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Smart SVC Placement for Loss Reduction in Power Systems: Tackling Generator Outages with IGEPO Optimization

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Abstract:

Increasing load demand and generator outages in power transmission networks can cause significant power losses and voltage instability. Addressing these challenges requires an optimal installation strategy for Static Var Compensators (SVC), which involves determining the best locations and sizes for the SVCs to ensure efficient, reliable, and cost-effective operation. Traditional optimization techniques often struggle with issues like local optima and inadequate exploration. This paper presents a novel approach, the Integrated Grasshopper Evolutionary Programming Optimization (IGEPO), which combines the Grasshopper Optimization Algorithm with Evolutionary Programming. The IGEPO method is applied to optimize the placement and sizing of SVCs, with the goal of minimizing losses, particularly during generator outages. Comparative studies on the IEEE 30-Bus RTS demonstrate that IGEPO outperforms both standalone Evolutionary Programming and the Grasshopper Optimization Algorithm in power system planning under normal conditions and during contingencies due to generator outages. Results are presented for the pre-SVC installation under both normal conditions and during generator outages to observe the impact of the outages and the subsequent SVC installation. The proposed algorithm has potential for broader applications and could be explored further in future studies.

Keywords: Optimization techniques, Grasshopper Optimization Algorithm, Power Loss Minimization, Integrated Optimization, Integrated Grasshopper Evolutionary Programming Optimization.

I. INTRODUCTION

Electricity consumption throughout the world has gradually increased over the decades following the demographic growth, increase in the number of people in urban areas, more economic development, and technological development [1]. The traditional ways of applying new plants and new transmission lines Construction to meet this increasing demand is often impossible because of high cost, environmental concerns and technology constraints. Thus, when making tactical and operational decisions, one has to enhance the cost effectiveness of existing systems, a component of which is the reduction of losses as from active power through the management of reactive power through FACTs. In this regard, one has found the use of FACTs devices as one of the most common strategies for the particular kind. FACTs are another control tool that was proposed by Hingorani in 1998 [2] to improve flexibility and dynamism of electrical variables in power systems with maintaining their security, stability, and reliability. This leads to an efficient utilization of the existing resources since power loss together with costs is minimized to increase the overall efficiency of the grid [3]. FACTs consist of numerous kinds of compensation equipment including the UPFC, SVC, TCSC, and STATCOM. Of them, SVC is unique of being the parallel connected device which can act as a variable capacitance or variable inductance. As mentioned earlier, SVC is used in many applications, some of which are voltage control in weak networks, minimum transmission losses, increasing transfer capability, small disturbance rejection, voltage control, and control of fluctuating power [4].

The choice of SVC in this study is influenced by its flexibility in handling numerous operations. However, the problem of achieving the best placement and sizing is a key challenge in enforcing the improvement of voltage stability using SVCs [5], [6]. To counter such complications, many optimization techniques have been advanced to reduce the power system losses or control voltages to IEEE or IET standards. If power voltage is not well maintained, then it results in reduction of span of the transmission cable in the system. For electrical power systems, accurate positioning of Static VAR compensators or SVCs is critical to loss minimization and the stability of the system, especially where there has been generators' trip. SVCs are very necessary for applications used in controlling the reactive power which in turn supports the compensation methods used to control fluctuations of the voltage and improve the sturdiness of the power grid. The proper application of optimization methods is essential for the identification of the right SVC locations and their capacities to enhance system efficiency [7]-[13]. The Grasshopper Optimization Algorithm (GOA) is a relatively recent metaheuristic that simulates grasshoppers' social behavior; it has shown excellent performance as a search algorithm and in terms of convergence in a number of fields, including power systems [9]. The hormonal based most new creation has been attached with GOA latest GOA formation which has been categorized as the Integrated Grasshopper Evolutionary Programming Optimization (IGEPO). This integration of the two types of methods makes use of the advantages of each in generating more efficient solutions to reducing power losses and in SVC placement [10]. Thus, it can be seen that generator outages present a major threat to power system reliability and efficiency. Hence, they asserted that the implementation of generator outages management within optimization frameworks is vital for operation resilience [11]. In any optimization algorithm, the initialization process is a significant determinant of convergence rates and solution quality; thus, strategic initialization procedures are valuable for improving the system's overall performance [12]. Some of the main goals include minimizing certain losses, increasing system availability, and adjusting operation costs based on multifaceted studies and comparisons with other techniques [13]-[15]. Despite these advancements, many metaheuristic algorithms struggle to balance exploration and exploitation, resulting in suboptimal solutions for real-world applications.

This paper presents smart SVC placement for loss reduction in power systems: tackling generator outages with IGEPO optimization. In this study, one of the major objectives of the utility is the achievement of an efficient loss minimization scheme incorporating a feasible plan for generator outages by applying the IGEPO method on the suitable SVC. This study highlights a new proposed optimization algorithm, termed IGEPO, combining the advantages of GOA and EP, to optimize SVC installation for loss minimization in power systems validation, particularly under generator outage conditions. Comparative studies on the IEEE 30-Bus RTS will demonstrate the effectiveness of the proposed method.

II. PROBLEM FORMULATIION

Minimizing power losses in power systems is critical for achieving operational efficiency and reducing costs, as such losses lead to wasted energy and increased expenses. Static Var Compensators (SVCs) play a vital role in enhancing power system stability and efficiency by providing rapid reactive power compensation, stabilizing voltage levels, correcting power factor, and increasing transmission capacity. However, generator outages—whether planned or unplanned—pose significant challenges, resulting in power imbalances, voltage instability, and increased losses. To address these issues, determining the optimal placement and sizing of SVCs during generator outages is crucial. An increase in reactive power can significantly raise power losses in the system, as shown in Fig. 1. This phenomenon occurs both before and after a generator outage. Comparing the profiles of these two scenarios reveals that during a generator outage, the loss profile is higher than under normal conditions. The mathematical equations for power loss can be expressed starting with (1).

$$S_i = P_i + jQ_i \tag{1}$$

The complex power injected into bus *i* can be expressed as:

$$S_i = V_i \sum_{k=1}^{N} V_k^* Y_{ik} \tag{2}$$

V_i : the voltage at bus *i*

$V_k{}^*$: the complex conjugate of the voltage at bus *k*

Y_{ik} : the admittance of the transmission line between bus *i* and bus *k*

N : the total number of buses

The power loss in the system is given by:

$$\text{Loss} = \sum_{n=1}^{k} (I_n^2 R_n) \tag{3}$$

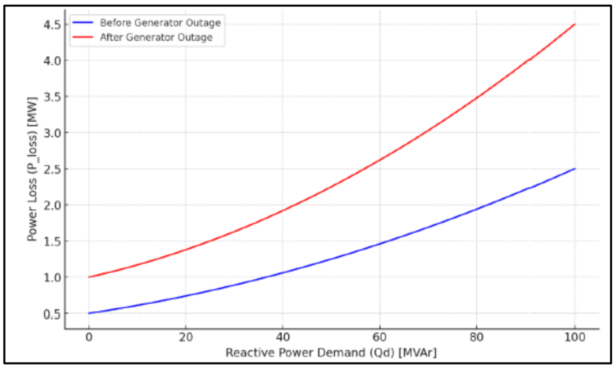

Fig. 1: The effect of generator outage under variations of reactive power in the system.

Fig. 1 illustrates the effect of a generator outage under different reactive power variations in the system. This study focuses on optimizing power system performance by minimizing losses during generator outages. It addresses challenges such as power imbalances through the strategic placement and sizing of SVCs. Traditional optimization methods often struggle to balance objectives like minimizing losses. To overcome this, the study proposes the Integrated Grasshopper Evolutionary Programming Optimization (IGEPO) method, which combines the exploration capabilities of the Grasshopper Optimization Algorithm (GOA) with the exploitation strengths of Evolutionary Programming (EP). The goal is to enhance overall optimization effectiveness. Comparative studies on the IEEE 30-Bus RTS validate IGEPO, offering a robust solution for efficient and smooth power system operation.

A. Conceptual Strategy for Loss Minimization

Fig. 2 illustrates the conceptual strategy for minimizing losses in a power system. Initially, a random number generator generates numbers used to determine the locations and sizes.

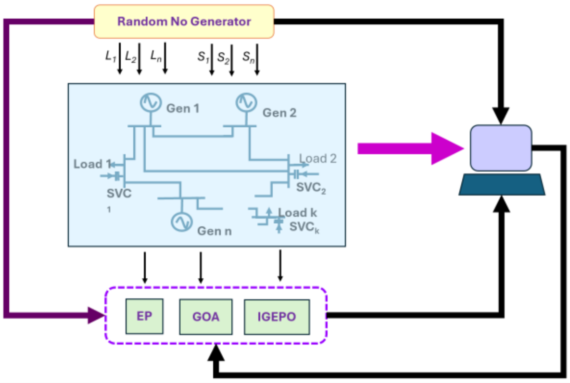

Fig. 2: Conceptual strategy for loss minimization

These numbers are then transmitted to the control center and subsequently integrated into the power transmission system. Similarly, the techniques EP, GOA, and IGEPO utilize the same random numbers to assign the compensating devices, which are validated within the power transmission network. Random number generator generates random numbers which will be utilized by the power system network. The random numbers represent the random locations and sizing of the SVC to be installed in the system. The number of control variables is given by 2n, where n is the number of SVC units to be installed into the system. The same random numbers will be utilized by all the three optimization techniques, i.e. EP, GOA and IGEPO.

III. OPTIMIZATION TECHNIQUES

This section introduces the proposed IGEPO algorithm, followed by descriptions of EP and GOA as benchmark techniques. IGEPO integrates EP and GOA, where the mutation operator of GOA is embedded into the original EP mechanics. GOA and EP are taken as the benchmarked techniques for the purpose of comparative study in the effort to highlight the performance of the proposed IGEPO.

A. *Evolutionary Programming*

Evolutionary Programming (EP) was first introduced by L. J. Fogel in the early 1960s as a State Machine Model [16], [17]. In the late 1990s, D. B. Fogel extended EP into an optimization tool used to solve various real-world problems, especially in engineering. Over the years, EP has effectively addressed numerous combinatorial and numerical optimization challenges. Unlike genetic algorithms, which focus on gene analysis, EP emphasizes the relationship between species' behaviors during the evolutionary process. EP simulates the evolution of species, focusing on behavioral development and the connection between parents and offspring. This approach suggests that an exceptional offspring can emerge independently of its parent’s characteristics [18]. The mechanics of EP are depicted in the flowchart of Fig. 3, highlighting essential processes such as initialization, fitness calculation in two phases, mutation, combination, tournament and convergence test, which determines convergence [19].

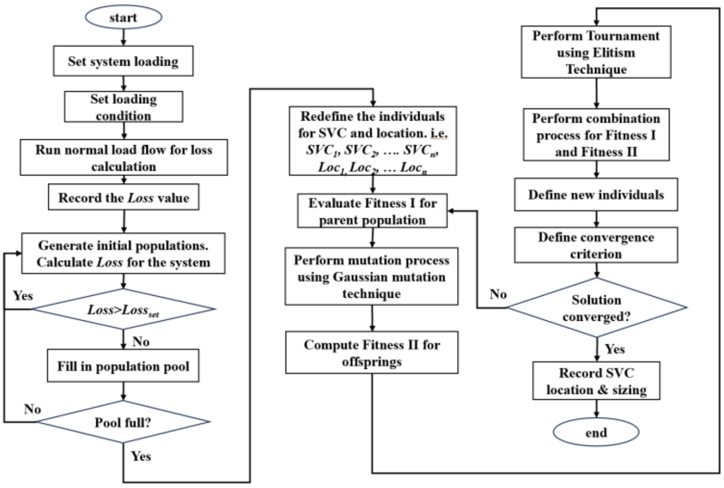

Fig. 3: Flowchart for Evolutionary Programming in SVC installation scheme

B. *Grasshopper Optimization Algorithm*

The Grasshopper Optimization Algorithm (GOA) replicates the foraging behavior of grasshoppers to solve complex optimization problems [7]. GOA employs agents that mimic grasshoppers, adjusting their positions based on social interactions, gravity, and wind advection to balance exploration and exploitation. This methodology allows GOA to adeptly navigate engineering and computational intelligence domains, avoiding local optima and converging on global solutions. GOA's process is illustrated in the step-by-step procedures as follows:

Step 1: Declaration Process

The first step in implementing GOA involves clearing the workspace and initializing essential parameters like bus numbers, load, and limit values to set initial conditions for the power system model. This includes loading the detailed bus and line data, assigning specified loads, and setting generator outage conditions to accurately prepare for the optimization process.

Step 2: Random Parameter Generation

In this stage, random individuals are generated to determine random locations or load buses and sizes for SVC installation. The power data for the selected buses is adjusted accordingly, setting up the initial state for the optimization process and enabling the algorithm to explore various configurations of reactive power injection.

Step 3: Initialize Population for GOA

After parameter generation, GOA initializes the population by defining variable boundaries and setting algorithm parameters such as iterations and population size. Agents' positions are randomly initialized within these bounds and sorted to identify the lowest loss values and corresponding bus locations. This diverse starting setup enhances the algorithm's ability to explore the search space effectively. During this initialization process, all the random individuals amounted of 20 values for each variable will ensure that all the fitness values are better than the preset fitness. These random individuals represent the random locations for the SVCs to be installed and the sizing of SVCs. In this study, fitness is power loss. Thus, the loss values computed using all the random individuals during initialization should be less than $loss_{set}$, where it was computed using the normal load flow process.

Step 4: Main Optimization Loop

The main optimization loop calculates fitness values for the population in each iteration, identifying the best fitness value and position. Agents' positions are updated using GOA equations, mimicking grasshopper swarming behavior through social interaction, gravity, and wind advection. Adjustments keep positions within boundaries, enforcing integer constraints on specific variables. Progress is displayed to monitor the algorithm's performance.

Step 5: Identify the Best Fitness, Optimal Sizing, and Location

GOA outputs result that include fitness values, optimal sizing, and the best location for minimizing losses, along with the best position. This comprehensive output assesses the algorithm's effectiveness in optimizing SVC installation in power system.

C. Proposed IGEPO Algorithm

The Integrated Grasshopper Evolutionary Programming Optimization (IGEPO) method is formulated to enhance the performance of the original EP technique. This improvement aims to mitigate premature convergence when addressing highly complex problems and to boost EP's global search capability. The flowchart is illustrated in Fig. 4. The step-by-step process of the proposed method is as follows:

Step 1:	Set the Loading Condition Setting the loading conditions is crucial for simulating various operational scenarios that the power system might face in real-world situations. This involves determining the electrical power demand or consumption at different buses within the system, particularly for the IEEE 30-bus system in this context.
Step 2:	Initialization This stage generates individuals to represent random buses as the locations and sizes of the SVCs to be installed. Random parameters for reactive power injection are generated, ensuring that all three selected buses are distinct, as in this study three units of SVCs are installed in the system. Losses are then calculated based on these new parameters when the random locations and SVC sizing are inserted into the system. If the new loss value is lower than the previously established initial loss, the parameters are saved in a predefined matrix and added to the individual pool. If not, the solution is rejected, and the loop process continues until the required number of accepted individuals is achieved. The iteration then stops, and the individual pool is populated with all the generated individuals.
Step 3:	Redefine the Initial Population The initial population stored in the accepted matrix is redefined for Fitness I calculation. This fitness calculation involves the parameters in power system model and analyzing the performance of each approach. The previously generated initial population, consisting of 20 individuals, as bus numbers as the random locations and reactive power to be injected into the buses represent the SVCs sizing.
Step 4:	Fitness I Calculation The loop for Fitness I calculation involves 20 iterations, corresponding to the number of individuals in the process. During each iteration, selected buses receive injections of reactive power, followed by a load flow analysis. Additionally, the power loss is computed, and all obtained fitness values are stored in the 'Fitness I' array.

Step 5

Update the Position Using GOA Equation

Optimization techniques are integrated with GOA to enhance the efficiency of reactive power support in power systems. Initially, random solutions are generated for bus positions and SVC values, followed by a fitness evaluation based on system losses. Mutation is introduced, controlled by parameters such as mutation strength and mutation probability, to explore new potential solutions. This process mitigates the risk of premature convergence, enabling the algorithm to find optimal configurations for reactive power compensation devices.

Mutation is described as follows:

$$\sigma_m = 0.1 \tag{5}$$

Generate random displacement for each individual:

$$\Delta_i = \sigma_m \cdot N(0,1) \tag{6}$$

Where $N(0,1)$ is a normally distributed random variable with mean 0 and standard deviation 1. Calculate new values after mutation:

$$X_i' = X_i + \Delta \tag{7}$$

$$Y_i' = Y_i + \Delta \tag{8}$$

Where X_i and Y_i represent the initial position and SVC values, and X_i' and Y_i' are the new values after mutation.

Step 6:

Fitness II Calculation

Similar to Fitness I, Fitness II calculation involves 20 iterations, each corresponding to an individual in the population. New configurations from mutations are applied to the system, and load flow analysis is conducted to evaluate their fitness values. New loss values are computed, and the fitness values are stored in the 'Fitness II' array.

Step 7:

Combination and Tournament

Populations from Fitness I and Fitness II are merged into a combined matrix, sorted in ascending order based on the fitness values stored in the 8th column. This column represents the fitness values, while columns 2 to 7 indicate the locations and sizes of the SVCs (3 variables each).

Step 8:

Convergence Check

The maximum and minimum fitness values are determined from the combined matrix. If both values are less than or equal to 0.0001, the function halts the optimization process, indicating convergence. If not, the process resumes at Step 3, incrementing the iteration counter to continue optimization.

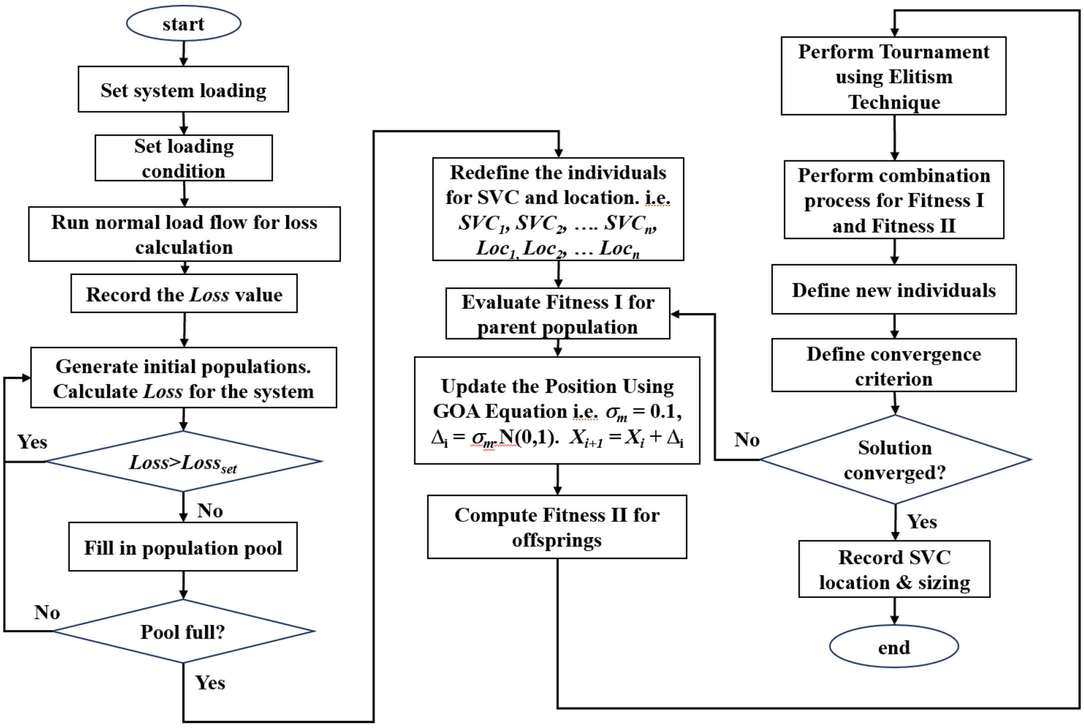

Fig. 4: Flowchart for the Proposed IGEPO in SVC installation optimization scheme

IV. RESULTS AND DISCUSSION

This section presents the results and discussion of the study. The outcomes for loss values when three load buses (Buses 20, 29, and 30) were subjected to reactive load increments are shown under various conditions: pre-generator outage, post-generator outage, pre-SVC installation, and post-SVC installation. Additionally, the initial randomness in the results for SVC locations and sizing are highlighted, illustrating the variability during the initialization phase. Comparative studies results on the optimal solutions are compared among the proposed IGEPO, GOA and EP in the effort to highlight the superiority of IGEPO technique.

A. Test System

Fig. 5 shows the single-line diagram of the IEEE 30-bus RTS, a widely used model in both industry and academic research for studying real power systems [20]. In this study, the IEEE 30-Bus RTS is used to optimize SVC placement and sizing for loss minimization. This system comprises six generator buses, 28 load buses, and 41 transmission lines.

B. Initialization Process

The initialization process assigns random parameters to represent the locations and reactive power settings of SVCs with the goal of minimizing system losses. The focus of this study is on installing three SVC units strategically to reduce overall system losses, as indicated by a reduction in the $loss_{set}$ value. Figs. 6 to 11 display the scatter plots of the initial random configurations of the parameters. These figures visually demonstrate the diversity of configurations explored during the initialization phase, showing the variability in SVC placements and their effects on system losses. Specifically, the figures depict the random configurations during initialization at Q_{d20} = 20 MVAR, Q_{d29} = 10 MVAR and Q_{d30} = 10 MVAR respectively.

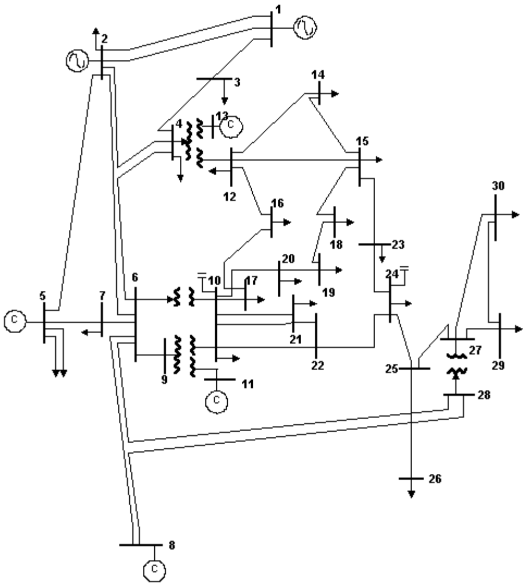

Fig. 5: Single line diagram for IEEE 30-bus RTS

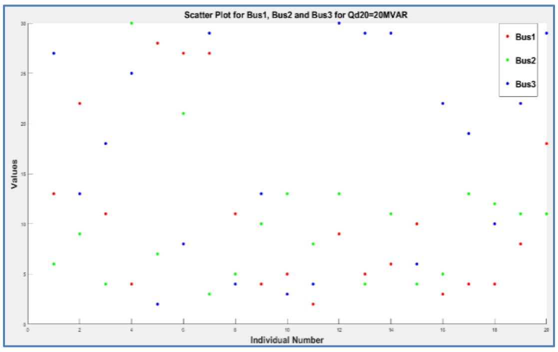

Fig. 6: Random Locations during Initialization at Q_{d20} = 20 MVAR

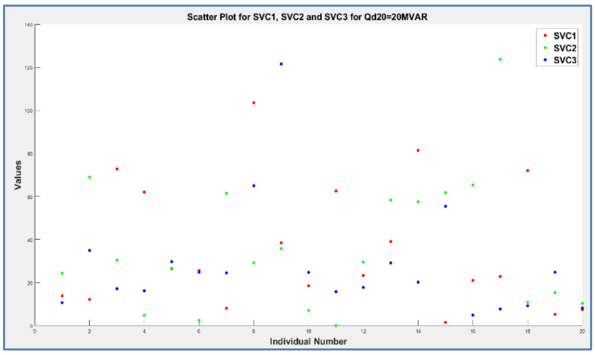

Fig. 7: Random Sizing during Initialization at Q_{d20} = 20 MVAR

Figs 6, 8, and 10 illustrate scatter plots representing the locations for at Q_{d20} = 20 MVAR, Q_{d29} = 10 MVAR and Q_{d30} = 10 MVAR respectively. Each variable is assigned 20 individuals, resulting in a total of 60 individuals for the three random locations. The values range between 1 and 30, indicating the random locations generated during the initialization process in the IEEE 30-Bus RTS. Additionally, the random parameters for reactive power injection must satisfy certain conditions prior to optimization process. For instance, Bus 1, Bus 2, and Bus 3 must be assigned distinct locations during initialization. The scatter plots in Figs. 6, 8, and 10 highlight the random nature of the locations selection. The data points are spread across the bus numbers, suggesting that the initialization process allows exploration across the entire bus system. This distribution of locations increases the diversity of potential solutions in the optimization process, laying the groundwork for effective SVC placement that minimizes system losses.

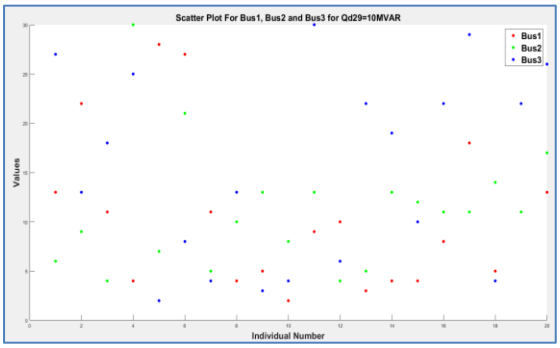

Fig. 8: Scatter Plot for Random Locations during Initialization at Q_{d29} = 10 MVAR

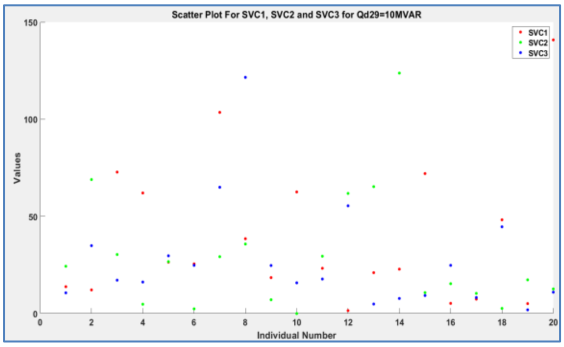

Fig. 9: Scatter Plot for Random Sizing during Initialization at Q_{d29} = 10 MVAR

On the other hand, Figs. 7, 9 and 11 illustrate the scatter plot for the sizing of SVC_1, SVC_2 and SVC_3 for Q_{d20} = 20 MVAR, Q_{d29} = 10 MVAR and $Qd30$ = 10 MVAR respectively. These values are random in nature which ensure that the fitness value of each individual is better than $fitness_{set}$. The random sizes are filtered such that the fitness value of each individual is better than the predefined fitness threshold. This indicates that every configuration in the scatter plots has undergone a selection process to ensure that it contributes positively to loss minimization. The filtering mechanism serves to eliminate unfit individuals from the population, optimizing the sizing of SVC units from the outset. The scatter plots from Figs. 6 to 11 collectively demonstrate the diversity of initial solutions explored during the optimization process. By generating a wide range of random locations and sizes, the initialization phase sets the foundation for robust and effective optimization. The fact that only configurations with better fitness than the set threshold are selected ensures that subsequent optimization steps, such as those using IGEPO, EP, or GOA, start with a well-rounded pool of potential solutions. This improves the convergence rate and the quality of the final SVC placement and sizing solutions, directly contributing to loss minimization and overall system efficiency.

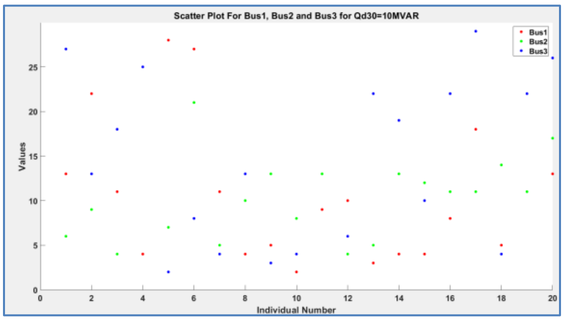

Fig. 10: Scatter Plot for Random Locations during Initialization at Q_{d30} = 10 MVAR

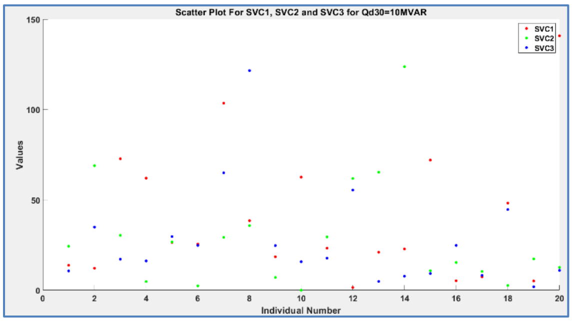

Fig. 11: Scatter Plot for Random Sizing during Initialization at Q_{d30} = 10 MVAR

Tables 1, 2, and 3 present the random values for locations and sizing corresponding to $Qd20$ = 20 MVAR, $Qd29$ = 10 MVAR and $Qd30$ = 10 MVAR, respectively. In these tables, the random locations and sizing of the SVCs intended for installation within the system are initially generated. These values are selected to ensure that the fitness values are lower than the loss values before the SVCs are installed. Each individual in the table must exhibit a loss value lower than the predetermined loss setpoint. If any individual's loss value exceeds this threshold, the individual is discarded, and new random parameters are generated until the conditions are met and the pool is populated. Similar observations apply to Tables 2 and 3, where the random locations and sizing ensure that all loss values are below the set threshold.

The same approach applies to the tabulation of Table 2 and Table 3, where each individual must have a loss value below the respective loss setpoint. This process will continue until the pool of 20 individuals is fully populated. The loss value plays a critical role in the initialization process, ensuring that all conditions are met before the parameters are saved and the individual pool is filled.

Table 1: Results during Initialization at Q_{d20} = 20 MVAR

Individual number	*Bus 1*	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC 3 (MVAR)*	*Losses (MW)*
1	13	6	27	13.8260	24.3298	10.6595	20.9198
2	9	4	5	78.9507	24.0125	77.6561	20.8891
3	9	4	14	70.8570	43.4650	15.7454	20.8759
4	22	9	13	12.1508	68.9644	34.9300	20.7732
5	9	22	13	30.0967	34.8911	65.4144	20.8774
6	11	4	18	72.7929	30.3723	17.1712	20.5544
7	20	12	13	32.2574	49.6937	2.6678	20.5592
8	11	19	6	56.0493	19.9940	39.2794	20.4981
9	4	30	25	62.0369	4.7758	16.2073	20.9166
10	21	19	8	30.0604	24.5905	42.1181	20.5563
11	11	5	4	103.5479	29.2506	65.0043	20.8198
12	4	10	13	38.5129	35.7691	121.5653	20.7905
13	5	13	3	18.4838	7.0878	24.7200	20.8638
14	18	27	10	8.9261	21.2454	71.0483	20.8953
15	2	8	4	62.5811	0.0009	15.7967	20.8724
16	21	19	21	3.9472	40.6722	27.2335	20.8852
17	13	20	12	65.7334	31.2674	61.2674	20.6977
18	2	7	5	78.9602	34.4887	50.8100	21.0025
19	10	4	6	1.5120	61.8258	55.4426	20.9298
20	12	20	12	0.0366	15.3980	43.8577	20.5739

Note: $loss_{set}$ = 21.0056 MW

Table 2: Results during Initialization at Qd29 = 10 MVAR

Individual number	*Bus 1*	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC 3 (MVAR)*	*Losses (MW)*
1	13	6	27	13.826	24.3298	10.6595	20.6346
2	22	9	13	12.1508	68.9644	34.93	20.8619
3	11	4	18	72.7929	30.3723	17.1712	20.7822
4	4	30	25	62.0369	4.7758	16.2073	20.5038
5	28	7	2	26.4459	26.7228	29.7079	20.805
6	27	21	8	25.552	2.4112	24.8121	20.5907
7	27	3	29	8.0628	61.4937	24.5326	20.7664
8	11	5	4	103.5479	29.2506	65.0043	20.7106
9	4	10	13	38.5129	35.7691	121.5653	20.8554
10	5	13	3	18.4838	7.0878	24.72	20.7313
11	2	8	4	62.5811	0.0009	15.7967	20.7363
12	9	13	30	23.2867	29.4977	17.7529	20.6137
13	5	4	29	39.0676	58.3613	29.1629	20.8034
14	6	11	29	81.4159	57.5576	20.2141	20.6683
15	10	4	6	1.512	61.8258	55.4426	20.8317
16	3	5	22	21.0308	65.3124	4.8827	20.7024
17	4	13	19	22.8371	123.7435	7.7486	20.7773
18	4	12	10	72.0421	10.7639	9.2549	20.7946

19	8	11	22	5.2398	15.3611	24.8087	20.8438
20	18	11	29	7.4172	10.3622	8.2225	20.3958

Note: $loss_{set}$ = 20.8632 MW

Table 3: Results during Initialization at $Qd30$ = 10 MVAR

Individual number	*Bus 1*	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC 3 (MVAR)*	*Losses (MW)*
1	13	6	27	13.826	24.3298	10.6595	20.6432
2	22	9	13	12.1508	68.9644	34.93	20.8503
3	11	4	18	72.7929	30.3723	17.1712	20.776
4	4	30	25	62.0369	4.7758	16.2073	20.4383
5	28	7	2	26.4459	26.7228	29.7079	20.8098
6	27	21	8	25.552	2.4112	24.8121	20.6123
7	11	5	4	103.5479	29.2506	65.0043	20.7072
8	4	10	13	38.5129	35.7691	121.5653	20.8445
9	5	13	3	18.4838	7.0878	24.72	20.725
10	2	8	4	62.5811	0.0009	15.7967	20.7298
11	9	13	30	23.2867	29.4977	17.7529	20.3631
12	10	4	6	1.512	61.8258	55.4426	20.8345
13	3	5	22	21.0308	65.3124	4.8827	20.6958
14	4	13	19	22.8371	123.7435	7.7486	20.768
15	4	12	10	72.0421	10.7639	9.2549	20.7899
16	8	11	22	5.2398	15.3611	24.8087	20.8355
17	18	11	29	7.4172	10.3622	8.2225	20.5395
18	5	14	4	48.239	2.6355	44.6505	20.7044
19	28	11	22	5.115	17.3233	1.9047	20.8093
20	13	17	26	140.8439	12.6472	10.9834	20.8245

Note: $loss_{set}$ = 20.8558 MW

C. Optimal Location and Sizing

Table 4 summarizes the results for optimal locations when Q_{d20} is increased from 20 MVAR to 100 MVAR, using EP, GOA, and the proposed IGEPO, before a generator outage occurs in the system. For instance, at Q_{d20} = 100 MVAR, the optimal locations determined by EP are Bus 17, Bus 5, and Bus 20. Under the same reactive power loading, IGEPO identifies Bus 19, Bus 20, and Bus 5 as the optimal locations with the corresponding SVC sizing to be installed into the system of 52.9373 MVAR, 30.1033 MVAR and 108.8579 MVAR before the generator outage.

Table 4: Optimal Location for Loading Variation at Bus 20 before Generator Outage

Technique	Q_{d20} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	20	11	19	6	56.0194	19.9756	39.2452
	40	20	12	13	32.2572	49.6918	2.6555
	60	5	8	20	104.3461	119.1607	104.3813
	80	20	19	24	37.1281	71.4052	58.3412
	100	**17**	**5**	**20**	**62.3643**	**105.1364**	**136.502**
GOA	20	6	19	7	40.7875	15.9058	28.0966
	40	7	19	15	6.5981	43.5271	9.9388
	60	21	19	4	38.1404	75.7811	3.6478
	80	2	7	20	81.2306	93.4049	106.8923
	100	**10**	**20**	**17**	**11.34**	**92.2045**	**30.2478**
IGEPO	20	13	11	20	26.3041	8.6606	25.3855

40	20	13	5	56.9045	17.6416	127.0478
60	13	19	4	47.3036	47.9579	61.9262
80	20	13	3	129.7316	6.3166	119.6156
100	**19**	**20**	**5**	**52.9373**	**30.1033**	**108.8579**

Additionally, Table 4 presents the results for optimal sizing under the same reactive power loading. The optimal sizing determined by EP requires 62.3643 MVAR for SVC1, 105.1364 MVAR for SVC2, and 136.502 MVAR for SVC3 which need to be installed at Buses 17, 5 and 20. In comparison, the GOA technique suggests installing 11.34 MVAR, 92.2045 MVAR, and 30.2478 MVAR into the system for the same reactive power loading which need to be installed at Buses 10, 20 and 17. Detailed results for other reactive power loadings are also included in the table.

Table 5 provides the results for optimal locations and sizing for SVCs when Q_{d20} is varied from 20 MVAR to 100 MVAR during a generator outage at Bus 2. IGEPO identifies Bus 22, Bus 4, and Bus 20 as the optimal locations under this loading condition, with the corresponding SVC installation values of 52.9373 MVAR, 30.1033 MVAR, and 108.8579 MVAR, respectively.

Table 5: Optimal Location for Loading Variation at Bus 20 with Generator Outage at Bus 2

Technique	Q_{d20} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	20	11	19	6	56.0143	19.9741	39.2421
	40	20	19	12	33.679	34.9933	97.8911
	60	2	10	20	81.8807	137.6307	39.9576
	80	20	19	24	37.1271	71.4041	58.3404
	100	**17**	**5**	**20**	**62.3629**	**105.1348**	**136.5008**
GOA	20	11	17	20	0.7339	34.9923	115.2514
	40	16	19	3	80.8806	60.2989	43.778
	60	11	19	8	66.5885	3.0993	39.6884
	80	19	8	3	12.6391	25.6815	79.3858
	100	**20**	**9**	**28**	**111.201**	**105.0463**	**13.572**
IGEPO	20	20	24	13	26.3041	8.6606	25.3855
	40	20	8	11	56.9045	17.6416	127.0478
	60	13	4	20	47.3036	47.9579	61.9262
	80	20	6	12	129.7316	6.3166	119.6156
	100	**22**	**4**	**20**	**52.9373**	**30.1033**	**108.8579**

Meanwhile, GOA identifies Bus 20, Bus 9, and Bus 28 as the optimal locations, while EP identifies Bus 17, Bus 5, and Bus 20. Table 5 also presents the optimal sizing for these conditions. For instance, the optimal sizing determined by EP is 62.3629 MVAR, 105.1348 MVAR, and 136.5008 MVAR, which need to be installed at Bus 17, Bus 5, and Bus 20, as highlighted in the table.

Table 6: Optimal Location for Loading Variation at Bus 20 with Generator Outage at Bus 13

Technique	Q_{d20} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	**20**	**11**	**19**	**6**	**56.0194**	**19.9756**	**39.2452**
	40	20	12	13	32.2572	49.6918	2.6555
	60	5	8	20	104.3461	119.1607	104.3813

	80	20	19	24	37.1281	71.4052	58.3412
	100	17	5	20	62.3643	105.1364	136.502
GOA	**20**	**4**	**20**	**13**	**0.7339**	**34.9923**	**115.2514**
	40	13	6	20	80.8806	60.2989	43.778
	60	19	2	16	66.5885	3.0993	39.6884
	80	6	20	17	12.6391	25.6815	79.3858
	100	20	2	15	111.201	105.0463	13.572
IGEPO	**20**	**11**	**20**	**17**	**114.3041**	**27.1081**	**24.3782**
	40	12	5	20	40.9334	5.4685	45.4552
	60	20	19	14	24.923	28.707	26.5299
	80	20	21	20	71.0908	-11.2741	32.7062
	100	14	20	20	-5.7137	36.0838	77.2096

Similarly, Table 6 presents the results for optimal locations and sizing for SVCs when Q_{d20} is varied from 20 MVAR to 100 MVAR during a generator outage at Bus 13. IGEPO identifies Bus 11, Bus 20, and Bus 17 as the optimal locations at Q_{d20} = 20 MVAR, with corresponding SVC installation values of 114.3041 MVAR, 27.1081 MVAR, and 24.3782 MVAR, respectively. In contrast, GOA identifies Bus 4, Bus 20, and Bus 13 as the optimal locations, while EP identifies Bus 11, Bus 19, and Bus 6. The same approach is applied to the loading conditions at Bus 29 and Bus 30, with the optimal locations and sizing identified as shown in Table 7 and Table 8. For instance, under a loading variation of Q_{d29} = 10 MVAR before a generator outage, EP defines Bus 4, Bus 30, and Bus 25 as the optimal locations, with corresponding optimal sizing of 7.4172 MVAR, 10.3622 MVAR, and 8.2225 MVAR, as shown in Table 7.

Table 7: Optimal Location for Loading Variation at Bus 29 before Generator Outage

Technique	Q_{d29} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	**10**	**4**	**30**	**25**	**7.4172**	**10.3622**	**8.2225**
	15	27	3	29	81.3662	57.53	20.185
	20	27	3	29	8.0267	61.4508	24.4714
	25	4	30	25	62.0369	4.7758	16.2073
	30	5	29	4	75.066	57.5757	41.5239
GOA	10	5	18	29	19.8944	14.8692	6.2817
	15	11	13	29	22.4482	36.1503	78.7168
	20	29	10	3	14.8694	10.5678	13.1169
	25	13	6	29	18.3064	25.3139	50.7389
	30	14	16	29	17.8422	23.98	132.2493
IGEPO	10	20	16	29	76.9856	10.8446	27.6903
	15	29	5	24	15.8619	18.5635	123.5997
	20	4	11	29	22.1947	30.3332	13.5563
	25	29	4	11	139.9012	33.3262	127.2227
	30	29	5	2	13.6046	50.165	121.0529

Table 8: Optimal Location for Loading Variation at Bus 29 with Generator Outage at Bus 2

Technique	Q_{d29} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	10	18	11	29	7.4172	10.3622	8.2225
	15	6	11	29	81.3662	57.53	20.185
	20	27	3	29	8.0267	61.4508	24.4714
	25	4	30	25	62.0369	4.7758	16.2073
	30	5	29	4	75.066	57.5757	41.5239
GOA	10	29	23	4	19.8944	14.8692	6.2817
	15	29	8	4	22.4482	36.1503	78.7168
	20	29	24	12	14.8694	10.5678	13.1169
	25	4	15	29	18.3064	25.3139	50.7389
	30	19	29	13	17.8422	23.98	132.2493
IGEPO	**10**	**9**	**29**	**12**	**76.9856**	**10.8446**	**27.6903**
	15	17	29	13	15.8619	18.5635	123.5997
	20	29	8	16	22.1947	30.3332	13.5563
	25	8	29	9	139.9012	33.3262	127.2227
	30	10	29	2	13.6046	50.165	121.0529

This approach is also applied to the other two techniques to identify optimal locations for the loading condition at Bus 29. For the same reactive power loading solved using IGEPO, the optimal locations after the generator outage at Generator 2 in the system for Q_{d29} = 10 MVAR are identified as Bus 9, Bus 29, and Bus 12, with corresponding optimal sizing of 76.9856 MVAR, 10.8446 MVAR, and 27.6903 MVAR, respectively, as highlighted in the table. Table 9 presents the results for optimal locations and sizing for SVCs when Q_{d29} is varied from 10 MVAR to 30 MVAR during a generator outage at Bus 13. EP identifies Bus 5, Bus 29, and Bus 4 as the optimal locations, while GOA identifies Bus 14, Bus 29, and Bus 13. Detailed results for other reactive power loadings are provided in the same table.

Table 9: Optimal Location for Loading Variation at Bus 29 with Generator Outage at Bus 13

Technique	Q_{d29} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	10	4	30	25	61.9937	4.748	16.728
	15	27	3	29	8.0255	61.4613	24.5001
	20	27	3	29	8.0227	61.4498	24.4842
	25	4	30	25	62.0369	4.7758	16.2073
	30	**5**	**29**	**4**	**75.065**	**57.5754**	**41.5294**
GOA	10	8	27	11	27.6411	14.4026	114.019
	15	7	30	29	8.7111	7.8013	16.4172
	20	29	20	16	38.2434	6.9192	41.6205
	25	29	13	17	47.8899	135.9531	13.5845
	30	**14**	**29**	**13**	**8.7234**	**64.9786**	**95.2836**
IGEPO	10	3	29	7	28.838	14.4239	6.5461
	15	5	7	29	47.2654	7.2383	21.3549
	20	29	2	17	23.1187	105.8557	15.9843
	25	29	13	8	9.7797	31.922	28.3125
	30	5	29	4	71.2597	53.775	37.7159

Table 10: Optimal Location for Loading Variation at Bus 30 before Generator Outage

Technique	Q_{d30} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	**10**	**9**	**13**	**30**	**23.2415**	**29.4662**	**17.726**
	15	9	13	30	23.2867	29.4977	17.7529
	20	4	30	25	62.0369	4.7758	16.2073
	25	4	30	25	62.0369	4.7758	16.2073
	30	29	6	8	47.8434	94.3393	18.9707
GOA	10	2	29	9	22.0278	20.7151	8.5245
	15	15	30	15	18.7707	29.855	23.414
	20	30	20	8	126.6807	23.3393	13.7491
	25	30	21	19	47.1259	45.4744	38.2877
	30	29	27	6	13.2276	15.981	92.1754
IGEPO	**10**	**30**	**8**	**9**	**21.5984**	**27.8094**	**16.0646**
	15	9	13	30	23.5395	29.7505	18.0057
	20	9	13	30	25.9117	36.4536	64.3652
	25	28	3	30	120.3978	77.5099	10.7773
	30	10	29	4	47.4582	15.6005	82.6972

Table 10 presents the results for optimal locations when Q_{d30} is increased from 10 MVAR to 30 MVAR, solved using EP, GOA, and the proposed IGEPO technique, before a generator outage is experienced in the system. For example, at Q_{d30} = 10 MVAR, the optimal locations identified using EP are Bus 9, Bus 13, and Bus 30. In contrast, under the same reactive power loading, IGEPO identifies Bus 30, Bus 8, and Bus 9 as the optimal locations before the generator outage. Detailed results for other reactive power loadings are provided in the same table. Table 11 provides the results for optimal locations and sizing of SVCs when Q_{d30} is varied from 10 MVAR to 30 MVAR during a generator outage at Bus 2. IGEPO identifies Bus 30, Bus 9, and Bus 28 as the optimal locations at Q_{d30} = 30 MVAR. The corresponding SVC installation values are 47.4582 MVAR, 15.6005 MVAR, and 82.6972 MVAR, respectively.

Table 11: Optimal Locations and Sizing for Q_{d30} during Generator Outage at Bus 2

Technique	Q_{d30} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	**10**	**9**	**13**	**30**	**23.2415**	**29.4662**	**17.726**
	15	9	13	30	23.2867	29.4977	17.7529
	20	4	30	25	62.0369	4.7758	16.2073
	25	4	30	25	62.0369	4.7758	16.2073
	30	29	6	8	47.8434	94.3393	18.9707
GOA	10	27	7	22	22.0278	20.7151	8.5245
	15	30	9	12	18.7707	29.855	23.414
	20	11	27	29	126.6807	23.3393	13.7491
	25	3	30	4	47.1259	45.4744	38.2877
	30	30	30	13	13.2276	15.981	92.1754
IGEPO	10	9	13	30	21.5984	27.8094	16.0646
	15	9	13	30	23.5395	29.7505	18.0057
	20	30	5	11	25.9117	36.4536	64.3652
	25	11	2	30	120.3978	77.5099	10.7773
	30	**30**	**9**	**28**	**47.4582**	**15.6005**	**82.6972**

Table 12 outlines the results for optimal locations and sizing for SVCs when Q_{d30} is varied from 10 MVAR to 30 MVAR during a generator outage at Bus 13. At Q_{d30} = 20 MVAR, EP identifies Bus 4, Bus 30, and Bus 25 as the optimal locations, while GOA identifies Bus 30, Bus 20, and Bus 12. The optimal sizing determined by IGEPO are 66.288 MVAR, -4.6007 MVAR, and 19.4587 MVAR, which need to be installed at Bus 28, Bus 3, and Bus 30, as highlighted in the table. Detailed results for other reactive power loadings are also available.

Table 12: Optimal Locations and Sizing for Q_{d30} during Generator Outage at Bus 13

Technique	Q_{d30} *(MVAR)*	Optimal location			Optimal sizing		
		Bus 1	*Bus 2*	*Bus 3*	*SVC1 (MVAR)*	*SVC2 (MVAR)*	*SVC3 (MVAR)*
EP	10	9	13	30	23.2504	29.4537	17.7262
	15	9	13	30	23.2867	29.4977	17.7529
	20	**4**	**30**	**25**	**62.0369**	**4.7758**	**16.2073**
	25	4	30	25	62.0369	4.7758	16.2073
	30	29	6	8	47.8427	94.3393	18.9722
GOA	10	6	4	30	6.9627	22.4195	4.136
	15	5	30	8	89.5627	30.202	5.021
	20	**30**	**20**	**12**	**14.6199**	**16.4513**	**47.7941**
	25	6	27	4	20.593	57.0328	49.7719
	30	29	27	10	14.0338	66.2988	84.3964
IGEPO	10	13	3	27	149.1441	14.6735	17.5478
	15	9	13	30	23.5835	29.7945	18.0498
	20	**28**	**3**	**30**	**66.288**	**-4.6007**	**19.4587**
	25	5	30	26	108.1328	33.6528	-0.8637
	30	17	27	8	17.9425	55.0943	15.5303

Table 13 summarizes the loss values (in MW) for various reactive power loadings, both before and after SVC installation, and under both normal and generator outage conditions, using the three optimization techniques: EP, GOA, and IGEPO. For instance, at Q_{d20} = 20 MVAR, the loss without a generator outage before SVC installation is 18.2559 MW, which reduces to 17.6566 MW after SVC installation optimized by EP. In the event of a generator outage, the loss before SVC installation is 21.0056 MW, which decreases to 20.4981 MW after SVC installation using EP. Similarly, under the same reactive power loading, GOA reduces the loss from 18.2559 MW to 18.0014 MW after SVC installation. For the IGEPO technique with Q_{d20} = 20 MVAR, the loss without a generator outage drops from 18.2559 MW before SVC installation to 17.5563 MW after SVC installation. During a generator outage, IGEPO reduces the loss from 21.0056 MW to 20.3919 MW after SVC installation. The results indicate that IGEPO consistently demonstrates substantial loss reduction after SVC installation across all loading conditions, underscoring its effectiveness in minimizing losses. Additionally, the result shows that the proposed IGEPO method achieves the lowest loss values for all loading variations at Bus 20, Bus 29, and Bus 30, demonstrating that IGEPO outperforms both GOA and traditional EP, regardless of the loading conditions.

Table 13: Losses Value with and without Generator Outage at Bus 20 before and after SVC Installation

Technique		Loss without Generator outage		Loss with Generator outage	
	Q_{d20} *(MVAR)*	*Before*	*After*	*Before*	*After*

		(MW)	*(MW)*	*(MW)*	*(MW)*
EP	**20**	**18.2559**	**17.6566**	**21.0056**	**20.4981**
	40	19.7678	17.8953	22.7643	21.3836
	60	22.7897	19.3242	25.8874	22.1345
	80	28.962	20.4412	31.7932	23.3497
	100	42.6276	19.4661	46.2123	22.3974
GOA	**20**	**18.2559**	**18.0014**	**21.0056**	**20.939**
	40	19.7678	19.2832	22.7643	21.7151
	60	22.7897	22.7529	25.8874	24.5546
	80	28.962	22.7252	31.7932	28.9067
	100	42.6276	17.8337	46.2123	22.4353
IGEPO	**20**	**18.2559**	**17.5563**	**21.0056**	**20.2893**
	40	19.7678	17.6726	22.7643	20.461
	60	22.7897	18.6306	25.8874	20.4302
	80	28.962	18.3941	31.7932	22.0156
	100	42.6276	19.115	46.2123	20.8532

IV. CONCLUSION

This paper presents a novel optimization technique, Integrated Grasshopper Evolutionary Programming Optimization (IGEPO), developed to improve the installation of static var compensators (SVCs) for efficient loss minimization in power systems, especially during generator outages. IGEPO integrates the strengths of two powerful algorithms: the Grasshopper Optimization Algorithm (GOA), which excels at exploring a wide search space, and Evolutionary Programming (EP), which focuses on refining solutions. This hybrid approach provides a comprehensive search mechanism, reducing the risk of getting stuck in local optima, a common problem in conventional optimization methods. By blending these two approaches, IGEPO ensures more balanced and efficient optimization. The primary objective of IGEPO is to determine the optimal placement and sizing of SVCs, which are crucial for controlling reactive power and reducing loss in power system. Finding the best locations and sizes for SVCs is challenging, especially in power systems experiencing generator outages that disrupt normal operations. IGEPO addresses this challenge by offering optimal solutions that minimize power system losses under varying loading conditions. A standout feature of IGEPO is its adaptability to the complexities of power systems with generator outages, which can cause increased system losses. IGEPO has shown its capability to adapt to these dynamic conditions, consistently finding the most effective SVC configurations, regardless of changing system demands. Tested on the IEEE Reliability Test System (RTS), IGEPO consistently outperformed traditional EP and GOA techniques, achieving the lowest power loss values across all loading scenarios. Beyond SVC installation, IGEPO's potential applications extend to optimizing power flow, enhancing voltage stability, and integrating renewable energy sources into the grid. Its adaptability makes it well-suited for modern power systems, which face increasingly complex network structures and the need for more efficient energy management. IGEPO could also be expanded to optimize energy storage systems, distributed generation units, and other critical components, ensuring that power systems remain efficient, reliable, and resilient as they evolve.

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