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Voltage Collapse Analysis of Nigerian 330kv 34 Bus Power System Using Swarm Particle Optimizer Predictor

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Abstract: *Voltage collapse analysis (VCA) plays an important role in stability studies and system operation of power system. Due to overloading or fault condition (system turbulence) the system can be stressed beyond its permissible limit thereby causing failure of power delivery. In order to study the effect of VCA on Nigerian 330kV 34-bus power system network, an Artificial Intelligence (AI) technique basedSwarm Particle Optimizer Predictor (sPOP) approach is proposed in this paper. Using sPOP, simulations were performed over several trial runs and the results portray the sPOP as a promising VCAtechnique for power system network planning.*

Keywords: *Artificial intelligence, optimization, power systems network, predictor, voltage collapse.*

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I. Introduction

The challenges of maintaining the stability of power systems networks coupled with the need to assure cost-effective operation demands proactive measures to be put in place. One major challenge refers to the need to prevent the occurrence of a voltage collapse to a power system network. Thus, voltage stability margins (VSM) have been proposed by several authors using a variety of techniques and frameworks in order to determine the critical state of power system and in turn alleviate the problem of voltage collapse (Jain and Rathod, 2019).

The process of determining the critical state refers to the need for VSMs that are optimized for a particular power system network. In this regard, there is the need to define a proper VSM that will work well and is robust to system-wide parameters.

Some important VSM metrics for voltage collapse studies include but not limited to the *L-index* (Moghavvemi and Omar, 1998), the stability factor *LQP* (Mohamed and Jasmon, 1995) and Fast Voltage Stability Index or *FVSI* (Musirin and TKA, 2002). However, in recent studies the aforementioned have been found to give inaccurate results when the power system network is stressed heavily (Ratra et al., 2018). Thus, the Quadratic Line Voltage Stability Index (Q-LVSI) was proposed and is considered in this paper.

Apart from the definition of the VSM in interest, another very important aspect in the voltage collapse studies is in the prediction of the VSM through time. This is typically done to determine the likelihood that a particular bus sequence will be the cause of system failure. Thus, the use of a predictor becomes valuable in this regard.

In this paper, a new approach to VCA of power system network that leverages on the solution capability of a PSO, a Q-LVSI with a sequence predictor based on machine intelligence is proposed. The objective is to determine through a consensus mining process, the most probable bus sequence that is fragile from a set of pareto-optimal bus sequences; these sequences are priors estimated by the SPO-Q-LVSI stage in the proposed solution. Thus, instead of simple ranking, a consensus estimate over a number of trial runs are performed to give more credible results.

II. Related Works

Man-Im et al (2019) used a voltage stability margin called the L-index earlier introduced in (Kessel and Glavitsch, 2000) in a multi-objective minimization optimal power flow problem. Their formulation used a chaotic mutation Stochastic Weight Trade-off (SWT) swarm intelligence technique based on non-dominated sorting particle swarm optimization (SWT-NS-SPO) which was applied to IEEE 30-bus power. Simulation resultscompared with some existing techniques such as NSGA-II, NSPSO, NS_CPSO etc showed that NS-SWT-NS-SPO is best as an optimizer.

Jayakansar et al (2010) proposed a ranking scheme based on standard feed-forward back-propagation trained artificial neural network and using L-index for voltage collapse prediction of weak lines of the IEEE 30-

bus with Thyristor Controlled Series Capacitor (TCSC) compensation. Standard feedforward neural network was used for matching the input (load variations) with line indexes computed after a variety of load flow simulations.The results of analysis showed that the line that gives most stability improvement i.e. with morenumber of lines improved can be identified when a step-by-step mutually exclusive installation of the TCSC on the discovered weak lines is used.

Chatterjee and Roy (2019) proposed a Catastrophic Failure Index (CFI) with signature analysis for early prediction of catastrophic failures of power system due to voltage collapse. Their proposed technique have been applied to the IEEE 30-bus with promising results.

Other methods of VCA include the use of Genetic Algorithm (GA) based reactive power dispatch for the minimization of the L-index to improve voltage stability (Devaraj and Roselyn, 2010), VSM improvement using PSO and Continuation Power Flow (CPF) techniques (Azadani et al., 2008), game theoretic approach for voltage stabilization (Avraam, 2018) and the Voltage Collapse Index (VCI) prediction based on the structural characteristics of the L-index (Adebayo et al., 2015).

III. Systems Methodology

The development of an optimization solution model requires that the objective (fitness or cost) function be pre-specified and that decision variables (solution variables) including the associated boundary conditions and constraints be clearly defined. For the case where a voltage collapse is imminent, there will be the additional requirement to determine the critical and most critical buses in the power system network. Considering the stability in the power system network voltage profile, there is also the added requirement of maintaining adequate compensation to bring the voltages close to reference values.

The flow chart shown in Fig.1 describes the systems level approach of the SPOP technique used in this study.

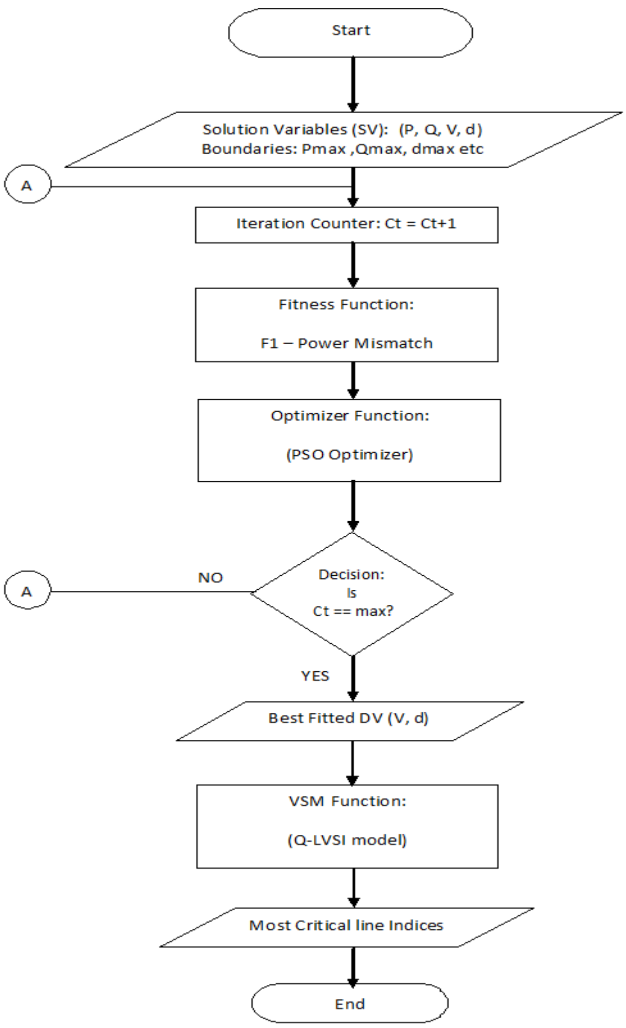

Fig.1: Flow chart of Swarm Particle Optimizer (SPOP) Methodology.

From Fig.1, the input data (solution variable boundaries) is first fed into the system whilst the optimizer parameters are pre-defined.

The optimizer then solves the network using appropriate load flow processing rules and calculations to fit the power mismatch to infinitesimal levels. This solving process is repeated a number of times to obtain a sequential solution vector; in this case the bus voltages and angles. These solution vectors are at the same time used by the Q-LVSI processor which performs the initial computations of the vulnerable bus interconnections (i.e. the lines that are vulnerable) in addition to the most vulnerable one at each iteration time step.

As the network is solved, and a certain number of trials are attained, the predictor stage is called upon to make predictions on the computed vulnerable lines by considering their index sequences as source input. Thus, any intelligent algorithm can be used here for making continual (one step-ahead) predictions but the auditory inspired machine intelligence technique called the AMI proposed in (Osegi and Anireh, 2019) is used instead. This is due to its simplicity and high level of precision in making continual learning predictions. The concept of this proposed technique is as shown in Fig.2.

The Q-LVSI computation technique, SPO and the AMI techniques are described succinctly in the following sub-sections.

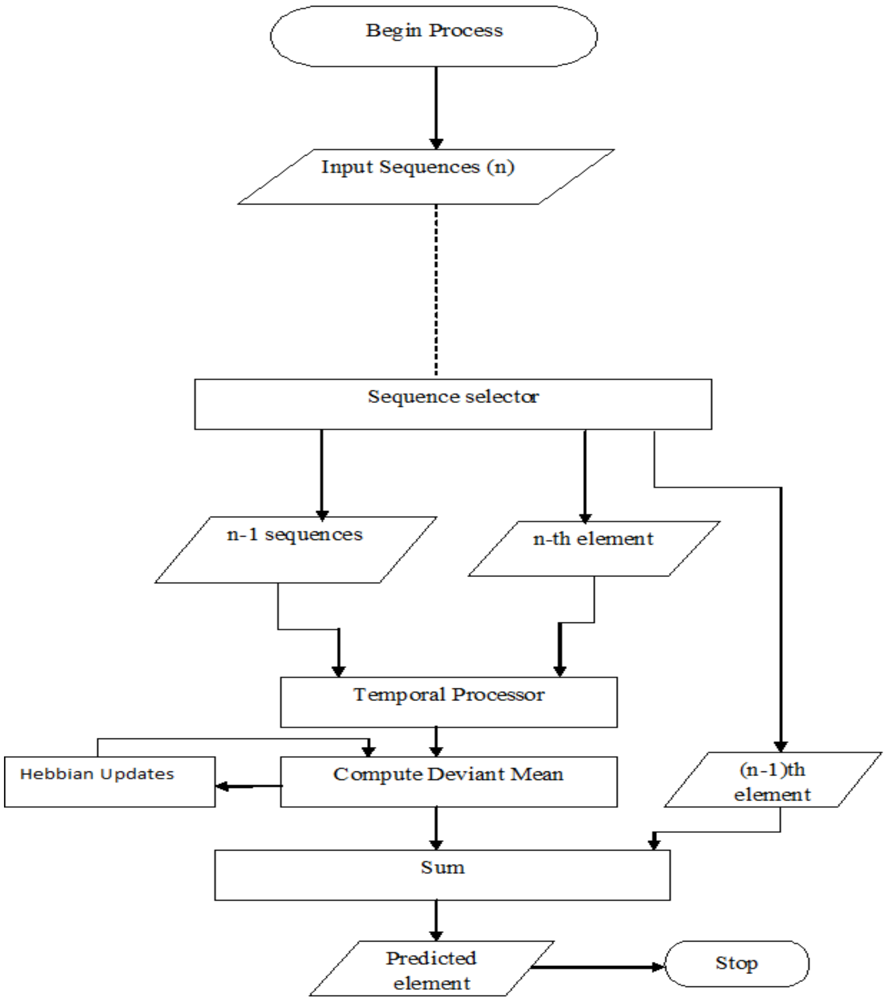

Fig.2: Solution Concept of AMI predictor. Source: (Osegi, 2020)

3.1. Q-LVSI Technique

Quadratic-LVSI (Q-LVSI) considers the line charging capacitances and transmission line resistances in the computation of a Voltage Stability Margin (VSM). It can be computed from the following model steps (Ratra et al., 2018);

Step1: Compute phase angle difference between receiving and sending end buses:

$\delta_{sR} = \delta_s - \delta_r$ (1)

Step2: Compute the A and B parameter representations from the impedances (Z) and admittances (Y) of all the lines at iteration I, as:

A(I,:) = 1 + Y(I,:) *Z(I,:)/2 (2)
B(I,:) = Z(I,:) (3)
where,
I = bus index number.
Step3: Using equations (2) and (3), compute the angle parts of A and B parameter representations respectively as:
α = ang(A) (4)
β = ang(B) (5)
Step 4: Using equations (1-2) and (4-5), compute the Q-LVSI as:

$$\frac{2V_R A\cos(\beta-\alpha)}{V_S \cos(\beta-\delta)} > 1 \tag{6}$$

3.2. Swarm Optimizer Technique

Swarm Particle Optimizer (SPO) is an AI strategy based on the concept of swarm particles. Introduced in the mid-90s by Kennedy and Eberhart (Kennedy & Eberhart, 1995), SPO enables particles to represent candidate solutions as velocity states and position states given a population of randomly perturbed. The randomization process is typically characterized by a continual update of weighted velocity vectors in addition to a randomized version of a position state. This state is a sum of the difference between a randomized previous best position state and a previous (initial) state. This position updates occurs at local and global levels (Sumathi &Paneerselvam, 2010). The operation in a SPO is described by the very simple formulas:

$$\begin{aligned} vel_{ij}(new) &= w * vel_{ij}(old) + c_1 rand_1(pbest_{ij}(old)) \\ &- pos_{ij}(old) + c_2 rand_2(pbest_{ij}(old)) - pos_{ij}(old) \end{aligned} \tag{7}$$

$$pos_{ij}(new) = pos_{ij}(old) + vel_{ij}(new) \tag{8}$$

The new positions are updated by adding the velocity updates obtained from equation (7) to the old positions obtained from equation (8).
where,
$rand_1$, $rand_2$ = random number between 0 and 1
w = inertia weight
c_1 = coefficient of self-recognition
c_2 = social coefficient
c_1, c_2 = 2.

3.3. Predictor Technique

The predictor technique employs the Auditory Machine Intelligence (AMI) algorithm developed in (Osegi and Anireh, 2019). This algorithm primarily uses the concept of mismatch negativity effect (MMN) introduced in (Näätänen et al., 1978). This effect have been found to exhibit very intelligent cognitive functions (Näätänen et al., 2007).
In the AMI predictor, two phases are employed:
1) The pre-prediction (phase1) where continual one step ahead predictions are made.
2) The post-prediction (phase2) where predictions are made many steps ahead.
In this research, the phase1 prediction is used.

The AMI performs its predictor operation using the computation of a single formula and does not necessarily require random fine-tuning during data pattern learning. In phase1, the AMI predictor temporally learns in an adaptive manner by computing and updating a mean deviant point as given in equation (9):

$$S_{dev(mean)} = \frac{\left(\left(\frac{\sum[S_{dev}]}{(n-1)}\right) + S_{deviant}\right) - 2}{n+1} \tag{9}$$

where,
n = number of data points in a temporal sequence
$S_{deviant}$ = the (n-1)th value of the temporal sequence

S_{dev} = the difference between $S_{deviant}$ and S_{stars}
S_{stars} = the (n-2)th values of the temporal sequence
S^* = sparse set of input sequences
The AMI predictions are then made using equation (10) as:

$$S_{pred} = S_{deviant} + S_{dev(mean)} \qquad (10)$$

where,

$$S_{deviant} = S_n^* - 1 \qquad (11)$$

$$S_{stars} = S_n^* - 2 \qquad (12)$$

The algorithms of the AMI predictor is as provided (see Algorithm 1 and 2).

Algorithm 1. AMI Processing Algorithm
1: Initialize S_{pred}, as prediction parameter, S_{stars}, as input sequences (standards) State, $S_{dev(mean)}$ as deviant mean, j as iteration counter.

2: for all $s \in s.S_{stars}$, && j > 1, do
3: Compute $S_{deviant}$and S_{stars} using equations (11) and (12)
4: $S_{dev} \leftarrow \|S_{deviant} - S_{stars}\|$ // deviations from standards
5: Compute $S_{dev(mean)}$ using equation (9)
6: Compute S_{pred} using equations (9 and 11)
7: Update $S_{dev(mean)}$ using Algorithm 2
8: end for

Algorithm 2. AMI Learning Algorithm
1: Initialize S_{pred}, as prediction parameter, S_{stars}, as input sequences (standards) State, $S_{dev(mean)}$ as deviant mean, $S_{diff(1)}$ as difference between S_{pred}, $S_{deviant}$+1 and $S_{diff(2)}$ as difference between $S_{dev(mean)}$ and $|S_{diff(1)}|$, l_p as correction factor or bias.

2: for all $s \in s.S_{stars}$ do
3: if $S_{diff(2)} > 0$
4: $S_{dev(mean)} \leftarrow S_{dev(mean)} - |S_{diff\ (1)}|$ // Weaken deviant mean by a factor, $|S_{diff(1)}|$
5: elseif $S_{diff(2)} < 0$
6: $S_{dev(mean)} \leftarrow S_{dev(mean)} + |S_{diff\ (1)}|$ // Reinforce deviant mean by a factor, $|S_{diff(1)}|$
7: else
8: $S_{dev(mean)} \leftarrow S_{dev(mean)} + l_p$
9: end if
10: end for

IV. Experimental Results And Discussions

In this section, the results of experiments using the proposed SPOP technique for voltage collapse studies of the Nigerian 330-kV 34-bus power transmission network are presented. In Fig.3 is shown the power system network diagram considered.

The data used in the simulations include theline data, bus data and power system generation and load data provided for power system stability studies (Ikeli, 2009). For the compensation experiments, a shunt MVARs of between 0 and 50MVARs are used for the VSM improvement. For the SPO part, the population size was set to 20 and the iteration steps set to 100. Constriction coefficients and damping factor are also 2.05 and 1.0 respectively. All simulations are performed in the MATLAB environment.

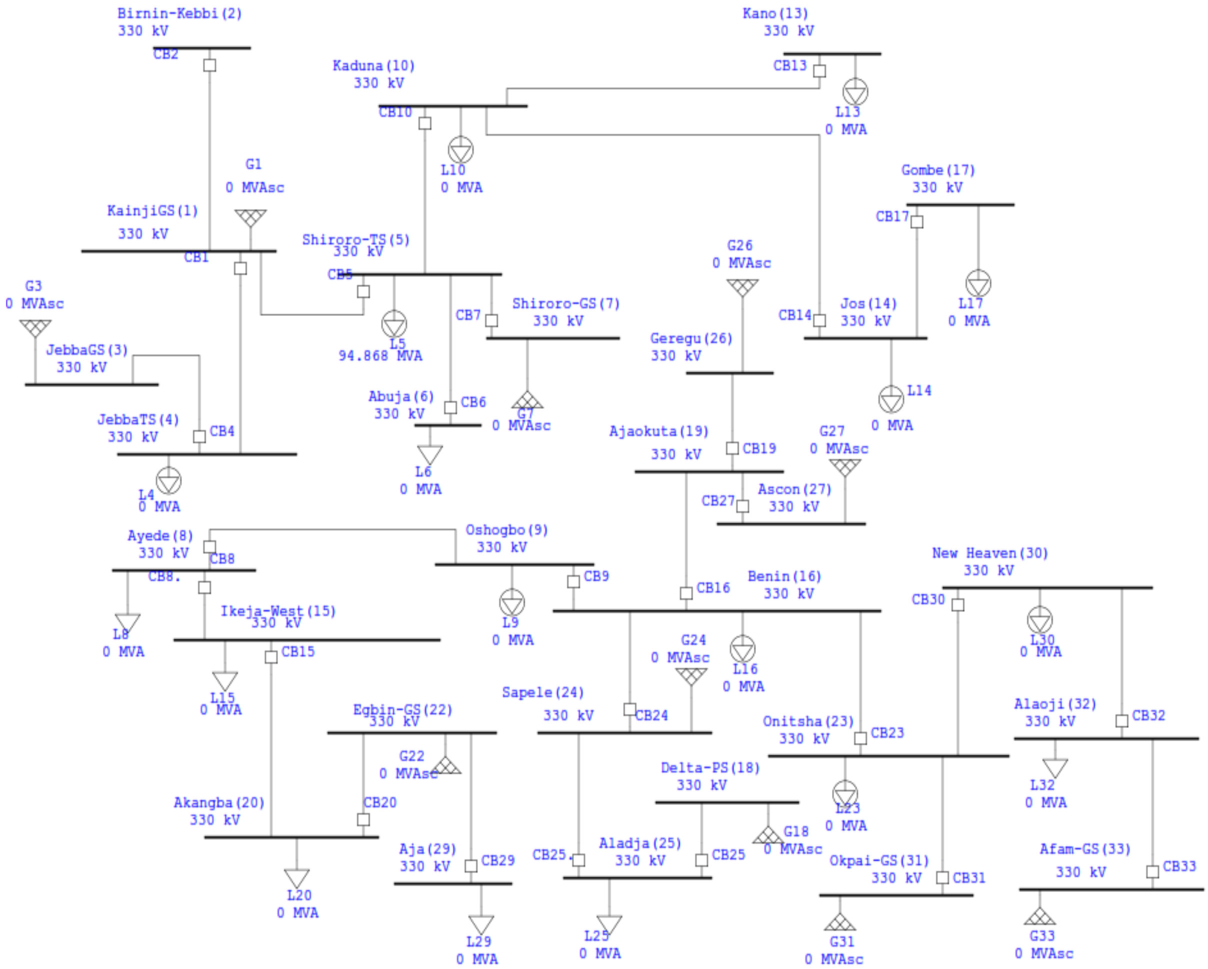

Fig.3: The Nigerian 330kV, 34 Bus, 11-machine Power Network

4.1. Power System Data

Thebus data nomenclature is provided in Table 1 while the transmission line parameters and power systems loading data (PV and PQ loading) are provided in Tables 2 and 3 respectively.

Table 1: Nomenclature of the 34 Bus 11-Machine Power Network

Bus No.	Bus Code*	Type of Bus	Bus Name
1	1	Slack	Kainji G.S
2	0	PQ	Bernin Kebbi
3	2	PV	Jebba G.S
4	0	PQ	Jebba T.S
5	0	PQ	Shiroro T.S
6	0	PQ	Abuja(katampe)
7	2	PV	Shiroro G.S
8	0	PQ	Ayede T.S
9	0	PQ	Oshogbo T.S
10	0	PQ	Kaduna T.S
11	2	PV	Olorunsongo G.S
12	0	PQ	Sakete T.S
13	0	PQ	Kano T.S
14	0	PQ	Jos T.S
15	0	PQ	Ikeja West T.S
16	0	PQ	Benin T.S
17	0	PQ	Gombe T.S
18	2	PV	Delta G.S
19	0	PQ	Ajaokuta T.S
20	0	PQ	Akangba T.S
21	0	PQ	Omotosho T.S
22	2	PV	Egbin G.S
23	0	PQ	Onitsha T.S
24	2	PV	Sapele G.S

25	0	PQ	Aladja T.S
26	2	PV	Geregu G.S
27	2	PV	Ascon G.S
28	2	PV	AES G.S
29	0	PQ	Aja T.S
30	0	PQ	New Heaven T.S
31	2	PV	Okpai G.S
32	0	PQ	Alaoji T.S
33	2	PV	Afam G.S
34	2	PV	Omoku G.S

Table 2: Transmission Line Parameters

From	To	R(p.u)	X(p.u)	B(p.u)	Tap
1	2	0.0122	0.0916	1.2100	1
1	4	0.0016	0.0120	0.3100	1
3	4	0.0002	0.0094	0.0000	1
4	5	0.0048	0.0360	0.0900	1
4	9	0.0021	0.0155	0.0700	1
5	6	0.0019	0.0142	0.3600	1
5	7	0.0003	0.0188	0.0000	1
5	10	0.0019	0.0142	0.3700	1
8	9	0.0054	0.0405	0.3300	1
8	15	0.0053	0.0406	0.4500	1
9	15	0.0065	0.0427	0.5500	1
9	16	0.0099	0.0742	0.9800	1
10	13	0.0090	0.0680	0.5200	1
10	14	0.0077	0.0582	0.7700	1
11	15	0.0021	0.0104	0.3100	1
12	15	0.0041	0.0305	0.4100	1
14	17	0.0104	0.0783	0.0100	1
15	16	0.0110	0.0828	0.0900	1
15	20	0.0004	0.0027	0.0500	1
15	21	0.0055	0.0414	0.3500	1
15	22	0.0012	0.0092	0.2000	1
16	18	0.0064	0.0405	0.1500	1
16	19	0.0038	0.0288	0.7600	1
16	21	0.0055	0.0414	0.5500	1
16	23	0.0054	0.0405	0.3800	1
16	24	0.0010	0.0074	0.1900	1
18	25	0.0010	0.0077	0.1000	1
19	26	0.0005	0.0038	0.3800	1
19	27	0.0006	0.0038	0.4000	1
22	28	0.0005	0.0036	0.3000	1
22	29	0.0003	0.0021	0.2000	1
23	30	0.0038	0.0284	0.3700	1
23	31	0.0049	0.0037	0.0900	1
23	32	0.0061	0.0455	0.0200	1
24	25	0.0025	0.0186	0.2400	1
28	29	0.0035	0.0206	0.3000	1
32	33	0.0010	0.0074	0.0900	1
33	34	0.0005	0.0038	0.3000	1

Table 3: System Loading Data including PV generation and PQ-Loading

Bus No.	MW	MVAR
1	520	--
2	40	-10
3	300	110(0)
4	140	30

5	90	30
6	160	70
7	400	140(0)
8	130	70
9	300	90
10	210	40
11	150	114(0)
12	50	-20
13	100	-30
14	120	60
15	500	50
16	250	43
17	70	38
18	280	100(0)
19	200	55
20	150	35
21	240	104(0)
22	700	108(0)
23	300	45
24	180	132(0)
25	100	58
26	190	126(0)
27	150	100(0)
28	130	150(0)
29	120	80
30	130	-78
31	150	100(0)
32	200	67
33	200	140
34	300	125

4.2. Experiments Without Compensation

The experimental results without compensation have been performed for a number of trial runs. For the first 20 trials, the Mean Absolute Percentage Error (MAPE) is reported in Fig.4.

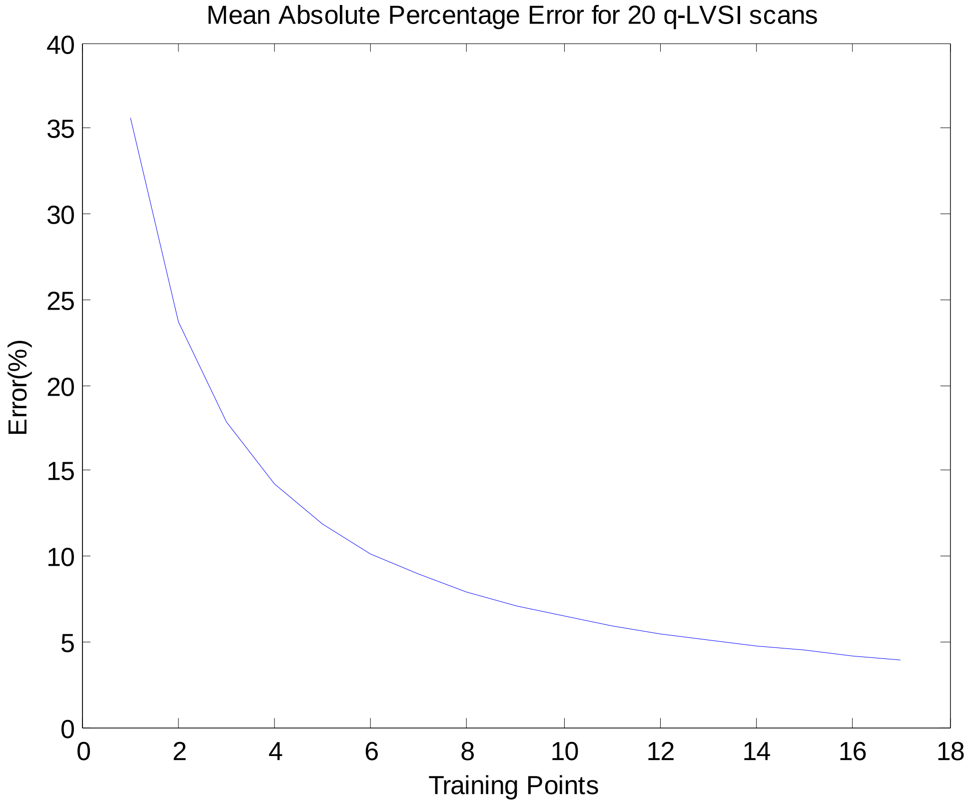

Fig.4: Fitness response (without compensation) for 20 trial runs

From the MAPE response plot (Fig.4), it is obvious that the prediction error performance improves as the trial run increases. This is further validated when the trial run number is increased to 200 (see Fig.5) i.e. the MAPE response start getting close to zero.

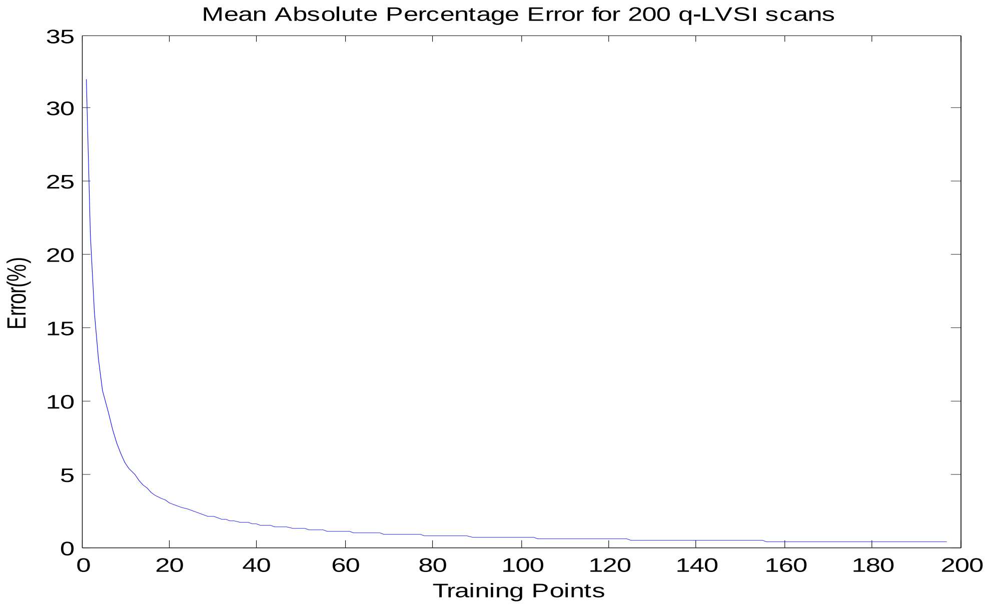

Fig.5: Fitness response (without compensation) for 200 trial runs

The predicted critical buses for 20 trial runs are shown in Table 4.

Table 4: System Loading Data including PV generation and PQ-Loading

From	To
22	29
19	27
32	33
23	31
16	21
9	16
23	31
15	22
16	18
32	33
8	15

From the Table 4, it is clear that the bus sequence 23-31 is the most critical one. It was also discovered that when the trial run was set to 200, the same bus sequence was also found to be the most critical one.

4.2. Experiments With Shunt Compensation

In this experiment, shunt capacitive MVARs are added to the buses and the SPOP technique adaptively compensates the power network. The result in bus voltages before and after compensation for 20 trial runs is given in Table 5.

Table 5: Bus voltage response before and after compensation for 20 trial runs

Bus No.	Before Cmpensation	After Cmpensation
1	1.0000	1.0000
2	0.9627	0.9870
3	1.0000	1.0000
4	0.9616	0.9864
5	0.9621	0.9860
6	0.9614	0.9780
7	1.0000	1.0000
8	0.9629	0.9808
9	0.9620	0.9798
10	0.9612	0.9706
11	1.0000	1.0000
12	0.9577	0.9678
13	0.9587	0.9875
14	0.9620	0.9834
15	0.9666	0.9813
16	0.9618	0.9790
17	0.9606	0.9697
18	1.0000	1.0000
19	0.9611	0.9787
20	0.9617	0.9867
21	0.9625	0.9793
22	1.0000	1.0000
23	0.9616	0.9873
24	1.0000	1.0000
25	0.9586	0.9846
26	1.0000	1.0000
27	1.0000	1.0000
28	1.0000	1.0000
29	0.9684	0.9790
30	0.9614	0.9815
31	1.0000	1.0000
32	0.9620	0.9877
33	1.0000	1.0000
34	1.0000	1.0000

From the results in Table 5, the added shunt compensation improves the voltage response profile adaptively by the SPO without the need for manual specification or selective compensation.

V. Conclusions And Future Work

This research has employed a hybrid neuro-swarm solution to the problem of Voltage Collapse Prediction.The proposed solution has been applied to the Nigerian 330kV 34-bus power transmission network using a Swarm Particle Optimizer-Predictor (SPOP) approach including a new voltage stability index – the Q-LVSI, a popular and powerful swarm intelligence technique (PSO) and a recent machine intelligence technique – the AMI.

The results showed that collapse bus sequence predictions can be improved as the numbers of search trials are increased. In addition, adaptive shunt compensation by the SPOP shows improvement in bus voltage profile and thus obviating the need for selective compensation.

Future work should study the robustness of the proposed approach under varying loading conditions. Also, other power transmission networks including the various IEEE bus topologies. Also, comparisons should be made with other swarm-optimizertechniques.

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