© JUL 2024 | IRE Journals | Volume 8 Issue 1 | ISSN: 2456-8880

PSO-Symbolic Regression Based Voltage Stability Analysis for the Nigerian 330kv Transmission Network

BLUE-JACK, K. Q[1], OJUKA, O. E[2], BALA, T. K[3], WOKOMA, B. A.[4]
[1, 2, 3, 4] *Department of Electrical and Electronic Engineering, Rivers State University, Port Harcourt, Nigeria*

Abstract- This review explores the analysis of the Nigerian 330kV transmission network profile using Particle Swarm Optimization (PSO). The primary purpose of this study is to evaluate the effectiveness of PSO in optimizing the performance and stability of the Nigerian power transmission network, addressing prevalent issues such as voltage instability and inefficient power distribution. The Nigerian 330kV transmission network faces significant challenges, including frequent voltage collapses and suboptimal power flow, leading to reliability and efficiency concerns. These problems are exacerbated by the network's non-linear dynamics and the increasing demand for electricity. Addressing these challenges requires advanced optimization techniques capable of providing robust solutions. The study employs an improved PSO approach to determine the optimal sizing and placement of shunt injection capacitor banks within the transmission network. By using PSO, the research aims to enhance the network's voltage stability and overall performance. The methodology involves detailed simulations of the Nigerian 330kV network, considering various load scenarios and generator configurations. Additionally, a Symbolic Regression (SR) model fitting technique is used to represent solution states and account for deviations from optimal capacitor bank MVARS across load buses. The results demonstrate that PSO optimization significantly improves the voltage profile of the transmission network, achieving an 8.4% enhancement. Furthermore, the SR model effectively represents the solution states with minimal error deviations, ensuring accurate and reliable performance assessments. The study highlights the potential of PSO and SR in addressing complex power system problems, and promoting the adoption of AI-based solutions in the energy sector. In conclusion, this review underscores the importance of advanced optimization techniques like PSO in improving the performance and stability of power transmission networks. The findings advocate for policies that support the integration of AI and machine learning approaches in power system analysis and optimization, paving the way for a more resilient and efficient energy infrastructure in Nigeria.

Indexed Terms- Optimization, PSO, Symbolic Regression, Transmission Network, Voltage Stability

I. INTRODUCTION

The electricity produced in Nigeria, by the generating companies is connected to the power grid via Nigeria's Transmission Company. This power is then transmitted through the primary transmission network (330kV) from TCN to the substations, then to the distribution substations, and lastly to the users. For the transmission of electricity, alternating current is used, this is due to its ability to evolve from one voltage level to another with a minimal loss of power with the use transformers [1]. The transmission of this power takes place at a voltage, of 33kV to the various zones with respect to the load shedding formula through the primary substations. The received voltage is brought down to a lower voltage of 11kV by a stepdown transformer. After which it is transmitted to secondary distribution transformers close to the users. This medium voltage is further stepped down to the voltage used by the consumers (usually 220 to 240V) by the secondary distribution transformers [2]. Though, clients such as Refineries, Flour mills, cement factories, rice mills, etc. get their electricity directly from the distribution line.

II. LITERATURE REVIEW

2.1 Extent of Past Studies on Capacitor Placement and Sizing

The problem of which bus should a capacitor bank be sited and how much MVAR compensation should be allocated to such a bus for voltage profile improvement has been an ongoing research exercise in the power systems field. In the research field, the Shunt Capacitor Banks (SCBs) – a low cost and approximately lossless power system voltage stabilization element [3], has found applications in a large number of power networks. Historically, it is well documented the ability to implement intelligent switching functions to capacitor banks used in shunt compensation and hence voltage profile improvement [3].

Recently, some research studies have been carried out using the Artificial Intelligence (AI) approaches particularly that related to Artificial Neural Networks (ANNs), Deep ANNs (DANNs), Swarming Optimization (SO) and hybridization schemes of the aforementioned approaches. This presents a key research direction in the field as the process of automatically determining the size and bus locations of reactive power compensators can be achieved in near real time via simulations.

In [4], a DANN in which the hyper-parameters were trained by Particle Swarm Optimization (PSO) was used to estimate the compensation value required and the optimal location of reactive (shunt) compensation considering the active (load) power, reactive power and the corresponding load connected bus id. They used a two-stage brute-force approach including a Newton-Raphson (NR) load flow algorithm (at first stage) and an optimal selection approach (second stage) with a well-defined random load generation scheme to synthesize the DANN training data and considering the IEEE- 14, 30 and 118 bus-bar systems. The authors reported 100% accuracy in the location of reactive compensation for all considered IEEE busbars when compared to the brute-force approach. They also reported slight percentage differences in the reactive sizing of the busbars (IEEE-14, 30) and 0% difference in IEEE 118 busbar.

In order to guard against an imminent voltage collapse, reactive power compensation via shunt capacitors was utilized in [5] for improvement of voltage profile of IEEE power network. Their proposed system applied a hybrid of swarming intelligence techniques comprising the Bee Colony Optimization Model (BCOM), the Particle Swarm Optimizer Model (PSOM) and the Ant Colony Optimizer Model (ACOM) for minimizing the voltage deviations at PQ buses. MATLAB simulation results indicated that the PSOM approach will exhibit the most stable response considering loading effects in the simulated power network.

[6] proposed the use of Rao-1 algorithms for shunt compensation of 330kV power system network in Nigerian with the goal of minimizing the Total Voltage Violation (TVV) in the system. From their simulation results, the Rao-1 optimizer exhibited completive results when compared to the approach based on PSO. The Rao-1 optimizer also exhibited faster computational run times.

[7] proposed the use of Artificial Bee Colony (ABC) algorithm for reactive power optimization and control considering transformers (on load tap changing) and reactive component (inductors and capacitors) switching for Nigerian 330kV power network. They reported a graded reduction in power losses for different loading conditions.

[8] applied an improved Bacterial Foraging Algorithm (iBFA) to the task of optimum reactive power compensation of a distribution feeder in Zaria, Nigeria in a bid to minimize active power loss and voltage deviation. They reported improved computational run-times, voltage profiles and reduced active power losses to the system.

[9] utilized bat algorithm based on weight sum method (WSM) as a tool for solving multi-objective optimization problem. Test results on the standard IEEE 12-bus, 33-bus, 69-bus and 85-bus feeders proved that the proposed algorithm is capable of maximizing voltage stability index and minimizing total active power losses. Comparative results from other solution algorithms validated the proposed algorithm.

III. METHOD

3.1 Analysis of the Network Improvement Technique

The Nigerian 330kV Transmission Network will be enhanced using shunt capacitor banks for reactive power compensation, reducing losses and improving operating voltage, primarily for reactive power supply. The following should be taken into consideration before installation of capacitor banks:

i. The magnitude of reactive power compensation required for improved system efficiency.
ii. Ratings of capacitor banks required.
iii. Location of capacitor banks.

Capacitor banks are usually placed at the load end to mitigate the losses in the circuit between the load and the feeder.

Equations (3.1 and 3.2) displays an adequate method of determining the size of capacitor banks required to improve overall system efficiency:

$$PF = \frac{kW}{kVA} \quad (3.1)$$

$$kVA = [(kW)^2 + (kVAR)^2]^{1/2} \quad (3.2)$$

Where PF = Power Factor,
kW= Active Power in kilowatts,
kVA = Apparent Power in kilo Vars,
kVAR = Reactive Power.

3.2 Proposed Load Flow Analysis and Optimization Technique

This research focuses on the application of particle swarm optimization (PSO) and symbolic regression (SR) methods for solving static load flow problems, specifically bus injection MVARs, and the entire systems solution architecture.

3.2.1 The Particle Swarm Optimizer Algorithm and Application Modeling

The PSO is a powerful and straightforward method for solving non-linear systems, such as power system networks. It uses a Newtonian representation, describing solution variables like bus voltages, angles, and associated parameters. The solution can be represented as follows.

The solution of a PSO may be represented as follows [7]:

Newton's representation as described by the velocity update calculation in (3.3):

$$vel_{ij}(new) = w * vel_{ij} + c_1 * r_1 * \left(pos_{ij}(best) - pos_{ij}\right) + c_2 * r_1 * \left(pos_{ij}(Gbest) - pos_{ij}\right) \quad (3.3)$$

The new position is also updated by adding the velocity update obtained in (3.3) to its old position as in (3.4):

$$pos_{ij}(new) = pos_{ij}(old) + vel_{ij}(new) \quad (3.4)$$

where,

r_1 : random number between 0 and 1
w : inertia weight
c_1: coefficient of self-recognition
c_2 : social coefficient
c_1, c_2 : 2
i : i_{th} iteration
j : j_{th} dimension

In a computational intelligent program, the PSO technique may be approached:

3.2.2 PSO Algorithm

Initialize a population of swarm particles, *n*, weight damping factor, w_{damp}, time step, *t*

Randomly initialize the particle position, *x* and its associated velocities, *v*

While stopping criterion is false do
$t = t+1$ (3.5)
Compute fitness value of each particle

$$x* = \arg\min_{t-1}^{n}\left(\begin{array}{l} f(x*(t-1)), f(x_1(t)), \\ f(x_2(t)), \ldots f(x_t(t)), \ldots f(x_n(t)) \end{array} \right);$$

For i =1 to n

$$x_t^{\#}(t) = \arg\min_{t-1}^{n}\left(f\left(x_t^{\#}(t-1)\right), f(x_t(t)) \right) \quad (3.6)$$

For j = 1 to Dimension
Update the jth dimension of x_t and v_t//x_t = *pos*, v_t = *vel*
Execute (3.5)
Execute (3.6)
End For
Update the weight damping, $w = w*w_{damp}$
End For
End While

3.2.3 Temporal PSO fine-tuning

This study proposes a damping model for routine 1 of the PSO, which can be adjusted to achieve local optimality in certain simulation trials, despite the fact that optimality may vary in practice.

$$w = w * w_{damp} * t \quad (3.7)$$

As can be seen in eqn (3.7), the weight damping factor is temporally adjusted as the PSO performs its optimization task. However, the model as described in eqn (3.7) will only hold if the global best cost (Gbest) or the best cost so far (Best Cost) is greater than a tolerance factor, say, t_f. This implies that our model is a conditional one. From initial experiments and simulation studies, a choice of $t_f = 0.05$ has been found to be a good starting point.

3.2.4 Symbolic Regression (SR) Modeling

The SR approach presents an automated way of representing interrelations among system variables. In this study, the standard model for representing solution parameters as genes is employed. In this regard, there is a terminal set comprising several alphabetic variable codes representative of solution variables and a function set comprising several key mathematical operators. The terminal and function sets are as modeled in eqn (3.8) and (3.9) respectively.

$$t_{set} = \{a, b, c, A, \ldots \mathrm{A}_n\}, \; \mathrm{A}_n \in \mathrm{A}_{set} \quad (3.8)$$

$$f_{set} = \{+, -, *, /, \ldots \Gamma_n\}, \quad \Gamma_n \in \Gamma_{set} \quad (3.9)$$

where,

A_{set} = Alphabet Set

Γ_{set} = Function Set

Here, the model equations, i.e., eqns (3.8) and (3.9) represent the gene individuals (dual gene) as in human or mammalian evolution. In order to assure a suitable representative model, the models in equation (3.8) and (3.9) are iteratively and recurrently evolved by a random perturbation process such that the best fitted individuals (members of the dual-gene set) that meet a fitness function criterion are selected.

IV. RESULTS AND DISCUSSION

4.1 Compensation Results on Overloaded Buses

One of the benefits derived from dynamic optimization approaches which follows the dynamic programming is in their unique ability to automatically discover solutions to highly complicated and non-linear problems. Using the Particle Swarming Optimizer (PSO) approach developed in this research study, the weak buses were automatically compensated and brought within tolerable results considering a 3-tier graded compensation procedure with MVAR upper bounds of 10MVARs, 50MVARs and 100MVARs.

In addition, percentage improvement factors from the perturbed (critical overloaded) states where no compensations were added to that when compensations are injected are computed and compared based on the aforementioned MVARs upper bounds. The results comparing the un-compensated overloaded case with the compensated one are as shown in Table 1.

Table 1 Automatic Compensation Results Using the PSO

Bus id	Vsol (C_{MVAR} = 0)	Vsol (C_{MVAR} = 10)	Vsol (C_{MVAR} = 50)	Vsol (C_{MVAR} = 100)
1	1.06	1.06	1.06	1.06
2	1.19	1.20	1.20	1.21
3	1.03	1.03	1.03	1.03
4	0.82	0.98	0.98	0.99
5	0.98	1.05	1.05	1.06
6	0.97	1.05	1.05	1.06
7	1.06	1.06	1.06	1.06
8	0.60	0.93	0.93	0.95
9	0.46	0.90	0.90	0.91
10	0.98	1.07	1.07	1.09
11	1.02	1.02	1.02	1.02

12	0.89	1.02	1.02	1.02
13	1.03	1.13	1.13	1.15
14	0.94	1.06	1.06	1.09
15	0.88	1.00	1.00	1.00
16	0.77	0.96	0.96	0.96
17	0.90	1.03	1.03	1.07
18	1.04	1.04	1.04	1.04
19	1.02	1.03	1.03	1.03
20	0.88	1.00	1.00	1.00
21	0.79	1.00	1.00	1.01
22	1.03	1.03	1.03	1.03
23	0.90	0.98	0.98	0.98
24	1.03	1.03	1.03	1.03
25	1.04	1.04	1.04	1.04
26	1.03	1.03	1.03	1.03
27	1.03	1.03	1.03	1.03
28	1.03	1.03	1.03	1.03
29	1.03	1.03	1.03	1.03
30	0.93	1.01	1.01	1.01
31	1.03	1.03	1.03	1.03
32	1.01	1.02	1.02	1.02
33	1.03	1.03	1.03	1.03
34	1.03	1.03	1.03	1.03

From table 1, It is also noticeable that the percentage improvement is greater for critical buses when compared to the rest. In particular, the collapsed bus - bus 8, will require a percentage improvement of 56% at the 10MVARs and 50MVARs level and a percentage improvement of 58% at the 100MVARs level while bus 9 will require a percentage improvement of 94% at the 10MVARs and 50MVARs level and a percentage improvement of 97% at the 100MVARs level.

Table 2 shows a summary of the percentage voltage profile improvement

Bus ID	Vsol (Q_{MVAR} = 0)	Vsol (p.u)$_{(10MVAR)}$	Q $_{(10MVAR)}$	Vsol (p.u)$_{(50MVAR)}$	Q $_{(50MVAR)}$	Vsol (p.u)$_{(100MVAR)}$	Q $_{(100MVAR)}$
1	1.06	1.06	0	1.06	0	1.06	0
2	1.19	1.2	4	1.2	6	1.21	11
3	1.03	1.03	0	1.03	0	1.03	0
4	0.82	0.98	4	0.98	5	0.99	10
5	0.98	1.05	4	1.05	6	1.06	11
6	0.97	1.05	5	1.05	6	1.06	10
7	1.06	1.06	0	1.06	0	1.06	0
8	0.6	0.93	5	0.93	5	0.95	11

9	0.46	0.9	4	0.9	6	0.91	10
10	0.98	1.07	4	1.07	5	1.09	10
11	1.02	1.02	0	1.02	0	1.02	0
12	0.89	1.02	5	1.02	5	1.02	11
13	1.03	1.13	4	1.13	5	1.15	10
14	0.94	1.06	4	1.06	6	1.09	10
15	0.88	1	4	1	6	1	11
16	0.77	0.96	5	0.96	5	0.96	11
17	0.9	1.03	5	1.03	5	1.07	10
18	1.04	1.04	0	1.04	0	1.04	0
19	1.02	1.03	4	1.03	6	1.03	10
20	0.88	1	5	1	6	1	10
21	0.79	1	5	1	6	1.01	10
22	1.03	1.03	0	1.03	0	1.03	0
23	0.9	0.98	5	0.98	6	0.98	11
24	1.03	1.03	0	1.03	0	1.03	0
25	1.04	1.04	5	1.04	6	1.04	10
26	1.03	1.03	0	1.03	0	1.03	0
27	1.03	1.03	0	1.03	0	1.03	0
28	1.03	1.03	0	1.03	0	1.03	0
29	1.03	1.03	4	1.03	5	1.03	10
30	0.93	1.01	5	1.01	6	1.01	10
31	1.03	1.03	0	1.03	0	1.03	0
32	1.01	1.02	5	1.02	6	1.02	11
33	1.03	1.03	0	1.03	0	1.03	0
34	1.03	1.03	0	1.03	0	1.03	0
	0.954705882	1.027647059	2.794117647	1.027647059	3.470588235	1.033235294	6.411764706

From the table above, the percentage voltage profile increase is given by:

$$V\% = \frac{\text{New} - \text{Base X } 100}{\text{Base}} = \frac{1.03 - 0.95}{0.95} = 8.4\%$$

From the figure 1, the voltage improvement before and after perturbation. The result shows that the improvement after perturbation improved significantly.

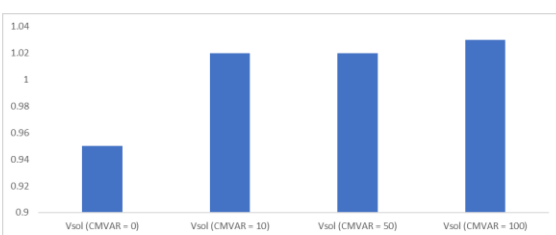

Figure 1 Voltage Profile Improvement before and after Perturbation

This Bar Chart was generated from table 1 to show the Summary of Percentage Voltage Profile Improvement before and after network perturbation.

In figure 2 Bar Chart Comparing 0 CMVAR and 10 CMVAR is shown. And from the result indications, it shows that the Vsol (CMVAR=10) has a higher performance and improvements, This Bar Chart shows voltage profile improvement before and after perturbation of the various buses.

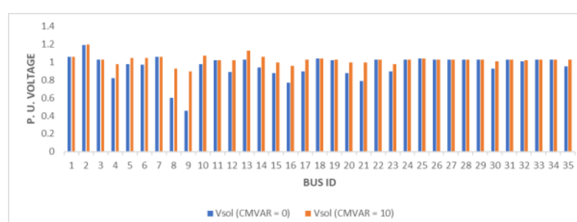

Figure 2 Bar chart Comparing 0 CMVAR and 10 CMVAR

Figure 3 bar chart shows the comparison between 0 CMVAR and 100 CMVAR

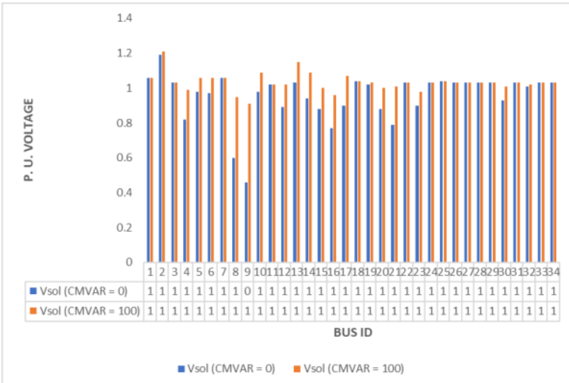

Figure 3 Bar Chart Comparing 0 CMVAR and 100 CMVAR

By comparing the three different boundary conditions, it is seen that an average of three banks were assigned to each of the bus bars when a 10MVAR bank was injected into the network. But when a 50MVAR was injected (used as perturbation) an average of four banks were designated to each bus and finally a six bank per bus was seen when a 100MVAR was used. See table 3 below:

Table 3 Total no of Banks

MVAR	Vp.u.	Average no of Bank/bus	Total no of Banks for 34 Buses
10	1.03	3	3 x 34 = 102
50	1.03	4	4 x 34 = 136
100	1.03	6	6 x 34 = 204

CONCLUSION

Currently, studies on power system networks are evolving, with a growing interest in dynamic programming approaches to address numerous problem areas. Artificially Intelligent (AI) systems play a crucial role in this evolution by promoting diversity. Their inherent non-linear dynamics make them suitable for solving complex non-linear power system issues. In this research, an enhanced Particle Swarm Optimization (PSO) method was employed to solve the problem of optimal shunt injection capacitor bank sizing and placement in the 330kV power network. A Symbolic Regression (SR) model fitting technique was also used to represent the solution states, considering the deviation from the maximum solved capacitor bank MVARS and their individual allocation across load (PQ) buses. The study focused on automatic shunt compensation using machine learning (PSO) and Inductive Modelling (SR) for adaptive load flow solutions and representative modeling of the power system. Simulation studies were conducted on both large and small power networks, including the Nigerian 330kV, 34-Bus, 11-generator network, and the IEEE 6-Bus, 2-generator network. The simulations demonstrated that PSO optimization could effectively and automatically size and allocate shunt capacitor injection MVARs into the power systems while minimizing voltage instabilities. The system voltage profile improved by 8.4%, and the SR adequately modeled the solution states with error deviations as low as +/-5MVARS.

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