J. Electrical Systems 20-10s (2024): 283-296

[1]Muhammad Haziq Aiman Muhamad Syukor

[2*]Ismail Musirin

[3]Nor Azwan Mohamed Kamari

[4]Azlina Abdullah

[5]Nur Farahiah Ibrahim

[6]Siti Rafidah Abdul Rahim

[7]Rahmatul Hidayah Salimin

[8]Muhamad Hatta Hussain

Hybrid-Squirrel-Search Evolutionary Programming Algorithm (HSSEPA) in Distributed Generation Installation for Voltage Security Improvement

Journal of Electrical Systems

Abstract: - The increasing load demand in a power transmission network can lead to voltage insecurity, requiring the need for increased generation capacity. Therefore, it is necessary to take measures towards this situation, which can be referred to as a compensation process. An optimization process will be required to determine the optimal location and sizing of the compensation devices. The optimal sizing and location of the compensation devices will require an optimization process to ensure efficient, dependable and cost-effective operation. However, certain optimization techniques are prone to getting trapped in local optima and lack of exploration. This paper presents a new optimization technique which integrates the traditional Evolutionary Programming (EP) and Squirrel Search Algorithm termed Hybrid Squirrel Search Evolutionary Programming Algorithm (HSSEPA). The algorithm is used to optimize the sizing and location of distributed generation Type 3 for improving voltage security in power system. Comparative studies between HSSEPA with the independent EP and SSA on IEEE 30-Bus RTS reveal its superiority in terms of achieving better security improvement.

Keywords: Optimization techniques, Squirrel Search Algorithm, Distributed Generation, Voltage Security Improvement

I. INTRODUCTION

Distributed generation (DG) is generally described as the integration of a new field into the power generation process. It is defined as the utilization of small and adaptable electricity generation supplies by utilities, with the main purpose of giving an advantages to the customers and power transmission system [1]. Normally, distributed generation will be installed near to the power end user. This is to minimize the occurrence of losses that commonly arise when electrical energy is transmitted over a long transmission line. The performance of power system can be improved and maintained with the integration of DG. Some of the benefits are the improvement of voltage

[1,2,4,5]Power System Operation Computational Intelligence Research Group (POSC), School of Electrical Engineering, College of Engineering, Universiti Teknologi MARA, 40450 Shah Alam, Selangor, Malaysia.

[3]Department of Electrical, Electronic and Systems Engineering, Faculty of Engineering & Built Environment, Universiti Kebangsaan Malaysia, Malaysia.

[3]Electric Mobility and Inteligent Vehicle Technologies, Centre for Automotive Research (CAR), Faculty of Engineering & Built Environment, Universiti Kebangsaan Malaysia, Malaysia.

[4]Department of Electrical and Electronics Engineering, College of Engineering, Universiti Tenaga Nasional, 43000 Kajang, Selangor, Malaysia.

[6,8]Faculty of Electrical Engineering & Technology, Universiti Malaysia Perlis, Kampus Pauh Putra, 02600, Arau, Perlis, Malaysia.

*Correspondin author: [2]ismailbm@uitm.edu.my.

Email: [1]haziq.syukor@gmail.com, [3]azwank@ukm.edu.my, [4]aazlina@uniten.edu.my, [5]nurfarahiahibrahim@uitm.edu.my, [6]rafidah@unimap.edu.my, [7]rhidayah@uitm.edu.my, [8]muhdhatta@unimap.edu.my.

profile, reduction in loss and improvement in power system security. The most importantly is that it can cut the cost of power generation [2]. It is crucial to optimally locate the position of DG and to find the optimal sizing in power system since the integration of DG can potentially increase the fluctutaion of system functioning and modify the configuration of the grid [3], [4]. DG can be divided into 4 types which are Type 1, Type 2, Type 3 and Type 4 as reported in [5] . For the DG Type 1, DG will have the capability to inject real power (P). One important example for DG Type 1 is solar photovoltaic system where solar photovoltaic panels will convert sunlight into electrical energy. The next type of DG is DG Type 2 where DG will only have the capability to inject reactive power only (Q). For this type, it will function at a power factor of 1.0, which is also known as unity power factor. For the next DG type, is DG Type 3, which will have the capability to inject both the real power (P) and reactive power (Q). An example of DG type 3 is synchronous generator. Lastly, DG Type 4 has the capability of DG to inject real power (P), however it will consume reactive power (Q). Several studies have been conducted in the past. Among the important study is the work conducted in [6]. M. Abdel-Akher et al. [6] primarily examines the evaluation of a distribution systems which are connected to the DG units. For this technique, the most vulnerable branches will be identified which are highly prone to entering an unstable region for DG allocation. The method that has been employed is the Newton-Raphson load-flow which determined the steady-state of the power transmission network and there was a total of 90-bus distribution system for this proposed method. On the other hand, Amaresh Gantayet et al. [2] also highlighted the importance of DG installation in power system. This study investigated the effects of DG on the voltage profile, voltage stability and power losses in power transmission system. There were two types of DG beig considered i.e. DG Type 2 and DG Type 3. The work conducted by Khalid S. Aljebreen et al. [7] highlighted important difference from others proposed method. The main difference is the power flow solution which was bidirectional where it could flow in two opposite directions. The issue of the voltage stability index on a mesh system was investigated, where the main objective of the study was to improve the voltage stability and minimize system losses. K. Divya et al. [8] has proposed a study concerning the optimal sizing and location of DG using Particle Swarm Optimization (PSO). The PSO algorithm highlighted the significance of parameter selection, namely the inertia weight, for achieving search capability and global search. Voltage stability Index (VSI) has been employed to determine the optimal location and sizing of the DG and also the effects of DG on power transmission system efficiency. Work by Bazilah Ismail et al.[9] can also be highlighted as one of the important studies. This work has proposed a study on the determination of the most optimal location for integrating a Wind Power Plant (WPP). DigSILENT PowerFactory 16 has been employed as the model-building tool while the benchmark system that has been implemented is the IEEE 30 bus test system. On the other hand, Florina et al.[10] has proposed a method where optimal location of DG is identified using the fuzzy logic and clustering method. The clustering techniques are divided into the partitioning method and hierarchical methods. Other than that, one of the most popular approaches for clustering is the k-means method. For this method, it will be used to determine the optimal location of DG and to identify the partitioning of optimal distribution networks. Bikash Kumar et al.[11] has conducted a study on the optimal placement and sizing of DG using grasshopper optimization technique. It is a metaheuristic optimization algorithm that draws and inspiration from the natural behavior of grasshoppers. Grasshoppers optimization techniques have been identified as a group of optimization techniques that are inspired by nature such as squirrels, bees, and ants. Grasshopper optimization technique is a computational framework that uses the behavior of grasshoppers to solve the optimization issues by replicating their social behaviors. Apparently, numerous methods have been studeid and investigated. The non-optimal solution of DG may lead to over-compensation or under-compensation phenomena. It can be seen that there are many approaches and methods that have been done to find the optimal location and sizing of DG. However, most of the algorithms are developed to obtain the same objectives. Nevertheless, those optimizations will be different in terms of their robustness and flexibility. Other than that, most of the metaheuristic algorithms fail to balance exploration and exploitation, leading to poor results for real-life complex optimization problem.

This paper presents Hybrid-Squirrel-Search Evolutionary Programming Algorithm (HSSEPA) in distributed generation installation for voltage security improvement. In this study a new optmization technique is proposed termed HSSEPA. HSSEPA integrates the operators in squirrel search algorithm (SSA) into the original mechanics of Evolutinary Programming (EP) as an effort to achieve better optimal solution. Voltage security improvement is indicated by a line-based voltage stability index (*FVSI*) value, ranging from 0 at no-load to 1.0 at its stability limit. A comparative study between HSSEPA with the independent EP and SSA on IEEE 30-bus system RTS has been performed to demonstrate the superiority of the proposed HSSEPA in achieving better optimal solution indicating better voltage security improvement.

II. PROBLEM FORMULATION

Fast Voltage Stability Index (*FVSI*) was derived by Ismail Musirin and Rahman in [12] . This is derived based on the transmission line of a 2-bus power system model. The general equation is given by:

$$FVSI_l = \frac{4\, Z_l^2\, Q_r}{V_s^2\, X_l} \tag{1}$$

where:

Z_l	:	line impedance
X_l	:	line reactance
Q_r	:	receiving end power
V_s	:	sending end voltage

FVSI is a utility employed to analyze voltage stability in power transmission systems. The level of instability will be represented by the *FVSI* value ranging from 0 to 1.0. When the value of line index is closer to 1.00, it signifies that the system has reached its limit of stability. The change in load could result in an abrupt decrease in voltage on the related bus. The *FVSI* value is employed to identify the limit at which the maximum capacity is reached before voltage collapse occurs. This enables the implementation of essential measures to prevent any violation of the system's capacity. Other than that, by the implementation of *FVSI*, it can help to identify the most vulnerable bus or line in the power system. The most vulnerable or weakest bus will be identified when the value of *FVSI* is closest to 1.00. This allows for estimating the possibility of system failure, allowing for proactive measures to prevent such occurrences.

A. *Conceptual Strategy for Voltage Security Control*

Figure 1 shows the conceptual strategy for voltage security control in this study. Firstly, a random number generator is placed which will produce random numbers which will be assigned for random locations and sizing of the distributed generation. The random number generated by the random number generator will be sent to the system data. These variables will become the control variable to control the optimization process, depending on the designated objective function. These variables consisting of a population of individuals which are random in nature will be fed into the optimization techniques. Apparently, the same individuals within the control variables are utilized by all the optimizer, namely the EP, SSA and HSSEPA. The flow of random individuals will be bi-directional and continuously connecting the transmission system as the validation model.

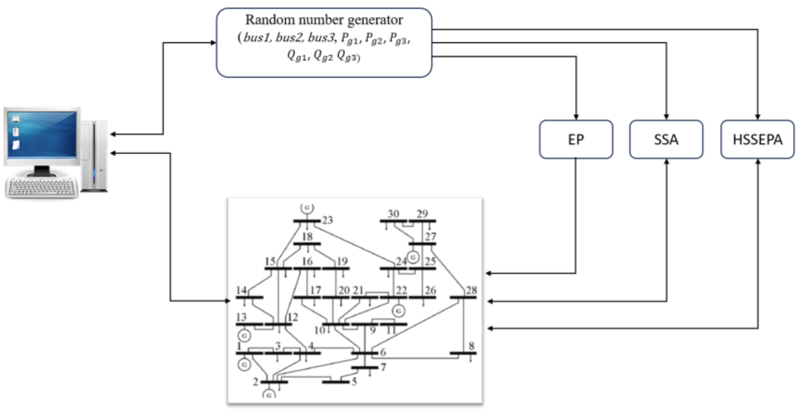

Figure 1: Conceptual strategy for Voltage Security Control

III. OPTIMIZATION TECHNIQUES

A. Evolutionary Programming

In the beginning of the 1960s, L.J. Fogel in [13], [14] proposed the idea of Evolutionary Programming as a State Machine Model. Following that, in the late 1990s, D.B. Fogel widened the idea of EP, which was subsequently transformed into an optimization tool that has been utilized to solve a variety of problems in the real world, particularly in the field of engineering. Over the past few years, EP has been successfully resolving a large number of combination and numerical optimization issues. In comparison with genetic algorithms, EP focuses on the relationship between the behaviors of different species during the evolutionary process. This is because EP replicates the evolution of species rather than analyzing genes [15]. In EP, the main objective is the development of species behavior, which results in the formation of a behavioral relation between parents and offspring. This behavioral relation indicates that an excellent offspring might exist without considering its parent. Figure 2 below shows the flowchart for EP mechanics for DG Type-3 allocation in voltage security improvement. The EP procedure encompasses initialization, statistical analysis, mutation, and competition. Initially, a random selection of control variables forms the starting population, drawn from a uniform distribution within their specified boundaries. The fitness score (f_i) of each individual is influenced by both the objective function and the environment. Statistical analysis involves determining the maximum, minimum, sum, and average fitness values for the current generation. In the mutation phase, a new population called offspring is generated from the existing population (parent). Any modified values that surpass their limits are adjusted to fit within those limits. Mutation enables fitter individuals to produce more offspring for the succeeding generation. The whole process can be divided into 2 parts, namely: -

- Normal load flow
- Optimization process of Type-3 DG installation

Normal Load Flow: This process is the pre-optimization process, conducted to evaluate the status of the system security. The system security is indicated by the value of *FVSI*, as the indicator. Apparently, this value is rather high when a disturbance is under consideration and experienced by the system.

Optimization Process: In the optimization process, DG Type-3 will be installed into the system, ensuring that the *FVSI* value is reduced once optimal solution has been achieved. The detail description for this part will be explained in the mechanic of EP.

The mechanics of EP in solving the Type-3 DG installation are explained in the following steps as pictorially presented in the flowchart appeared in Figure 2: -

Step 1: Initialization Process.

Same as the other techniques, random parameters will be generated for active and reactive power injection at the random load buses. The generated random parameters must satisfy the conditions before it can be saved in the pe-designed pool. For Type-3 DG installations, 3 sets of random variables will be generated depending on how many units of DGs are to be installed. For instance, 9 control variables will be generated to denote P_{g1}, P_{g2}, P_{g3}, Q_{g1}, $Q_{g2,}$ $Q_{g3,}$ Loc_1, Loc_2 and $Loc_{3.}$ Each control will have several individuals. Conventionally, 20 individuals for each control variable are considered adequate to start with the optimization process. A higher number of individuals will lead to exhaustive optimization process and will not help the performance of the optimization solution. Apparently, the size of the matrix for the initialization process will be *20 by 9*. All the individuals will be inserted into the system data, followed by the calculation of fitness value, i.e. *FVSI* values. When the 20 individuals are inserted into the system, each individual will lead to the calculation of *FVSI*. Thus, 20 fitness values are computed which should be less than the *FVSI* value computed during te normal load flow, where EP was not yet implemented, and DG Type-3 was not installed into the system.

Step 2: Fitness 1 Calculation.

At this stage, Fitness I calculation is conducted utilizing the parent random individuals. For the first iteration only, the fitness values computed in his process should be the same as the fitness values during initialization process since we are using the same random variables. The selected bus will undergo injection of both real and reactive power, followed by the load flow study. In addition, it is necessary to determine the voltage stability index, i.e. the *FVSI*. Subsequently, it is necessary to save all the acquired fitness values in the ‘Fitness I’ matrix or array.

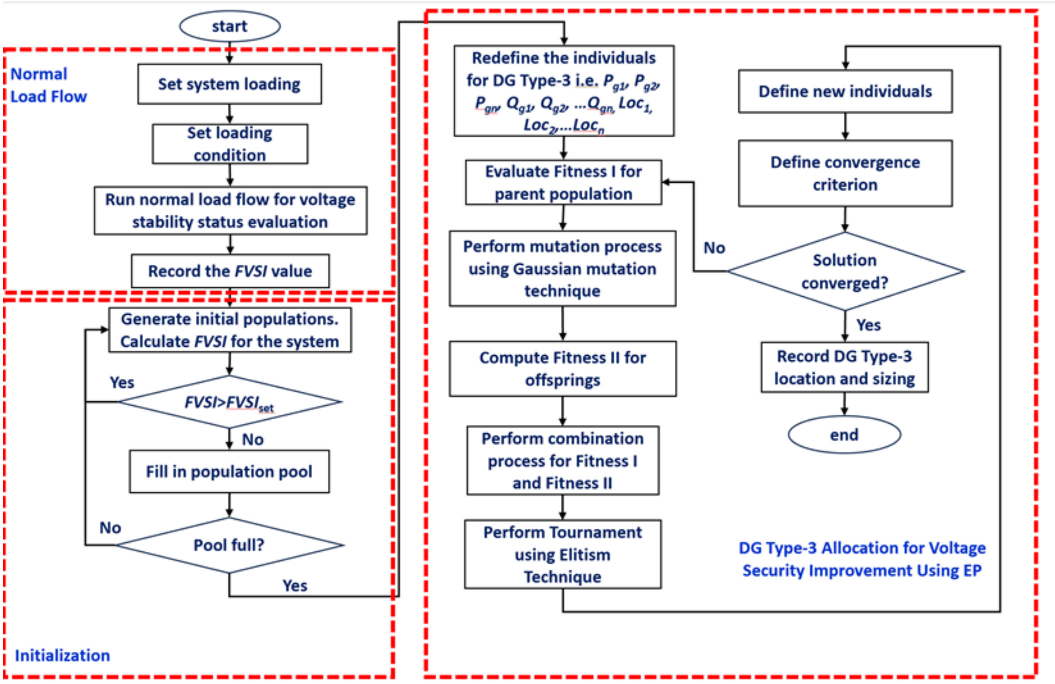

Figure 2: EP Technique Flowchart for DG Type-3 Allocation in Voltage Security Improvement

Step 3: Mutation Process

Mutation process is conducted to breed the children or offsprings of he individuals. These individuals will experience a mutation process that gives rise to new individuals, referred to as offspring or progeny. The matrix size remains consistent with that of the parent population. The mutation process employs the Gaussian mutation operator for execution.

$$X_{i+m} = X_{i,j} + N(0, \beta(X_{j\max} - X_{j\min}) \cdot \frac{f_i}{f_{\max}}) \tag{2}$$

X_{ij} is the old individuals of each variable, β is the search space, where $0<\beta<1.00$, $X_{j\,max}$ is the maximum value of each control variable, f_i is the fitness value of individual i^{th} and f_{max} is the maximum fitness value of the individuals.

Step 4: Fitness II Calculation

Fitness II calculation is conducted to calculate the second fitness, i.e. Fitness II. This process utilizes the children or the offsprings for the Fitness II calculations.

Step 5: Combination Process

Combining the populations of the parents and the offspring with the appropriate fitness values is the next step that needs to be completed. The overall number of individuals doubles as a result of this procedure. The population size of the merged population is 40 rows by 9 columns if the population of the original parents is, let's say, 20 rows by 9 columns. The number of control variables was indicated by the number of columns.

Step 6: Tournament and Selection

Tournament and selection processes are two cascading processes, conducted in series. Tournament identifies the ranking of the individuals in accordance with the fitness values. There are several tournament processes which can be applied, such as elitism, pairwise comparison, roulette wheel or any other suitable tournament technique. In this study, the elitism approach was implemented. On the other hand, selection process identifies survivors for the next evolution or iteration. New individuals' definition is conducted to identify the candidates for the next optimization process. The survivors are defined for the candidates for the next evolution.

Step 7: Convergence Test

Convergence test is crucial such that the optimal solution can be achieved once the stopping criterion is met. These survivors become the parents for the next evolution. The stopping criterion, typically set at less than 0.0001, is based on the difference between the maximum and minimum fitness. This can be mathematically given by: -

$$Fit_{max} - Fit_{min} < 0.0001\_ \tag{3}$$

B. Proposed HSSEPA

Hybrid Squirrel Search Evolutionary Programming (HSSEPA) is proposed with an improvement of EP, aimed to reduce the problem of premature convergence when solving highly complex problems and enhance the global search ability of EP. The step-by-step procedure of the proposed method is illustrated in Figure 3. The whole process can be divided into 2 parts, namely: -

- Normal load flow
- Optimization process of Type-3 DG installation

Normal Load Flow: This process is the pre-optimization process, conducted to evaluate the status of the system security. The system security is indicated by the value of *FVSI*, as the indicator. The process similar for those implemented in the traditional EP. Apparently, this value is rather high when a disturbance is under consideration and experienced by the system.

Optimization Process: In the optimization process, DG Type-3 will be installed into the system, ensuring that the *FVSI* value is reduced once optimal solution has been achieved. The detail description for this part will be explained in the mechanic of HSSEPA.

Step 1: Loading Condition Setting.

It is important to set the loading conditions because they accurately recreate all of the different operational scenarios that the power system may encounter in real-world situations. Setting the loading conditions means determining the electrical power demand or consumption at various buses within the system which in this case is the IEEE 30-Bus RTS.

Step 2: Initialization Process.

Same as the EP technique, random parameters will be generated for active and reactive power injection at the random load buses. The generated random parameters must satisfy the conditions before it can be saved in the pe-designed pool. For Type-3 DG installations, 3 sets of random variables will be generated depending on how many units of DGs are to be installed. For instance, 9 control variables will be generated to denote P_{g1}, P_{g2}, P_{g3}, Q_{g1}, Q_{g2}, Q_{g3}, Loc_1, Loc_2 and Loc_3. Each control will have several individuals. Conventionally, 20 individuals for each control variable are considered adequate to start with the optimization process. A higher number of individuals will lead to exhaustive optimization process and will not help the performance of the optimization solution. Apparently, the size of the matrix for the initialization process will be *20 by 9*. All the individuals will be inserted into the system data, followed by the calculation of fitness value, i.e. *FVSI* values. When the 20 individuals are inserted into the system, each individual will lead to the calculation of *FVSI*. Thus, 20 fitness values are computed which should be less than the *FVSI* value computed during te normal load flow, where EP was not yet implemented, and DG Type-3 was not installed into the system.

Step 3: Initial Population Definition.

Definition of the random control variables are conducted since we will be using the same parents generated during initialization process. Similar parents or individuals will be used in Fitness I calculation, for the first iteration only. The new parents for the second iteration onwards will rely on the survivors after the tournament process. There are a total of 20 individuals confining all the parameters such as the bus number as the random locations, real and reactive power that will be injected into the buses.

Step 4: Fitness I Calculation.

Similar Fitness I calculation is conducted in HSSEPA as those in EP. At this stage, Fitness I calculation utilizes the parent random individuals. For the first iteration only, the fitness values computed in his process should be the same as the fitness values during initialization process since we are using the same random variables. The selected bus will undergo injection of both real and reactive power, followed by the load flow study. In addition, it is necessary to determine the voltage stability index, i.e. the *FVSI*. Subsequently, it is necessary to save all the acquired fitness values in the 'Fitness I' matrix or array.

Step 5: Update the Position Using SSA Equation.

For this step, it will start with the random selection of another squirrel. One individual will be randomly selected based on the 20 individuals to generate a random squirrel position. After that, all the variables inside the random individual that has been chosen will be identified as a random location. Based on the random individual and variables that have been generated, the position of the random squirrel will be updated using the SSA equation. This step is an essential part of the proposed method. The proposed method is trying to travel through the search space in order to possibly discover more effective solutions by updating the position of the squirrels according to their existing positions and the impact of other randomly selected squirrels.

$$x_{i+1} = x_i + \alpha * \exp(-\delta * E) * (x_{random} - x_i) \tag{4}$$

where

x_{i+1}	:	Updated parameter
x_i	:	Current parameter
x_{random}	:	Random squirrel position
α	:	Scaling factor controlling the step size of the update.
δ	:	Parameter which control the influence of the exploration and exploitation of the algorithm.
E	:	Evolution step current iteration

This phase is an essential part of the proposed method. The proposed method is trying to travel through the search space in order to possibly discover more effective solutions by updating the position of each squirrel according to their existing positions and the impact of randomly selected squirrels.

Step 6: Fitness II Calculation

Fitness II calculation is conducted to calculate the second fitness, i.e. Fitness II. This process utilizes the children or the offsprings for the Fitness II calculations. The size of the array to store these individuals are the same as that in Fitness I. The only difference is that, Fitness II calculation utilizes the offsprings bred from the SSA mutation scheme.

Step 7: Combination and Selection

Combination ad Selection are two consecutive serial processes involving Fitness I and Fitness II populations. Combining the populations of the parents and the offspring with the appropriate fitness values is the next step that needs to be completed. The overall number of individuals doubles as a result of this procedure as those experienced in EP. The population size of the combined population is 40 rows by 9 columns if the population of the original parents is, let's say, 20 rows by 9 columns. The number of control variables was indicated by the number of columns.

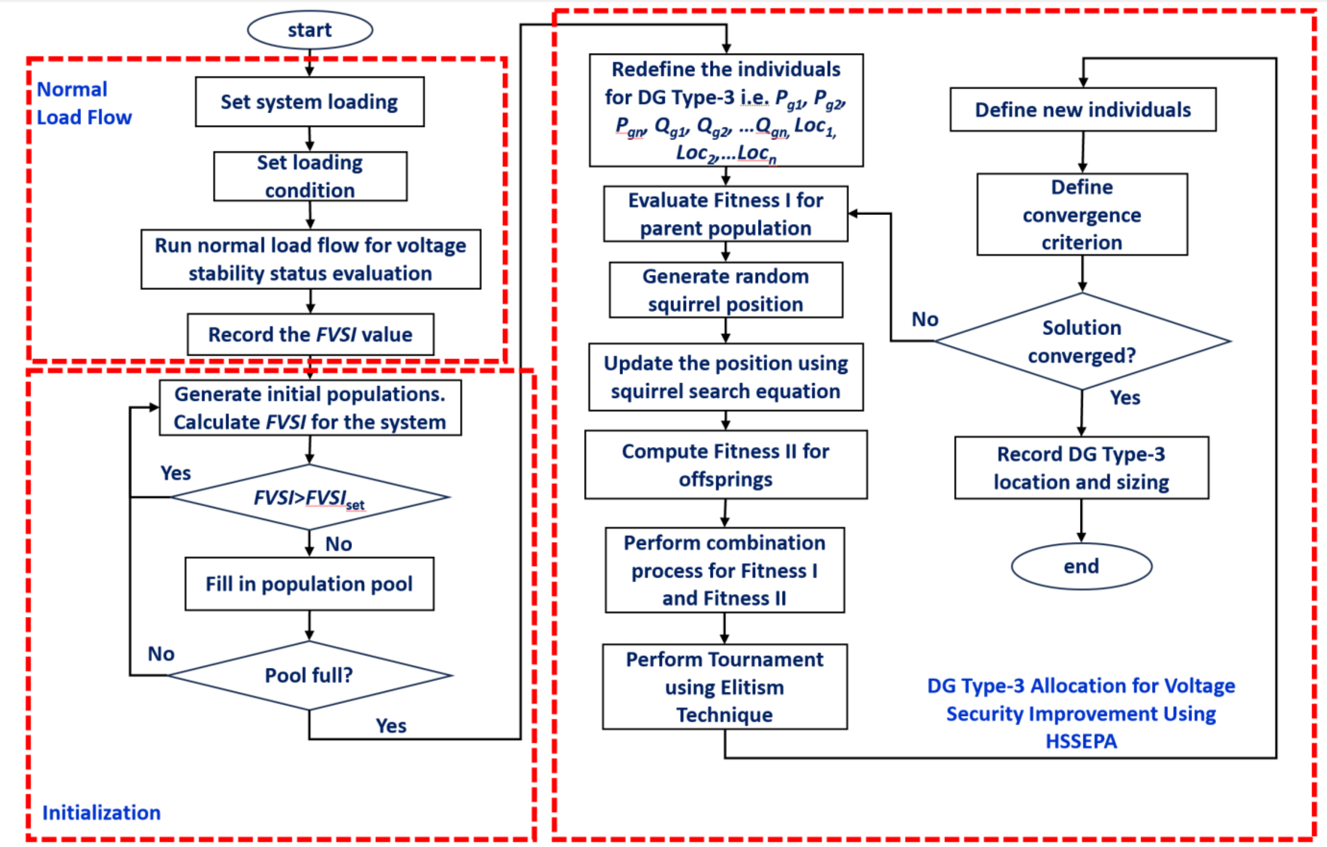

Figure 3: Proposed HSSEPA Technique for DG Type-3 Allocation in Voltage Security Improvement

The combined population for Fitness I and Fitness II will undergo a tournament process, in the effort to identify the survivors of the fittest. In this study, elitism technique is implemented where the individuals are sorted in accordance with fitness values. Either it is going to be sorted in ascending or descending order, it depends on the objective function. For minimization of fitness as the objective function, the individuals will be ranked in accordance with the lowest fitness and voce versa for the maximization of the fitness value.

Step 8: Convergence Test

Based on equation (3), the maximum and minimum fitness values will need to be defined on the combination matrix of Fitness I and Fitness II. This equation helps to determine whether the maximum and minimum fitness values are lower than or equal to 0.0001. If the condition is true, the function will execute the return statement and completely stop the optimization process where it is considered that the optimization process has reached a state of convergence. However, if the condition is false, it will go back to Fitness I calculation, bringing the surviving individuals for the iteration counter to proceed with the optimization process.

IV. RESULT AND DISCUSSION

This section describes the results and discussion for DG Type-3 allocations for the purpose of voltage security improvement under several loading scenarios. It was validated on a reliability test power system model, namely IEEE Reliability Test System (RTS).

A. Test System

Figure 4 shows the single line diagram of the IEEE 30-Bus RTS. The IEEE 30-Bus RTS is a reliable test model of a real power system, and it has been extensively utilized in both industrial and academic studies. For this comparative study, IEEE 30-Bus RTS has been utilized to validate the optimal location and sizing for DG. This enables the implementation of essential measures to prevent any violation of the system's capacity. This system has 6 generators buses, 28 load buses and 41 transmission lines. Chosen load buses will experience the load variation to demonstrate the impact of DG installation on voltage security improvement.

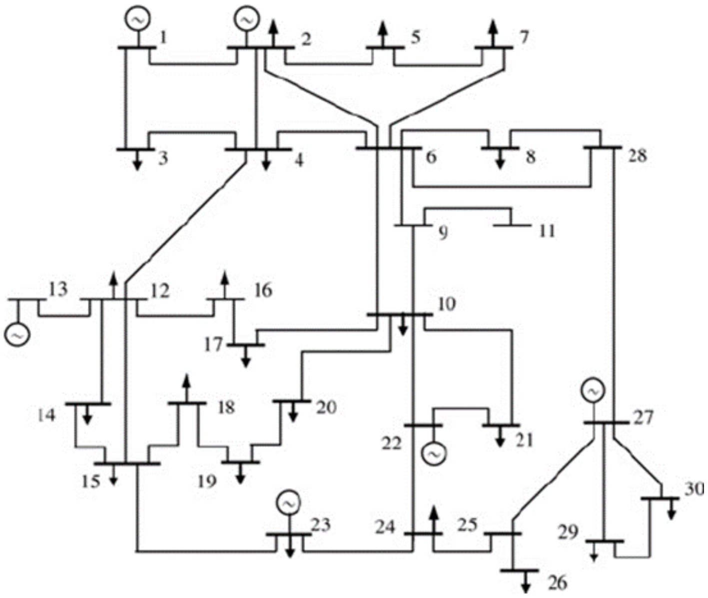

Figure 4: IEEE 30 Bus RTS

B. Results during Initialization Process.

Initialization process generated all the random individuals which represent the locations, real power, and reactive power for the distributed generation (DG). For this case, DG Type-3 is used, where both real and reactive power will be injected into the system to improve the voltage security condition. For this study, 3 units of DG are installed into the system to improve the voltage security of the system represented by the reduction in *FVSI* value.

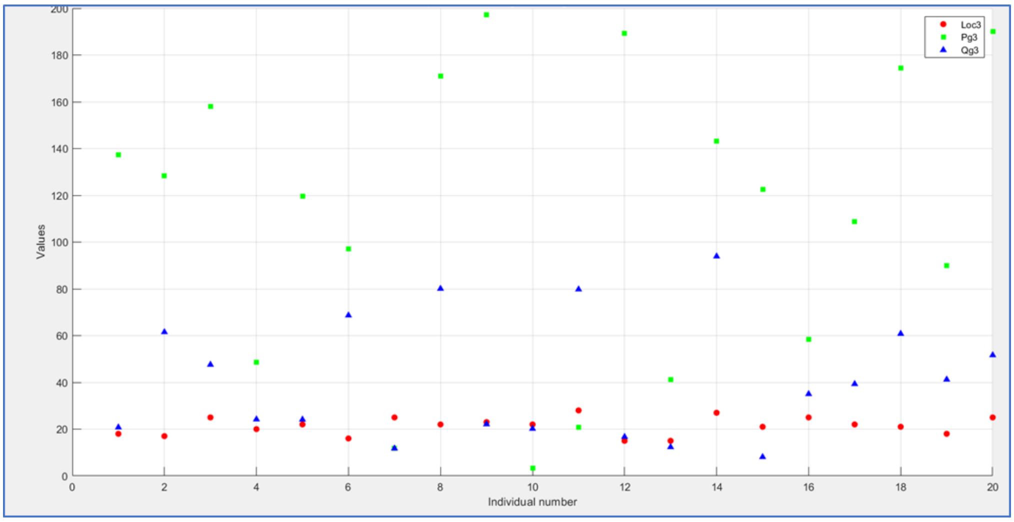

Figure 5: Random initialization at Qd26 = 15 MVAR

The scatter plot illustrated in Figure 5 and Figure 6 present the results for random individuals during initialization process. These figures present the random individuals during initialization at Q_{d26} = 15 MVAR, and Q_{d29} = 15 MVAR, respectively. There are 20 individuals for each control variable. For this study, since we have three control variables for location, P_g sizing and Q_g sizing, the total number of control variables is 9, making the total individuals of 180. In Figure 5, the plot with the red color determines the location of the buses which are supposedly to be less than 30 since we uses 30 bus system. The plot with the green color and blue color indicates the amount of real and reactive power that will be injected into the system. Same understanding will be applied 6 where it presents the random individuals during initialization at Q_{d29} = 15 MVAR. Other than that, random parameters for reactive power injection need to satisfy certain conditions before it can be generated. Bus 1, Bus 2 and Bus 3 need to be different locations during the initialization process. Permitting Bus 1, Bus 2 and Bus 3 to be identical may lead to situations where a bus will be injecting real and reactive power into itself. These circumstances may not correspond to the actual physical conditions of power system. All the random individuals for each individual will ensure that the computed FVSI value is less than the *FVSI* value computed during the normal load flow, where DGS are not yet installed into the system and no optimization process is implemented.

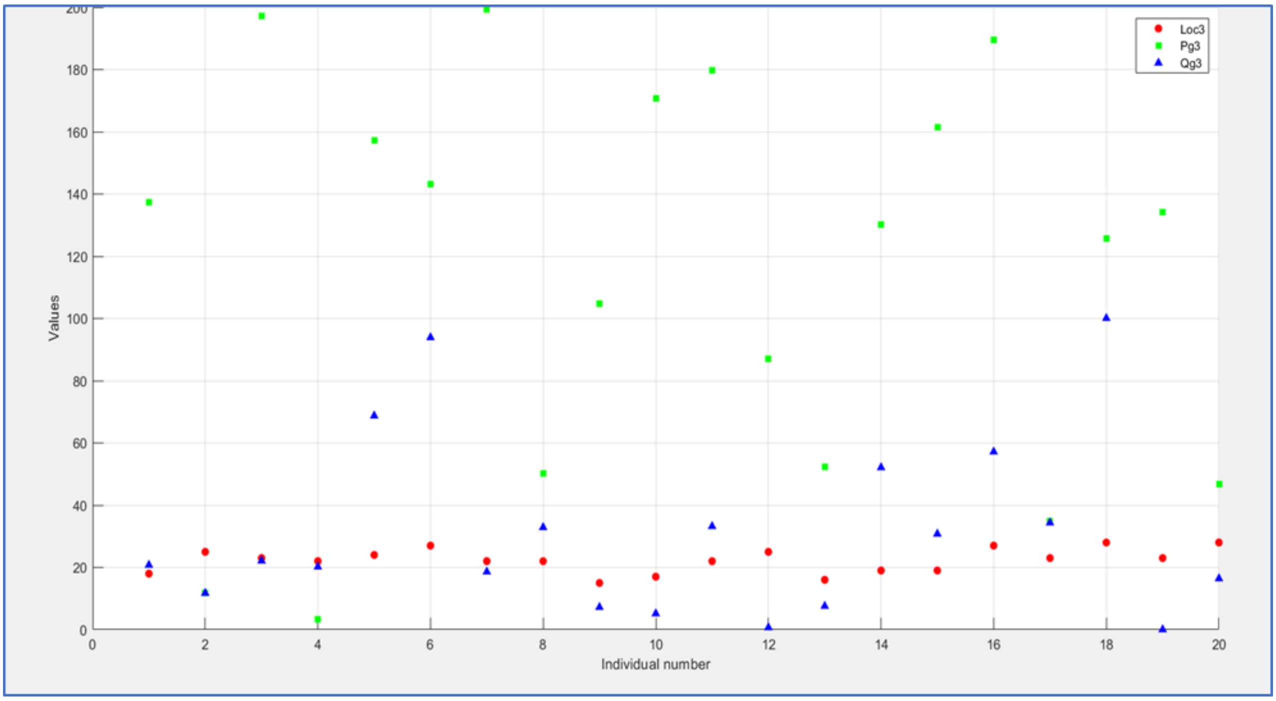

Figure 6: Random initialization at Qd29 = 15 MVAR

TABLE I: RANDOM PARAMETERS AT Q_{d26} = 15 MVAR

Individual number	*Bus 1*	*Bus 2*	*Bus 3*	P_{g1} (MW)	P_{g2} (MW)	P_{g3} (MW)	Q_{g1} (MVAR)	Q_{g2} (MVAR)	Q_{g3} (MVAR)	*FVSI*
1	18	25	20	137.7419	129.5531	63.0734	35.3914	13.1030	6.1078	0.2785
2	23	24	21	48.1022	83.7994	71.4301	1.5162	3.0913	67.3021	0.3436
3	23	28	24	155.8918	31.2258	180.6468	40.8056	107.6807	66.4437	0.3222
4	23	28	22	121.0267	58.0399	152.1540	86.6038	8.5277	18.6809	0.3500
5	23	18	22	109.1290	108.8177	59.6664	16.7606	2.1880	18.8139	0.3359
6	20	24	14	169.9312	167.1724	62.3338	21.5642	40.6457	12.3182	0.3177
7	28	21	20	18.6198	93.9294	48.3044	121.4099	10.1103	28.2716	0.2918
8	17	28	23	123.7950	163.3649	70.1331	11.0635	128.5560	36.5681	0.2728
9	24	20	18	65.4269	159.8403	16.3204	24.8876	22.4256	9.5425	0.3119
10	19	16	21	159.4685	127.3089	186.8439	26.2176	18.1554	117.1608	0.3273
11	23	28	20	33.5363	185.8233	40.8815	2.9845	147.9038	54.9501	0.3154
12	15	30	19	70.5913	82.4843	47.4847	25.9234	11.7009	37.4059	0.3112
13	28	21	15	131.8056	2.6613	114.4863	44.8466	25.5883	31.2676	0.2900
14	19	21	17	58.2061	13.2302	16.8085	1.5377	60.3854	1.4190	0.3468
15	26	23	27	198.4385	40.2393	180.2217	41.8329	26.8081	137.2360	0.3204
16	15	21	23	48.6367	92.6458	142.9417	60.1255	17.3057	18.2680	0.3253
17	17	24	27	182.9088	177.2741	96.6530	31.2654	42.8342	28.0576	0.2653
18	22	15	24	175.4621	182.3902	81.8010	49.1935	8.0839	49.2791	0.2983
19	28	25	21	196.1663	77.3317	199.4999	80.5822	57.9696	19.2536	0.3325
20	17	28	21	123.2516	149.6011	179.5056	15.3745	24.7035	54.3127	0.3045

TABLE I and TABLE II tabulate the results for random individuals during initialization process for Q_{d26} = 15 MVAR, and Q_{d29} = 15 MVAR. There are 20 individuals in each table. For each of the individual number, there will be a total of 9 variables which are Bus_1, Bus_2, Bus_3, P_{g1}, P_{g2}, P_{g3}, Q_{g1}. Q_{g2} and Q_{g3}. Bus_1, Bus_2, Bus_3 will represent the location of the bus. P_{g1}, P_{g2}, P_{g3} represent the total amount of real power that will be injected into the bus and

Q_{g1}. Q_{g2} and Q_{g3} represent the total of reactive power that will be injected into the bus. In TABLE I, the maximum value of *FVSI* for this loading condition is 0.3514. This value is the voltage stability index, *FVSI* value before the installation of DG into the system. The *FVSI* value, is denoted as $FVSI_{set}$. During initialization process, all the individuals when being inserted into the system will ensure that the computed fitness value is less than the $FVSI_{set}$. We can discover that all the FVSI values tabulated in TABLE I are less than the $FVSI_{set}$, which implies that all the random individuals has passed the inequality constraint, where $FVSI < FVSI_{set}$.

TABLE II: RANDOM PARAMETERS AT Q_{d29} = 15 MVAR

Individual number	*Bus 1*	*Bus 2*	*Bus 3*	P_{g1} *(MW)*	P_{g2} *(MW)*	P_{g3} *(MW)*	Q_{g1} *(MVAR)*	Q_{g2} *(MVAR)*	Q_{g3} *(MVAR)*	*FVSI*
1	15	25	28	71.7907	199.6774	58.4698	66.0795	20.5304	122.1513	0.2502
2	24	28	21	190.4616	128.0634	190.8880	20.8673	20.8673	10.7492	0.2504
3	22	15	28	96.9820	99.4591	34.3712	2.8963	0.7558	101.5851	0.2283
4	17	25	23	15.8621	133.6940	163.3326	12.6153	12.6547	36.0376	0.2493
5	18	23	27	172.4738	112.2401	161.0414	42.3669	31.8153	78.3756	0.1658
6	17	24	28	26.6425	119.4639	184.0358	16.6702	40.7247	61.7701	0.1842
7	25	19	28	141.1341	36.5216	174.8205	44.0453	8.1864	41.9197	0.2160
8	17	27	28	125.8421	76.5171	69.9657	36.2573	9.9175	59.6772	0.2037
9	17	15	28	122.4889	169.4456	195.3745	29.2351	4.8308	89.8977	0.2204
10	16	28	24	100.9793	9.4741	98.3248	33.7424	36.9764	23.4020	0.2403
11	14	25	28	18.9302	110.3699	84.9718	16.7262	13.9549	49.0361	0.2123
12	27	23	19	182.2080	137.5224	120.6525	87.3837	46.5630	19.4609	0.2085
13	26	18	24	28.6379	3.6544	88.0371	11.2685	8.1739	41.3198	0.2375
14	18	17	28	102.3174	97.8513	26.8141	13.0160	46.4927	68.8289	0.2516
15	16	28	29	176.0310	185.4650	4.5402	35.7501	59.8209	30.8480	0.1762
16	19	28	23	105.5569	71.1285	25.8510	6.4882	109.5158	9.7923	0.2196
17	16	25	29	37.7832	147.9322	106.8898	63.0836	22.9372	34.0281	0.2597
18	15	17	28	141.7436	164.4671	169.0193	8.1061	13.5854	82.5834	0.2288
19	14	21	28	21.5055	189.9604	109.1093	10.4816	34.1649	94.6836	0.2164
20	17	22	28	12.8375	196.2090	73.6830	4.7121	1.3394	70.6608	0.2338

The same scenario is observed in TABLE II. Each of the individual in the table are less than $FVSI_{set}$. Otherwise, the parameters will be rejected and, and it will repeat the process where new random parameters will be generated to satisfy the conditions until it fills up the pool. This process will be repeated until the individual pool of 20 has been filled. *FVSI* value plays a vital role in the initialization process since it will help to ensure that it satisfies the conditions before the parameters can be saved and fill up the individual pool. These random individuals are all the parents for the first iteration, which will go through the optimization process either EP or the proposed HSSEPA. These are the controlling individuals which will lead to the optimal solution.

C. Optimal Location and Sizing

TABLE III tabulates the results for optimal locations for voltage security improvement for loading variation at Bus 26 when 3 units of DG Type-3 are installed into the system. Bus 26 was subjected to reactive load variation from 5 MVAR to 30 MVAR. On the other hand, TABLE IV tabulates the results for optimal locations when 3 DGs Type-3 when reactive load variation was subjected to Bus 29. The results for sizing of the 3 DGs are presented in TABLE V and TABLE VI, which will be discussed later. Apparently, the locations are optimal, solved using the three optimization techniques i.e. EP, SSA and proposed HSSEPA. For load variation at Bus 26, power system planners or operators can make choices using the technique they decided at any chosen reactive loading condition. For instance, Using HSSEPA at Q_{d26} = 30 MVAR, Buses 28, 26 and 24 are the optimal locations to install 3 units of DGs Type-3. But is SSA is chosen, Buses 27, 16 and 28 are the optimal locations. Results for other reactive loading conditions for all the optimization techniques can be referred to the same table. On the other hand, if reactive loading variation occurs at Bus 29, TABLE IV can be referred for the information. For instance, at Q_{d29} = 30 MVAR, Buses 16, 22 and 27 are the optimal locations for 3 units of DG Type-3 to be installed into the system.

The results for optimal sizing for P_g and Q_g involving reactive load variation at Bus 26 and 29 can be referred to TABLE V and TABLE VI. In TABLE V, using EP as the optimization technique, at Q_{d26} = 5 MVAR, a total of 133.126 MW and 21.6871 MVAR need to be injected to Bus 24. This will also require installing 90.2685 MW and

54.4181 MVAR at Bus 28 and 172.3279 MW and 8.9197 MVAR to be installed at Bus 18. This installation will cause a reduction of FVSI value from 0.2020 to 0.1177, indicating improvement of voltage security. These results have been highlighted in TABLE III for the optimal location and TABLE V for the optimal sizing in P_g and Q_g, with the corresponding *FVSI* values.

Next for the SSA technique at Q_{d26} = 5 MVAR, 39.3966 MW and 1.5549 MVAR needs to be installed at Bus 25, 24.3503 MW and 46.0234 MVAR at Bus 28 while 101.3272 MW and 5.5379 MVAR at Bus 18 to achieve optimal solution. There is a reduction in *FVSI* values from 0.2020 to 0.1219. The results at the same reactive loading, solved using HSSEPA 66.591MW and 4.0304 MVAR to be installed at Bus 25, 23.1234 MW and 35.7522 MVAR at Bus 28 and 101.4281 MW and 6.2990 MVAR at Bus 18 to achieve optimal solution. This initiative will cause a reduction in *FVSI* value from 0.2020 to 0.1172. The same approach an be used to analyze the results reactive loading condition at Bus 29 in TABLE VI. In general, the proposed HSSEPA also managed to demonstrate superior results in terms of achieving the highest *FVSI* reduction, in particular reactive loading at 30 MVAR. At Q_{d26} = 30 MVAR, the *FVSI* value has been reduced from 0.8657 to 0.4406, indicating superior voltage security improvement achieved by HSSEPA over EP and SSA. In general, the proposed HSSEPA is superior that EP and SSA in most cases. However, when load variation at Bus 29 was conducted, EP and SSA slightly outperformed HSSEPA. Nevertheless, HSSEPA still managed to perform well at other load variations.

TABLE III: OPTIMAL LOCATION FOR LOADING VARIATION AT BUS 26

Technique	Q_{d26} *(MVAR)*	Optimal location		
		Bus 1	*Bus 2*	*Bus 3*
EP	**5**	**24**	**28**	**18**
	10	16	29	27
	15	25	23	18
	20	27	26	20
	25	25	23	18
	30	25	23	18
SSA	**5**	**25**	**28**	**18**
	10	27	19	22
	15	17	24	27
	20	26	27	24
	25	25	26	22
	30	27	16	28
HSSEPA	**5**	**25**	**28**	**18**
	10	27	20	22
	15	26	25	21
	20	22	23	26
	25	26	25	22
	30	28	26	24

TABLE IV: OPTIMAL LOCATION FOR LOADING VARIATION AT BUS 29

Technique	Q_{d29} *(MVAR)*	Optimal location		
		Bus 1	*Bus 2*	*Bus 3*
EP	5	25	28	24
	10	25	28	24
	15	16	29	27
	20	16	29	27
	25	28	18	25
	30	22	15	27
SSA	5	18	28	29
	10	28	17	23
	15	18	23	27
	20	18	27	28
	25	25	17	29
	30	25	27	16
HSSEPA	5	18	28	26
	10	18	27	17
	15	18	23	27
	20	16	18	17
	25	29	20	28
	30	16	22	27

TABLE V: OPTIMAL SIZING FOR LOADING VARIATION AT BUS 26

Technique	Q_{d26} *(MVAR)*	Optimal sizing						FVSI	
		P_{g1} *(MW)*	P_{g2} *(MW)*	P_{g3} *(MW)*	Q_{g1} *(MVAR)*	Q_{g2} *(MVAR)*	Q_{g3} *(MVAR)*	Before	After
EP	**5**	**133.126**	**90.2685**	**173.2739**	**21.6871**	**54.4181**	**8.9197**	**0.2020**	**0.1177**
	10	185.1101	80.6267	143.0725	12.0866	12.1292	93.8743	0.2248	0.1654
	15	163.1864	74.3819	137.2203	62.0338	1.8695	20.7595	0.3514	0.2172
	20	70.2105	27.9674	48.6713	19.3732	4.8685	24.2007	0.4919	0.2945
	25	163.186	74.3819	137.2203	62.0338	1.8695	20.7595	0.6529	0.3811
	30	163.1864	74.3819	137.2203	62.0338	1.8695	20.7595	0.8657	0.4711
SSA	**5**	**39.3966**	**24.3503**	**101.3272**	**1.5549**	**46.0234**	**5.5379**	**0.2020**	**0.1219**
	10	118.3925	198.9643	187.3736	32.6074	32.1992	98.4176	0.2248	0.1728
	15	182.9088	177.2741	96.653	31.2654	42.8342	28.0576	0.3514	0.2653
	20	193.7998	144.5373	21.2517	44.0269	105.2178	44.5301	0.4919	0.2000
	25	26.7337	74.9948	75.6612	4.8142	26.5596	94.3504	0.6529	0.4132
	30	72.4628	123.9055	143.9062	51.5167	121.3576	69.9766	0.8657	0.4992
HSSEPA	**5**	**66.5291**	**23.1234**	**101.4281**	**4.0304**	**35.7522**	**6.2990**	**0.2020**	**0.1172**
	10	112.4289	194.6336	177.4332	31.6730	35.3153	92.5208	0.2248	0.1727
	15	178.8141	88.9340	171.2625	68.1378	58.2682	22.5978	0.3514	0.1666
	20	12.7553	143.6699	63.2467	17.4549	46.1822	23.1161	0.4919	0.2092
	25	113.3563	101.8880	165.4995	44.1155	51.2541	22.4095	0.6529	0.1512
	30	**138.5898**	**86.0809**	**148.1510**	**54.9024**	**11.7430**	**103.8106**	**0.8657**	**0.4406**

TABLE VI: OPTIMAL SIZING FOR LOADING VARIATION AT BUS 29

Technique	Q_{d29} *(MVAR)*	Optimal sizing						FVSI	
		P_{g1} *(MW)*	P_{g2} *(MW)*	P_{g3} *(MW)*	Q_{g1} *(MVAR)*	Q_{g2} *(MVAR)*	Q_{g3} *(MVAR)*	Before	After
EP	5	52.719	149.9492	170.8587	2.2272	14.4239	21.5607	0.2025	0.1360
	10	52.7121	149.9495	170.8646	2.2173	14.4304	21.5572	0.2111	0.1497
	15	185.0745	80.5894	143.0379	12.0632	12.1134	93.8548	0.2613	0.1529
	20	185.0881	80.6127	143.0359	12.0825	12.0933	93.8579	0.3573	0.1667
	25	179.0109	36.367	20.7435	36.513	73.4384	79.7863	0.4646	0.3428
	30	136.3312	118.9529	40.8306	40.0805	32.7873	56.1575	0.5987	0.3639
SSA	5	5.6875	160.2876	81.1169	4.3029	26.7488	3.1715	0.2025	0.1322
	10	53.7075	85.735	144.2483	77.7952	0.5256	12.4462	0.2111	0.1553
	15	172.4731	112.2401	161.0411	42.3667	31.8152	78.3755	0.2613	0.1658
	20	125.6558	183.0208	167.8277	45.4789	65.5045	81.352	0.3573	0.2112
	25	195.2667	129.4904	44.6103	41.7656	85.2432	25.8181	0.4646	0.3134
	30	45.4091	4.2374	126.2128	67.588	7.9008	47.0184	0.5987	0.3762
HSSEPA	5	28.3533	138.9017	80.5646	6.5148	28.7937	5.2056	0.2025	0.1210
	10	135.7076	127.1350	171.8510	25.3471	52.0436	32.4401	0.2111	0.1465
	15	172.4684	112.2374	161.0421	42.3658	31.8208	78.3717	0.2613	0.1658
	20	130.0439	144.8442	157.8082	14.6159	21.7576	80.3748	0.3573	0.2270
	25	78.3130	57.8133	97.8148	38.5573	6.2705	94.8883	0.4646	0.1997
	30	13.6285	117.8579	134.5101	9.5287	83.9057	38.4839	0.5987	0.3801

V. CONCLUSION

This paper has proposed a new optimization technique termed HSSEPA for DG Type-3 installation in voltage security improvement scheme for power transmission systems. The proposed HSSEPA which integrated the element of SSA into the traditional EP managed to achieve better voltage security reduction in most cases. Reactive load variation at 2 chosen load buses demonstrated the ability of HSSEPA to outperform EP and SSA, especially at the higher reactive loading condition. However, it also acceptable to state that HSSEPA may experience non-dominant results compared to EP and SSA in certain reactive loading condition. Implementation on IEEE 30-Bus RTS demonstrates the ability of HSSEPA to perform well in the voltage security improvement scheme. The proposed HSSEPA can be further explored to solve other power system optimization problems with minor alterations. It is also feasible for implementation in larger networks.

ACKNOWLEDGMENTS

The authors would like to acknowledge the contribution and support by UniversitiTeknologi MARA, Universiti Kebangsaan Malaysia (UKM), Universiti Tenaga Nasional (UNITEN) and Universiti Malaysia Perlis, Malaysia (UniMAP) for a joined research. This research is financially supported by Universiti Kebangsaan Malaysia and Ministry of Higher Education, Malaysia (MOHE) under project code: GUP-2022-010.

REFERENCES

[1] Y. Y. Adajah, S. Thomas, M. S. Haruna, and S. O. Anaza, "Distributed Generation (DG): A Review," in 2021 1st International Conference on Multidisciplinary Engineering and Applied Science, ICMEAS 2021, Institute of Electrical and Electronics Engineers Inc., 2021. doi: 10.1109/ICMEAS52683.2021.9692353.

[2] Siksha "O" Anusandhan University, Institute of Electrical and Electronics Engineers, Institute of Electrical and Electronics Engineers. Kolkata Section, and India. Department of Science and Technology, PCITC-2015 proceedings : 2015 IEEE Power, Communication and Information Technology Conference (PCITC) : 15-17 October, 2015, Siksha "O" Anusandhan University, Bhubaneswar, India.

[3] "13. Research_on_distributed_generation_technologies_and_its_impacts_on_power_system".

[4] C. Chinese Association of Automation. Youth Academic Annual Conference (33rd : 2018 : Nanjing Shi, M. IEEE Systems, Chinese Association of Automation, and Institute of Electrical and Electronics Engineers, Proceedings, 2018 33rd Youth Academic Annual Conference of Chinese Association of Automation : May 18-20, 2018, Nanjing, China.

[5] S. Kalpana, A. Deepika, and R. Arthi, "An Energy Efficient Squirrel Search Algorithm for Cognitive Wireless Sensor Networks," in 2021 International Conference on System, Computation, Automation and Networking, ICSCAN 2021, Institute of Electrical and Electronics Engineers Inc., Jul. 2021. doi: 10.1109/ICSCAN53069.2021.9526368.

[6] IEEE Staff and IEEE Staff, 2011 IEEE Energy Conversion Congress and Exposition.

[7] K. S. Aljebreen, A. E. Hussein, and M. A. Abido, "Optimum Allocation of Distributed Energy Resources for Voltage Stability Enhancement and Loss Reduction," in EUROCON 2023 - 20th International Conference on Smart Technologies, Proceedings, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 227–232. doi: 10.1109/EUROCON56442.2023.10199025.

[8] Sri Eshwar College of Engineering, Institute of Electrical and Electronics Engineers, Institute of Electrical and Electronics Engineers. Madras Section, and IEEE Computer Society, 3rd International Conference on Advanced Computing and Communication Systems : ICACCS 2016 : January 22-23, 2016, "Sri Eshwar College of Engineering" Campus.

[9] "10. Voltage_stability_indices_studies_on_optimal_location_of_wind_farm_in_distribution_network".

[10] Institute of Electrical and Electronics Engineers and Universitatea Politehnică București. Facultatea de Inginerie Electrica, 2017-10th International Symposium on Advanced Topics in Electrical Engineering (ATEE).

[11] Keonjhjar. D. of E. E. Government College of Engineering, Keonjhjar. D. of C. S. and E. Government College of Engineering, Institute of Electrical and Electronics Engineers. Kolkata Section. Bhubaneswar Subsection, and Institute of Electrical and Electronics Engineers, International Conference on Computational Intelligence for Smart Power System and Sustainable Energy (CISPSSE-2020) : (29-31, July 2020).

[12] S. J. Chuang, C. M. Hong, and C. H. Chen, "Improvement of integrated transmission line transfer index for power system voltage stability," International Journal of Electrical Power and Energy Systems, vol. 78, pp. 830–836, Jun. 2016, doi: 10.1016/j.ijepes.2015.11.111.

[13] D. B. Fogel and L. J. Fogel, "An Introduction to Evolutionary Programming". Springer.

[14] L. Fang, "The New Adaptive Evolutionary Programming," ICMLC 2010.

[15] K. Chellapilla, "Brief Papers Combining Mutation Operators in Evolutionary Programming," 1998.

[16] R. Rautray et al., "ASSIE: Application of Squirrel Search Algorithm for Information Extraction Problem," in 2021 International Conference in Advances in Power, Signal, and Information Technology, APSIT 2021, Institute of Electrical and Electronics Engineers Inc., 2021. doi: 10.1109/APSIT52773.2021.9641165.

[17] V. Bharti, B. Biswas, and K. K. Shukla, "QL-SSA: An Adaptive Q-Learning based Squirrel Search Algorithm for Feature Selection," in 2022 IEEE Congress on Evolutionary Computation, CEC 2022 - Conference Proceedings, Institute of Electrical and Electronics Engineers Inc., 2022. doi: 10.1109/CEC55065.2022.9870311.

[18] H. Hu, L. Zhang, Y. Bai, P. Wang, and X. Tan, "A Hybrid Algorithm Based on Squirrel Search Algorithm and Invasive Weed Optimization for Optimization," IEEE Access, vol. 7, pp. 105652–105668, 2019, doi: 10.1109/ACCESS.2019.2932198.

[19] Sichuan Institute of Electronics and Institute of Electrical and Electronics Engineers, 2018 IEEE 4th International Conference on Computer and Communications (ICCC) : December 7-10, 2018, Chengdu, China.

[20] V. P. Sakthivel, M. Suman, and P. D. Sathya, "Combined economic and emission power dispatch problems through multi-objective squirrel search algorithm," Appl Soft Comput, vol. 100, Mar. 2021, doi: 10.1016/j.asoc.2020.106950.