American Journal of Engineering Research (AJER)
e-ISSN: 2320-0847 p-ISSN : 2320-0936
Volume-9, Issue-2, pp-78-86
www.ajer.org
Research Paper Open Access

Threshold-Constraint and Swarm Intelligence-Based Load Flow Analysis forSteady State Stability Studies oftheNigerian 132-KVPower Transmission Network

Anthony A. Oko, Christopher O. Ahiakwo, Dikio C. Idoniboyeobu,and Sunny Orike*

Department of Electrical Engineering, Rivers State University, Port-Harcourt, Nigeria
Corresponding Author:Sunny Orike

ABSTRACT:*The current rising demand in power in Nigerian cities in the South-South zone has led to the undesirable impact on the power capacity of the generating units serving this region. In this paper, we present a steady stability approach, which uses a swarm intelligence technique called Bee Colony Optimization (BCO) for solving the Nigerian 132-kVsub-transmission network, Port-Harcourt zone (PH-132-kV). We present results of steady-state analysis of some buses in the PH-132-kV network from the maximum load-ability point of view by randomly varying the reactive loading at these buses whilst modifying the displacement angle threshold condition of a Maximum Power Point Identification Tracking (MPPIT) routine within the Swarm intelligence best search loop. The results reported very variable Pmax before conditioning and reasonable stable Pmax after conditioning indicating the sensitive nature of the studied power network during high reactive loading and the value of displacement angle signal threshold conditioning.*

KEYWORDS: *load flow, power systems, steady state stability, swarm intelligence*

Date of Submission: 4-02-2020 Date of acceptance: 20-02-2020

I. INTRODUCTION

Rationalizing an investment in a facility's infrastructure can be a difficult prospect for any plant engineer or technician, often requiring extensive justification. Investments are considered as "low-risk" when power supply is reasonably stable.At the very basic level, thepossibility for a reliable power supply in any given power system requires that the steady state stable conditions be met. One way of evaluating this requirement is to consider its state of maximum loading. In this context, we say that the electrical networks power system supply will be in steady state when its maximum load-ability point does not exceed a specified limit. This limit is important as it enables the determination of the maximum power that can be transmitted by the power system whichin turn can help inform the power systems engineer on optimizing improvement strategies.

Stability represents a very vital area in the field power system network control, operation and optimization. Conventional stability has been the ones in real power, such as steady state stability, dynamic stability and transient stability. The instability phenomenon means the transmission lines where receiving end power system variables get much lower values than the nominal ones. In an electrical power system network, steady state instability is characterized by progressive decline of voltages or currents caused by the inability of the network to meet the increasing load demand. The process of power instability is generally triggered by some form of disturbance or change in operating conditions which create increased demand for power which is in excess of what the system is capable of supplying. Large and small disturbances in network operating conditions can lead to an increase in reactive power demand. Thus, efficient and reliable power system network contingency analysis techniques are needed to avert the consequent instabilities and threats to power infrastructure which can lead to voltage collapse.

Steady state stability condition corresponds to the operating state of the electrical power system network, which is characterized by gradual or relatively slow (incremental) changes. For example, the load is gradually applied, at a rate sufficiently slow in comparison with the natural frequency of oscillation of the major part of the system or with the rate of change of field flux in the rotating machine in response to the variation in load. Based on operating modes, the steady state may be classified as:

(a) Static steady state – in which the operating equilibrium is without voltage regulators, speed governors, etc. The excitation voltages here are usually assumed to be constant.

(b) Dynamic steady-state – in which automatic voltage regulators and well-designed excitation systems are used to maintain the terminal voltages constant at specified points.

"This requirement of steady-state stability has been an active area of research and the problem defined as a maximum power point identification problem (MPPITP). A power flow program provides the steady state solution of a power system scenario.In a power flow program, the initial conditions for stability assessment, fault analysis, power quality and contingency analysis are typically provided for. Load flow analysis produces steady-state values of voltage magnitude and phase angle of each bus in the power system. This information can be used to calculate other system variables such as power losses, which are needed for operation and planning studies. Further, the application of load flow analysis can be seen in power system markets studies.

Generally, power system network based on their operation conditions can be categorized into well and ill-conditioned systems. A well-conditioned system is a network including low/medium loading, where the conventional methods, such as Gauss-Seidel and Newton-Raphson methods, can be utilized to find the steady-state information of the grid. A power system considers as ill-conditioned due to the high R/X ratio of transmission lines, radial structure of the network and/or the loading of the system approaching towards Maximum Loading Point (MLP). An example of an ill-conditioned system is the distribution system, where its topology commonly includes a tree-like structure with a high ratio of R/X lines. The steady-state stability of distribution and transmission systems is greatly affected in ill-conditioned systems. Thus, in such situations, the methods of conventional load flow cannot converge or may result in unreliable/inaccurate solutions. In the case of ill-conditioned systems, researchers are mostly concerned in ensuring the load flow convergence and systems operation are within the boundary of feasible zones" [1].

II. REVIEW OF LITERATURE

Power system load flow solutions are characterized by feasible or non-feasible points – a situation attributed to the parabolic nature of the system bus voltages and angles. Feasible power flow regions are described by multiple real solutions for the state variables - magnitude and angle of bus voltages, under consideration. For infeasible power flow regions, "there are two different complex solutions for the state variables, which are not admissible from a technical point of view" [1]. The divergence of conventional power flow methods, such as Newton–Raphson (*NR*) or Gauss–Seidel (*GS*), may be associated with infeasible power flow regions, or with a feasible region, but with a starting point out from the convergence radius of the solution method.

In order to solve the aforementioned problem, some researchers have studied the problem in the context of load flow solutions using classical methods based on heuristics as in [2], using continuation power flow, temperature conditioned continuation power flowand the use of a security constrained genetic algorithm [3]-[5]. More recent researches studies have investigated the potential of swarm intelligence (SI) techniques with promising results such as in[5]-[8]. SI was introduced in [9], describing a technique that are population based and stochastic and that are useful in combinatorial optimization problems [10]. Swarm Intelligent Optimization Algorithm (SIOA) typically involves the collective intelligent behavior of social insects, animals or particles some examples which include flock of birds or fish schools, swarm of bees or particles, or colonies of ants that interact locally to form functional global patterns; within the context of swarm intelligence, the behavior of these organisms appear orchestrated [11]-[13]

Swarm intelligent Optimization algorithms (SIOA) also belongs to a class of nature inspired techniques called meta-heuristics [13], some examples of which include: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), Crow Search Algorithm (CSA), Bat Algorithm, Bee Colony Optimization (BCO), etc. Some popular SIOAs that have been recently and successfully used in power systems stability studies include: the Particular Swarm Optimization (PSO) and the Bee Colony Optimization (BCO).However, in a swarm intelligence load flow, the displacement angles may diverge by very wide margins making it difficult to obtain reliable estimates of the maximum load ability or power point.

In our proposed solution, we provide a stability criterion where the maximum displacement angle between the ends of the considered (loaded) transmission line is threshold-constrained to a marginal (small enough) value in a swarm-intelligence load-flow solution.This is an important operation that leads to the computation of a threshold-constrained Maximum Power Point Index (TMPPI). Thus, our primary objective is two-fold:

- First, we seek to develop a swarm evolutionary technique/program for solving a power system network in the context of a constrained load flow analysis.
- Second, we develop a threshold technique within the load flow program for identifying the optimal set of displacement angles for maximum power point identification in the steady state.

III. MATERIALS AND METHODS

This section presents the details of the solution technique including the concept of Load Flow solutions in the context of Feasible and infeasible regions, Bee Colony Optimization (BCO) and the proposed maximum power point identification conditioning strategy.

Concept of Load Flow Solution

Load flow solution represents an important and primary requirement in the stability analysis of power networks. The solution points of a poorly or good conditioned power systems network may be represented as 2-dimensional spaces where power system variables e.g. load buses or real and reactive powers of generating units (see Fig.1). In the figure, solution points are represented by solid (red) dots at different levels of load flow solutions [11].

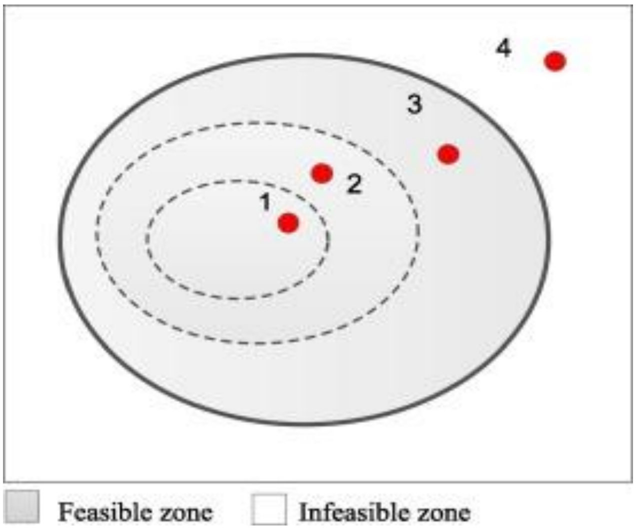

Fig. 1.Feasible and infeasible regions in a load flow solution [1]

In the diagrammatic load flow solution shown in Fig.1, there exist feasible and infeasible solution zones which represent points or regions of solvable, probably solvable or insolvable load flow models respectively. For instance, at point 4 (outermost region) there exists no solution to the load flow model. This graphical categorization enhances the process of analysis and makes it far easier to interpret. In a well-conditioned load flow model/system, there are no violations in load as the levels of operation such as in tripping loads are within their specified boundaries; this is even true during contingencies ill conditioned systems are represented by the second and third zones as there exists violations in system parameter levels (e.g. during an undervoltage or overvoltage state) [1].In general, load flow analysis may give multiple solutions except at the Maximum Loadability Point (MLP) where the solution point is one. In practical load flow solutions, there exists a functional relationship between the power system network voltage and system loading; this functional relationship is depicted in Fig. 2 where the solvable region is shaded in grey. Load flow solutions outside the boundary region have no solutions and in this context are defined, as an infeasible zone. It is important to emphasize here that “the solvability of load flow equations is related to the loading of the system” [1].

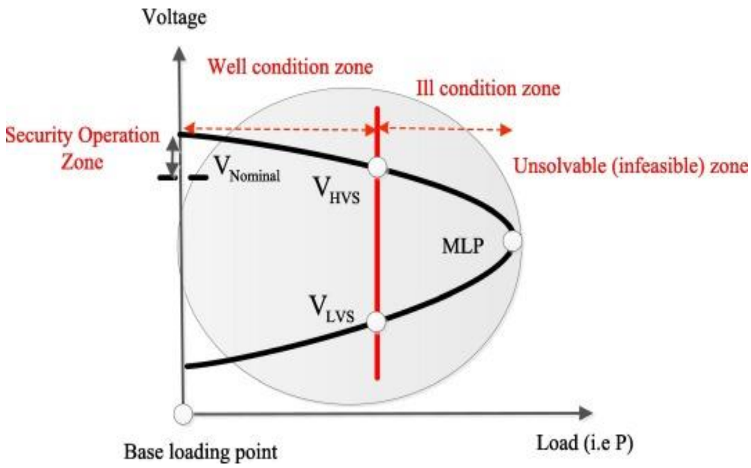

Fig. 2.Load flow solution boundaries and operating zones [1]

In a typical load flow solution, there are two likely categorizations namely the "Low Voltage Solutions (LVS) and High Voltage Solutions (HVS)" [1]. An LVS is typically represented as low voltage profiles with unstable equilibrium solution point(s). On the other hand, an HVS is represented by well stabilized power system parameters and hence solution points. The HVS and LVS meet at saddle-node bifurcation point (which occurs at MLP) as system loading is increased. At this point, further increases in system loading will result in the unavailability of the load flow solutions. An LVS may also occur during cascading failures leading to a condition termed "Critical Voltage Stability Point (CVSP)" [1]. This situation is depicted in Fig.1.

Bee Colony Optimization

The "Bee Colony Optimization (BCO)" is a swarm evolutionary computing strategy that utilizes an explorative and exploitative behavior of groups of Honey Bees [12], [14-16]. It uses a three-phase foraging strategy to find a global optimum point which includes the directed searchforuseful food sources using an 'employed bee' phase, the selection of foods with best qualities using an 'onlooker bee' phase and the search for new food sources using 'scout bee' phase. Both the employed and onlooker bees perform exploitative functions while the scout bee performs exploratory function. An onlooker bee transforms to a scout bee once its exploitative duties are over.

With respect to natural food sourcing, "the employed bees systematically investigate the food sources in which the amount of nectar is high. Then, onlooker bees follow the nectar information shared by the employed bees to further exploit the food sources with high content. Bees share the information about the direction, distance and nectar quality of the food source with the other bees in the colony via the waggle dance, a communication mechanism that depicts collective signaling. Scout bees on the other hand, are responsible for the randomized discovery of new food locations once the nectar amount is fully consumed in an already discovered food source. The location of a food source in the artificial bee colony algorithm represents a possible solution to the problem. The nectar quality of the food source is represented by the objective function of the solution"[17].

In the proposed technique, BCO is used for load flow optimization.The flowchart describing the BCO technique is as shown in Fig.3. The basic steps for a BCO program arefollows:

Listing1: BCO Steps

Step1: A sequences of food sources (real value points) are created randomly.
Step2: A computation and an update of fitness valuesof these food sources are carried out.
Step3: A roulette wheel selection of best fitted values and corresponding food sources; any food source not selected is discarded.
Step4: Replacement of the abandoned food sources.

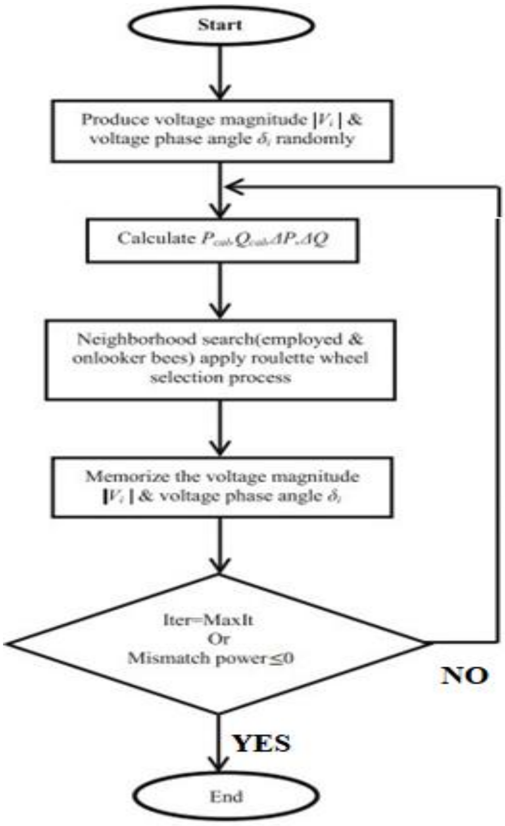

Fig. 3.BCO scheme for load flow optimization

The mathematical operations describing the BCO technique is as provided in the following paragraphs [18]:

1) Food sources represented by real valued numbers (at different positions) are initially generated randomly using the model as:

$$pos_{ij} = pos_{\min j} + \varsigma_o \left(pos_{\max j} - pos_{\min j} \right) \tag{1}$$

2) A position update is performed by an enhanced bee by replacing bee fitness information (old nectars) with new ones when a new and bettersolution is found. Enhanced bees are updated based on the following model:

$$pos_{ij}^{j} = pos_{ij} + \varsigma_{ij} \left(pos_{ij} - pos_{kj} \right) \tag{2}$$

3) A fitness based probability is used by an onlooker bee to select a fitted solution. This probability is defined as:

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{3}$$

4) A random replacement of abandoned food sources (non-updated food sources) with choice search space compliant random food sources after a number of earlier trial searches (called limit trials) have been performed. This is defined by the model:

$$pos_{ij} = pos_{\min j} + rand[0,\ 1]\left(pos_{\max j} - pos_{\min j} \right), \quad for\ j \in \{1, 2, \ldots, D_{im}\} \tag{4}$$

Where:

pos_{ij} = position of food source *i* in direction *j*

$pos_{\min j}$ = lower bound of x_i in direction *j*

$pos_{\max j}$ = upper bound of x_i in direction *j*

SN = food source number
D_{im}= dimension of the problem
ς = randomized number between -1 and +1
ς_o = randomized number between 0 and +1
fit_i = fitness value of solution i

Maximum Power Point Identification
The points of maximum power points typically represent the steady stability or maximum loadability limits of the power systems. As the reactance loading is gradually varied, it changes in proportion to the input.For short transmission lines, the maximum power transferable between two interconnecting busesis computed as:

$$P_{\max} = \left[\left(\frac{V_r}{Z} \right)^2 \left[\frac{V_s}{V_r} Z - R \right] \right]^{\delta - \beta = 0} \tag{5}$$

Where:
V_s = sending end (or source generator) voltage
V_r = system voltageat the receiving end
Z = the impedance of the transmission line
δ = displacement angle of V_s
β = the impedance angle of the transmission line

From (5) it is obvious that the value of P_{max}will be unity at the maximum point.
However, as stated earlier in aforementioned section, this model may fail to give reliable estimates for wide variations in displacement angles. Thus, the scheme provided in Listing 2 is used to update (5) as in the following paragraph:
Listing2: Steady-state Stability Index Computation
Step1: Initialize $\text{load}_{\text{increment}}$ *as reactive loading parameter*, $\text{line}_{\text{data}}$, *as transmission line data*, k_1*and* k_2*as bus sites.*
Step2: for *all* $i \in \text{i.load}_{\text{increment}}$ *do*
Step3: *find* $Z_o \leftarrow (\text{line}_{\text{data}} == k_1 \& \text{line}_{\text{data}} == k_2)$ *//Linedata for bus* k_1, k_2 *link*
Step4: $Z_n \leftarrow \text{abs}\ \{\text{line}_{\text{data}}(\text{Zo},3) + \text{j.*line}_{\text{data}}(\text{Zo},4) + \text{i.load}_{\text{increment}}\}$*// Z_n extracts the Resistance and Reactance to compute the Impedance*
Step5: $R_n \leftarrow \text{line}_{\text{data}}(\text{Zo},3)$ *// Resistance*
Step6: *Compute Pmax according to (5)*
Step7: end for

IV. RESULTS AND DISCUSSION

The results report the loadability performance of the interconnecting Afam (Bus 1) to Alaoji (Bus 2) bus. The results are divided into two parts: the first part reports the maximum loadability situation without the threshold conditioning and the second part reports the situation with conditioning. Incremental reactance loading is performed at values of 0.02 multiplied by a factor of 10 and a BCO-LFA program based on the Listing 1 is run within the MATLAB programming environment in order to solve the power network and in addition compute the MPPI of the considered interconnecting bus.

Maximum Loadability Point – No thresholding
In this experiment, the threshold constraints are neglected and the simulation is performed considering the aforementioned conditions. The result is as shown in Fig.4. The results indicate a wide variation from the expected stability value of about 0 to 1. The computed P_{max} is never close to the required stability value of 1.

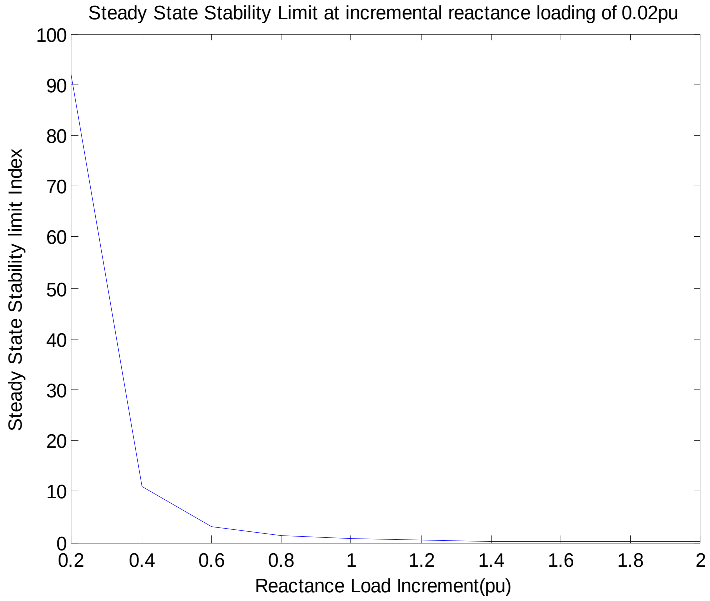

Fig. 4.Steady state stability limit index estimates at 10 different reactance load increments (step = 0.02pu) using BCO-LFA- no thresholding

Maximum Loadability Point – Withthresholding

In this experiment the thresholding constraint is enforced in accordance to Listing 2 to find the best fitting displacement angles that gave the maximum power transfer. The result is shown in Fig.5 for five different set points of 0.02, 0.03, 0.04, 0.05 and 0.06. The result clearly shows the proximity to the expected values of the solution. However, there are some diverging responses of the different settings (see Table 1).

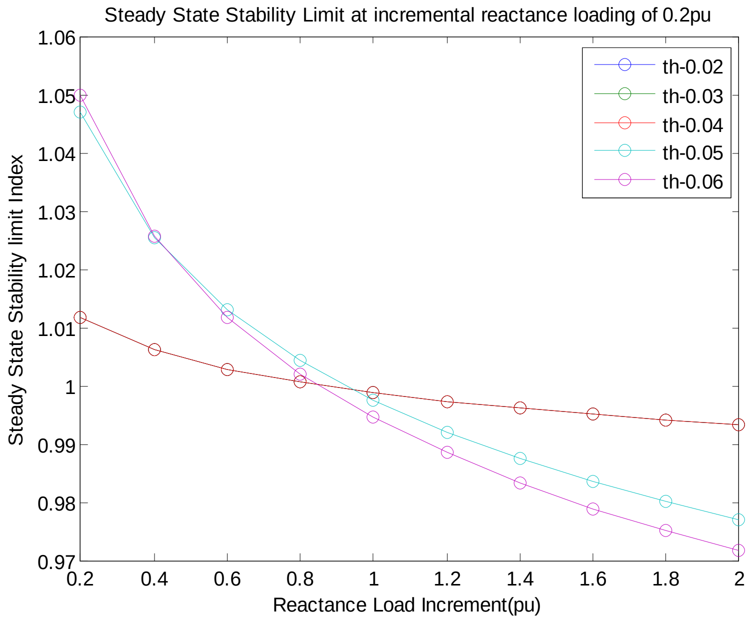

Fig. 5.Steady state stability limit index estimates at 10 different reactance load increments (step = 0.2pu) using BCO-LFA- with thresholding

Table 1: Comparative results forbase threshold (th) settings

th-0.02	th-0.03	th-0.04	th-0.05	th-0.06
1.01167	1.01167	1.01167	1.04702	1.04999
1.00610	1.00610	1.00610	1.02541	1.02574
1.00285	1.00285	1.00285	1.01297	1.01181
1.00056	1.00056	1.00056	1.00425	1.00205
0.99878	0.99878	0.99878	0.99753	0.99455
0.99734	0.99734	0.99734	0.99208	0.98845
0.99611	0.99611	0.99611	0.98749	0.98333
0.99505	0.99505	0.99505	0.98353	0.97892
0.99412	0.99412	0.99412	0.98005	0.97504
0.99329	0.99329	0.99329	0.97695	0.97158

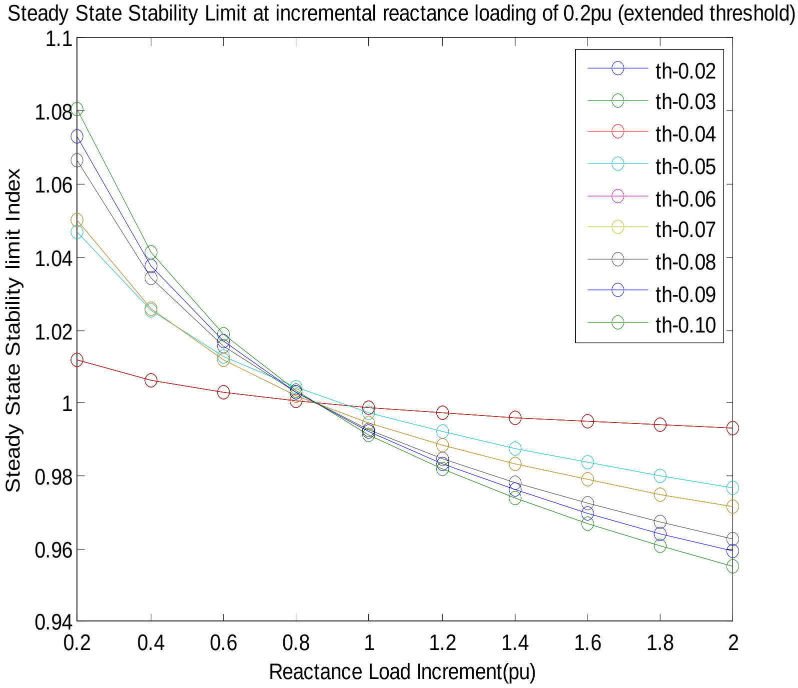

Fig. 6.Steady state stability limit index estimates at 10 different reactance load increments (step = 0.2pu) using BCO-LFA- with extended thresholding

As evidenced in Fig. 5, the expected values of the different threshold settings decrease as the reactance is increased. In particular, for the first 3 threshold settings, the calculated steady state stability limit (SSSL) indices are similar so there is a superimposition of the third setting on the first two (see the Legend of threshold setting 3 in Fig. 5). In addition, the point of convergence (MPPI point) for any setting is approximately 1.0 and at a reactance of about 0.85p.u. When the reactance is less than 0.90p.u, the SSSL is high for high thresholds. For reactance values greater than 0.85p.u, the situation is reversed i.e. the SSSL is low for high thresholds and high for low thresholds. It can also be observed that a threshold setting of 0.04 is somewhat in the middle of the different responses and may be considered as the least divergent setting.

In Fig.6 is shown an extended case where the threshold conditioning is increased to a maximum factor of 0.10. As in Fig.5, for the first three threshold settings, the calculated indices are similar; in addition the fifth and sixth settings (*th* = 0.06 and *th* = 0.07) are similar. The result also goes to show that increasing the threshold beyond a factor of 0.06 does not lead to any less divergent response as the stability indices keeps on falling widely as the reactance loading is increased and at higher thresholds (see Fig.6 and Table 2). In this case, the most divergent threshold setting is at 0.10.

Table 2: Comparative results for extended threshold (th) settings.

th-0.02	th-0.03	th-0.04	th-0.05	th-0.06	th-0.07	th-0.08	th-0.09	th-0.10
1.01167	1.01167	1.01167	1.04702	1.04999	1.04999	1.06637	1.07292	1.08039
1.00610	1.00610	1.00610	1.02541	1.02574	1.02574	1.03404	1.03734	1.04110
1.00285	1.00285	1.00285	1.01297	1.01181	1.01181	1.01559	1.01709	1.01879
1.00056	1.00056	1.00056	1.00425	1.00205	1.00205	1.00270	1.00296	1.00325
0.99878	0.99878	0.99878	0.99753	0.99455	0.99455	0.99282	0.99214	0.99137
0.99734	0.99734	0.99734	0.99208	0.98845	0.98845	0.98482	0.98338	0.98176
0.99611	0.99611	0.99611	0.98749	0.98333	0.98333	0.97810	0.97604	0.97371
0.99505	0.99505	0.99505	0.98353	0.97892	0.97892	0.97232	0.96972	0.96679
0.99412	0.99412	0.99412	0.98005	0.97504	0.97504	0.96725	0.96419	0.96072
0.99329	0.99329	0.99329	0.97695	0.97158	0.97158	0.96273	0.95926	0.95533

V. CONCLUSION

This paper proposes a swarm intelligence load flow solution called BCO-LFA for the steady state stability analysis of the Nigerian 132kV sub-transmission power network (PH-Zone) in the context of the maximum loadability or maximum power transferable between the interconnected buses. The results of simulations are indicative of the need for threshold conditioning as the standard swarm intelligence solutions vary considerably. In future, variants of the proposed swarm intelligence technique and other swarm intelligence techniques will be investigated including the development of higher order steady state analytic models.A new concept of threshold-constraint has been proposed in this research. This enables the determination of steady state stability maximum power point limits within the load flow program from an optimal set of displacement angles.

REFERENCES

[1]. Karimi, M., Shahriari, A., Aghamohammadi, M. R., Marzooghi, H., Terzija, V. Application of Newton-based load flow methods for determining steady-state condition of well and ill-conditioned power systems: A review. International Journal of Electrical Power & Energy Systems, 113, 298-309 (2019).

[2]. Hu, Z., Wang, X. Efficient computation of maximum loading point by load flow method with optimal multiplier. IEEETransactions on Power Systems, 23(2), 804-806 (2008).

[3]. Kazemi, A., Badrzadeh, B. Modeling and simulation of SVC and TCSC to study their limits on maximum loadability point. International journal of electrical power &energy systems, 26(8), 619-626 (2004).

[4]. Rahman, M., Cecchi, V., Miu, K. Power handling capabilities of transmission systems using a temperature-dependent power flow. Electric Power Systems Research, 169, 241-249 (2019).

[5]. Acharjee, P. Identification of maximum loadability limit and weak buses using security constraint genetic algorithm. International Journal of Electrical Power & Energy Systems, 36 (1), 40-50 (2012).

[6]. Malathy, P., Shunmugalatha, A. Application of swarm based intelligent computing algorithms for dynamic evaluation of maximum loadability of transmission network. Journal of Computational Science, 21, 201-222 (2017).

[7]. Mahdad, B., Srairi, K. Security optimal power flow considering loading margin stability using hybrid FFA–PS assisted with brainstorming rules. Applied Soft Computing, 35, 291-309 (2015).

[8]. Gnanambal, K., &Babulal, C. K. Maximum loadability limit of power system using hybrid differential evolution with particle swarm optimization. International Journal of Electrical Power & Energy Systems, 43(1), 150-155 (2012).

[9]. Beni, G., Wang, J. Swarm Intelligence in Cellular Robotic Systems, Proceedings ofNATO Advanced Workshop on Robots and Biological Systems, Tuscany, Italy, June 26-30. Applied Mathematics and Computation, 3, 268-308 (1989).

[10]. Sumathi, S., Paneerselvam, S. Computational intelligence paradigms: theory & applications using MATLAB. CRC Press (2010).

[11]. Eberhart, R. C., Kennedy, J. Particle swarm optimization. Proceedings of IEEE International Conference on Neural Network, Perth, Australia, 1942-1948 (1995).

[12]. Ekinci, S., Demirören, A. Modeling, simulation, and optimal design of power system stabilizers using ABC algorithm. Turkish Journal of Electrical Engineering & Computer Sciences, 24(3), 1532-1546 (2016).

[13]. Askarzadeh, A. A novel metaheuristic method for solving constrained engineering optimization problems: crow search algorithm. Computers & Structures, 169, 1-12 (2016).

[14]. Karaboga, D., Okdem, S., Ozturk, C.Cluster based wireless sensor network routing using artificial bee colony algorithm. Wireless Networks, 18 (7), 847-860 (2012).

[15]. Ahiakwo, C. O., Orike, S., Ojuka, E. Application of Neuro-Swarm Intelligence Technique to Load Flow Analysis, American Journal of Engineering Research, 7(8), 94-103 (2018).

[16]. Anireh, V. I. E., Osegi, E. N. ABC-PLOSS: a software tool for path-loss minimization in GSM telecom networks using artificial bee colony algorithm. International Journal of Swarm Intelligence, 4 (1), 20-37 (2019).

[17]. Kalaycı, C. B., Karagöz, S., Karakaş, Ö. Bee colony intelligence in fatigue life estimation of simulated magnesium alloy welds. International Journal of Fatigue, 127, 36-44 (2019).

[18]. Bansal, J. C., Sharma, H., Arya, K. V., Nagar, A. Memetic search in artificial bee colony algorithm. Soft Computing, 17 (10), 1911–1928 (2013).

Oko*et al*. (2020). "Threshold-Constraint and Swarm Intelligence-Based Load Flow Analysis for Steady State Stability Studies ofthe Nigerian 132-KV Power Transmission Network". *American Journal of Engineering Research (AJER)*, vol. 9(02), 2020, pp. 78-86.