirements and the aging state of infrastructure. Thus, ensure efficient, secure, and reliable grid operation, as well as to encourage diversification of resources, intelligent approach to voltage stability monitoring is essential. Several voltage stability indices (VSIs) have been proposed and derived by researchers for pre-determining the voltage stability condition of a power system. The earlier form of these indices is the P-V and Q-V curves which are powerful tools used for determining credible information about the voltage stability condition as a function of the system loading at different operating points using load flow analysis [1]. However, the dependability of some of these tools for precise indication of the state of the power systems can be verified and enhanced using applicable artificial intelligence and machine learning tools. The Adaptive neuro-fuzzy inference system (ANFIS) is a Fuzzy Logic (FL)-based expert system enhanced with the learning capabilities of artificial neural network (ANN). It has become one of the vital faces of contemporary data analytics and predictive tools for engineering systems implementation, operation, and control [2-3]. The notable advantage of the ANFIS model over the basic ANN model is its ability to use the fuzzy rules to process linguistic information alongside ANN's numerical data processing capabilities. Hence, classification and identification of unlabeled data and undescribed patterns can be effectively achieved [4].

From reviewed studies, the fuzzy logic expert system has proven to be sufficiently efficient in the optimal incorporation of power flow conditioning devices for monitoring and improving conditions of power systems especially with integration of variable energy sources [5-8]. A multiple inputs fuzzy neural network model enhanced with one output unit was developed for voltage stability monitoring and enhancement of power system loadability margin in [9]. The input parameters to the developed model are the real and reactive power uncertainties, generator powers, bus voltages, and the parameters of the network conditioning device, which is the static VAR compensator (SVC). Diverse sequences of nonlinear fuzzy membership functions were introduced to achieve the transformation of the input variables into the fuzzy domain. Strategic feature reduction algorithms were enacted to reduce the input data set to facilitate fast and accurate performance in predicting the target output *i.e.*, maximum load limit applied to IEEE 30-bus and IEEE 118-bus systems. FL-based distribution network reconfiguration strategy with two-fold random and fuzzy information of load and renewable energy uncertainties was developed for power loss reduction and voltage stability enhancement using a modified PSO algorithm in [10]. The authors in [11] employed the expert FL system to determine the detailed critical information for monitoring and improving the voltage stability and the low voltage ride-through (LVRT) capability of an integrated power system. The FL-based control scheme increased the accuracy of the voltage stability information obtained for the optimal incorporation of the SVC.

The focus of this study is to investigate the capability of the ANFIS model for voltage stability prediction and to make informed recommendation on its deployment as a veritable tool for comparing the performance of four conventional line VSIs, namely LQP, FVSI, NLSI, and LMN [12], for precise voltage stability monitoring on power system networks. The result of this study provides information on the various existing line voltage stability monitoring tools and their adaptability for intelligent voltage stability monitoring. The remaining content of this manuscript is as follows: section 2 discusses the conceptualization of the mathematical models and methods adopted for the study. In addition, this section includes the derivation and definition of adequate conditions for voltage stability in power systems, the development and performance analysis of the proposed ANFIS-VSI models, and data preparation/feature description for training and validation of the ANFIS models. Finally, the study's results are presented and elucidated in Section 3, and the conclusion is presented in Section 4

II. Modelling and Methods

A. *voltage stability indices (VSI)*

The simple mathematical tools used for primary and approximate estimation of the voltage instability levels in a power system network are known as voltage stability indices (VSIs), using steady-state load-flow parameters.

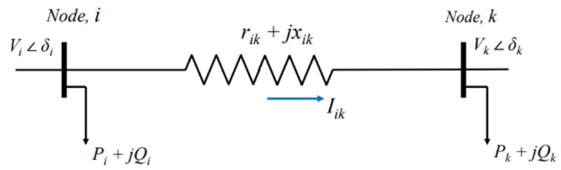

Fig. 1. A simple two-nodes transmission network [13].

For illustration, in the two-bus transmission network model shown in Figure 1, the relationship between the bus voltage and the real and reactive loading is shown in figure 2.

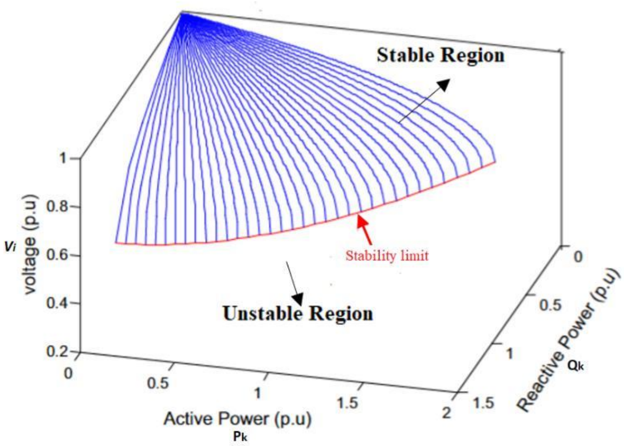

Fig. 2. voltage stability illustration using the PQ–V curve [14].

The corresponding line flow equation and consequent voltage stability condition are derived accordingly [13,14]. For the transmission network, the sending and receiving end buses are represented with the subscript notation *i* and *k*, respectively; (*P, Q*) is the complete description of the active power and reactive power loading at any bus, respectively. In addition, the voltage magnitude and corresponding phase angle at any bus is represented by the notation *V* and δ, respectively; the active and reactive parameters of the transmission lines are the reactance and resistance defined as *r* and *x*, respectively. Consequently, the power transfer equation at any receiving end bus *k* is derived:

$$P_k + jQ_k = (V_k \angle \delta_k)\left(\frac{V_i \angle \delta_i - V_k \angle \delta_k}{r_{ik} + jx_{ik}}\right)^* \tag{1}$$

$$(P_k r_{ik} + x_{ik} Q_k) + j(r_{ik} Q_k - x_{ik} P_k) = V_i V_k \cos(\delta_i - \delta_k) - jV_i V_k \sin(\delta_i - \delta_k) - V_k^2 \tag{2}$$

Further simplification of equation (2) gives a non-linear function which describes the voltage stability relationship in power system networks as expressed by equation (3). For stability to be maintained, the roots of equation (3) must be unique positive, and real; thus, equation (4) gives the specific condition governing the voltage stability of a given power system network.

$$V_k^4 + 2V_k^2(P_k r_{ik} + Q_k x_{ik} - 0.5V_i^2) + (P_k^2 + Q_k^2)(r_{ik}^2 + x_{ik}^2) = 0 \tag{3}$$

$$(P_k r_{ik} + Q_k x_{ik} - 0.5V_i^2)^2 + (P_k^2 + Q_k^2)(r_{ik}^2 + x_{ik}^2) \geq 0 \tag{4}$$

From equation (4), some VSIs for monitoring grid steady-state voltage stability based on transmission line criticality are derived using parameter approximation as given below.

$$\underline{LMN} = \frac{4x_{ik}Q_k}{(V_i \sin(\theta - \delta))^2} \tag{5}$$

$$\underline{FVSI} = \frac{4Z_{ik}^2 Q_k}{V_i^2 x_{ik}} \tag{6}$$

$$\underline{LQP} = 4\left(\frac{x_{ik}}{V_i^2}\right)\left(Q_k + \frac{P_i^2 x_{ik}}{V_i^2}\right) \tag{7}$$

$$\underline{NLSI} = \frac{4(P_k r_{ik} + Q_k x_{ik})}{V_i^2 \cos^2 \delta} \tag{8}$$

In this study, the performance of the above VSIs (equations 5 - 8) was comparatively analyzed using ANFIS models for the IEEE 30 bus system in normal loading and overload conditions to validate the parameter selection and derivation by approximation. *LMN*, *FVSI*, *LQP*, and *NLSI* are common conventional line voltage stability indices available in the literature; $z = r + jx$ is the line impedance, θ is the impedance/load angle, δ is the phase angle difference between the sending and receiving end bus voltages. Conventionally, the values of these indices for each line must range from 0 (for high stability condition) to 1.0 (for poor stability condition). Any value above 1.0 indicates a voltage collapse condition due to the extreme severity of the corresponding line.

B. *ANFIS model for voltage stability monitoring*

The basic fuzzy inference systems (FIS) are developed using the 'if-then' probabilistic rules. By this, the FIS can model decision-making qualitatively without specific distinctive quantitative annotations [15]. One versatile and well-adopted FIS is the ANFIS model, which has enhanced capability with the infusion of adaptive multilayer feedforward artificial neural network procedures. In this study, ANFIS models are developed to monitor and predict the power system's voltage stability condition based on steady-state load flow analysis-based voltage stability analysis procedure with VSIs as output. As illustrated below, important power system line parameters, bus power injections, and voltage details are deployed as the input features for the ANFIS implementation.

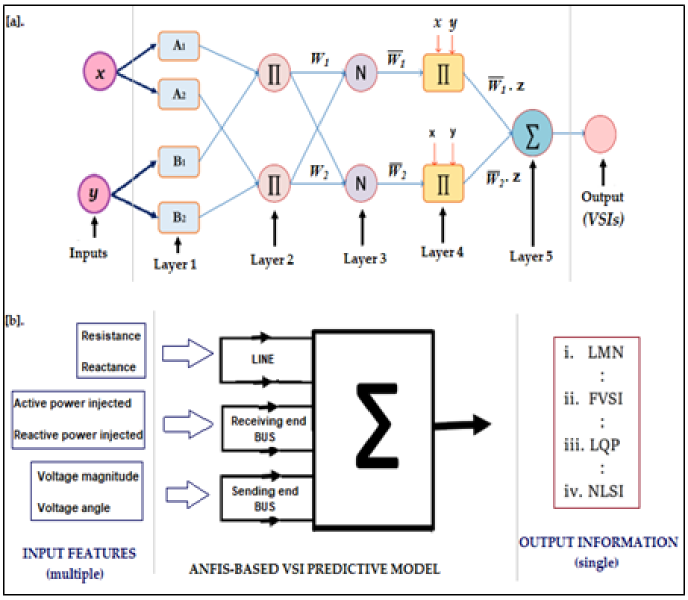

Fig. 3(a). five-layer architecture of ANFIS model [15]; (b). schematic of the implemented ANFIS-VSI model.

For the developed ANFIS model, Takagi–Sugeno fuzzy system with backpropagation gradient descent learning and least square error methods for output parameters estimation is deployed [15]. The ANFIS model organization contains five stages of information processing: fuzzification, multiplication, normalization, de-fuzzification, and summation, as illustrated in figure 3. An ANFIS model with multiple inputs (x,y) and single output (f) is implemented with two 'if-then' rules following the first-order Takagi-Sugeno model:

$$Rule\ 1\text{:}\ \ if\ x\ is\ A_1\ and\ y\ is\ B_1, then\text{:}\ f_1 = p_1x + q_1y + r_1$$
$$Rule\ 2\text{:}\ \ if\ x\ is\ A_2\ and\ y\ is\ B_2, then\text{:}\ f_2 = p_2x + q_2y + r_2$$

such that (A_k, B_k) are the fuzzy pairs, f_i gives the output in line with a specific fuzzy rule, and (p_k, q_k, r_k) are the ANFIS vital training parameters:

- The first layer is the square adaptive nodes for fuzzification which gives the membership grade and shows the agreement between the data variables.

$$O_k^1 = \mu_{A_k}(x);\ \ O_k^1 = \mu_{B_k}(y),\ \ k = 1,2 \tag{9}$$

- The second layer is the multiplicator which receives and applies appropriate weight to the input values from the first layer considering the influence of each membership function.

$$O_k^2 = w_k = \mu_{A_k}(x) \cdot \mu_{B_k}(y),\ \ k = 1,2 \tag{10}$$

- The third consists of fixed and non-adaptive nodes for the normalization of all the calculated firing strengths:

$$O_k^3 = \overline{w_k} = \frac{w_k}{w_1+w_2},\quad k = 1,2 \tag{11}$$

- The fourth layer is the defuzzification layer that deploys a first-order polynomial function for establishing the effect of the k-th fuzzy rule on the ANFIS model output (where $\overline{w_k}$ is the normalized firing strengths of each fuzzy rule.):

$$O_k^4 = \overline{w_k}(p_kx + q_ky + r_k) = \overline{w_k}f_k,\ \ k = 1,2 \tag{12}$$

- The last layer of the ANFIS architecture involves summing up all the incoming values from layer 4 for adequate translation into expected output values.

$$O_k^5 = \sum_k \overline{w_k}f_k = \frac{\sum_k \overline{w_k}f_k}{\sum_k \overline{w_k}} \tag{13}$$

The subtractive clustering approach is deployed in this study for tuning the training parameters for improved data handling [16]. The following performance metrics are used to analyze and validate the performance of implemented ANFIS models:

- Mean Absolute Percentage Error (MAPE):

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{\left|VSI_i^{cal.} - VSI_i^{pred.}\right|}{VSI_i^{cal.}} \times 100\%\right) \tag{14}$$

- Percentage Relative Root-Mean-Square Error (RRMSEp):

$$RRMSEp = \sqrt{\frac{\frac{1}{N}\sum_{i=1}^{N}\left(VSI_i^{cal.} - VSI_i^{pred.}\right)^2}{\sum_{i=1}^{N}\left(VSI_i^{pred.}\right)^2}} \times 100\% \tag{15}$$

- Coefficient of correlation (R):

$$R = \sqrt{1 - \left\{\frac{\sum_{i=1}^{N}\left(VSI_i^{cal.} - VSI_i^{pred.}\right)^2}{\sum_{i=1}^{N}\left(VSI_i^{cal.} - VSI_i^{mean}\right)^2}\right\}} \tag{16}$$

N is the data length, $VSI^{cal.}$ is the target VSI value, $VSI^{pred.}$ is the predicted VSI value/ANFIS output and VSI^{mean} is the mean of the target VSI values. For efficient predictive modeling, the value of $MAPE$ and $RRMSE_p$ is expected to be close to zero percent and a value of R close to 1.0 gives an efficient model that shows that the input features significantly influence the target [17].

III. Simulation, Results, and Discussion

A. Feature/data selection and simulation procedure

The ANFIS model is developed in Matlab 2022a using a hp EliteBook PC with Intel(R) Core (TM), i7-8650U processor with an average speed of 1.90GHz. As illustrated in figure 3, six power system parameters are considered as the input features determined from the transmission line data and the load-flow solution for six different PQ load levels. These are the line resistance and reactance pair (r_{ik},x_{ik}), active and reactive power injected at the receiving bus (P_k,Q_k), the bus voltage information at the sending bus (V_i) and the phase angle difference of voltages at both ends of the transmission line (δ_{ik}). The target/ prediction output is the values of the four VSIs considered one after the other (LMN; $FVSI$; LQP; or $NLSI$). The volume of the dataset deployed for training and testing the

ANFIS model is obtained by solving the power flow problem at different PQ-load levels.

TABLE 1. ANFIS MODEL IMPLEMENTATION PARAMETERS.

Parameters	Values
Number of input features	6
Number of output features	1
Training data length	172
Testing data length	74
Clustering radius	0.50
Epochs	500
Initial step size	0.01
Step size decrease rate	0.09
Step size increase rate	1.10

The real (P) and reactive (Q) loads at all the nodes/buses are step-wisely increased, and the load flow solution is ensured to be within the convergence limit for each load step. With the base PQ-load as the reference, PQ-loads at all buses are stepwise and uniformly increased by 10 percent up to 50 percent. The load-flow solution and corresponding voltage stability indices are evaluated and recorded for implementing the ANFIS model. Thus, the data length, $\boldsymbol{L_{data}}$ is (6 x $N_{br.}$), and the input data size is (6 x $N_{br.}$) by 6 and the output data size is (6 x $N_{br.}$) by 1; where $\boldsymbol{N_{br.}}$ is the number of lines/branches in the power system network. For the ANFIS-VSI model implementation, 70 percent of the entire data is selected as the training data set $\boldsymbol{L_{train}}$, and the remaining data are considered for testing $\boldsymbol{L_{test}}$ using a clustering radius, r = 0.5. Thus, for the IEEE 30-bus system with 41 lines, $\boldsymbol{L_{data}}$ = 246 ($\boldsymbol{L_{train}}$ = 172, and $\boldsymbol{L_{test}}$ = 74); the voltage magnitudes at all buses for the six load levels are shown in figure 4, and the ANFIS implementation parameters are presented in table 1.

B. Result discussion

For several runs of the VSI prediction models, the error performance metrics are calculated and recorded. Figures 5 and 6 show prediction performance curves and regression plots for the best run (with minimum *MAPE* values) for the four considered ANFIS-VSI models, respectively. The *MAPE*, *RRMSEp* and *R* values for the runs with minimum and maximum *MAPE* and the average of all the runs are recorded in summary table 2.

From the results, it is observed from the three considered performance metrics that the four ANFIS-VSI models indicate that the four VSIs have sufficient abilities for monitoring the voltage stability condition of power systems. FVSI, with an average MAPE value of 4.7429%, for ten simulation runs over a range of 2.0870% to 6.6574%, has the best performance efficiency for voltage stability indication.

ANFIS-FVSI model performance trend is supported by the average *RRMSEp* = 0.2078%, which is the lowest out of all the VSIs and the best average value of R = 0.99888. The LMN-ANFIS model recorded the next performance with average *MAPE* = 5.6165%, *RRMSEp* = 0.3230%, and *R* = 0.99862. The NLSI-ANFIS model recorded an average *MAPE* = 12.4684%, *RRMSEp* = 0.3052%, and *R* = 0.99759.

The VSI with the least performance for ANFIS predictive analytics is the *LQP* with *MAPE* values ranging between 11.9994% and 16.5558% with the average *MAPE* = 14.7167%; the *RRMSEp* = 0.3006% and *R* = 0.99718. Both the *RRMSEp* and *R* values show significant performance efficiency for the four VSIs, and the differences in *RRMSEp* and *R* do not show much information on the superiority of one VSI over the other.

However, from the *MAPE* values, the order of performance efficiency of the four steady-state voltage stability indices indicates a sufficiently high level of agreement between the estimated and predicted values of *FVSI*. Thus, the *FVSI* is established as being more consistent for voltage stability monitoring out of the considered VSIs. The recorded *MAPE* values are consistent with the prediction curves of the four VSIs considering the test dataset as presented in figure 5 and the regression and data distribution plot for all the datasets as shown in figure 6.

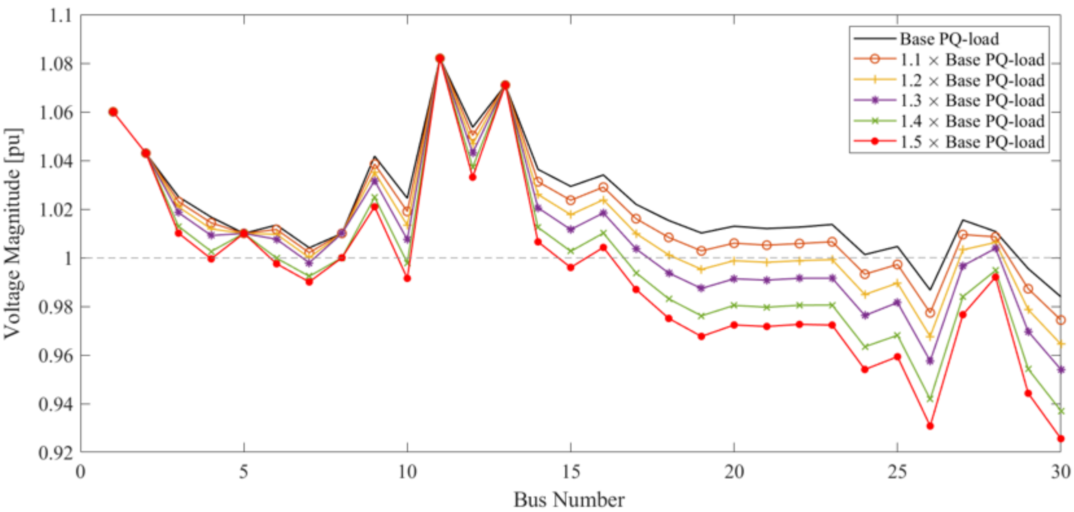

Fig. 4. Bus voltage magnitudes at different PQ load levels

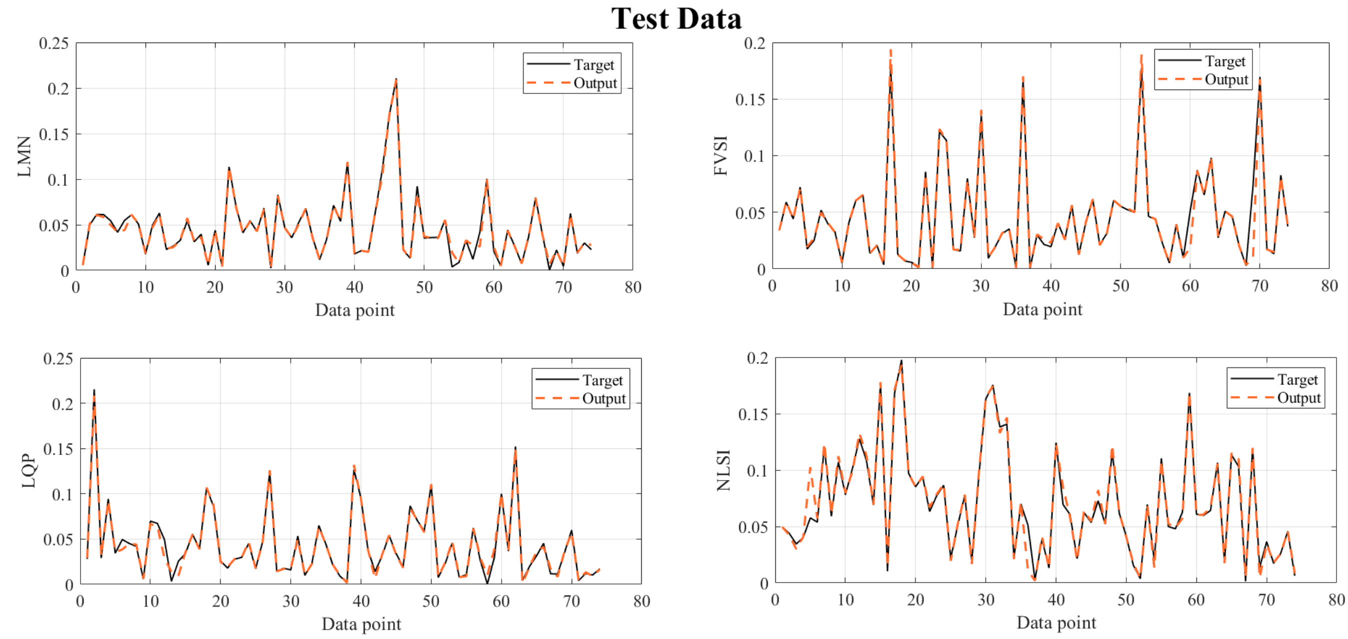

Fig. 5. Predicted versus target VSI values for the testing dataset (74 data points)

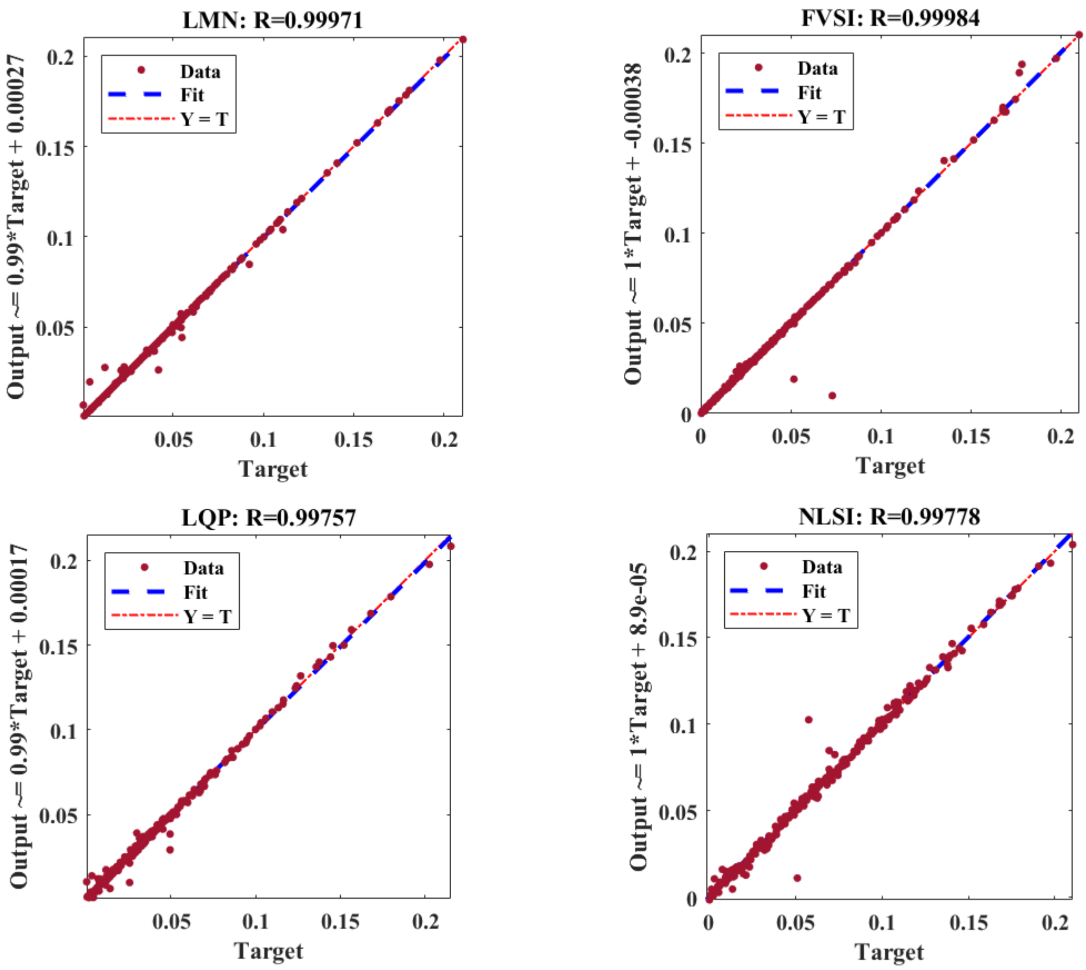

Fig. 6. Regression analysis of predicted and target VSI values.

TABLE 2. SUMMARY OF ANFIS-VSI MODELS PERFORMANCE.

VSI	RUNS	MAPE (%)	RRMSEp (%)	R
LMN	Minimum	3.2732	0.1871	0.99971
	Maximum	9.9997	0.3289	0.99722
	Average	5.6165	0.3230	0.99862
FVSI	Minimum	2.0870	0.1787	0.99984
	Maximum	6.6574	0.3140	0.99311
	Average	4.7429	0.2078	0.99888
LQP	Minimum	11.9994	0.2237	0.99757
	Maximum	16.5558	0.3338	0.99703
	Average	14.7167	0.3006	0.99718
NLSI	Minimum	10.6755	0.2445	0.99778
	Maximum	15.0701	0.3130	0.99631
	Average	12.4684	0.3052	0.99759

IV. CONCLUSION

Most often the available voltage stability indices are judged to be inconsistent in their performances, especially as the system load increases and the system operation advances towards the stability limit. Thus, the performance of some steady-state line VSIs for monitoring the voltage stability condition of power systems was compared in this study using the machine learning-based intelligent prediction approach based on ANFIS model. Vital power system load flow and voltage stability parameters estimated at different loading conditions are adopted as data for the ANFIS implementation. The performance of the implemented ANFIS-VSI models was carried out using statistical analysis and error estimation of the difference between the targets and the ANFIS predicted outputs (*i.e.*, *MAPE*, *RRMSEp*, and *R*). From the simulation results, the consistency of *FVSI* as a more reliable tool for effective voltage stability monitoring, is established, followed by *LMN*, *NLSI*, and *LQP* in that order. The analysis reported in this work will be extended to contemporary machine learning and deep learning models for performance and parameter validation for intelligent systems-based voltage stability analysis and this can help power system planners and operators devise smarter diagnostic tools for making informed and more precise decisions for power system security planning.

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