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Comparison of UPFC and TCFC for Optimal Power Loss Minimization on the Nigerian 330kv Power Transmission System

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Abstact:- In this work neural network controlled UPFC and TCSC device was used for the reduction of losses in power transmission network. The main problem addressed in this work is the optimal placements and control of UPFC and TCSC for the minimization of power transmission networks. To address these problems, Artificial Neural networks and genetic algorithm be used for the control and placements of the FACTS devices respectively for optimal active power loss reduction. The novel contribution of this work is to produce a model and train ANN for UPFC control using critical disruptive voltage and thyrist or firing and variation. Genetic algorithm was used for the optimal placement of the FACTS devise in the MATLAB/SIMULINK model of the Nigeria 330KV transmission system. Findings showed that the proposed neural network controlled UPFC achieved better active and reactive power loss reduction that the TCSC. It outperformed the TCSC by 6.08% in the reduction of active loss and by 15.34% in the reduction of reactive power loss in the power system.

Keywords:- *TRAINING, NEURAL NETWORK, UPFC, TCSC.*

I. INTRODUCTION

The importance of electric power in today's world cannot be overemphasized, for it is the key energy source for industrial, commercial and domestic activities. Its availability in the right quantity is essential to advancement of civilization. Electrical energy produced through the use of transmission lines run from one place to another. As a result of the physical properties of the transmission medium, some of the transmitted powers are lost to the surroundings. The overall effect of power losses on the system is a reduction in the quantity of power available to the consumers. As such, adequate measures must be put in place to reduce power losses to the minimum (Bamigbola, O et. Al, 2014).

Ideally, losses in an electric system should be around 3 to 6%. In developed countries, it is not greater than 10%, however, in developing countries, the percentage of active power losses is around 20%. Therefore, utilities in the electric sector are currently interested in reducing it in order to be more competitive, since the electricity prices in deregulated markets are related to the system losses(Magadum, M.R.B et. Al, 2016)

Electricity that is been generated from the power station, needs to be transmitted to the end users, through transmission and distribution lines. This transmitted energy is not without losses, but the capacity to transmit at minimal losses is what this dissertation entails.

Transmission of electricity in Nigeria is through the nation grid, which could be in 330kV or 132kV. Transmission grid is a network that consist of conductors carried on steel towers in between transformer stations, which conveys generated power from power stations to major load centres, and interconnecting all power stations to form a solid network that is accessible to all load centres.

In electricity supply to final consumers, losses refer to the amounts of electricity injected into the transmission and distribution grids that are not paid for by users(Bayliss C.R, 2001). Energy losses arise due to technical and non technical losses as power flows through the network. These technical losses are inherent in the system and can be reduced to an optimum level.

Technical losses are due to the current flowing in the electrical network and include line losses, copper resistance and iron losses of transformers (iron losses in transformer include both hysteresis and eddy current loss, these losses are minimized by using steel of high silicon content for the core and by using very thin laminations).Non- technical losses are more dominant in the lower levels of distribution networks, they include unauthorized line tapping, equipment vandalization, and inaccuracies of meter reading which will lead to inaccurate customer billing e.t.c.(Lukman D & Blackburn T.R , 2004) . Transmission of power and energy must be done at minimum technical and non-technical loses which are referred as Total Losses during transmission(H. S. Labo, 2010),(M S Bhalla, 2013)

The problem addressed in this paper is the optimal placements and control of UPFC& TCSC for the minimization of power loss in power transmission networks. To address these problems, Artificial Neural Networks and genetic algorithm be used for the control and placements of the FACT devices respectively for optimal active power loss reduction.

Scope of this paper covers optimal placement and control of UPFC for power loss minimization on transmission systems.

Comparative analysis of the performance of UPFC with TCSC under load variations in the minimization of active and reactive power losses on transmission networks.

Evaluation of losses under load variation on transmission system.

Authors(s)	Title of Article	Work done	Research gaps
Mohd Herwan Sulaiman et. al., 2014	Loss Minimisation by Optimal Reactive Power Dispatch Using Cuckoo Search Algorithm	This paper presents a Swarm Intelligence (SI) technique namely Cuckoo Search Algorithm (CSA) which is inspired by parasitic behaviour of Cuckoo birds in reproduction strategy to obtain loss minimisation by solving the Optimal Reactive Power Dispatch (ORPD) problem. The proposed CSA is used to find the optimal combination of control variables such as generator voltages, tap changing transformers' ratios and the value of reactive compensation devices in order to minimise the loss of the transmission system. Simulation was used to validate the work.	The authors did not evaluate the performance of the proposed transmission loss minimization method under load variation.
Uthen Leeton et. al, 2010	Power loss minimization using optimal power flow based on particle swarm optimization	The authors proposed a particle swarm optimization based optimal flow technique for power loss minimization. The work describes optimal power flow based on particle swarm optimization in which the power transmission loss function is used as the problem objective. In this paper, to minimize the overall power losses four types of decision variables are participated. They are i) power generated by power plants, ii) specified voltage magnitude at control substations, iii) tap position of on-load tap-changing transformers and iv) reactive power injection from reactive power compensators. Particle swarm optimization (PSO) is well-known and widely accepted as a potential intelligent search methods for solving such a problem. Therefore, PSO-based optimal power flow is formulated and tested in comparison with quasi-Newton method (BFGS), genetic-based (GA-based) optimal power flow. For the validation of the loss minimization scheme propose, a 6-bus and 30-bus IEEE power system are employed. Findings used showed that the proposed technique performed better than the BFGS and the GA-in the minimization of power loss.	A merit of the work is that the performance of the proposed method was evaluated and compared under 6 and 30 bus power systems, however the authors did not asses the proposed loss minimization technique under load variations.

Table 1: The summary review of related literature and knowledge gaps is given in the following tabulation.

II. METHODOLOGY

The Unified Power Flow Controller (UPFC) is the FACTS device used in this work for the proposed minimization of power loses in the Nigerian 330KV power system. The strategy adopted in this study is the placement and control of the UPFC device to optimally control current and voltage so as to reduce ohmic and corona losses in the power system. Neural network controller is used to control the injection and adsorption of active and reactive power by the UPFC so that current and voltage are dynamically controlled. This allows power to be transmitted at the lowest current possible(in order to reduce ohmic loss) and at an operating voltage level not exceeding the critical disruptive voltage (in order to reduce losses due to corona).

Genetic Algorithm will be used to compute the optimal locations for the installation of the FACTS devices.

The digital model of the Nigerian 330KV power system will be created in MATLAB/SIMULINK software for the evaluation of the performance of the neural network based UPFC. Simulation studies will be carried out to evaluate the ability of the UPFC to ensure that power is transmitted at minimal losses.

Transmission system faults and contingencies that cause rise in transmission current and voltages will be simulated. This will be done in order to determine the performance of the FACTS device in ensuring transmission loss minimization in the case study network.

III. THE MODEL OF THE UPFC NEURAL NETWORK CONTROLLER

The strategy for the loss minimization is the intelligent control of the FACTS device in order to put under control the rise in current (to reduce ohmic losses) and voltage beyond the level that causes corona. The shunt and series controllers of the UPFC is for the control of reactive power injection into or absorption from the power system in the events of irregular rise in transmission current or rise in voltage above the critical disruptive voltage. The neural network control is to generate the right levels of amplitude modulation ratios (mE, mB) and phase angles (i.e firing angles δE, δB,) of the control signal of each VSC in the UPFC. Figure 1.0 shows the functional model of the UPFC with the neural network controller.

For the control of the UPFC for the injection of the right active and reactive power in order to adapt the transmission system power flow for loss minimization, two neural network controllers are used: One for the control of the series VSC and the other for the control of the shunt VSC.

The proposed neuro-controller is a multi-layer feed forward network trained with Modified Recursive Prediction

Error Algorithm (MRPE). Although the gradient descent algorithm can also be used train neural network models, it does not converge as quickly as the MRPE algorithm.

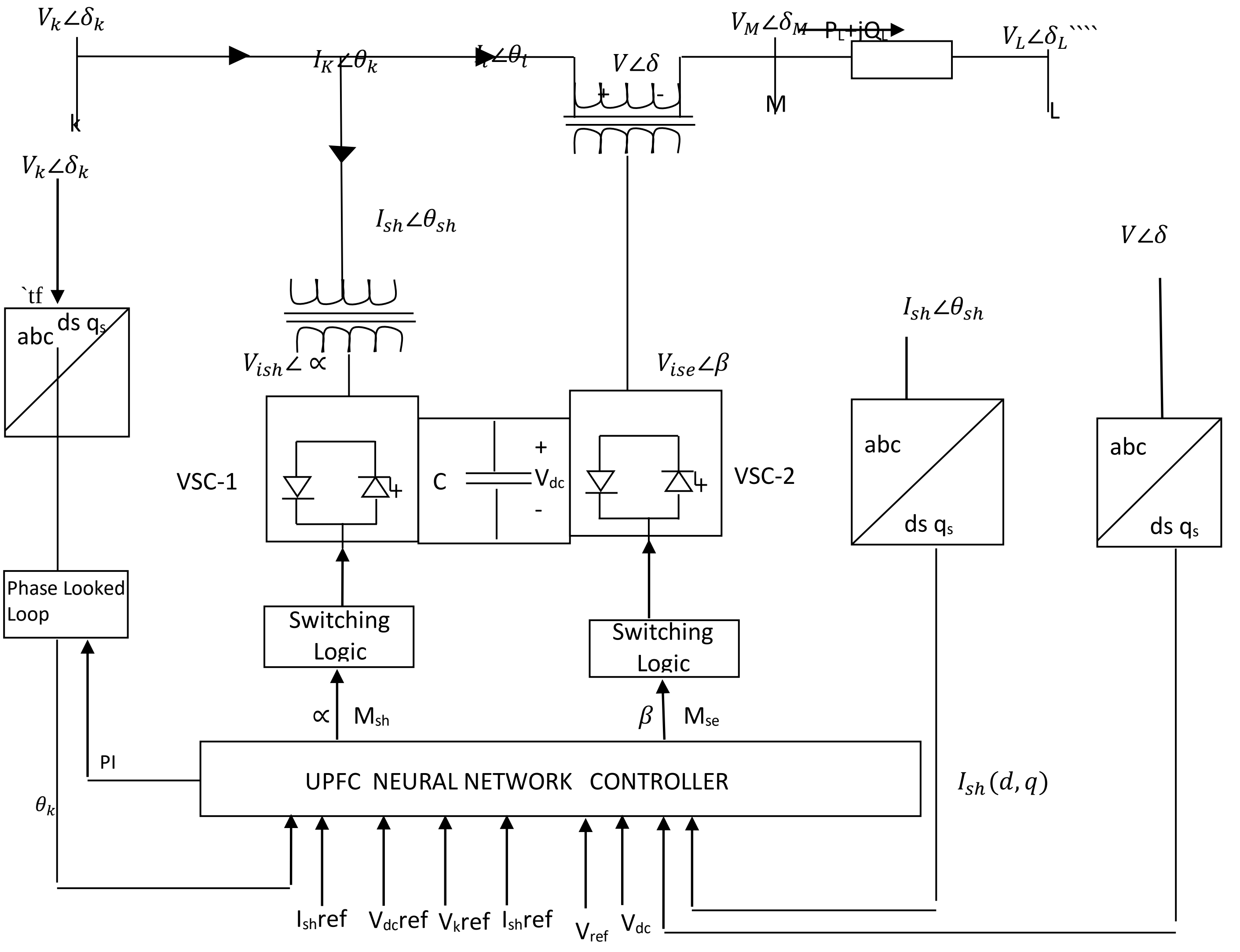

Fig. 1: The UPFC Functional model

The neural network controls the injection of real and reactive power by the UPFC into the transmission line such that the current and voltage is put under control, so that ohmic and corona losses are minimized. The main objective of the series converter is to produce an ac voltage of controllable magnitude and phase angle, and inject this voltage at fundamental frequency into the transmission line, exchanging real and reactive power at its ac terminals through the series connected transformer. The shunt converter provides the required real power at the dc terminals; thus, real power flows between the controller shunt and series ac terminals through the common dc link.

- Inputs to the UPFC series Neural network controller:
  - Shunt converter(i.e. shunt VSC) reference current: $I_{sh_{ref}}$
  - Link capacitor reference voltage: $V_{dc_{ref}}$
  - Critical disruptive voltage: V_0
  - Operating voltage reference: V_{ref}
  - Active power injected at node j: P_j
  - Reactive power injected at node j: Q_j
  - Active loss at the i^{th} and $(i+1)th$ bus: $P_{loss\ i,i+1}$
  - Power balance deviation: P_{dev}
  - Minimum voltage constraint deviation: $V_{min_{dev}}$
  - Maximum voltage constraint deviation: $V_{max_{dev}}$

- Output of the UPFC series neural network controller:
  - amplitude modulation ratio : *mE*
  - firing angle: δE

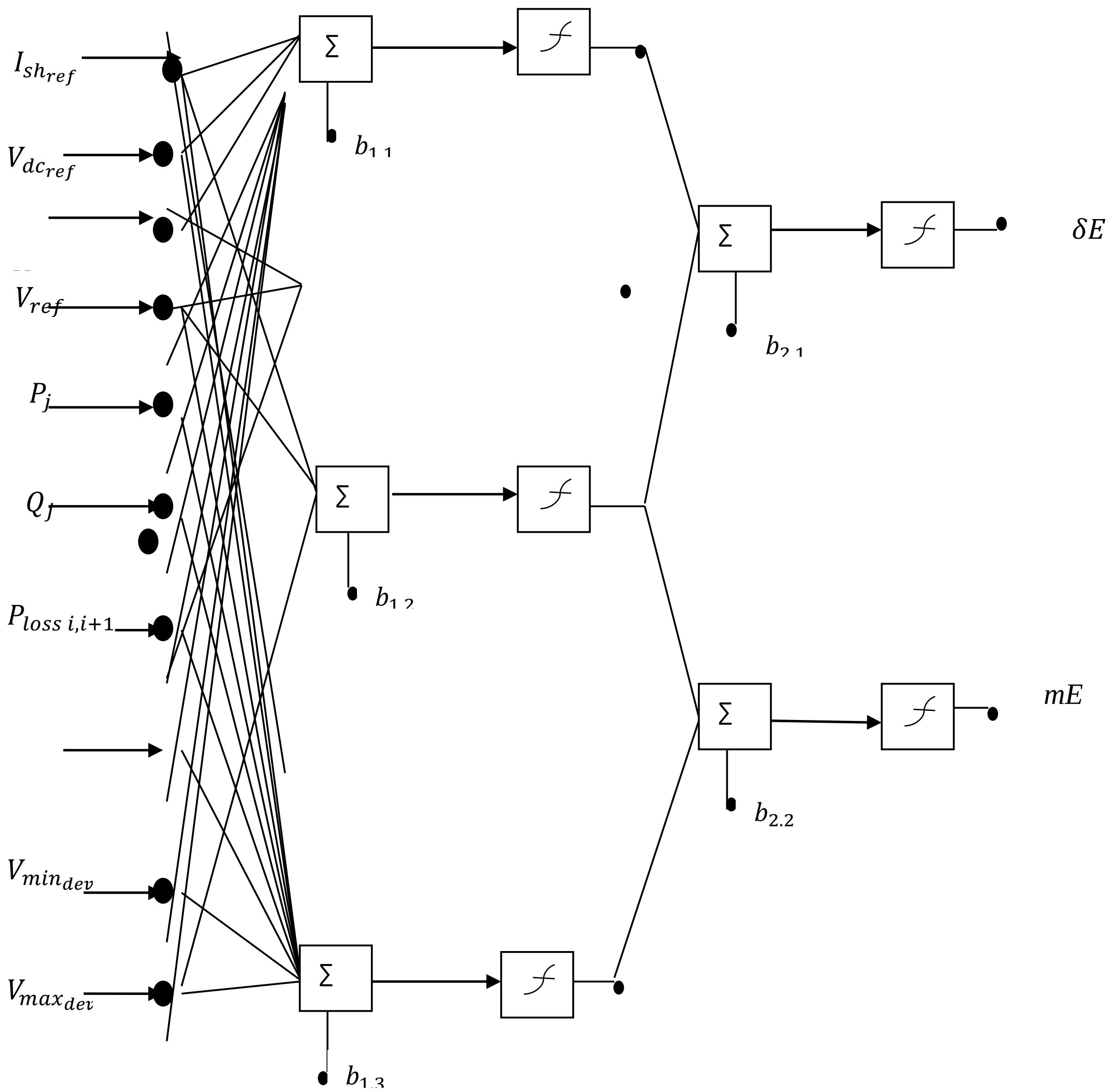

Fig. 2: The model of the Neural network for the control of the UPFC

IV. MODELING NN CONTROL TCSC

For the TCSC to control power flow to minimize losses on the transmission line, it has to be appropriately controlled to inject variable capactive reactance X_{TCSC} into the transmission line. The NN has to be trained to use appropriate inputs to output the appropriate angle of extinction required to control the switching of the anti-parallel thyristors (T_1 and T_2) of the TCSC.

The functional model of the TCSC with the neural network controller is shown in figure 1.2. As can be seen, the TCSC is connected between bus K and L on the transmission line.

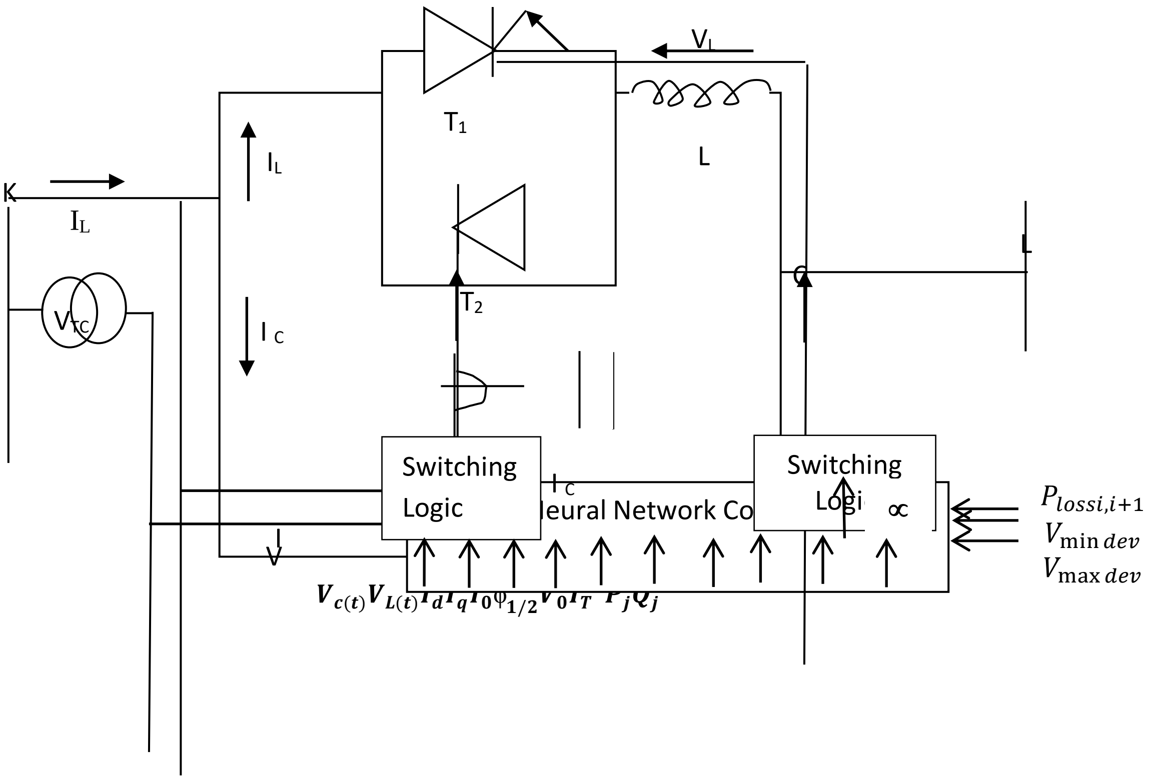

Fig. 3: Functional Model of TCSC with Neural Network Controller

The main components of the TCSC circuit are the capacitor (C), the inductor (L) in parallel with the capacitor and the two anti-parallel thyristors (T_1 and T_2). Parameters that relate with each of these components are part of the input to the neural network. The operation of the TCSC involves discrete actions and is periodic in nature whereby on the anti-parallel thyristors of the TCSC conducts during a portion of a half-cycle of the power frequency and is turned-off during the remainder of the cycle. The other anti-parallel thyristor repeats the conduction/non-conduction during the next half-cycle and vice-versa. The duration and timing of the thyristor conduction is based on the triggering or switching logic and is controlled by the neural network controller.

During the conduction interval of a thyristor, the TCSC is modeled as a parallel LC circuit as given in equation (1.0) and (1.1) (Hisham Othman, 1996)

$$C\frac{dv}{dt} = (I_d coswt - I_q sinwt + I_0) - I_T \quad (1.0)$$

$$\frac{L\, dI_T}{dt} = V_L \quad (1.1)$$

Or in state space form

- $$x = Ax + B\, I_{dqo} \quad (1.2)$$

Where

$$x = \begin{bmatrix} V \\ I_T \end{bmatrix},\ A = \begin{bmatrix} \frac{Coswt}{C} - \frac{sinwt}{C} & \frac{1}{C} \\ 0 \quad 0 & 0 \end{bmatrix}, I_{dq0} = \begin{bmatrix} I_d \\ I_q \\ I_0 \end{bmatrix}$$

A and B are the system and input matrix respectively. I_{dqo} are the d, q *and* 0 components of the curents (i.e based on the d_{qo} cordinate frame).

I_T is the total current injected into the terminal of the TCSC.

During the turn-off period of the thyristor, the TCSC is modeled as a series capacitor as given in equation (1.3) (Hisham Othman, 1996).

$$C\, \frac{dv}{dt} = I_d\, coswt - I_q sinwt + I_0 \quad (1.3)$$

- Inputs to the TCSC Neural Network Controller
  From the structure and analysis of the dynamics of the TCSC, the variable relating to the capacitor, indicator and two anti-parallel thyristors are among the inputs to the neural network controller.
  - Capacitor voltage at the present instant: $V_{c(t).}$
  - Indicator voltage at the present instant: $V_{L(t)}$.
  - d component of the line current: I_d.
  - q component of the line current: I_q.
  - (i.e zero crossing) component of the line crossing: I_0.
  - $\phi_{1/2}$ change in thyristor triggering instant during half cycle.
  - Total current injected at the terminal of the TCSC: I_T
  - Critical disruptive voltage: V_0

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- Active power injected at node j: P_j
- Reactive power injected at node j: Q_j
- Active loss at the i[th] and (i + 1)[th] bus: $P_{lossi,i+1}$
- Power balance deviation: P_{dev}
- Minimum voltage constant deviation: $V_{\min dev}$
- Maximum voltage constant deviation: $V_{\max dev}$

- Output of the TCSC neural network controller:
  - The extinction angle ($\propto$)

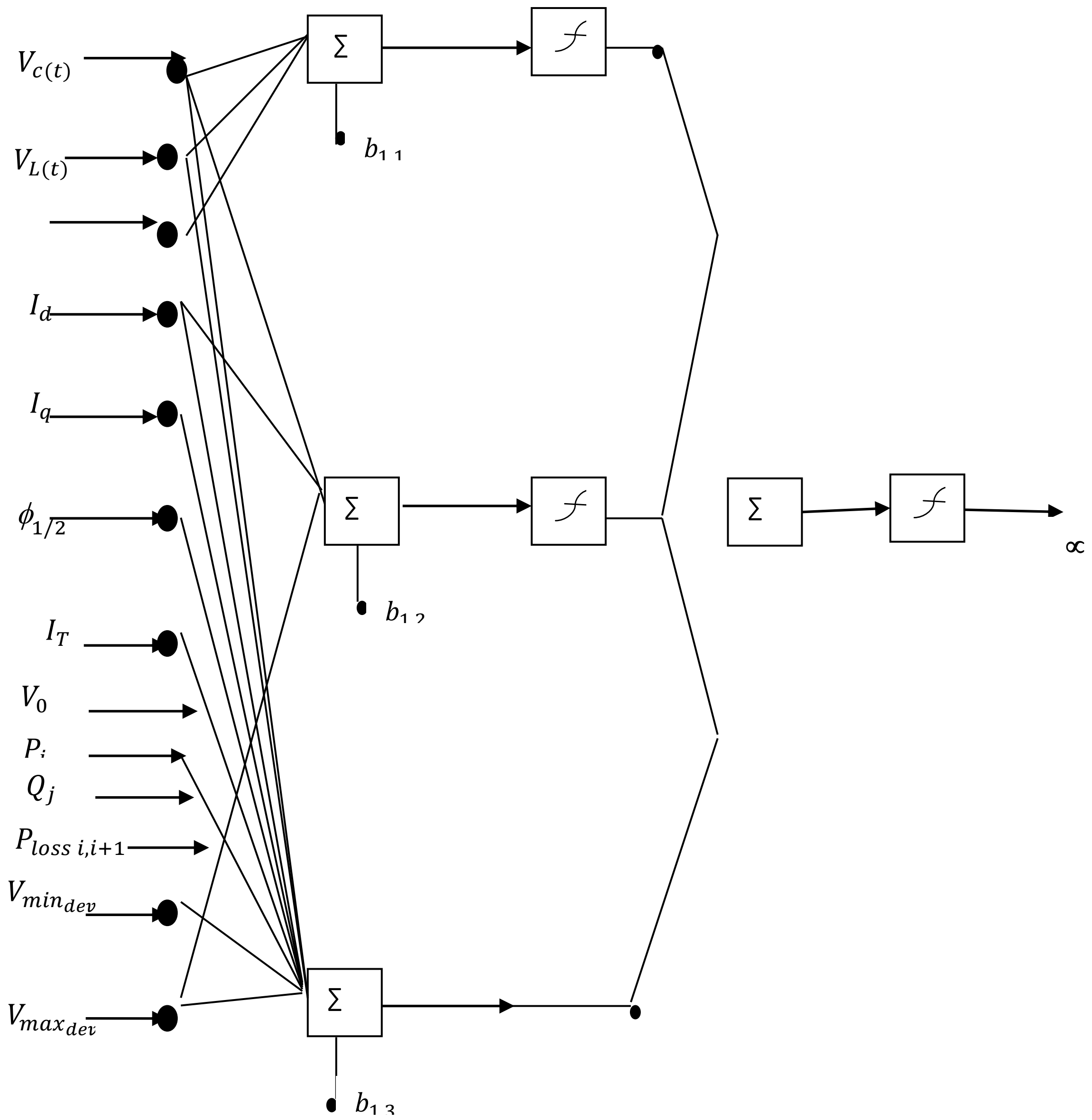

Fig. 4: Model of the Neural Network for the Control of TCSC

V. IMPLICATION FOR THE TRAINING OF THE NN

The basis for training the NN is to obtain data sets involving the input and output parameters that would be used as examples for the NN. For this, simulations is carried out to obtain the set of X_{TCSC} corresponding to varying the angle of extinction ($\propto$) from 90^0-180^0 (at steps of and X_{TCSC} that reduces power loss corresponding to various system values of currents, voltages, impedances and the critical voltage are extracted from simulation workspace as examples for training the TCSC neural network.

VI. PLACEMENT OF THE UPFC USING GENETIC ALGORITHM

Optimal location has to be located for the placements of FACTS devices. Less optimal placement of these devices would generate less optimal results or even result to negative power flow which would increase rather than reduce losses. Genetic algorithm is used in this work for the placement of the UPFC on the transmission network. The task is for genetic algorithm to use evolutionary computing technique to compute the optimal location for the placements of the FACTS device for optimal loss reduction. Hence the objective function for the placement is the minimization of power loss.

In the genetic algorithm, the individuals are coded to chromosomes that contain variables of the problem. The configuration of chromosomes to reach the optimal installation of the UPFC has two categories of parameters, those are UPFC location and parameters setting (*VcR and VvR*) as coherent model parameters for UPFC. The chromosome for the proposed algorithm is indicated in Table 1.1.

Objective Function	**Location of UPFC**	***VcR***	***VvR***

Table 2: The Chromosome of Proposed GA.

- The first group of chromosomes inside the individual points to the positions locations of UPFCs hardware in the power system. This group defines in which transmission line the UPFCs should be structured.
- The second group (which starts from the first set end) describes the value of *VcR* of series SVS. The limits for that set are randomly determined according to the working range [0.001, 0.3].
- At last, the third set (which starts form the second set end) describes the value of *VvR* of shunt SVS. The limits for this set are randomly determined according to the range [0.8, 1.2].

Three items move a genetic algorithm: mutation rate, crossover rate and population size. The GA is a search procedure that can be used to constrained problems; the constraints can be concerned with the fitness function. In that algorithm, issues for optimization that should be executed on the fitness function and all equality and inequality constraints concerning the UPFC equations. The structure of the GA execution is separated into the following three constituent phases namely: initial population generation, fitness evaluation and genetic operations.

The process of the implementing the GA technique is described in the following steps:

- Phase 1: Definitions for the optimization controlling parameters such as the population size, crossover and mutation and their probabilities, maximum generation number, stopping criterion. In addition, the power flow data is defined.
- Phase 2: Generation a primary population for individuals, this process performed for optimizing variables, which are the positions, and the parameters setting of UPFC. Three chromosomes for the individual show a meaningful point inside the optimization problem's region solution.
- Phase 3: Fitness function: Using the objective function, the individual's fitness inside the population is calculated. The fitness is computed by considering the fitness function Ft. Fitness function is one of the most important processes in genetic algorithm, applied to identify the best chromosome. In the proposed method, the voltage and angle injecting values generated in the above stage are injected to the system and after injecting the values, the power loss is computed. Minimization of the total power loss (consisting of the ohmic and corona losses) is taken as the fitness function. This entails the minimization of equation 1.8

i.e. Ft = $min(T_{loss})$

The population on-line performance P(n) is defined as

$$P(n)=\frac{1}{P}\sum_{p=1}^{N}F_t^n(p) \qquad n=0,1,\ \ldots\ldots\ldots,\ T-1 \tag{1.4}$$

Where

N = Total population size;

T = total generations;

Ft p = the fitness function of the pth chromosome in the nth generation.

- Phase 4: GA depends on genes rules and the Darwin principle of the survival of the fittest, so the worse individuals is eliminated. The evolutionary process continues with the most highly fit members to generate a new population, keeping information for the next generation. That process is preformed by comprising selection, crossover, and mutation.

ISSN No:-2456-2165

To maintain diversity in the population, the variable distance dij between two solutions X(i) and X(j) is considered.

$$d_{ij} = \sqrt{\sum_{k=1}^{S} \left(\frac{X_k^{(i)} - X_k^{(j)}}{X_k^{max} - X_k^{min}} \right)^2} \quad 1.5$$

Where
S: the number of the variables included in the optimizes X_k^{max} and X_k^{min} respectively the upper and the lower bounds of variables of K_k respectively.

- Phase 5: Trying multiple epochs with the selection, crossover, and mutation until achieving the desired individuals for the new generation. Then the fitness values are used, which are the best and which are the worst, to rank the individuals, and the ranking process is used to define the selection probability. Considering the individual at rank i:

$$\text{Probability}_i = \frac{1}{\|P\|}\left(2-\alpha+(2\alpha-1)\frac{i-1}{\|P\|-1}\right) \quad 1.6$$

Where α is the selection bias and its value between 1, 2; higher values for more directing the cursor on selecting only the well individuals. The best individual in the population is thus selected with the probability $\frac{\alpha}{\|P\|}$; the worst individual is selected with the probability $\frac{2-\alpha}{\|P\|}$. That procedure keeps the best individual in the new next generation.

- **Phase 6:** Generation maximum number defines the stopping point of the system. Let z denote the bits number inside the chromosome and N population size as mentioned before, then the expected number of generations until convergence is, E (NG) = 1.4 N (0.5ln (z) +1) This is valid for random mating with recombination but without selection and mutation. This procedure causes small selection intensities to decrease the probability to find the optimum. Reaching to the maximum number and achieving both function and constraints with the final best individual lead to end the procedure and prints the final result.

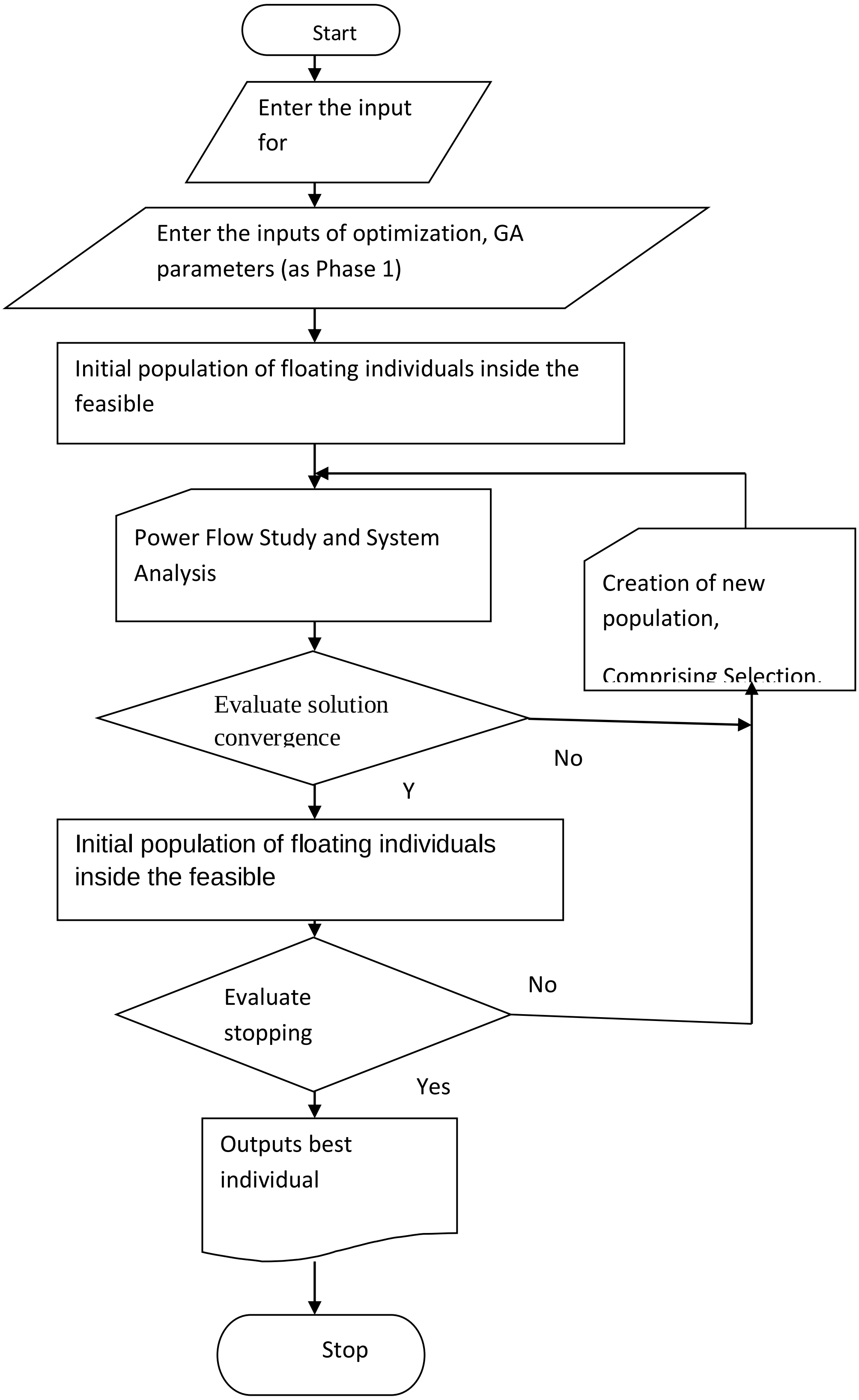

Fig. 5: Flow estimating best location(best individual) for UPFC using genetic algorithm

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VII. TEST AND SIMULATIONS

For the simulation, the single line diagram of the Nigerian 330kV power transmission network is used to create the SIMULINK digital model of the case study power system. The single line diagram of the case study network used is given on figure 6. The power system consists of 14 generators, 67 buses, 39 load points and 111 transmission lines. The generator data and line data of the case study power system is given on table 3.

The case study power system is modeled in MATLAB/SIMULINK. Figure 1.9. shows the SIMULINK model of the power system without the neural network controlled UPFC installed.

VIII. TRANSMISSION LOSS REDUCTION FOR LOAD VARIATION WITH UPFC INSTALLED IN THE POWER SYSTEM

Simulations are carried to compute the location for placement of the FACTS devices(i.e. UPFC and the TCSC.) . In the simulation carried out, the FACTS device placement genetic algorithm was coded in MATLAB m-file program. The source code of the genetic algorithm program used to compute the location of placement of the FACTS device is given on training the neural network model. The algorithm computes the optimal location for the placement of the FACTS device. When loaded into memory, it communicates with the load flow program via the MATLAB program workspace, from where it reads the values of load flow variable. The genetic algorithm program outputs the bus locations for the optimal placement of the UPFC device. Running the genetic algorithm program a number of iterations would give the optimal location for placement of corresponding number of FACTS devices. However one iteration for placement of one UPFC device was executed in the simulation carried out. From simulation out put, the UPFC was placed between bus 16 (at Jos T/S) and bus 39(at Markurdi). The SIMULINLK(the digital model) of the Nigerian 330KV network given in Figure 1.9.

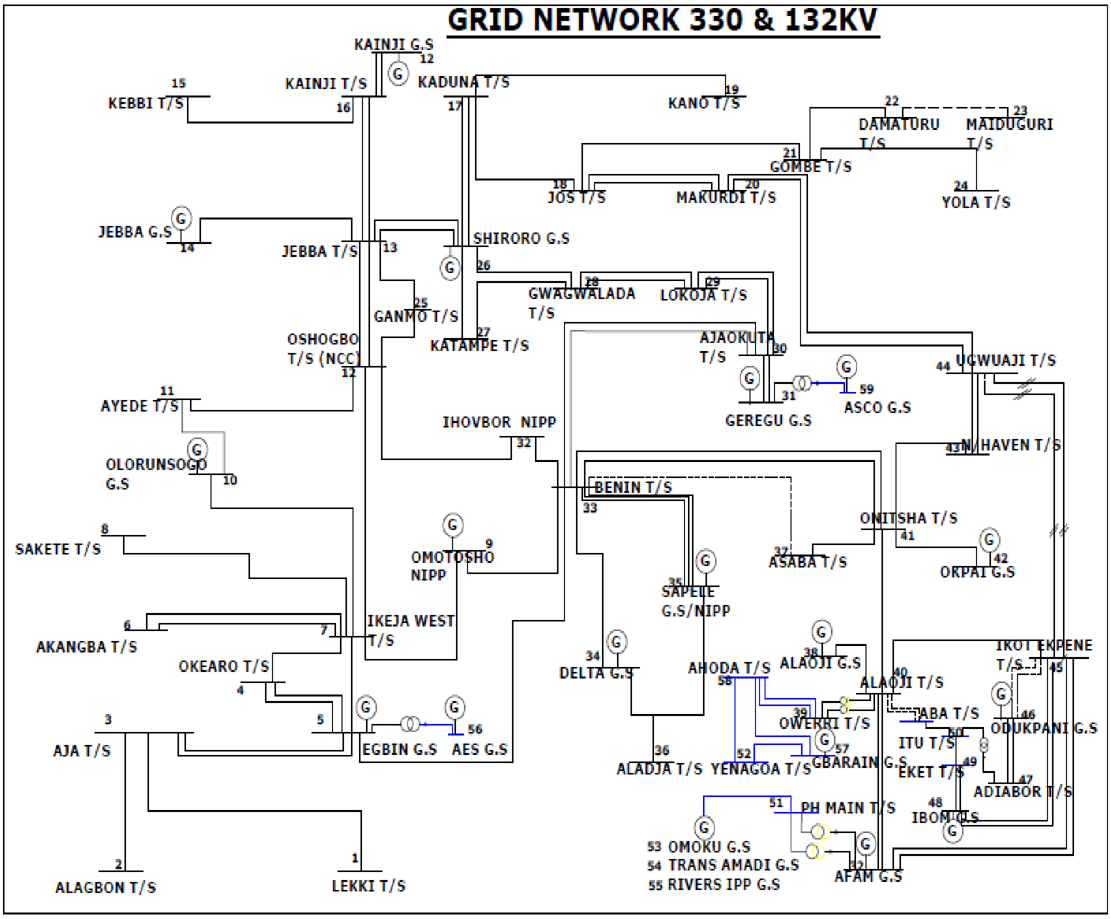

Fig. 6: Single line diagram of the Nigeria 330/132kV power system.

There are 14 synchronous generations in the system. The base voltage is 330KV and 100MVA

Generator Station	Generation	Rated Voltage	Voltage Pv
Kainji	292mw	332kv	1.0060
Jebba	404mw	312kv	0.9455
Shiroro	450mw	320kv	0.9697
Egbini	611mw	335kv	1.0151
Sapele	68mw	332kv	1.0060
Delta	470mw	318kv	0.9636
Geregu	144mw	319kv	0.9677
Omotosho	187.5mw	305kv	0.9242
Olominsogo gas	163.6mw	300kv	0.9090
Geregu NIpp	150mw	331kv	1.0030
Sapele NIpp	113.1mw	320kv	0.9692
Olorunsogo NIpp	130.9mw	316kv	09576
Omotosho NIpp	228mw	347kv	1.05151
Okapia	363mw	331kv	1.0030

Table 3: GENERATOR DATA

IX. TRAINING THE NEURAL NETWORK MODEL

For the training of the neural network values for the inputs have to be determined, from which the training dataset is obtained.

A. *The critical disruptive voltage*

Critical disruptive voltage is given by:

$$V_0 = 21.1 M_0 \delta \ln \frac{d}{r} \quad 1.7$$

Where

M_0: irregularity factor

$M_0 = 1\ for\ polished\ conductor$

$= 0.98 \rightarrow 0.92 for\ dirty\ conductor$

$= 0.87 \rightarrow 0.8\ for\ stranded\ conductor$

$$\delta = \frac{3.92b}{273+t} (air\ density\ factor) \quad 1.8$$

Under standard conditions (temperature and pressure), the value of $\delta = 1$

d = the spacing of the conductors

r = the radius of the conductors

In the case study power system i.e. the Nigerian 330KV transmission line, the 50Hz transmission line consists of 1.5cm radius stranded conductor spaced at 300cm.

Using this data, the critical disruptive voltage V_0 is (substituting into equation 1.7,

$$V_0 = 21.1 \times 1 \times 1 \times \ln \frac{3}{0.015}$$

$$V_0 = 111.79 kv/phase$$

B. *The link capacitor reference voltage*

The link capacitor reference voltage used as input to the neural network controller model is obtained from the graph of UPFC dc link dynamic voltage (step response) response graph as obtained from the reference(   ). The graph is shown in figure 1.6.

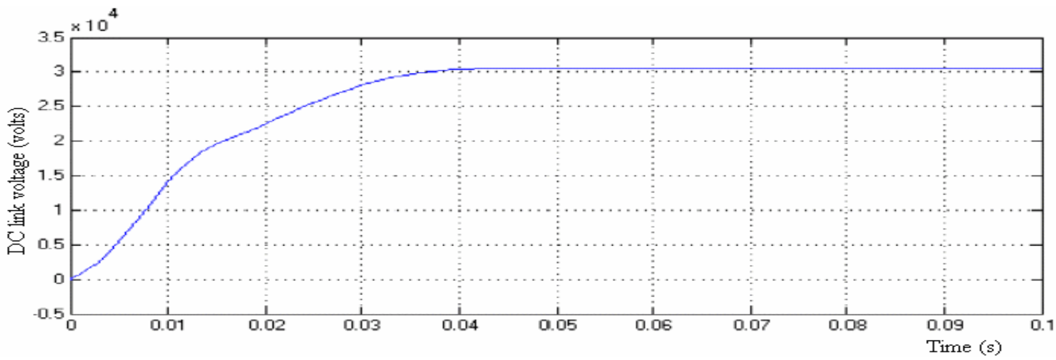

Fig. 7: UPFC dc capacitor link voltage step response [source:]

From figure 6, the set point of the link capacitor voltage happens to be at 3×10^4 volts.

The active power injected at the node $,P_j$, The reactive power injected at the node j, Q_j , and the active loss at the i^{th} and $(i+1)^{th}$ bus $P_{loss\ i,i+1}$ are obtained dynamically during simulation run by Newton-Rapshon solvers in MATLAB program.

The minimum voltage deviation $V_{min_{dev}}$ is the difference between 0.95 p.u and the lowest bus voltage in per unit. The maximum voltage deviation $V_{max_{dev}}$ is the difference between 1.05 p.u and the highest bus voltage in per unit.

X. GENERATING THE DATASET FOR THE TRAINING OF THE NEURAL NETWORK

The MATLAB/SIMULINK model of the case study power system (given in figure 1.7) is used with load variations at bus 49 to generate data for the training of the neural network. The load is varied from 100MW to 500MW , at increments of 10% (i.e. at increments of 10MW). For each variation of load , load flow is carried out to find the power losses and bus voltages. For each sequence of variations the firing angle settings of the UPFC Thyristor are varied between 0 to 180° in increments of 18° (i.e. 10% of the effective angle sweep). For each complete sequence of the load variation & load flow, the firing angle associated with the least active power loss is taken. The procedure is repeated for the full range of load and firing angle variation. This gives a total of 41 instances of the load and angle variations. The dataset obtained is shown in table 1.3.

Load(MW)	Active loss(p.u)	Reactive loss (MW)	UPFC thyristor firing angle (deg.)
100	0.0352	0.108	54
110	0.0315	0.0757	18
120	0.0483	0.2194	144
130	0.0302	0.0643	108
140	0.0331	0.09	18
150	0.0305	7.0674	90
160	0.8452	0.0924	126
170	0.0417	0.1631	18
180	0.0339	0.0968	162
190	0.0304	0.066	144
200	0.0391	0.1428	90
210	0.0451	0.1926	54
220	0.03	0.0628	54
230	0.0318	0.0787	72
240	0.0784	0.4796	90
250	0.0302	0.0645	18
260	0.0299	0.0618	54
270	0.0338	0.0924	54
280	0.04	0.1482	72
290	0.0378	0.1248	162
300	0.0156	4.1883	72
310	0.0518	0.2357	90
320	0.4309	0.0711	18
330	1.0337	0.0946	72
340	0.0389	0.1254	108
350	0.0306	0.0681	54
360	0.0391	0.1403	108
370	0.0304	0.0665	36
380	0.0301	0.0641	90
390	0.03	3.0614	36
400	0.0335	0.0902	162
410	0.0317	0.0778	18
420	0.0915	0.0665	108
430	0.0399	0.1409	144
440	0.0301	0.0633	18
450	0.033	0.0638	36
460	0.0307	10.0685	144
470	0.0307	0.0713	90
480	0.0708	0.0674	54
490	0.0308	0.0699	36
500	0.0321	0.0812	144

Table 4: extracted dataset for the training of the ANN controller for the UPFC

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The SIMULINK Neuro-fuzzy Designer is the tool used for carrying out the training. The dataset was divided into three portions: one part is for training, the second part for checking and the third part for testing. Testing also means validation of the model.

Model validation is the process by which the input vectors from input/output data set are presented to the trained ANN model to see how well the model predicts the corresponding dataset output value. The training process adapts the neural weights of the neural network.

The training parameter was set to 40 epochs. **Figure8** gives the result of the training. **Figure 8** shows that the training error (i.e. the root mean square error for the training) degraded to about 0.0139. This value is much smaller than 0.5. In the training output shown in **figure 8**, the checking error is on top the training error. The training error appears as diamond, the checking error appears as star. The checking error decreases up to a certain point in the training, and then increase. The checking error is not large, a large checking error indicates that either more training data is required, or the membership function has to be modified. The training error and the checking error as shown in **figure 8** are low.

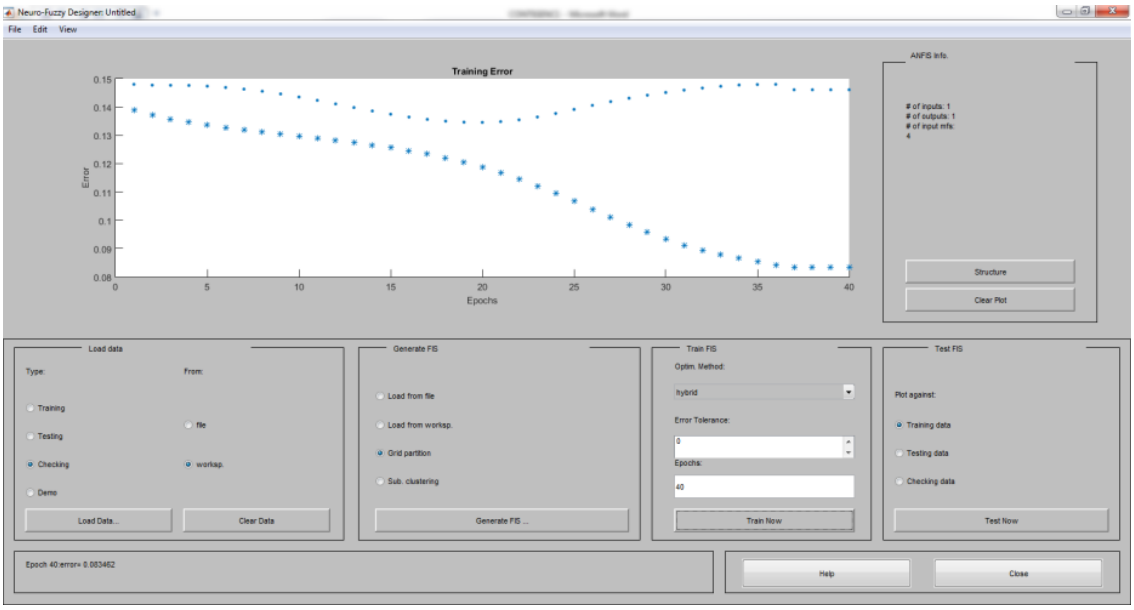

Fig. 8: Result from training showing achieved training error and checking error

A. Testing the data against the trained ANN model:

The testing dataset allows for checking the generalization capability of the resulting ANN controller for the UPFC . The result of the ANN model validation is shown in **figure 9.**

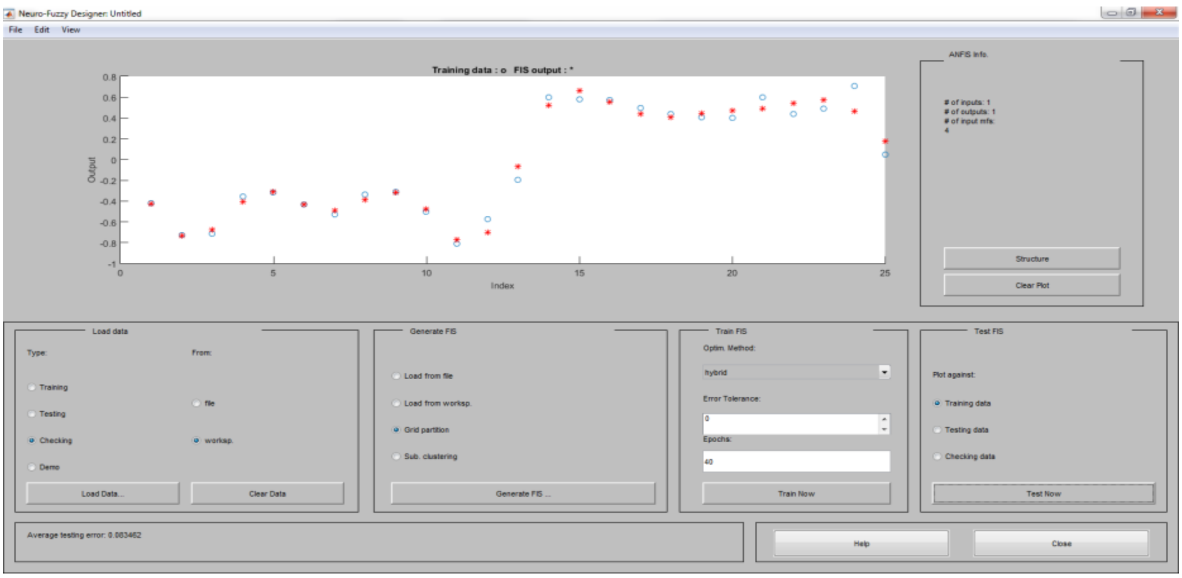

Fig. 9**:** Result from model testing (i.e. model validation) showing correlation of training and testing plots.

The closeness of the two graphs (that is the plot of the training and the testing data (validation data)) indicates that the trained ANN network can be used for predicting or estimating and classifying future data.

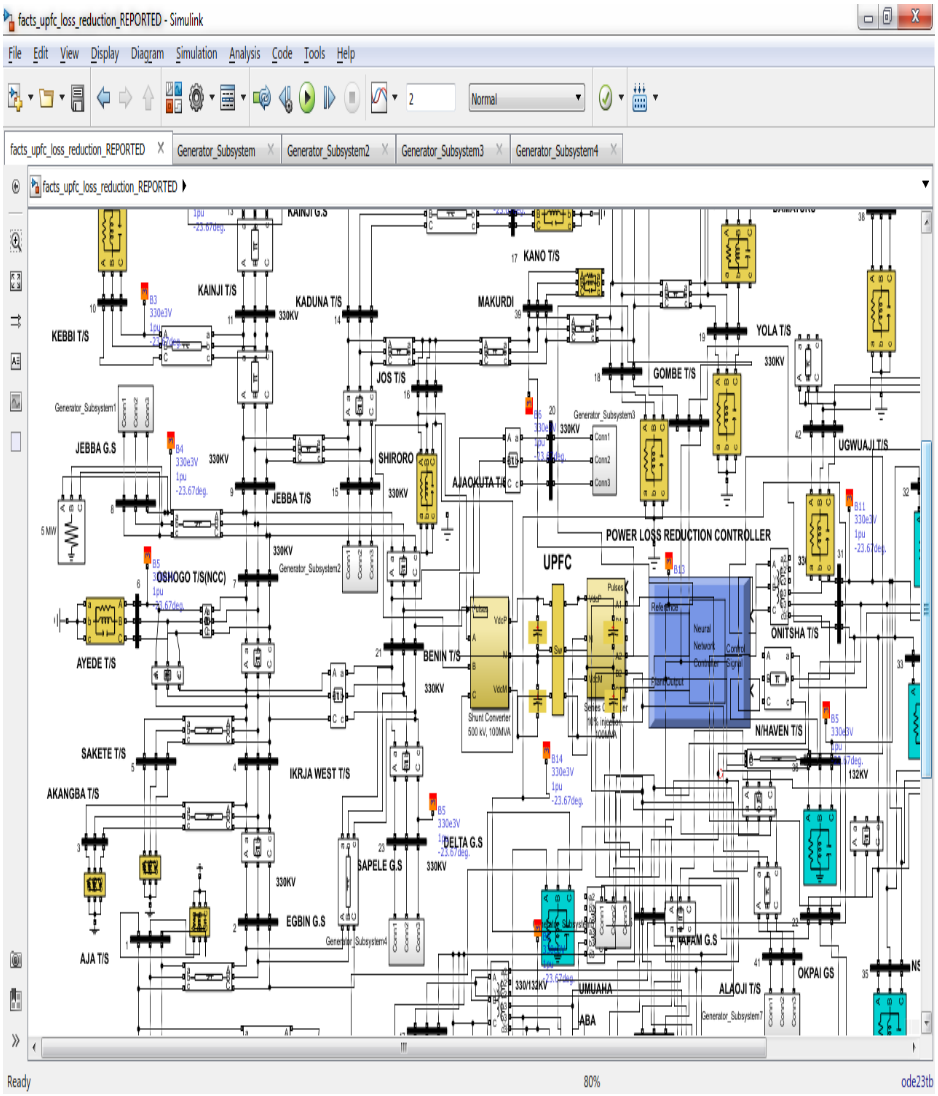

Fig. 10: SIMULINK model of the power system with UPFC installed at the optimal location determined using genetic algorithm

The simulation model of the power system is shown in figure 10 with the UPFC placed at the selected location. With the placement of the UPFC in the power system, load variation simulation is carried out to evaluate the impact of the UPFC on loss reduction in the power system.

With the placement of the UPFC and installation of the NN power loss reduction controller, variations of load at bus 49 is carried out as done in the previous scenarios (i.e. in the case of the power system without the UPFC installed) to evaluate the reduction of active and reactive losses in the system due to the installation of the UPFC.

With the UPFC installed in the power system, similar evaluation is carried out as in the case of the power system without the installation of the UPFC.

Load variations of 198MW, 297MW, 396MW, 495MW and 594MW loads drawn at bus 49 respectively with UPFC installed. The base value of 100MVA was used.

Load variation(MW)	**Total active power loss(p.u)**	**Total Reactive power loss(p.u)**
198	7.8838	55.8455
297	10.7512	59.7880
396	11.5169	64.7305
495	12.4826	66.6730
594	13.4483	73.6155
Total	**56.0828**	**320.6525**

Table 5: Variation of power losses with load in the power system with UPFC installed

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The trend that can be observed from Table 5 is that as the load increases, the active and reactive losses increase. From Table 5, to observe this trend visually, the variations of active power loss with load and the variations of reactive power losses with load are plotted as shown in Figure 2.0 and Figure 12 respectively.

The total active and reactive losses of the power system after the installation of the UPFC are **56.0828 p.u** and **320.6525 p.u** respectively. These values are lower than the case of the power system without the proposed neural network controlled UPFC installed. This shows that the UPFC reduced both the active and reactive powers in the system.

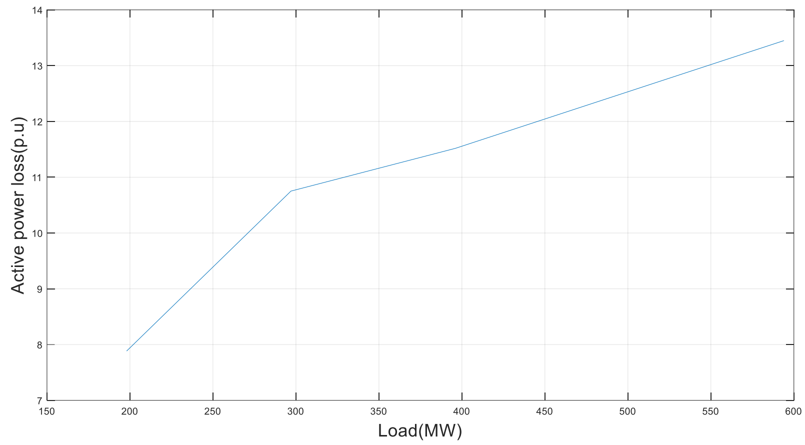

Fig. 11:Variation of active power loss with load variation with UPFC installed.

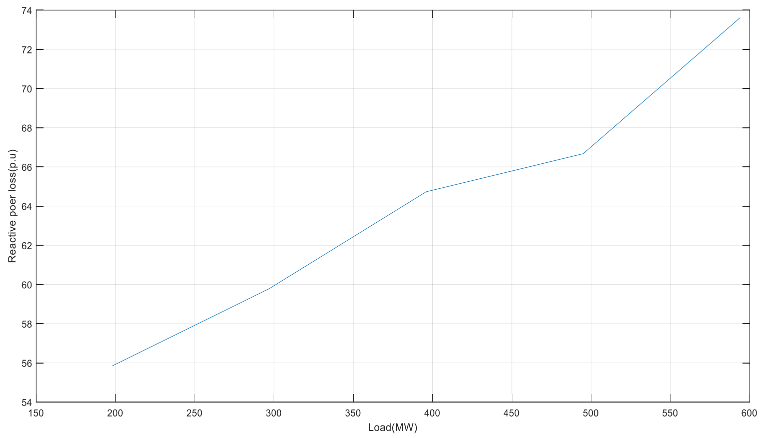

Fig. 12:Variation of active power loss with load variation with UPFC installed

Figures 11 and 12 show relationship between active and reactive power losses with load variations in the power system. It can be noticed that the trend in the relationships have similarities with the case of the power system without the UPFC installed. However there are differences in the trajectories of the graphs. A close comparison will show the quantitative difference existing between the trend of the active and reactive losses with and without the UPFC installed. To carry out the comparison, the values of losses with load variation for the power system with and without the UPFC will be tabulated together in order to closely examine the loss reduction as a result of the installation of the UPFC. For visual comparison the variation of the active and reactive losses without load will be plotted together.

Load variation(MW)	**Total active power loss(p.u)**	**Total Reactive power loss(p.u)**
198	9.5191	58.8223
297	11.1730	64.8940
396	12.2386	77.8341
495	13.3138	85.5993
594	13.8244	98.1942
Total	**60.0689**	**385.3439**

Table 6: Variation of power losses with load in the power system with TCSC installed

The trend that can be observed from Table 6 is that, as in the case of the UPFC as the load increases, the active and reactive losses increase. From Table 6, to observe this trend visually, the variations of active power loss with load and the variations of reactive power losses with load are plotted as shown in Figure 13 and Figure 14 respectively.

The total active and reactive losses of the power system after the installation of the TCSC are **60.0689 p.u** and **385.3439p.u** respectively. These values are lower than the case of the power system without the installation of any of the FACTS devices. This shows that the TCSC reduced both the active and reactive powers in the system. However, the active and reactive loss with the TCSC installed are larger than the active and reactive losses with the UPFC installed.

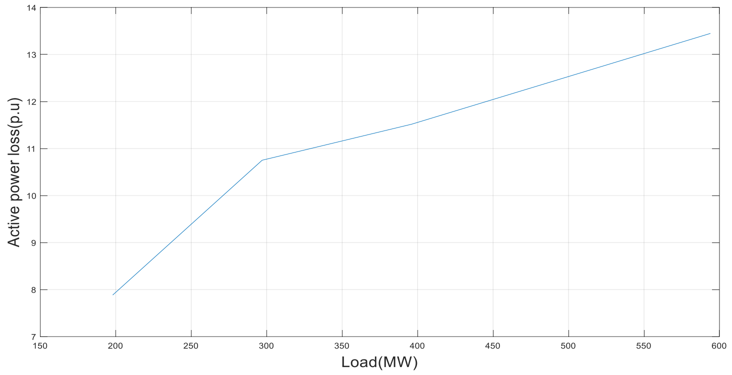

Figure 13: Variation of active power loss with load variation with TCSC installed

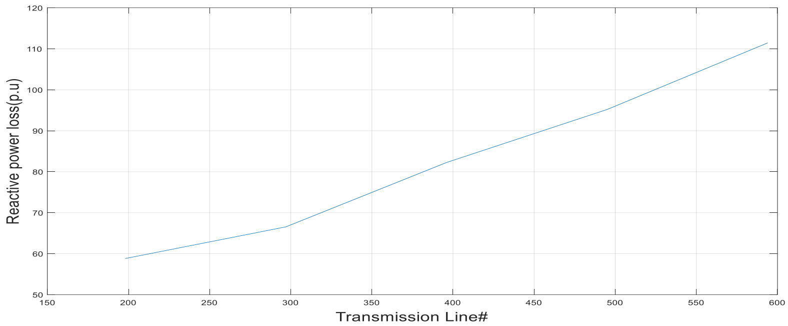

Figure 14: Variation of reactive power loss with load variation with TCSC installed

XI. COMPARISON OF ACTIVE AND REACTIVE LOSSES REDUCTION WITH UPFC AND WITH TCSC INSTALLED IN THE POWER SYSTEM

From the results obtained so far, combining results in tables 5 and 6, table 7 gives the values for the comparison of systems losses with TCSC and with the UPFC.

Load variation (MW)	Active power loss(P.U)			Reactive power loss(P.U)			Active power loss reduction(%)		Reactive power loss reduction (%)	
	Without FACTS	With TCSC	With UPFC	Without FACTS	With TCSC	With UPFC	With TCSC	With UPFC	With TCSC	With UPFC
198	11.1730	9.5191	7.8838	60.7648	58.8223	55.8455	14.8026	29.44	3.1967	8.10
297	12.1387	11.1730	10.7512	68.4904	64.8940	59.7880	7.9555	11.43	5.2509	27.71
396	13.1044	12.2386	11.5169	84.1944	77.8341	64.7305	6.6069	12.15	7.5543	23.12
495	13.8587	13.3138	12.4826	97.1322	85.5993	66.6730	3.9318	9.93	11.8734	31.36
594	14.7901	13.8244	13.4483	113.3895	98.1942	73.6155	6.5293	9.07	13.4009	33.08
Average	13.01	12.01	11.22	84.794	77.07	64.130	7.965	14.404	8.255	24.67

Table 7: Comparison of active and reactive loss reduction for load variations with TCSC and with UPFC installed in the power system

From the summary tabulation of Table 6, both the TCSC and UPFC achieved reduction of active and reactive power losses in the power system. However, the proposed UPFC outperformed the TCSC in the reduction of both active and reactive power losses.

With the use of the TCSC, the active power loss in the system was reduced by 7.965% whereas with the use of the UPFC the active power loss was reduced by 14.04%. For the reactive power loss, the TCSC reduced the reactive loss by 8.255% whereas the UPFC reduced the reactive loss by 24.67%. The UPFC outperformed the TCSC by 6.08% in the reduction of active loss and by 15.345% in the reduction of reactive power loss. This shows that the neural network controlled UPFC achieved a better loss reduction than the TCSC.

XII. CONCLUSION

Electrical energy supplied and transmitted through the use of transmission lines run from one place to another. As a result of the physical properties of the transmission medium, some of the transmitted powers are lost to the surroundings. The overall effect of power losses on the system is a reduction in the quantity of power available to the consumers. Power loss leads to high cost of power generation, transmission and distribution.

In this work neural network controlled UPFC was used for the reduction of losses in power transmission network. In the modeling of the neural network controller for the UPFC , the input parameters of the neural controller includes power system variables that relates to the control of ohmic and corona losses on transmission lines.

The Nigerian 330KV power grid was used as case study for the evaluation of the proposed power loss reduction system. The digital model of the case study power system with the proposed neural network controlled UPFC integrated was created in the MATLAB/SIMULINK programming environment.

Results obtained showed that the proposed system achieved an average active power loss reduction of 14.40% and an average reactive power loss reduction of 24.67%. The performance of the ANN based UPFC was compared with that of the TCSC. Findings showed that the proposed neural network controlled UPFC achieved better active and reactive power loss reduction than the TCSC. It outperformed the TCSC by 6.08 % in the reduction of active loss and by 15.345% in the reduction of reactive power loss in the power system.

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