

Data Analytics for Substation Overloading Assessment of Solar Integrated Distribution System

Jagdish Prasad Sharma

Abstract: It is an important concern to supply uninterrupted power to consumer under competitive environment. Therefore, available reserve margin of substation transformer is utmost concerns for power utilities due to its direct effects on power quality, reliability and revenue loss. This research work focus on data analytics application to predict substation overloading assessment for integrated distribution system. This paper has developed three adaptive neural fuzzy interface system (ANFIS) to predict the available substation reserve margin by considering base case and different solar integration scenarios. The ANFIS models were trained and tested using stochastic data obtained from load flow computation for a modified IEEE 37 feeder. To train ANFIS models, input variables are taken as “voltage unbalance factor, feeder power loss to load ratio, maximum branch loading, voltage deviation, and minimum power factor”, while target variable is taken as substation reserve margin”. All predications of ANFIS models are compared with those values obtained from load flow computation. It was found that predicated results have good agreement with load flow computational data and R-squared value fall in the range of 0.9182 to 0.9173. The proposed research work is useful to predict operational performance of integrated solar distribution system in smart grid environment.

Keywords: Solar energy, substation reserve margin, adaptive neural fuzzy interface system, data analytics.

I. INTRODUCTION

The losses of transmission and distribution are majorly occurred in the distribution system. According to the central authority of India it was reported 21.04% of the year 2017-18[1]. These losses are a key deciding factor for utilities in predicting investment, new extension works, renovation works and effective evaluation of networks. Therefore, utilities are enforced for solar photovoltaic system integration with low voltage or medium voltage network. As DG integration has a great impact on voltage profile, power flow, operational practices and fault level. An integrated distribution system has to ensure quality, reliable, economic and stable power supply. The major technical challenge is to decide the penetration level of DG with optimal performance on the distribution system. In the recent restructured environment, the concept of smart grid in power system has evolved significantly. The DG integration impact study is a significant concern to understand feeder behavior before implementing smart grid at distribution level. As the

electricity consumption pattern, appliance voltage sensitivity, construction and operation of distribution network greatly affected the optimal performance of an integrated distribution network. Therefore, an intelligent system should have a greater adaptability in accordance with above distinguish factors affecting optimal performance. In smart grid, intelligent and optimization techniques are utilized for optimal performance of the power system. In this context, ANFIS model found reliable for solving such predictive problems highly depend on the operator.

An ANFIS model is proposed to minimize energy consumption for communication networks [2]. Adaptability of learning contents is a seriously challenging task in the digital era. An ANFIS model is designed to enhance the learning process for mobile learners [3]. A density of biodiesel compared experimental data with predication by ANFIS and Radial Basis Function (RBF) [4]. A feasibility and rapidity of power flow solution for IEEE 39 bus system has demonstrated by ANFIS [5]. ANFIS is effectively employed for obtaining optimal network reconfiguration of distribution network [6]. ANFIS implemented to predict a technical loss for low voltage distribution system [7]. Annual electricity load forecasting by ANFIS model recommended for planning the electricity system on the Bali Island [8]. The DG integration have greatly influenced by sizing, location and a penetration level of DG. In this context, a study was analyzed for modified IEEE 37 node test feeder. This feeder has voltage sensitive and time varying load pattern [8]. This paper is an extension of ref. [8] and its results are utilized to train and testing ANFIS models. In the present work, the substation reserve margin was predicted using three ANFIS models. The input variables for these models were “voltage unbalance factor, feeder power loss to load ratio, maximum branch loading, voltage deviation, and minimum power factor”. Moreover, this study aimed to compare linear fitting of all predictions with load flow computational values for substation reserve margin.

II. TEST SYSTEM AND DATA COMPUTATION

A. Test System and data preparation

Unbalance is occurred in practical distribution feeders due to construction and operational aspects. This unbalance phenomenon degrades power quality and led underutilization of feeder margin. A forward backward sweep based load flow computation was done for a modified IEEE 37 node test feeder under different solar photovoltaic system integration

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scenarios [9]. For ANFIS model, input variables are “voltage unbalance factor, feeder power loss to load ratio, maximum branch loading, voltage deviation, and minimum power factor” and substation reserve margin as predicted variable. Each above indices are computed at each 15-minute metering time interval for a whole day under different scenario as mentioned in table 1. The penetration level of DG is evaluated on the basis of substation transformer capacity (2.5 MVA) and DG is considered to operate at unity power factor [9].

Table- I: DG integration scenarios

Scenario	DG Details		
	Penetration level	Case	DG node location
Scenario-0	0%	Base Case	Without DG integration
Scenario-1	10 %	DG case1	725,724,742,702,718,735,736,728,740,732
Scenario-2	15 %	DG case 2(a)	728, 718, 724, 725, 732, 736, 702, 735, 740, 742
	15 %	DG case 2(b)	702,718, 724, 725, 728, 732, 736, 735, 740, 742
Scenario-3	38 %	DG case3	701, 710, 732, 740

The test feeder without distribution generation integration are considered as Scenario-0. In Scenario-1, ten distributed systems having equal capacity of 2.50 KW are taken. Scenario-2, a single 375 KW capacity DG connected at single node and 0.465 KW capacity DG was connected at rest of nine nodes. In scenario 3, four different capacity DG systems were connected at 701 (6% penetration level), 710 (11% penetration level), 732 (3% penetration level), and 740 (8% penetration level).

The six above performance indices are computed for 96 metering time interval under all five different scenarios [9]. The selection criteria for above six parameters is mentioned in table 2.

Table-II: Selection criteria of parameters

Parameters	Criteria for data set selection	Data Size	
		Actual data size	Selected data size
Branch loading	Maximum value of all phase	3*96*5	1*96*5
Substation reserve margin	Actual value	1*96*5	1*96*5
Minimum power factor	Minimum value of all phase	3*96*5	1*96*5
Feeder power loss to load ratio	Maximum value of all phase	3*96*5	1*96*5
Voltage unbalance factor	Actual value	1*96*5	1*96*5
Voltage deviation factor	Maximum value of all phase	3*96*5	1*96*5

The selected data sets were normalized in a comparable range by Eq. (1). The resulting normalized values for both training and checking variable with adopted features are presented in Fig. 1 and 2 as boxplot. In boxplot, 25th and 75th percentiles for normalized data represent by the bottom and top edges, respectively. Also, median is depicted by central mark. The most extreme data are plotted individually using the '+' symbol. Fig. 1 shows that the normalized features maintain the probabilistic distribution they had before the normalization.

$$X_{\text{Normalized}} = \frac{X_{\text{actual}} - \min(X)}{\max(X) - \min(X)} \quad (1)$$

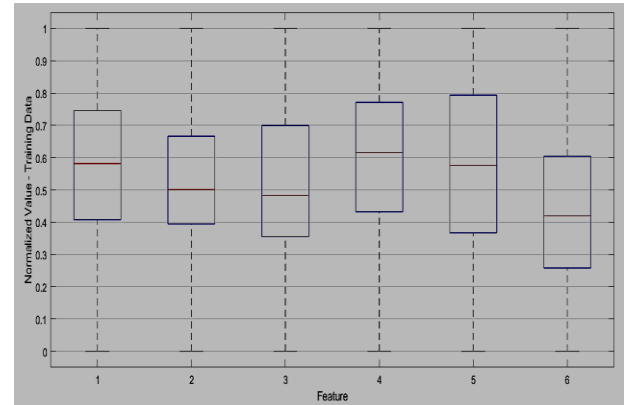


Fig. 1. Normalization of training data

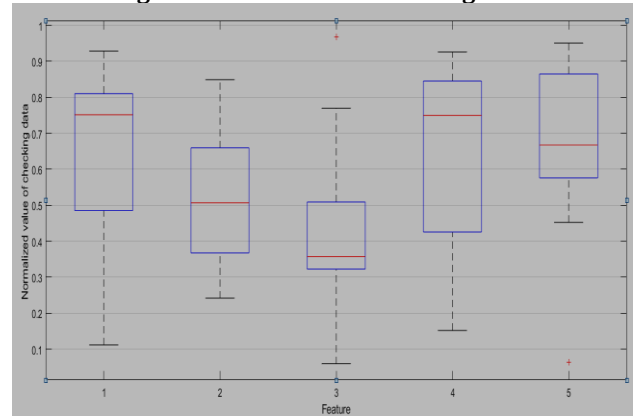


Fig. 2. Normalization of checking data

B. Adaptive neuro-fuzzy inference system

ANFIS model has developed with five input variables as “voltage unbalance factor, feeder power loss to load ratio, maximum branch loading, voltage deviation factor, and minimum power factor”. A single output for this model is substation reserve margin as illustrated in Fig. 3.

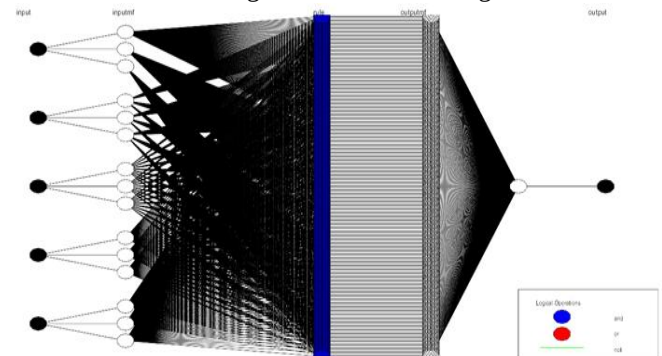


Fig. 3. Structure of ANFIS model for a five input single output

Table-III: ANFIS structure information

Parameter	ANFIS Model		
	ANFIS-I	ANFIS-II	ANFIS-III
Number of nodes	5	5	5
Membership Functions	Gaussian	Triangle	Generalized bell

Parameter	ANFIS Model		
	ANFIS-I	ANFIS-II	ANFIS-III
Epoch Number/ Fuzzy rules	40/243	40/243	40/243
Parameters linear/ nonlinear	243/30	243/45	243/45
Error-Training/ Checking	0.000867 /0.00426	0.001147 /0.00334	0.000860 /0.004124
Number of nodes	5	5	5

The ANFIS models have five layers and will automatically tune according to the training data set. In this paper three different membership functions such as “Gaussian Shaped, Triangle Shaped, and Generalized bell shaped” are utilized to model ANFIS separately. The major concerns for ANFIS modelling are type of membership functions, selection of data sets for training/testing/checking, epoch number, optimization technique. Layer 0 serve as input layer and layer 1 evaluate membership function for the three inputs. Layer 2 calculates the firing strength of 243 rules and its output normalized in layer 3. The substation reserve margin is computed by taking the overall sum of layer 3 outputs. It was found that generalized bell shaped function has least RMSE and layer 3 uses constant defuzzifier. In this work, training set (80%), testing set (10%), and checking set (10%) was randomly obtained from data set. A fuzzy inference system is generated by the grid partitioning method and hybrid training optimization method.

III. RESULTS AND DISCUSSIONS

ANFIS models has developed in MATLAB environment by using computational data sets. Three different membership functions such as “Gaussian Shaped, Triangle Shaped, and Generalized bell shaped” are utilized to model ANFIS separately.

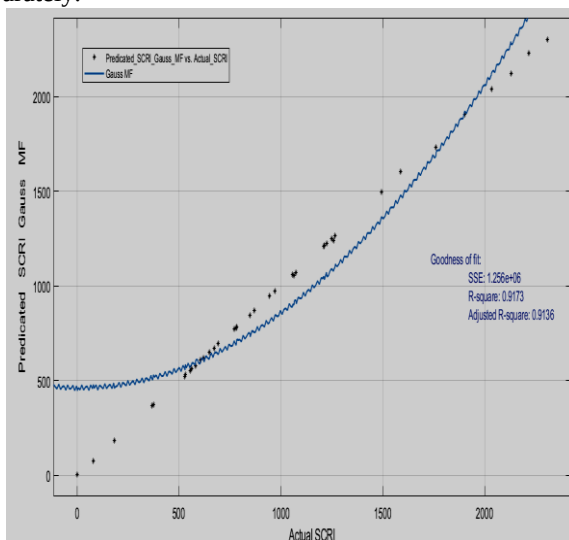


Fig. 4. ANFIS-I prediction and computation values

It was found that ANFIS models with generalized bell shaped function have least RMSE. For better accuracy of actual substation reserve margin, the tested data of ANFIS models are multiplied by the base KVA margin (2500 KVA). Then data fitting was tested on all three ANFIS models. R-squared (R2) value of ANFIS models varies from 0.9182 to 0.9173.

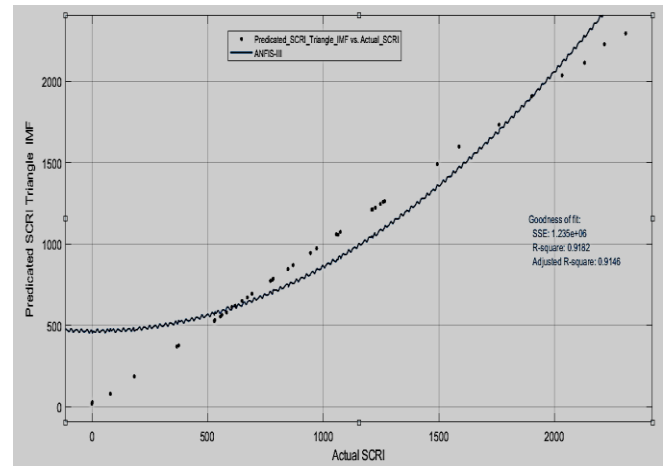


Fig. 5. ANFIS-II prediction and computation values

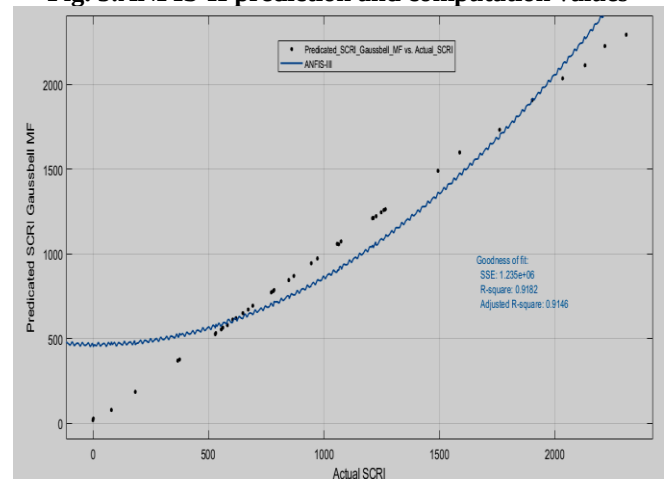


Fig. 6. ANFIS-III prediction and computation values

IV. CONCLUSIONS

This research work is an application of data analytics to predict substation overloading assessment for integrated distribution system. Under competitive environment, power utilities are needed to supply reliable and qualitative power to consumers. Therefore, it is essential to have adequate reserve margin to protect substation transformer against overloading conditions. In this paper, ANFIS models have developed to predict the substation reserve margin as a function of “voltage unbalance factor, feeder power loss to load ratio, maximum branch loading, voltage deviation, and minimum power factor”. The data sets for training and testing of models have considerable diversity in terms of DG integration scenarios, unbalance characterization of feeder and voltage sensitive load models. A comparison between computational and predicted values of substation loading margins has good correlation as demonstrated in figure 4 to 6. It is observed that R-squared value of ANFIS models float in the range of 0.9182 to 0.9173.

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Dr. Jagdish Prasad Sharma, holds Doctorate in the area of “Power and Energy” and holds M. Tech. degree in “Power Systems” from Malaviya National Institute of Technology Jaipur. He had fifteen years plus of blend experience in academics and industry. Prior to venturing into the field of academia, he has worked as Assistant Engineer in Chhattisgarh State Electricity Board, Raipur for 4 years and 06 months in the area of power distribution system. His teaching experience includes, teaching subjects like –Electrical Machines, Power system, Modeling and Simulation, Industrial Electronics, Disaster Management etc. His area of interest is Modeling & Simulation, Soft computing, Power system and Renewable energy system. He is recipient of full travel international travel support from the Science and Engineering Research Board (SERB), New Delhi in faculty cadre. His research work is recognized by (a) Prof. Dr.-Ing. Hartmut Hinz Frankfurt University of Applied Sciences, Germany, (b) Electrical Research and Development Association (ERDA), Vadodara, and (c) Prof. Kyung Chun Kim, Pusan National University, South Korea. He had published many researcher papers with IEEE, Springer and reputed publisher. He received best paper award certificate for “Application of Solid State Fault Current Limiter on Express Feeder for Voltage Sag Mitigation” in 2014 IEEE International Conference on Computational Intelligence and Computing Research, Dec. 18 - 20, 2014. He is also contributing to various national and international events through various committee membership, paper presentation, reviewer and editorial membership.