Impact of MW-Generation Participation Factors on Closest Saddle Node Bifurcation Point

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ARTICLE INFO

Article history:
Received: 6 December 2024
Revised: 16 March 2025
Accepted: 1 June 2025
Online: 20 July 2026

Keywords:
Wind turbine
Squirrel cage induction generators (SCIG)
Diesel genset
Islanded mode
Hybrid renewable energy

ABSTRACT

The determination of the closest saddle-node bifurcation point (CSNBP) for power systems is a crucial problem in ensuring system stability. Typically, CSNBP is identified with fixed MW generation participation factors influenced by economic considerations. In these instances, the objective is to minimize the distance to the voltage collapse point (VCP) while considering changes in the directions of real and reactive power. This paper describes a novel algorithm for obtaining CSNBP which is maximized with respect to MW-generation participation factors. Hence a Max-Min problem has been formulated. The optimized solution has been obtained by the developed algorithm using the Arithmetic Optimization Algorithm (AOA), Sine Cosine Algorithm (SCA), and Rao-1 techniques. The developed approach has been implemented on IEEE test systems with 6 and 25 buses. The results obtained have been compared for these three optimization techniques based on statistical inferences such as computational efficiency, convergence speed, frequency of convergence, and optimized objective function as compared to SCA and Rao-1.

1. INTRODUCTION

The algorithms for reactive power optimization (RPO) and real power optimization (APO) are essential to overcome operational problems and ensure the power system operation that is both safe and efficient. These algorithms aim to minimize fuel costs and system losses while keeping line flows and bus voltages within certain limits. To maintain the line flows within the limits, APO usually involves rescheduling of MW-generation, while RPO focuses on rearranging reactive power control parameters to keep the bus voltages within the limits [1]. Under moderate load conditions, these two subproblems are often solved separately, neglecting the coupling between active power and voltages as well as phase angles and voltages [2]. In the past, voltage security studies primarily focused on bus voltage magnitude by itself. However, it was later recognized that voltage magnitude by itself does not offer a complete understanding of voltage security. Voltage stability has emerged as an important consideration in voltage security assessment and control [3]. Consequently, voltage stability, in addition to voltage magnitude, is now considered to ensure adequate voltage security.

In situations where controllability through generator-bus voltage, shunt compensation &on-load tap changers (OLTCs) is limited or lost, maintaining voltage security becomes more challenging. Under such stressed conditions, the coupling between MW-generation and voltage security becomes crucial, considering the significant impact of MW line flows on bus voltages. The voltage profile can be improved and the static voltage stability limit increased by rescheduling the MW-generation. This becomes particularly significant when the voltage collapse point is being approached by the power system.

Voltage collapse refers to a condition where the voltage levels in the system drop significantly, leading to a loss of stability and potential system-wide blackout. Rescheduling MW-generation helps to alleviate voltage stress and improve the voltage profile, thereby reducing the risk of voltage collapse. To maintain acceptable voltage levels and increase the static voltage stability margin, operators can optimize active power generation. Ensures stable and safe operation of the power system.

Schlueter [4] observed that conventional reactive power control methods may not always be sufficient to ensure an adequate voltage stability margin or voltage profile in power systems. This can be due to limitations in the power network

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or constraints on reactive power generation. To address this issue, researchers have explored the concept of re-routing real power flows along transmission lines through MW-generation shifts. The first to employ linear programming techniques in 1988 to improve the voltage of load buses by adjusting real power generation. A technique focused on avoiding voltage instability by strategically rescheduling real power generation. A gradient search technique was used to find the best MW-generation dispatch that increases voltage levels and the voltage stability margin [5]. Provided an approach for finding the shortest path to voltage collapse or calculating CSNBP using the PSO methodology [6] offered a technique that uses MW-generation rescheduling to optimize the load flow Jacobian's minimal eigen value, improving voltage stability developed a strategy to prevent voltage collapse by maximizing loadability using a modified BBPSO approach with MW-generation shifts. These studies highlight the importance of real power generation rescheduling through MW-generation shifts to improve voltage stability margins, enhance voltage profiles, and mitigate the risk of voltage collapse. By strategically redistributing real power flows, it is possible to address the limitations of traditional reactive power control & ensure adequate voltage security in power systems [8].

In a power system, the loadability limit or point of collapse can be attributed to two main factors: thermal limits and voltage collapse [7, 9]. Thermal limits describe the maximum current that a power system's transformers and transmission lines can handle without going above its thermal ratings. Excessive line losses, voltage dips, and possible equipment overheating or damage can result when the power flow in a transmission line approach or surpasses its thermal limit. Extending the system's operating range might endanger its reliability and stability. Contrarily, voltage collapse is related to the stability of power system voltage. When the reactive power resources of the system are insufficient to keep the load bus voltage at appropriate levels, voltage instability may result. As a result, the voltage magnitude can decrease, leading to inadequate voltage profiles and potential voltage collapse. Long transmission lines, in particular, can exacerbate voltage stability issues due to reactive power losses and voltage drop in the line. Comparative descriptions of the latest work for MW-generation and distance to voltage collapse (VC) point are summarized in Table-1.

Table 1. Comparative Evaluation of Various Approaches Using Relevant Literature Studies

Authors	Year	Contribution	Objective Function	Decision Variable			Statistical Inference
				Load Scenario	MW-Generation	Reactive Power	
Wang et al. [10]	2023	Present an efficient online generation rescheduling method for associated power systems that mainly depends on synchronized ambient data to improve the damping of probable critical modes.	Determination of the generation rescheduling amount	×	√	×	√
Castro and Gonz´alez-Cabrera	2022	Provide the modeling of planning for short-term generating capacity growth for a multi-terminal VSC-based HVDC transmission	Total (operating & planning, etc.) costs	×	√	√	×
Qien et al. [12]	2021	For multi-objective optimum dispatch of active power, provide a modified version of the beetle antennae search method with a BP power flow prediction model.	MOAPD	×	√	×	√
Kaur and Dhillon [13]	2021	Thermal power plants' economic generation scheduling (EGS) is determined using the Hill-Climbed Sine-Cosine algorithm.	EGS	×	√	×	√
Ghorbani et al. [14]	2020	Several innovative indices have been provided to assess resilience in the power generation industry.	Composite resiliency index and Loss of critical load factor	√	×	×	×
Salazar et al. [15]	2020	Provided a method for determining SNBP based on the extended functional method.	Maximize SNBP	√	×	×	×
We have proposed a novel algorithm for obtaining CSNBP which is maximized with respect to MW- generation shift factors based on AOA techniques.			maximizes the margin for minimum voltage stability.	√	√	×	√

The collapse point's shortest path (MVA) is a worst-case proximity indicator. This mainly depends on reactive power control variables (RPCV). In case of exhaustion of RPCV MW-generation shift is utilized to optimize CSNBP. The paper's primary contributions are addressed;

- A max-min problem has been formulated which is a function of MW-generation shifts factor. A solution to the max-min problem provides worst case loadability margin in case of an uncertain load scenario.
- The shortest distance to the collapse point has been maximized with respect to MW-generation shift factors based on load scenario directions.
- AOA, SCA, and Rao-1 algorithms have been implemented to obtain optimum MW-generation shift factors and load scenarios. Based on statistical inferences, AOA outperforms the other two methods. Impact of MW-generation Participation Factors on Closest Saddle Node Bifurcation Point.

In this paper, the focus is on determining the maximum loadability limit from the perspective of voltage collapse in power systems. The literature review reveals that MW generation shifts have been employed to enhance voltage stability under stressed loading conditions. These shifts have been achieved by utilizing proximity indicators or directly enhance the SNBP of the power systems. However, none of the previously mentioned research articles have specifically optimized the CSNBP with respect to MW-generation shifts. The CSNBP represents the closest point to the voltage collapse where an SNB occurs. Optimizing the CSNBP with MW-generation shift is essential because it determines the load increase direction that maximizes the loadability limit. This approach is particularly relevant in scenarios with heavy loading conditions where uncertainties can significantly impact the system's behavior. The proposed methodology provides a comprehensive framework for improving voltage stability and figuring out the upper limit of loadability of the power system. By employing MW-generation rescheduling in an optimized manner, operators can effectively manage the system's loading conditions, mitigate the risk of voltage collapse, and ensure a reliable and stable power supply. The formulated problem has been solved using three optimization techniques i.e. AOA, SCA and Rao-1 algorithm. Section-2 introduces the problem formulation for obtaining the optimum MW-generation shift factor. Section-3 presents a solution methodology. It explains the underlying principles and steps of the algorithm, highlighting its effectiveness in solving the formulated problem. Section-4 describes a detailed analysis of the research findings & includes a thorough discussion of the results obtained. Section-5 highlights the contributions of the research.

2. FORMULATION OF THE PROBLEM TO DETERMINE THE BEST MW-GENERATION SHIFT FACTORS

Voltage stability and SNBP or collapse point are explained with the help of PV-curve shown in Figure 1. As load in a specific direction increases voltage decreases. It is further observed that there are two voltage values, one higher and another low value for a specific load.

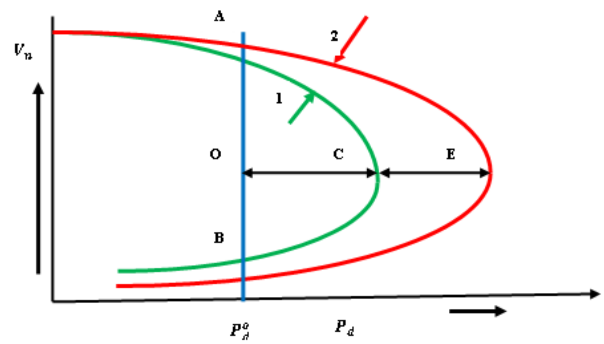

Fig. 1. Representation of Distance to SNBP with and without MW Generation Shift Factor (1- Without MW generation shift PV-curve, 2- With MW generation shift PV-curve).

These are labeled as A and B points shown in the PV-curve. "A" - represents a stable operating point (SOP) and "B" – represents an unstable operating point (UOP). As the load further increases two points come closer and at collapse point C the two points merge and this collapse point is known as SNBP. The load increase OC is known as voltage stability margin or distance to SNBP. Now the distance to SNBP depends on load increase scenario. There will be a load increase direction for which the distance to voltage collapse is least. Such a PV-curve is shown in Figure 1. Now the distance to new SNBP is OE. In the next case, MW-generation participation factors are varied and the distance SNBP will vary. Hence objective is to obtain direction of load increase as well as MW-generation participation factors which maximizes the shortest distance to SNBP.

Usually, various generators share the load based on economic considerations. The objective here is to determine MW-generation participation for each generator which maximizes the minimum voltage stability margin. In this sense, MW-generation shift factors are the control variable to be determined in addition to worst's loading scenario. Hence the objective function is expressed as

$$J = \underset{\underline{\sigma}}{\text{Max}} \{ \underset{\underline{d}}{\text{Min}}\ L \} \qquad (1)$$

where, $\underline{\sigma}$ - Vector of generation participation factor, $\underline{d}$ – Load change direction, L – Voltage stability margin in terms of MVA. The objective function (1) is maximized with respect to σ and minimized subject to $\underline{d}$. The following constraints are accounted for.

(a) Power flow

$$F\left(\underline{v}, \underline{\delta}, \underline{p}\right) = 0 \tag{2}$$

where, $\underline{v}$ - Voltage vector, $\underline{\delta}$ - Phase angle vector, $\underline{p}$ - Load continuation parameter which depends on load increase scenario $\underline{\mathrm{d}}$.

(b) Constraints on generation participation factor

$$0 \le \sigma_l \le 1 \tag{3}$$

$$\sum_{l=1}^{NG} \sigma_l = 1 \tag{4}$$

(c) Constraints on load change direction is given by

$$\underline{d} = [\Delta \mathrm{P}, \Delta \mathrm{Q}]^{\mathrm{T}} \tag{5}$$

Each component $\Delta \mathrm{P_i}$ and $\Delta \mathrm{Q_i}$ are independent. Thus, it flows

$$-1 \le \Delta \mathrm{P_i} \le 1 \tag{6}$$

$$-1 \le \Delta \mathrm{Q_i} \le 1 \tag{7}$$

It provides search in all possible directions. Further, the search direction is converted to a unit vector as

$$\underline{\mathrm{d}} = \frac{d}{\|d\|} \tag{8}$$

The performance index (J) given by (1) is optimized subject to (2)-(7).

3. SOLUTION METHODOLOGY

In this study, the formulated problem described in Section 2, which helps to identify the most suitable MW-generation participation for each generator to maximize the minimum voltage stability margin, has been solved using the proposed algorithm, SCA and Rao-1 techniques.

3.1 AOA

The AOA [16] is a populations-based metaheuristic algorithm that takes inspiration from the arithmetic operators' distributive character. The proposed algorithm follows a two-stage optimization process, namely exploration and exploitation shown in Figure 2. These stages are essential for efficiently finding an optimal solution within the search space.

Exploration Stage: During the exploration stage, the proposed algorithms explore new areas or regions within the search space in search of potential optimal solutions. This process is crucial for diversifying the search and avoiding getting stuck in local optima. In the proposed algorithm, exploration is achieved using the logarithm (log) and exponential (exp) operators. These operators generate high-density values that enable the algorithm to sections of the search space in a methodical.

Exploitation Stage: The exploitation stage involves refining and improving the solutions in the vicinity of already visited areas that show promise in terms of fitness values. The goal is to fine-tune the potential solutions and get to the optimal solution. In the proposed algorithm, exploitation is carried out using the addition (+) and subtraction (-) operators. These operators allow the algorithm to adjust the potential solutions based on their fitness evaluations.

By order to effectively balancing the explorations and exploitations, the suggested algorithm navigate the search for the optimal values of the MW-generation shift factors that maximize the minimum voltage stability margin. Exploration helps the algorithm cover a wide range of potential solutions, while exploitation focuses on refining the solutions to obtain better fitness values. This balance ensures that the proposed algorithm can effectively explore and exploit the search space to finds the good possible solution of MW-generation participation for each generator that maximizes the minimum voltage stability margin. The steps that follow are used to Solve the proposed problem using the algorithm.

Step-1: Generate the initial population of generation participation factors as

$$Y_i^{(0)} = [\ \sigma_{i^1}^{(0)}, \sigma_{i^2}^{(0)} .. \sigma_{i^l}^{(0)} \ldots\ \sigma_{i^{NG}}^{(0)}\ ]^T \tag{9}$$

$$i = 1, .., \ldots, M$$

where, NG - Total number of generator buses. σ_{il} - is a randomly generated participation factor in i^{th} vector for l^{th} generator. Each σ_{il} is generated as a random digit from a uniform distribution [0, 1] i.e.

$$\sigma_{il} = U_{il} \tag{10}$$

where, U_{il} - is a random digit between [0,1]. Since further each σ_{il} is to satisfy constraints (3), the following relation is used

$$\sigma_{il} = {\sigma_{il}}\Big/{\textstyle\sum_l^{NG} \sigma_{il}} \tag{11}$$

Equations (9) and (10) will ensure satisfaction of constraints (3) and (4).

Step-2: Set the number of iterations, $(k = 1)$.

Step-3: Find the shortest distance to VC ($L_i^{(k-1)}$) for every solution vector $\mathrm{Y_i^{(k-1)}}$. This is obtained by each randomly selected $\underline{d_i}$. Continuation or repeated power flow is used for this purpose. Call this distance to be $L_i^{(k-1)}$, $i = 1, .., \ldots, M$

$$L_i^{(k-1)} = \sqrt{\sum[\Delta P_i^{(k-1)}]^2 + \sum[\Delta Q_i^{(k-1)}]^2} \tag{12}$$

This is a subproblem and Sine Cosine algorithm (SCA) has been used to solve and obtain $L_i^{(k-1)}$.

Step-4: To evaluate the math optimization accelerator ($MOAc$) function, use equation (13).

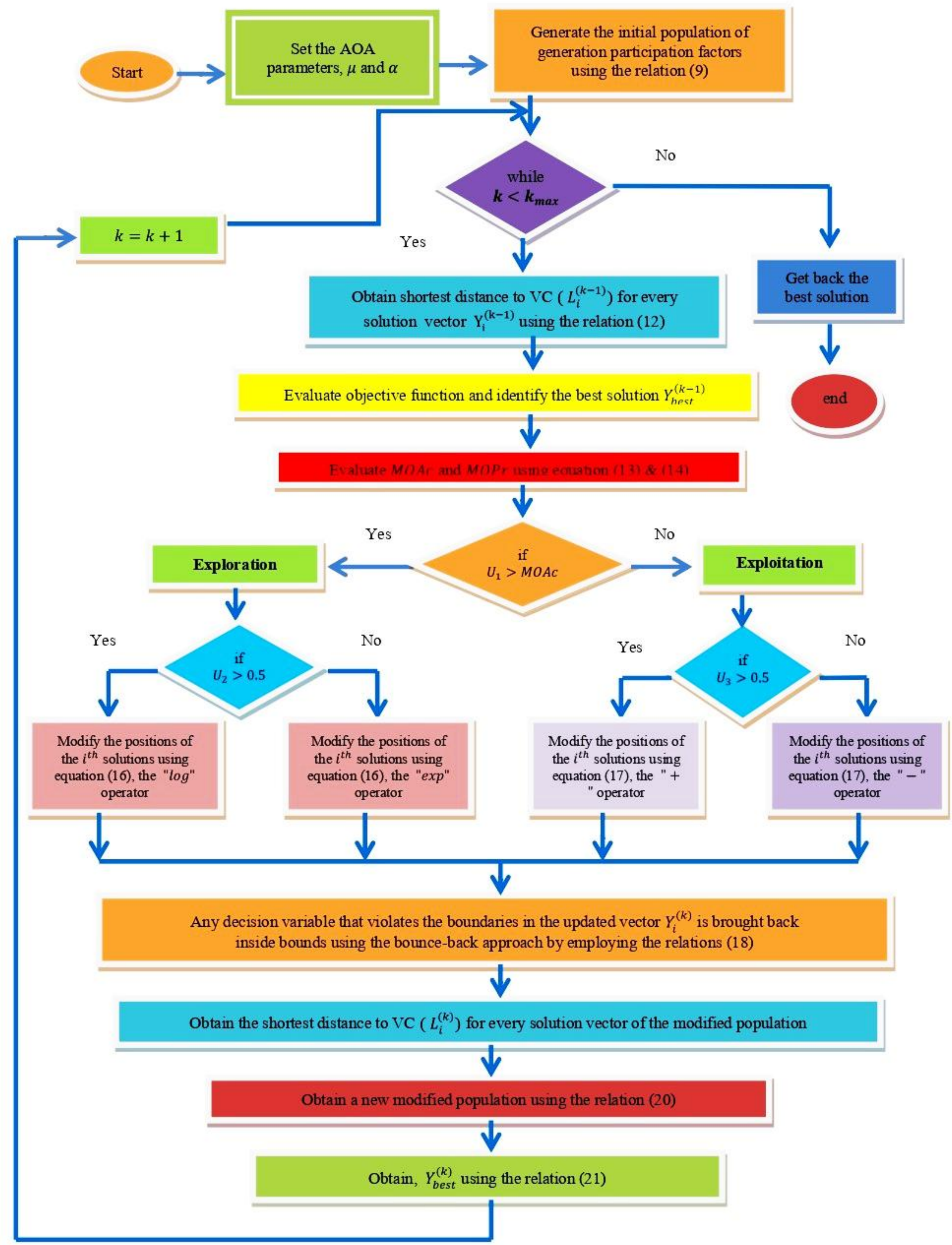

Fig. 2. Flowchart for the AOA Approach.

$$MOAc(CI_k) = Min + CI_k\ ((Max - Min)/k_{max})\ (13)$$

where, CI_k &k_{max} – are the current & max. no. of iteration. Max&Min - are the upper & lower bounds of the accelerator function.

Step-5: Utilizing equation (14), determine the mathematical optimization probability ($MOPr$) function.

$$MOPr(CI_k) = 1 - \frac{CI_k^{\frac{1}{\alpha}}}{K_{max}^{\frac{1}{\alpha}}} \quad (14)$$

The value of the sensitive parameter (α) is [1.0 to 5.0].

Step-6: Using equation (15), identify the stage.

$$\text{Phase} = \begin{cases} Exploration & if\ U_1 > MOAc \\ Exploitation & Otherwise \end{cases} \quad (15)$$

where, U_1, U_2 and U_3 - are random digits between [0, 1].

Step-7: Exploration stage**;** the solution is modified using equation (16).

$$Y_i^{(k)} = \begin{cases} Y_{best}^{(k-1)} * \log\left(abs\left((MOPr + \epsilon) * \left((\overline{Y}_i - \underline{Y}_i) * \mu + \underline{Y}_i\right)\right)\right) if\ U_2 > 0.5 \\ Y_{best}^{(k-1)} * \exp(MOPr + \epsilon) * ((\overline{Y}_i - \underline{Y}_i) * \mu + \underline{Y}_i), \quad Otherwise \end{cases} \quad (16)$$

The stochastic scaling coefficient (μ) is [0.5], and is a tiny positive integer value (ϵ).

Step-8: Exploitation stage**;** the solution is modified using equation (17).

$$Y_i^{(k)} = \begin{cases} Y_{best}^{(k-1)} - (MOPr) * \left((\overline{Y}_i - \underline{Y}_i) * \mu + \underline{Y}_i\right) & if U_3 > 0.5 \\ Y_{best}^{(k-1)} + (MOPr) * ((\overline{Y}_i - \underline{Y}_i) * \mu + \underline{Y}_i), & Otherwise \end{cases} \quad (17)$$

Step-9: Any decision variable that violates the boundaries in the updated vector $Y_i^{(k)}$ is brought back inside bounds using the bounce-back approach by employing the relations (18).

$$\sigma_{ij}^{(k)} = \begin{cases} 0.5 - 0.5\,U,\ if\ \sigma_{ij}^{(k)} < 0 \\ 0.5 + 0.5\,U,\ if\ \sigma_{ij}^{(k)} > 1 \end{cases} \quad (18)$$

whewe, U - is a random digit from [0,1].

Step-10: Converts each $Y_i^{(k)}$ to satisfy equation (3) as

$$Y_i^{(k)} = {Y_i^{(k)}}\Big/{\sum_l \sigma_{il}^k} \quad (19)$$

Thus, modified population is obtained which satisfies constraints (3) and (4)

Step-11: Obtain the shortest distance to VC for every solution vector of the modified population as per the algorithm $L_i^{(k)}, i = 1, .., ..., M$.

Step-12: Obtain a new modified population as follows

$$Y_i^{(k)} = \begin{cases} Y_i^{(k-1)},\ if\ L_i^{(k)} \leq L_i^{(k-1)} \\ Y_i^{(k)}, \quad if\ L_i^{(k)} > L_i^{(k-1)} \end{cases} \quad (20)$$

Step-13: Obtain, $Y_{best}^{(k)}$.

$$Y_{best}^{(k)} = arg.Max\ L_i^{(k)}(Y_i^{(k)}) \quad (21)$$

It is a solution vector for which the shortest distance to voltage collapse (SDVC) is maximum.

Step- 14: If $k > k_{max}$, stop iterating, otherwise continue step 6 with an increased iteration count of $k = k + 1$. The proposed methodology is presented using the flow chart shown in Figure 2.

3.2 SCA

The steps that follow are used to implement the algorithm to solve the proposed problem.

Step-1 to **step-3** Same as in section-3.1.

Step-4 Update the population

$$Y_i^{(k)} = \begin{cases} Y_i^{(k-1)} + bSin\ (2\pi U_1)\left|2U_2 G_{best}^{(k-1)} - Y_i^{(k-1)}\right|,\ if\ U_3 \leq 0.5 \\ Y_i^{(k-1)} + bCos\ (2\pi U_2)\left|2U_2 G_{best}^{(k-1)} - Y_i^{(k-1)}\right|,\ otherwise \end{cases} \quad (22)$$

where, U_1, U_2 and U_3 - are random digits from [0, 1] and 'b' is a control parameter that is varied and selected as

$$b = a - \frac{a.k^*}{k_{max}} \quad (23)$$

where, 'a' - is a constant that is greater than say $a = 2$. k^*, k_{max} - are current & maxi. no. of iterations. $G_{best}^{(k-1)}$ - is the best solutions in the previous iteration.

In fact:

$$G_{best}^{(k-1)} = \text{arg. Max}\ \{\ L_i^{(k-1)}(Y_i^{(k-1)})\} \quad (24)$$

Step-5: Any decision variable that violates the boundaries in the updated vector $Y_i^{(k)}$ is brought back inside bounds using the bounce-back approach by employing the relations (16).

$$\sigma_{ij}^{(k)} = \begin{cases} 0.5 - 0.5\,U,\ if\ \sigma_{ij}^{(k)} < 0 \\ 0.5 + 0.5\,U,\ if\ \sigma_{ij}^{(k)} > 1 \end{cases} \quad (25)$$

where, U - is a random digit from [0,1].

Step-6: Convert each $Y_i^{(k)}$ to satisfy equation (3) as

$$Y_i^{(k)} = {Y_i^{(k)}}\Big/{\sum_l \sigma_{il}^k} \quad (26)$$

Thus, modified population is obtained which satisfies constraints (3) and (4).

Step-7: Obtain the shortest distance to VC for every solution vector of the modified population as per the algorithm $L_i^{(k)}, i = 1, .., ..., M$.

Step-8: Obtain a new modified population as follows

$$Y_i^{(k)} = \begin{cases} Y_i^{(k-1)}, & if\ L_i^{(k)} \le L_i^{(k-1)} \\ Y_i^{(k)}, & if\ L_i^{(k)} > L_i^{(k-1)} \end{cases} \qquad (27)$$

Step-9 Obtain, $G_{best}^{(k)}$.

$$G_{best}^{(k)} = arg.Max\ L_i^{(k)}(Y_i^{(k)}) \qquad (28)$$

It is a solution vector for which the SDVC is maximum.

Step- 10 If $k > k_{max}$, stop iterating, otherwise, continue step 4 with an increased iteration count of $k = k + 1$.

The SCA technique of the proposed methodology is presented using the flow chart shown in Figure 3.

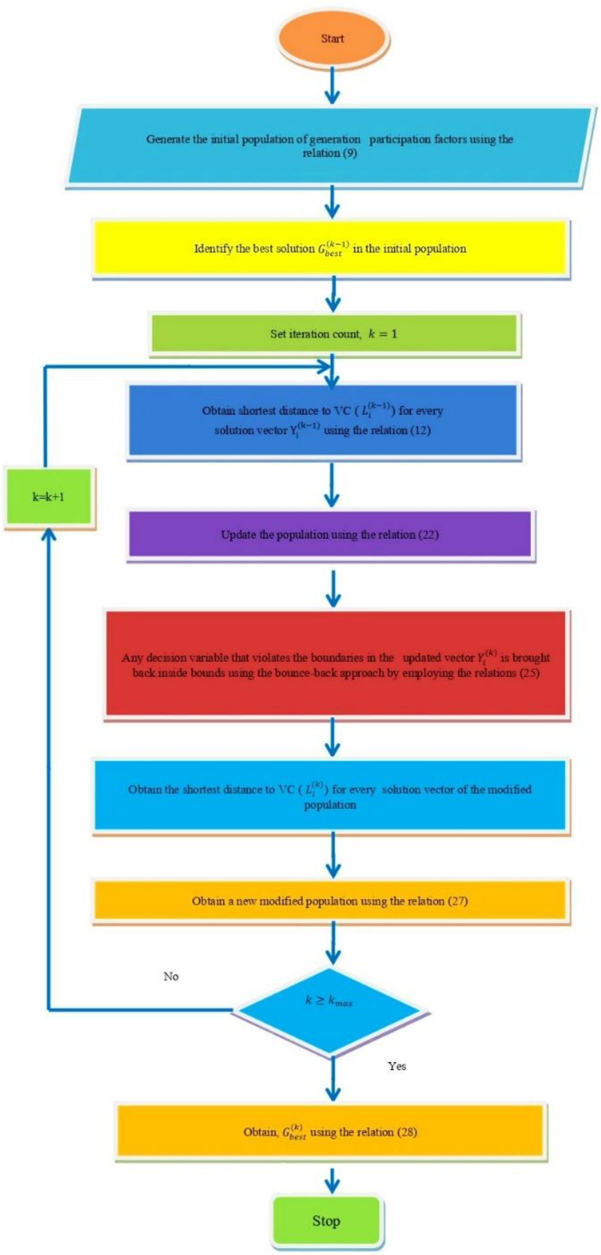

Fig. 3. Flowchart for the SCA Approach

4. RESULTS AND DISCUSSIONS

Three algorithms i.e. AOA, SCA and Rao-1 algorithm, were developed to calculate the optimal generation participation factors. These methods were put to use on IEEE 6-bus & 25-bus test systems. The objective of the study was to maximize the CSNBP in terms of MW-generation participation factors. The implementation of these algorithms was performed using MATLAB R2019b software running on a computer system with an Inte l(R) Core (TM) i5-4590S CPU at 3.00 GHz and 4.00 GB RAM. The proposed algorithm was run on the test systems to obtain the CSNBP.

4.1 IEEE 6- Bus System

In the power system described, there are four load buses, two generator buses, and seven lines. The higher & lower bounds for the load bus voltages have been considered as 1.10 pu to 0.95 pu. The active power limitations for the first and second-generating buses are between 0.1000 pu and 1.0000 pu. The reactive power limits for the first generating bus range from -0.0500 pu to 2.0000 pu, and for the second PV bus, they range from -0.0500 pu to 1.0000 pu. Limits of 0.95 pu to 1.1 5pu, 0.00 pu to 0.055 pu, and 0.90 pu to 1.10 pu, respectively, have been assumed for the PV-bus voltages, shunt compensations & OLTCs.

Voltage stability in a stressed state depends on the reactive power control factors, such as PV-bus voltages, shunt compensations, and OLTCs. Rescheduling active power generation at the generators can raise the voltage stability margin if it is inadequate and cannot be improved by these modifications.

In the base case condition, the MW-generation participation factors are σ1 = 0.26 and σ2 = 0.74, indicating the proportion of active power generated by each generator. The maximum roadability with the shortest distance to VC is 0.570 pu, representing the maxi. load level that can be supported by the system while maintaining a minimum voltage stability margin (Figure 4).

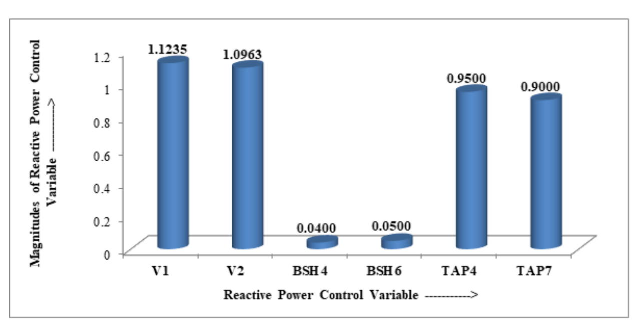

Fig.4. Reactive Power Control Variable for the Six-Bus System in Stressed Situations.

Iterations were set to a maximum of 1000. Several sets of randomly generated populations of generation participation factors were used as input. The process of selection was based on evaluation of an objectives function.

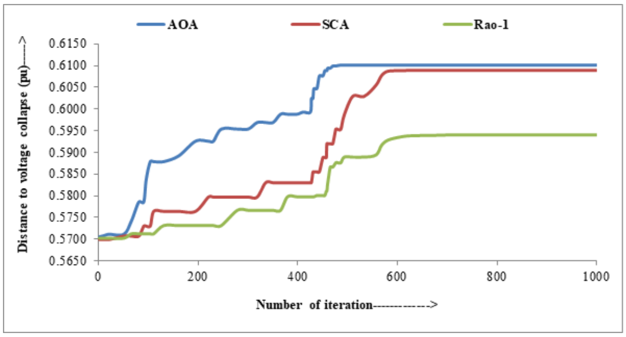

Fig. 5. Convergence of the Objective Function for a Six-Bus System Using Methods as a Function of Iterations

The optimal distance to voltage collapse (F = 0.610) was found for MW generation with participation factors $\sigma 1 = 0.55$ and $\sigma 2 = 0.45$ and control parameter ($\alpha = 3.5$, $\mu = 0.5$). After 486 iterations, the simulation run was terminated due to the convergence of the objective function's solution. The objective function and iterations for the most suitable settings of the parameters proposed algorithm, SCA, and Rao-1 are shown in Figure 5. It is used to visualize the optimization process and the convergence of the solution.

Table-2 gives the optimum generation participation factor, optimized shortest distance to VC, CPU time required, and the number of iterations with and without optimization MW-generation participation factors. Also included is the SDTVC using the methodology of without changing the MW generation participation factors as given in the base case condition. The results are provided in Table-2 for comparison a purpose which justifies this proposed algorithm. As is observed from Table-2, SDTVC is with and without optimizing MW-generation participation factors. Similarly, for 25-bus test systems, SDTVC is provided in Table-5, with and without optimization of MW-generation participation factors**.** A worst-case loading scenario refers to the maximum load condition at which the system becomes unstable or reaches its voltage collapse point. Usually, the voltage stability indicators or the distance to voltage collapse are monitored as the system load is continuously increased. Table-3 shows the worst-case load scenario based on the best parameter values for the proposed algorithm, SCA and Rao-1 algorithms.

Figure 6 presents a comparison of the base conditions of the objective function with the conditions after the generation of MW using proposed algorithm, SCA and Rao-1 methods. Table 4 compares the proposed algorithm with the SCA and Rao-1 approaches based on statistical inference. In this study, twenty runs were conducted for statistical inference, revealing that the proposed algorithm outperforms the other two based on the statistical parameters in Table 4.

Table 2. Algorithms compare for a Six-Bus Test System with and without Optimization MW-Generation Participation Factors

SDTVC with MW-Generation Shift Factor						SDTVC without MW-Generation Shift Factor
Methodology	**Generation Participation Factors**		**Distance to VC (pu)**	**Computational Time (Second)**	**No. of Iteration**	**Distance to VC (pu)**
	σ_1	σ_2				
AOA	**0.550**	**0.450**	**0.610**	**589**	**486**	**0.5564**
SCA	0.560	0.440	0.609	725	627	0.5490
Rao-1	0.612	0.388	0.594	978	714	0.5401

Table 3. Worst-Case Loading Scenario Based on the Most Effective Technique Parameter Values for a Six-Bus System

Bus No.	**Worst Case Loading Scenario ($\Delta P_i + j\Delta Q_i$)**		
	AOA	**SCA**	**Rao-1**
3	0.3820 + j0.0386	0.3830 + j0.0387	0.3901 + j0.3924
4	0.2341 + j0.0030	0.2342 + j0.0290	0.2353 + j0.0268
5	0.4616 – j0.0410	0.4618 – j0.0420	0.4677 - j0.0436
6	0.4380 – j0.0070	0.4290 – j0.0069	0.4265 - j0.0061

Table 4. Statistical Inference of the Objective Function for a Six-Bus System to Compare the AOA, SCA and Rao-1 Techniques Over the Course of 20 Runs

Optimization methods	Arithmetic's mean ($\bar{J}$)	Median (m)	Standard deviation (σ)	Best (J_{best})	Worst (J_{worst})	Converging frequency (f)	Level of confidence (γ)	Data chose for the engineering applications (c)	Standard error (ϵ)	Confidence interval (μ)	Length of confidence interval L
AOA	**0.6036**	**0.6028**	**0.0026**	**0.6100**	**0.6010**	**12**	**0.95**	**2.0452**	**1.1916E-03**	**0.6024≤ μ ≤0.6048**	**4.8742E-03**
SCA	0.6015	0.6009	0.0037	0.6090	0.5970	11	0.95	2.0452	1.6818E-03	0.5998≤ μ ≤0.6032	6.8794E-03
Rao-1	0.5848	0.5830	0.0054	0.5940	0.5780	08	0.95	2.0452	2.4945E-03	0.5823≤ μ ≤0.5873	10.2035E-03

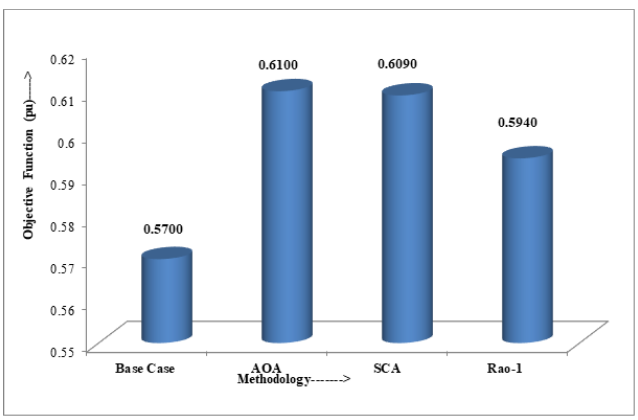

Fig. 6. Comparison of AOA Technique with SCA & Rao-1 Algorithm Based on the Purpose Function of a Six-Bus System.

4.2 25- Bus test system

In the power system described, there are twenty load buses and five generator buses, as well as thirty-five lines. The higher & lower bounds for the load bus voltages have been considered as 1.10pu to 0.95pu. The active power limits for the first generating bus range from 0.0000pu to 4.0000pu, and for the second, third, fourth, and fifth generating bus, they range from 0.0000pu to 2.0000pu. The reactive power limits for the first generating bus range from -0.0500pu to 3.0000pu, and for the second, third, fourth, and fifth generating bus, they range from -0.0500pu to 1.0000pu. Shunt compensations, OLTCs, and PV-bus voltages have all been assumed to have limits of 0.95 pu to 1.15 pu, 0.00 pu to 0.055 pu, & 0.90 to 1.10, respectively.

Under the base case stressed state, Figure 7 shows the Reactive power control factors, including shunt compensations and PV-bus voltages & OLTCs. In the base case condition, the MW-generation participation factors are $\sigma_1 = 0.350$, $\sigma_2 = 0.130$, $\sigma_3 = 0.205$, $\sigma_4 = 0.052$ and $\sigma_5 = 0.263$, indicating the proportion of active power generated by each generator. The maximum loadability with the shortest distance to VC is 1.0950pu.

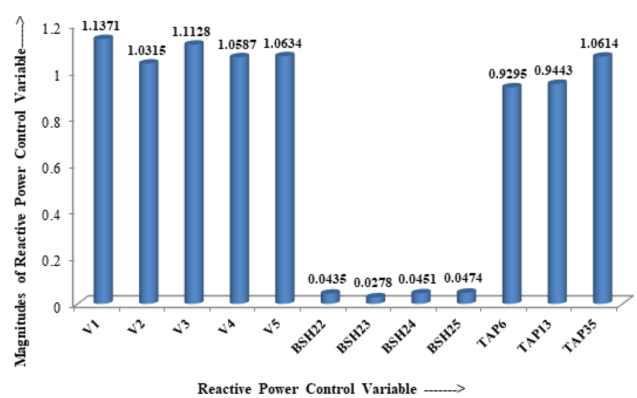

Fig. 7. Reactive Power Control Variable for the Twenty-Five-Bus System in Stressed Situations.

Iterations were set to a maximum of 1000. The optimal distance to voltage collapse (F = 1.1874pu) was found for MW generation with participation factors $\sigma1 = 0.251$, $\sigma2 = 0.312$, $\sigma3 = 0.151$, $\sigma4 = 0.122$ and $\sigma5 = 0.164$ and control parameter ($\alpha = 4.0,\ \mu = 0.5$). After 527 iterations, the simulation run was terminated because the solution to the aim function has resolved.

The objective function and iterations for the most suitable settings of the parameters proposed algorithm, SCA, and Rao-1 are shown in Figure 8. It is used to visualize the optimization process and the convergence of the solution.

Table-5 presents the optimum generation participation factor, optimized shortest distance to VC, CPU time required, and the number of iterations with and without optimization of MW-generation participation factors. Table-6 shows the worst-case load scenario based on the best parameter values for the proposed algorithm, SCA, and Rao-1 algorithms.

Table 5. Compares the Algorithms based on Methodology for a Twenty-Five-Bus Test System with and without Optimization MW-Generation Participation Factors

SDTVC with MW-Generation Shift Factor									SDTVC without MW-Generation Shift Factor
Methodology	Generation Participation Factors					Distance to Voltage Collapse (pu)	Computational Time (Second)	No of Iteration	Distance to Voltage Collapse (pu)
	σ_1	σ_2	σ_3	σ_4	σ_5				
AOA	**0.251**	**0.312**	**0.151**	**0.122**	**0.164**	**1.1874**	**693**	**527**	**1.0365**
SCA	0.249	0.323	0.149	0.118	0.163	1.1617	858	648	1.0228
Rao-1	0.254	0.332	0.138	0.115	0.161	1.1498	1062	775	1.0013

Table-6 Worst-case loading scenario based on the most effective technique parameter values for a twenty-five-bus system

Bus No.	Worst Case Loading Scenario ($\Delta P_i + j\Delta Q_i$)		
	AOA	SCA	Rao-1
6.	0.4112 + j0.3653	0.4118 + j0.3651	0.4121 + j0.3659
7.	0.0391 + j0.6750	0.0389 + j0.6853	0.0388 + j0.6865
8.	0.6813 + j0.0001	0.6812 + j0.0002	0.6810 + j0.0004
9.	0.1851 – j0.0498	0.1849 – j0.0497	0.1844 – j0.0490
10.	0.0398 – j0.0518	0.0397 – j0.0517	0.0392 – j0.0515
11.	0.1601 + j0.1411	0.1603 + j0.1413	0.1605 + j0.1417
12.	0.1581 + j0.3011	0.1561 + j0.3291	0.1543 + j0.3306
13.	- 0.0060 – j0.0767	-0.0059 – j0.0768	-0.0057 – j0.0771
14.	-0.1897 – j0.0801	-0.1899 – j0.0805	-0.1901 – j0.0810
15.	0.1756 + j0.3258	0.1756 + j0.3357	0.1755 + j0.3398
16.	0.1042 + j0.0869	0.1045 + j0.0866	0.1052 + j0.0861
17.	0.4389 – j0.2011	0.4386 – j0.2015	0.4379 – j0.2018
18.	- 0.1495 + j0.0695	-0.1485 + j0.0699	-0.1473 + j0.0701
19.	0.3998 – j0.0494	0.3998 – j0.0485	0.3999 – j0.0478
20.	0.1641 – j0.7950	0.1639 – j0.0794	0.1633 – j0.0805
21.	0.0707 + j0.6278	0.0710 + j0.6285	0.0718 + j0.6296
22.	0.5547 + j0.7847	0.5499 + j0.7855	0.5517 + j0.7863
23.	0.7948 – j0.0486	0.7948 – j0.0499	0.7949 – j0.0506
24.	-0.1681 – j0.0501	-0.1671 – j0.0499	-0.1658 – j0.0506
25.	-0.2481 + j0.0765	-0.2471 – j0.0759	-0.2465 – j0.0745

Table-7 Statistical Inference of the Objective Functions for a Twenty-Five-Bus System to Compare Technique Over the Course of 20 Runs

Opti. Methods	Statical Interface										
	$(\bar{J})$	(m)	(σ)	(J_{best})	(J_{worst})	(f)	(γ)	(c)	(ϵ)	(μ)	L
AOA	**1.1686**	**1.1672**	**0.0073**	**1.1874**	**1.1608**	**12**	**0.95**	**2.0452**	**0.7452E-03**	**1.1678≤ $\mu \le$ 1.1693**	**3.0482E-03**
SCA	1.1408	1.1384	0.0098	1.1617	1.1289	11	0.95	2.0452	1.0002E-03	1.1398≤ $\mu \le$1.1418	4.09924E-03
Rao-1	1.1269	1.1241	0.0125	1.1498	1.1095	09	0.95	2.0452	1.2839E-03	1.1256≤ $\mu \le$1.1282	5.2519E-03

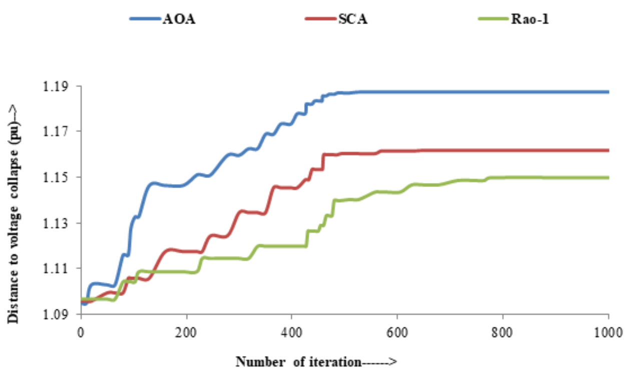

Fig. 8. Shows the Convergence of the Objective Function for a Twenty-Five-Bus System Using Methods as a Function of Iterations.

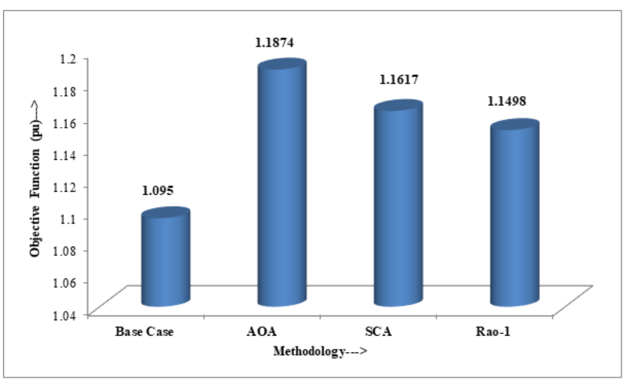

Fig. 9. Comparison of AOA Technique with SCA & Rao-1 Algorithm Based on the Objective Function for a Twenty-Five-Bus System.

Figure 9 shows a comparison of the base conditions of the objective function with the conditions after the generation of MW using proposed algorithm, SCA and Rao-1 methods. Table 7 compares proposed algorithm with the SCA and Rao-1 approaches based on statistical inference. For every statistical inference of the objective function in this investigation, twenty runs were used.

5. CONCLUSION

A novel strategy has been proposed for optimizing CSNBP with respect to MW generation rescheduling based on load scenarios. Hence a Max-Min problem has been formulated and solved using AOA, SCA, and Rao-1 techniques. These algorithms are adapted to handle the optimization problem and find the optimal MW-generation participation factors to satisfy the inequality constraints. The results obtained from these algorithms are presented for the two test systems. The algorithms may be easily implemented on large-size systems because:

- Extremely capable and fast computing facilities.
- The optimization algorithms used are capable of handling large dimensional problems.
- For medium-sized systems, the results can be presented explicitly in a more comprehensible way.

Hence these test systems are sufficient to provide validity of the algorithm. A comparison has been provided for three optimization techniques based on statistical inferences which are shown in Tables 4 and 7 for each of the test systems. The AOA technique demonstrates superior performance as compared to SCA and Rao-1. The optimization presented in this paper is of significant importance when the voltage stability margin is small in current operating conditions and load scenario is uncertain. In such a situation, MW rescheduling may increase margin. The model takes advantage of MW-generation participation to enhance voltage stability limits. Thus, maximizing voltage stability margin by optimizing SDTVC. None of the other formulations has tried it as a maximize problem.

ABBREVIATIONS

CSNBP	: Saddle-Node Bifurcation Point
VCP	: Voltage Collapse Point
AOA	: Arithmetic Optimization Algorithm
SCA	: Sine Cosine Algorithm
RPO	: Real Power Optimization
RPO	: Reactive Power Optimization
OLTCS	: On-Load Tap Changers
VC	: Voltage Collapse
RPCV	: Reactive Power Control Variables
SOP	: Stable Operating Point
UOP	: Unstable Operating Point
SDTVC	: Shortest Distance to Voltage Collapse.

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