Reducing Instability in Power Distribution Network Using Intelligent Control of System Load Frequency Changes

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Abstract: **This work presents reducing frequency instability in power distribution network using intelligent control of system load frequency changes. The study reviewed literatures and identified that load changes affects frequency which causes transient instability. Empirical study of the Independence Layout Injection 15MVA Substation was performed from the data collected at Enugu State Electricity Distribution Company (EEDC). From the study it was observed that critical time which are the peak periods are 13:00; 17:00 and 21:00hrs respectively and hence need automatic control. This was achieved using mathematical and structural modeling approach which employed data collection, self defining equations, and neural network, to develop a load frequency controller and then tested with Simulink. The result showed that the controller was able to monitor the load flow in the during the identified peak periods to control the load and hence maintain stable frequency.**

***Keywords*: Frequency Changes, Instability, Power Distribution, Neural Network, Substation, Load**

I. INTRODUCTION

In electric power system certain parameters like current, voltage and frequency can be controlled, while user load cannot be controlled but can be monitored manually by system operators to ensure that the peak load are not allowed to affect the margin and sensitivity of load flow. However most of the time, the load exceed the desired margin without the notice of the system operator, thereby causes transient instability among other problems as a result of load frequency changes. To solve this problem there is need for an intelligent system which monitors this load and ensue they do not exceed the desired limit. This will be achieved in this research using Load Frequency Controller (LFC) (Ashmoe and Battebury, 1974).

According to Bahtti and Hiyama (2009), LFC is the process of controlling real power output of generating units in response to changes in system frequencies and tie-line interchange within specified limit. It is one of the most important control problems in the design and operation of power systems, whose role is to keep the frequency unchanged by the load, to ensure that the correct values of interchanged power between control areas, to maintain each unit's generation at the most economic value and to ensure the non-violation of operating limits.

Different control strategies have been proposed in various epistemologies for the controller design. The most widely used were classical Proportional Integral (PI) and Proportional Integral Derivative (PID) controllers (Juang and Lu, 2006) due to their implementation simplicity.

The syntheses of these controllers are based on the power system model, but the variation nature of the model parameters or the system operating points leads to the degradation of the controlled system performances.

To rectify these problems, other emerging strategies have been proposed to enhance the performance of such classical controllers, Adaptive controllers, Robust genetic based controllers, Linear controller (Milan, 1972; Pan and Liaw, 1989; Rerkpreedapong et al., 2003; Shuda et al., 2012). Furthermore, the use of two degrees of freedom based PID controller in two and three areas considering some nonlinear constraints (Al-Amin and Kamrul, 2016). Other propositions based on fuzzy logic controller have been proposed in two area reheat-thermal systems (Khodaba and Hooshmand, 2010). The use of fractional controller has been also implemented by several researchers. However despite their success the performance load variation still affects the frequency stability.

This paper proposes to address the problem using Artificial Neural Network (ANN). This ANNs are biologically inspired perceptrons which are modeled to learn and make accurate control decisions. This will be adopted in this research and trained with the load to learn and control frequency to provide stability. To achieve this, literatures were review and presented in the table 1;

Table 1: Systematic Review of Relevant Literatures

AUTHOR	TITLE	TECHNIQUE	WORK DONE	RESEARCH GAP
Hassan et al. (2019)	Challenges and optimization of load frequency controller in conventional modern and future smart power system	Automatic load frequency controller	The study developed an automatic load frequency controller model and deployed for the stability of frequency variation due to load changes	Load changes was not considered
Yossef et al. (2019)	Voltage and frequency based load dependent analysis model for Egyptian power system network	Computational method	The study developed a model of load flow with frequency changes and used to analyze the effect of voltage stability in Egypt power system	Machine learning was not used
Chakrabarti and Srivastava (2015)	Power system load modeling under large and small disturbances using phasor measurement units data	Phasor measurement units	The study was able to assess the load flow behavior under uncertain times and in real time using synchophasor system in PMU	Machine learning was not considered
Jayasankar et al. (2017)	Estimating voltage stability index for power system security using artificial neural network	Artificial neural network	The study generate data of voltage stability index and train with ANN for prediction of voltage collapse	Frequency was not considered
Samuel et al. (2017)	Prediction of voltage collapse in electrical power system using new voltage stability index	New line stability Index	In the study the new line stability index was used to gauge the proximity of a given operating point to voltage instability.	The performance can be improved using artificial intelligence
Sharma et al. (2018)	Voltage stability assessment using artificial neural network	Artificial neural network	The study developed a neural network based load flow assessment and prediction model for voltage collapse	Frequency was not considered
Xu et al. (2016)	Voltage stability analysis based on adaptive fuzzy logic considering load fluctuation	Fuzzy logic	In the study the fuzzy logic was use to assess the load flow stability index of the IEEE based power system and predict instability	The performance can be improved to be more reliable using machine learning
Panda and Chauhan (2014)	Voltage collapse prediction by Neuro fuzzy scheme	Artificial Neural network and fuzzy logic	The study used artificial neural network to improve fuzzy logic inference engine used for the stability assessment of load flow index	Frequency was not considered

II. EMPIRICAL DATA COLLECTION

This paper collected data from of the Independence Layout 15MVA Injection Substation. The data of the feeder were collected from the EEDC on the 24th August 2021 for 24hours, considering the total load behavior and frequency change. The study showed that the average peak period are 13.00; 17:00 and 21:00 respectively and that frequency exceeds the standard of 49.05- 50.05 of the Nigeria Electricity Regulatory Commission; the model used to study the testbed are presented using the formulation below;

Problem Formulation of the Load Frequency Characteristics

Normally frequency is a function of load. When user load varies, it proportionally affects the stability of frequency, thus leading to fluctuations in the power system. The steady state load flow with frequency change is presented using the models below (Panda and Chauhan, 2014);

$$P_l = P_{lo}\left(1 + k_{pv}\ \frac{v-v_o}{v_o}\right)(1 + k_{pf}\ \frac{f-f_o}{f_o}) \qquad 1$$

$$Q_l = Q_{lo}\left(1 + k_{qv}\ \frac{v-v_o}{v_o}\right)(1 + k_{qf}\ \frac{f-f_o}{f_o} \qquad 2$$

where P_{lo}, Q_{lo} are real and reactive power at initial voltage (vo) and frequency (fo), f = w_e/2pi.

The overall load flow in the feeder is presented using the relationship between equations 1 and 2 and also the frequency function (f) to present the equation 3;

$$\sum P_{mi}(w_e) - P_{lqk}(w_e) \qquad 3$$

Since loads are not dependent on voltage signal but frequency; hence real power load variation is presented using the model in equation 4;

$$P_l = P_{lo}(1 + k_{pf}\ \frac{f-f_o}{f_o}) \qquad 4$$

Equation 3.4 presented the frequency variation due to changes in active power. Furthermore more since the frequency changes are independent of reactance, the frequency stability model is presented using the model in equation 5 (Panda and Chauhan, 2014);

$$\sum P_{mi}(1-l) - \sum P_{lqk} - \sum P_{lqk}\, k_{pfk}\,(\frac{f-f_o}{f_o}) \qquad 5$$

From the equation 3.5, the frequency change was deducted as;

$$\frac{f-f_o}{f_o} = \frac{\sum P_{mi}(1-l) - \sum P_{lqk}}{\sum P_{lqk} k_{pfk}} \qquad 6$$

III. DEVELOPMENT OF THE LOAD-FREQUENCY CONTROLLER

To develop the neural network controller, first the reference model of the plant (load) to be controlled must be defined mathematically using the non linear auto regressive model (NARMA) to present as;

y(k+d)=N(y(k),y(k−1),…,y(k−n+1),u(k),u(k−1),……u(k−n+1)) 7

Where u(k) is the system input load, N is the non linear function (frequency), and y(k) is the system output, n is the number of neurons. Now that it has been defined, neural network architecture in figure 2 was trained with the data using the model in equation 8 and back propagation algorithm (see figure 3).

ˆy(k+d)=f(y(k),y(k−1),…,y(k−n+1),u(k−1),…,u(k−m+1))+g (y(k),y(k−1),…,y(k−n+1),u(k−1),…,u(k−m+1))·u(k) 8

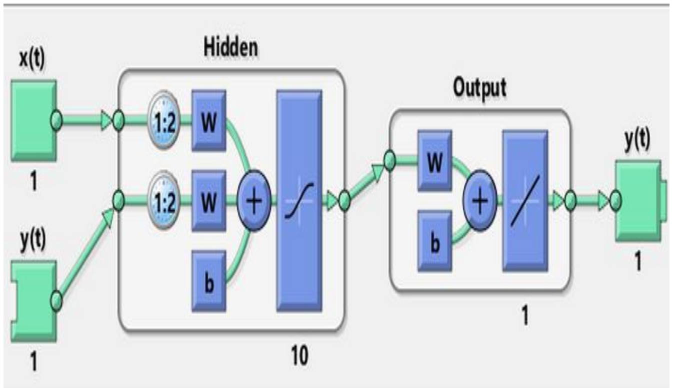

Figure 2: Structure of the artificial neural network

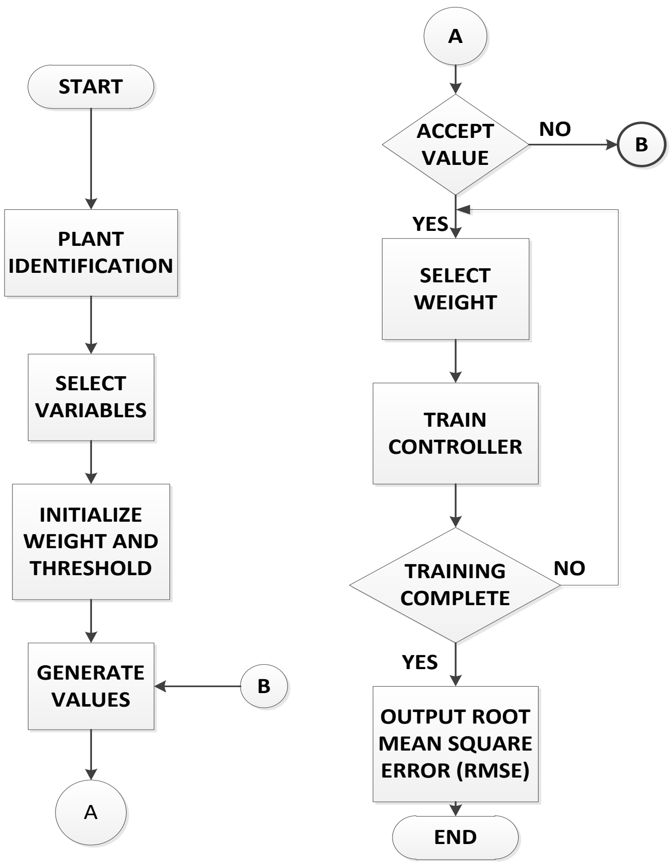

Fig 3: Flowchart for ANN Training Algorithm

Training of the Network

It was said that the Feed forward Back-propagation undergoes supervised learning with a finite number of patterns consisting of an input pattern and a desired output pattern (Valluru, 1995). At the input layer, the input pattern is presented. Then, the input layer neurons pass the activations to the next layer neurons i.e. those in the hidden layer. The outputs of the hidden layer neurons are obtained by introducing a bias, and also a threshold function, with activations determined by the weights and the inputs. The output from the hidden layer becomes the input to the output neurons, which process the input using an optional bias and a threshold function. Then the final output of the network is determined by the activations from the output layer.

During this training process, the aim is to achieve optimal number of hidden layer neurons and also the learning parameter (Okafor, 2017). So, through training of different combination of hidden layer neurons and the learning parameter, the optimal number of hidden layer neurons and the learning parameter were obtained. The following parameters as shown in tables 2 were used.

Table 2: Neural Network Parameters

Parameters	Values
Controller Training epochs	10
Size of hidden layers	10
Controller training segments	30
No. delayed reference input	2
Maximum plant output	3.1
Maximum plant input	15
Number of non hidden layers	2
Maximum interval per sec	2
No. delayed controller output	1
No. delayed plant output	2
Minimum reference value	-0.7
Maximum reference value	0.7

The training process was used to generate a reference load estimation model of the neural network controller as shown.

$$u(k+1) = \frac{y_r(k+d) - f[y(k),,,,,,y(k-n+1),u(k),,,,,,u(k-n+1)]}{g[y(k),,,,,,y(k-n+1),u(k),,,,,,u(k-n+1)]} \quad 9$$

The model in equation 9 presented the neural network controller developed for the control of over load in the distribution transformer. The model was generated after the training of the neural network model with the extracted data of the distribution transformer load flow.

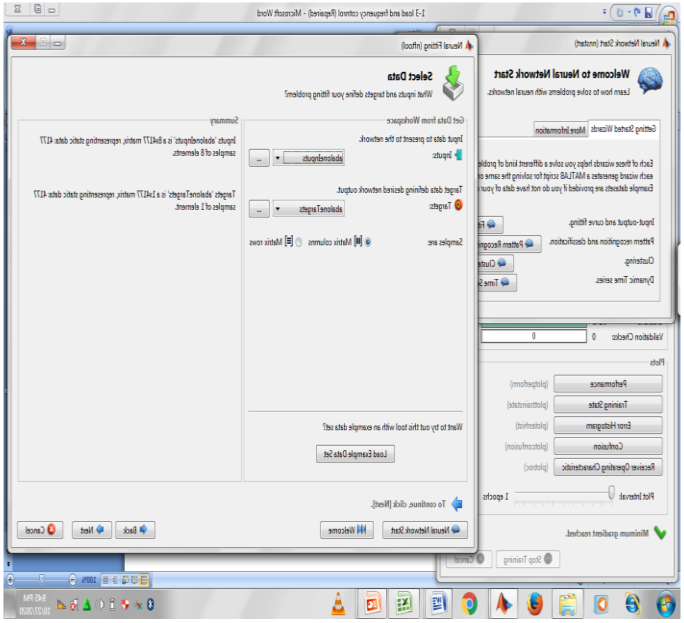

Figure 4: The neural network training tool

The Neuro Load estimation model

The model of the controller is based on the preceding horizon technique, which uses the reference model in equation 9 to make load estimation and ensure that any over load do not affect the power system. This technique is time series control tools used by neural network to control the classified frequency changes after training. The neural network controls the distributive network frequency response over the specified time horizon. The control is numerical optimization programs which determine the feature vectors that minimize the training performance criterion over the specified horizon as shown below;

$$J = \sum_{j}^{N2} yr(t+j) - ym\,(t\ +j))^{\wedge}2\ +\ p;\ \sum_{j=1}^{Nu} u'(t+j-1) - u'(t+j-2)2 \qquad 10$$

Where N_1, N_2, and N_u define the horizons over which the training error and the control features are evaluated. The u′ variable is the tentative feature vectors, y_r is the desired response, and y_m is the network model response. The p value determines the contribution that the sum of the squares of the control increments has on the performance index. The model consists of the neural network training model and the optimization block. The optimization block determines the values of u′ that minimize j, and then the optimal u is input to the network.

IV. IMPLEMENTATION

This paper was implemented using the mathematical model of the load frequency characteristic of the distribution transformer which is the load, the load frequency controller and then deployed in simulink using artificial neural network toolbox, control system toolbox and optimization toolbox. The simulink block is presented in figure 5;

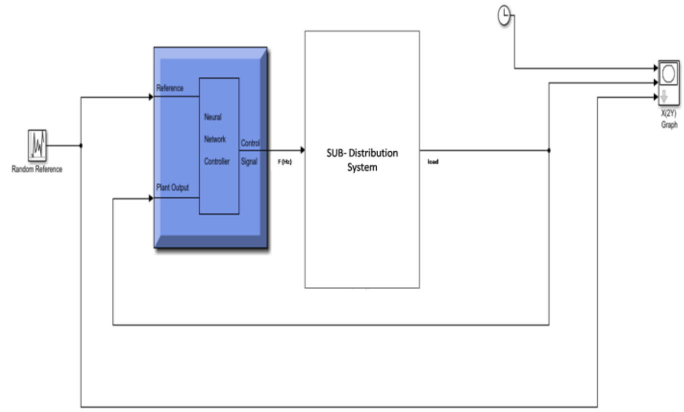

Figure 5: Simulink model of the neuro frequency controller

The simulink model shows how the controller was connected to monitor the load and control the distribution system from frequency instability. The monitoring was done collecting data of the transformer on hourly bases and then comparing with the reference model in equation 9 to detect over load and control using the load estimation model in equation 10.

V. RESULTS AND DISCUSSIONS

The result of the simulation model developed was discussed here. The simulation was done using the parameters in table 2, from the simulink running process, the neural network mean square error performance was reported using the model in equation 11;

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (A_I - B_i)^2 \qquad 11$$

Where A_i is the predicted values, B_i is the observed values, n is the number of feature points of the data. The MSE result is presented in the figure 5;

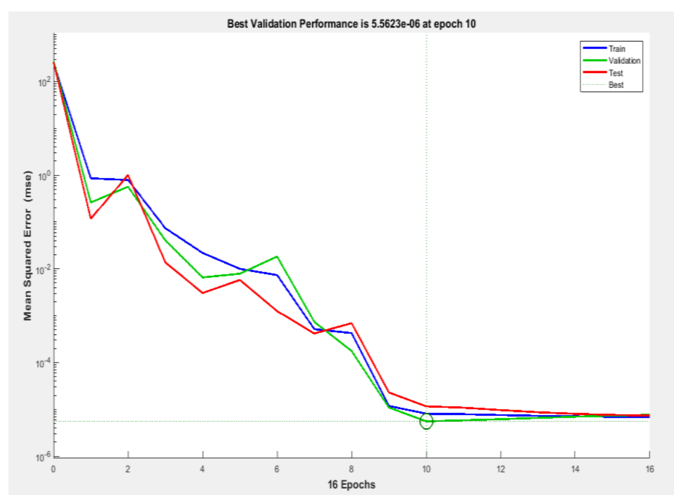

Figure 5: Mean Square Error Performance

The mean square error analyzer is an analytical tool for the evaluation of the neural network training performance. This tool simultaneously presents the training performance of the test, validation and training sets respectively.

From the result, the average MSE of the multi sets were computed and the result is 0.00055623 at epoch 10. The implication of the result showed that the MSE of the neural network based load frequency controller developed, recorded an error value approximately 0 (zero) which is very good.

The next result presented the regression result of the multi set using the model in equation 12;

$$R = f(X_i, \beta) + e_i \qquad 12$$

Where R is the dependent variable, f is the function, Xi is the independent variable, ß is the unknown parameters and e_i is the error terms.

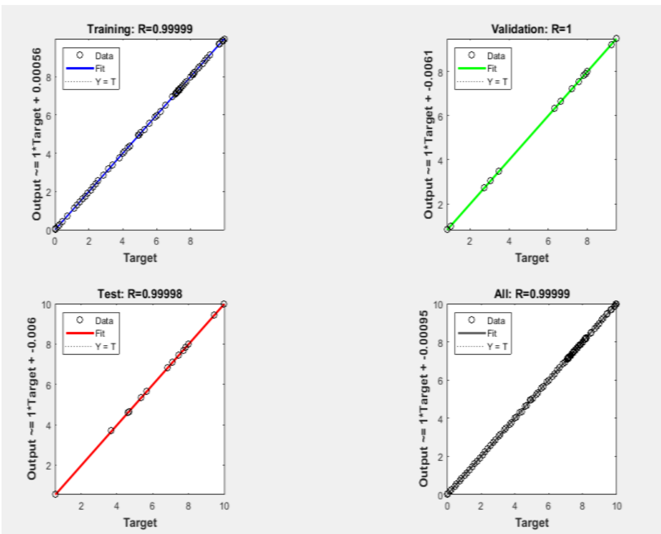

Figure 6: ROC analyzer

The result in figure 6 presents the training performance of the frequency controller developed with neural network; the aim of this ROC analysis is to achieve a regression result of or approximately 1. The result showed that the regression computed with the average of the three sets is 0.99999 which is approximately 1, implying good result. The results achieved were validated using tenfold cross validation model in equation 13;

$$CVA = \frac{1}{10}\sum_{1}^{10} \text{Ai} \qquad 13$$

Where CVA stands for Cross Validation Accuracy, A is the accuracy measure for each fold.

The model in the equation 13 was used to validate the result of the R and MSE respectively using computer aided approach and the value 0.9989 and 0.000520613Mu respectively.

System Integration

The load frequency controller developed was integrated at the testbed and then used to monitor and control over load. The performance was presented in the table 3;

Table 3: Performance of the Neuro Load-frequency controller

Time (hr)	Load Sum (MVA)	Frequency (Hz)
1	8.80	50.03
2	8.30	50.00
3	8.42	50.04
4	10.00	50.04
5	10.07	50.04
6	8.02	50.01
7	8.30	50.03
8	8.10	50.01
9	9.20	50.03
10	10.60	50.02
11	12.20	50.04
12	13.00	50.03
13	**07.50**	**50.03**
14	13.70	50.00
15	12.40	50.02
16	14.00	50.02
17	**08.80**	**50.03**
18	10.70	50.03
19	8.20	50.02
20	13.00	50.02
21	**6.60**	**50.03**
22	11.2	50.02
23	7.10	50.13
24	7.00	50.00

From the table 3 it was observed that the LFC was able to control the load during the critical times and ensured that the standard frequency limits were maintained. The result showed that at 13:00; 17:00 and 21:00 which are the critical times, when the load always exceed and caused change in frequency stability, the frequency controller was able to control the load and maintained stable frequency.

Table 4: Comparative result and analysis

Time (Hr)	Load with ANN (MVA)	Frequency (Hz) with ANN	Load without ANN (MVA)	Frequency (Hz) without ANN
1	08.80	50.03	8.80	50.03
2	08.30	50.00	8.30	50.00
3	08.42	50.04	8.42	50.04
4	10.00	50.04	10.00	50.04
5	10.07	50.04	10.07	50.04
6	08.02	50.01	8.02	50.01
7	08.30	50.03	8.30	50.03
8	08.10	50.01	8.10	50.01

9	09.20	50.03	9.20	50.03
10	10.60	50.02	10.60	50.02
11	12.20	50.04	12.20	50.04
12	13.00	50.03	13.00	50.03
13	**07.50**	**50.03**	**14.70**	**51.03**
14	13.70	50.00	13.70	50.00
15	12.40	50.02	12.40	50.02
16	14.00	50.02	14.00	50.02
17	**08.80**	**50.03**	**14.80**	**50.09**
18	10.70	50.03	10.70	50.03
19	08.20	50.02	8.20	50.02
20	13.00	50.02	13.00	50.02
21	**6.60**	**50.03**	**14.2**	**50.08**
22	11.20	50.02	11.2	50.02
23	07.10	50.13	7.10	50.13
24	07.00	50.00	7.00	50.00

The table 4 presented the comparative performance of the system when deployed with the LFC and without the LFC. The result showed that at the critical times which are 13; 17 and 21:00hrs respectively, the system without the LFC was not able to control the load and hence resulted to problem, while the result with the LFC was able to control the load and marinated stability.

VI. CONCLUSION

This work have successfully developed and implemented an improved distributive system load-frequency controller for the independence layout injection substation. The controller was developed using artificial neural controller and a frequency dataset extracted from the nonlinear frequency identified from the load as a nonlinear auto regressive model. This frequency developed is tagged the "Neuro Load-frequency controller" and have been implemented on the characterized system for improved performance. The result showed that the controller was able to control overload via accurate estimation of load flow and frequency changes

VII. CONTRIBUTION TO KNOWLEDGE

a) Load frequency controller was developed using artificial neural network
b) Frequency stability was achieved via the control of load

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