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Embedded Computational Intelligence Based Approach in Synergistic Optimization for Integrated Compensation Scheme in Power System Transmission Planning

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***Abstract:* -** This paper presents Embedded Computational Intelligence-Based Approach in Synergistic Optimization for Integrated Compensation Scheme in Power System Transmission Planning. In this study, newly embedded computational intelligence-based optimization technique abbreviated as (ECI) is proposed which integrates the standalone evolutionary programming (EP) technique and Jaya optimization mutation operator. The proposed integrated technique is termed Integrated Jaya-Evolutionary Programming (IJEP) technique. The proposed IJEP was implemented in integrated compensation scheme which combines the optimal reactive power dispatch (ORPD) and distributed generation (DG) in one embedded compensation strategy; performed on a reliability test model. Implementation of IJEP in the integrated ORPD-DG strategy is synergistic application. The primary objective is to minimize total power system losses through the synergistic application of ORPD and DG as compensation schemes. The efficacy of the proposed IJEP technique was validated on IEEE 26-Bus Reliability Test System (RTS), demonstrating its superior performance in optimizing power flow and minimizing losses compared to conventional methods. Comparative analyses were conducted using three approaches: the basic load flow study, standalone EP, and the newly proposed IJEP technique. The results consistently indicate that the IJEP approach outperforms the standalone EP, providing the most convincing results in terms of total loss minimization. The integration of the Jaya algorithm with evolutionary programming leverages the strengths of both methods, ensuring robust convergence and high-quality solutions. This study underscores the potential of the IJEP technique to enhance the efficiency and survivability of power systems by effectively integrating ORPD and DG strategy. The promising results from the IEEE 26-Bus RTS test case suggest that the IJEP technique is a viable and superior solution for power system optimization, offering significant improvements in loss reduction over traditional approach. These findings contribute to the broader goal of optimizing electrical power systems and highlight the practical benefits of integrating advanced optimization techniques in modern power system management.

Keywords: Transmission, compensation, ORPD-DG, conventional etc.

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INTRODUCTION

Power systems are becoming increasingly complex with the integration of renewable energy sources, the proliferation of distributed generation (DG), and the growing demand for electricity. Efficient management of these systems is essential to ensure reliability, stability, and cost-effectiveness. One critical aspect of power system management is the optimization of reactive power dispatch (RPD) and the integration of distributed generation, which play pivotal roles in minimizing power losses and enhancing system performance [1][2][3][4]. Reactive power management is vital for maintaining voltage stability and ensuring the reliable operation of power systems [5][6]. On the other hand, the integration of distributed generation offers several advantages, including improved voltage regulation, reduced line losses, and enhanced system resilience [7][8]. However, the simultaneous optimization of RPD and DG presents a complex optimization problem due to the nonlinear and nonconvex nature of power system equations [9]. To address these challenges, researchers have extensively investigated various optimization techniques for power system management. Evolutionary algorithms, such as genetic algorithms, particle swarm optimization, and evolutionary programming, have emerged as powerful tools for solving complex optimization problems in power systems [10][11][12][13]. These algorithms offer advantages such as robustness, flexibility, and the ability to handle nonlinear optimization problems with multiple objectives [14][15]. Moreover, hybridization of evolutionary algorithms has gained considerable attention in recent years. By combining the strengths of different algorithms, hybrid optimization techniques aim to achieve superior performance in terms of convergence speed and solution quality [16]. Rigorous review of several optimization techniques in addressing optimal placement of renewable distributed generation as reported in [17-19].

In this paper, we propose a novel approach for the synergistic optimization for the optimization of integrated ORPD-DG using the IJEP technique. The main objective is to minimize total power system losses while satisfying operational constraints. Implementation on IEEE 26-Bus Reliability Test System (RTS) to evaluate the effectiveness of the proposed method revealed its superiority over EP. The findings of this study are expected to provide valuable insights for power system operators and planners seeking to enhance the efficiency and survivability of power systems. This will benefit the electricity utility in a bigger spectrum once implemented on a practical system.

PROBLEM FORMULATION

Optimal Reactive Power Dispatch (ORPD) is a problem within Optimal Power Flow (OPF) which controls the reactive power flow of power system. In general, the main goal of ORPD is to minimize active power loss while meeting various operational constraints of the power system. The general formula for loss minimization can be expressed as:

$$f(x, u) \tag{1}$$

Limit to,

$$g(x, u) = 0$$

$$h(x, u) \leq 0$$

The dependent variables, x can be stated as:

$$x^T = [\, V_{L1} \ldots . V_{LN}, Q_{G1 \ldots} Q_{GN,} T_1 \ldots T_N] \tag{2}$$

The control parameters, u can be stated as follow:

$$u^T = [\, V_{G1} \ldots . V_{GN}, Q_{C1 \ldots} Q_{CN,} S_1 \ldots S_N] \tag{3}$$

Therefore, ORPD formula for loss minimization is expressed as: [16], [17]:

$$\min f_1(x_1, u_1) = P_{LOSS} \tag{4}$$

$$\sum_{k=0}^{NTL} g_k \ (V_i^2 + \ V_j^2 - 2V_iV_j \cos \delta ij) \tag{5}$$

DISTRIBUTED GENERATION

Table 1 tabulates the specification of types of distributed generation and limitations. Optimal allocation of distributed power units is important to minimize power loss while meeting the grid's active and reactive power requirements [18], [19]. Type 1 delivers only real power such as photovoltaic and microturbines and is injected into the main grid by converters or inverters. Type 2 DG can supply both real and reactive power. In addition, Type 3 DG injects only reactive power and operates at zero power factor. Lastly, Type 4 can supply active power while consuming reactive power. Distributed Generation (DG) can be divided into four main groups in terms of their ability to supply real and reactive power [18]. Types of DG can be further classified in Table 1. As far this study is concerned, DG Type 1 is the scope of limitation where the installation of DG embedded with ORPD will be in the form of real power injection only.

Table 1: Types of Distributed Generation and Limitations

Type of DG	Type of Generation	Power Limitation of DG
Type 1	Generate real power	Up to 5kW
Type 2	Generate reactive power	5MW to 50MW
Type 3	Generate real power Consume reactive power	50MW to 300MW
Type 4	Generate real power Generate reactive power	5kW to 5MW

In this paper, Type 1 DG is implemented to install distributed generation by the means of photovoltaic to minimize power loss in the power system. To find the optimal DG size, which supplies real power, can be express by the following equation:

$$P_{DGi} = P_{Di} - \frac{1}{A_{ii}} \sum_{\substack{j=1 \\ j \neq i}}^{n} \left(A_{ij} P_j - B_{ij} Q_j \right) \tag{6}$$

Optimization Technique

This section explains the mechanics of traditional Evolutionary Programming (EP), the traditional Jaya Optimization Algorithm (JOA) and the proposed Integrated Jaya-Evolutionary Programming (IJEP).

Evolutionary Programming

Evolutionary Programming (EP) was first introduced by Lawrence J. Fogel to simulate evolutionary processes and perform exploration of solution space based on the concept of Darwinian evolution [19]. The process of EP comprises of initialization, statistics, mutation and selection.

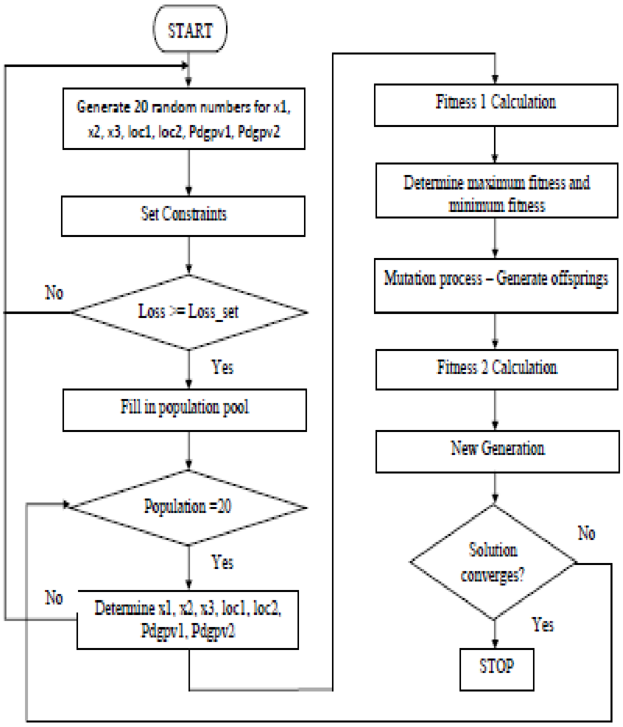

Figure 1**:** Flowchart of Evolutionary Programming (EP).

Figure 1 depicts the flowchart of EP method to illustrate the process of EP. In this case, 20 random individuals are generated for generators *x1*, *x2*, *x3* and DG location sizing i.e. location 1, location 2, sizing 1 and sizing 2. Constraint was set, in this case, Loss ≤ Loss_set. If the constraint is satisfied, then the individuals are filled in the population pool to form a population of 20 individuals.

The fitness of each individual is determined during Fitness 1 calculation process. This is to determine the maximum and minimum fitness of the individual. Next process is the breeding of offspring by the means of mutation. In this case, Gaussian Mutation Technique is applied. Like Fitness 1 calculation process, the purpose of Fitness 2 calculation is to determine the fitness of individuals utilizing the offsprings. Subsequent process called the combination is conducted which placing both the Fitness 1 and Fitness populations in an array, by means of cascading them together. New individuals will be transcribed for the next evolution in accordance with the top fitness values. Conventionally, for loss minimization as the objective function, the individuals with top half low fitness will be transcribed. This called the survivors of the fittest. A new generation is formed by determining the maximum and minimum fitness of the individual. The program will stop if the solution converges, which means the difference between maximum and minimum fitness is less than 0.0001.

Proposed Integrated Jaya-Evolutionary Programming

In this study, we proposed a hybrid technique called the Integrated Jaya-Evolutionary Programming (IJEP) by embedding Jaya optimization algorithm (JOA) into EP. The combination of the two optimization techniques is by modifying the mutation process in EP. In the proposed technique, JOA equation is implemented to the mutation process of EP to formulate the hybrid technique. The proposed IJEP technique help to achieve optimal allocation for DG sizing and minimize loss. In our approach to ORPD and DG sizing for loss minimization scheme, the process of proposed method is tested on IEEE 26-bus system. The process of IJEP is presented in step-by-step algorithm as follow:

Step 1: Call the system data and run the normal load flow to find the initial loss in the power system.

Step 2: Initialization process to generate a population of 20 random individuals with the range from 2 to 26 to represent the random locations for DG, 2 variables for DG sizing in real values form and 3 sizing for random values in ORPD in real values representing the reactive power dispatch.

Step 3: Constraint is set, $Loss \leq Loss_{set}$. If constraint is fulfilled, then the individuals fill in the population pool to form a population of 20 individuals.
Step 4: Perform Fitness 1 calculation to determine the fitness of each individual.
Step 5: Perform IJEP mutation process based on the modified equation using Jaya equation (7).
Step 6: The fitness of new generated individual is calculated by the process of Fitness Mutation.
Step 7: Compute Fitness II using the generated offsprings.
Step 8: Combination and tournament process. The combination process integrates Fitness I and Fitness II in cascode form. Tournament identifies the survivors of the fittest in accordance to the top fitness values subject to the designated objective function.
Step 9: Convergence test. A desired stopping criterion is set that controls the required accuracy. Conventionally, If the difference between maximum and minimum fitness is less than 0.0001 as the typical value, then optimal output solution is generated.

The process of Integrated Jaya-Evolutionary Programming is further depicted as flowchart in Figure 2.

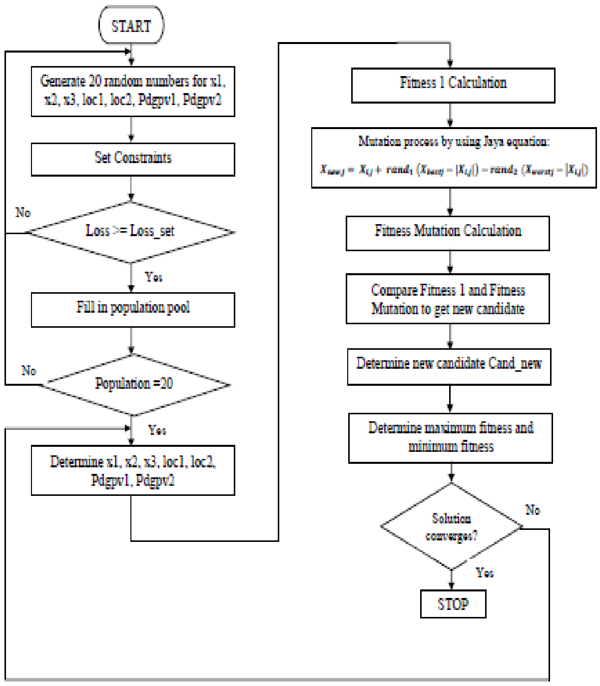

Figure 2: Flowchart for the Proposed Integrated Jaya-Evolutionary Programming (IJEP)

RESULTS AND DISCUSSION

Rigorous study has been conducted to solve the integrated ORPD-DG installation in one combined scheme. All the three techniques are implemented so that the merit of the proposed technique can be highlighted. All the three techniques involving the normal load flow, EP and proposed IJEP have been implemented on IEEE 26-Bus RTS to ORPD problems and DG sizing for loss minimization strategy. The proposed method is implemented using the MATLAB R2020a software and run on AMD Ryzen 3 CPU 2.6 GHz, 8GB RAM. In this study, the ORPD scheme considers only generators at Buses 2, 3 and 4 are considered. The rest of the generators did not involve in the ORPD scheme.

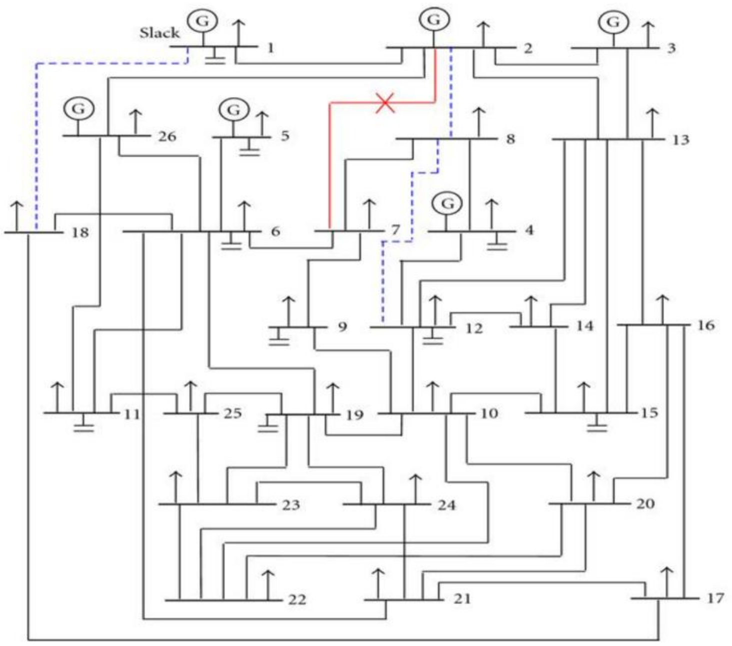

Figure 3: IEEE 26-Bus RTS System as the Test Model

The IEEE 26-Bus RTS consists of 5 generator bus, 20 load buses and one slack bus as depicted in Figure 3. Through this study, the reactive power was load gradually increased to 25MVAR, 50MVAR, 75MVAR, 100MVAR and 125MVAR involving Buses 14 and 16 for the optimization process data. Initially, normal load flow of the system was conducted to obtain the initial loss of the system without the integrated ORPD-DG installation as the compensation scheme, optimized using EP and IJEP.

A: Load Variation at Bus 14

During initialization process, all the individuals for each control variable are very random in nature; but these individuals lay down between the minimum and maximum bound of each control variable. Figure 4 illustrates the scatter plot during initialization process when Bus 14 was subjected to reactive power loadin of 50 MVAR. The scatter plot represents the locations and sizing DGs and sizing of ORPD on the chosen generators. Apparently, 7 variables are identified i.e. *x1, x2, x3, loc1, loc2, loc3*, P_{dgpv1} and P_{dgpv2}. *x1, x2* and *x3* represent the sizing of ORPD in MVAR in terms of the amount of reactive power in MVAR to be dispatched by generators at Bus 2, 3 and 4. On the other hand, *loc1* and *loc2* are the locations for the 2 DG locations with the corresponding size of P_{dgpv1} and P_{dgpv2}. This is DG of Type-1, where only real power is injected to the system as the second component of the compensation scheme. During this initialization process, all the results are random in nature as the initial population. But these values already satisfied the inequality constraints where the losses value should be less than the loss value during the pre-optimization process where EP and IJEP were not implemented yet in the system. Once the solution converges, all the variables will lead to only one common solution. Thus, we will have one value for *x1*, one value for *x2*, one value for *x3*. Initially, the values for *x1*, *x2* and *x3* are random during initialization. Optimal solution will only give one comon value for each control variable, *x1, x2* and *x3*. Similar phenomenon will be experienced for other control variables.

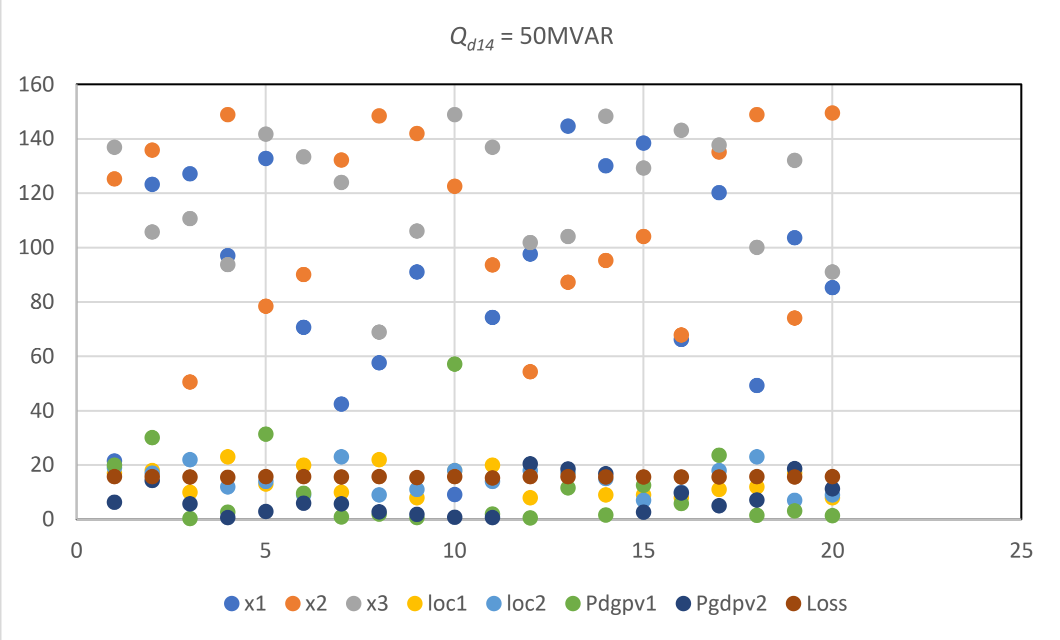

Figure 4: Initialization data at Q_{d14} = 50 MVAR

Table 2: Optimal Locations and Sizing for load variation at Bus 14 using IJEP

Q_{d14} (MVAR)	Gen 1 (x1) (MW)	Gen 2 (x2) (MW)	Gen 3 (x3) (MW)	*Loc 1*	*Loc 2*	DG1 (MW)	DG2 (MW)
25	97.83	21.38	138.87	22	22	0.53	0.74
50	109.76	114.34	140.47	17	22	2.06	0.68
75	135.74	138.42	148.07	21	8	4.88	4.44
100	**68.93**	**118.88**	**143.54**	**20**	**6**	**1.60**	**3.92**
125	78.47	141.08	86.18	21	12	1.20	1.75

The results tabulated in Table 2 show the optimal locations and sizing using the IJEP method with the reactive load varied from 25 MVAR to 125 MVAR at Bus 14. When the reactive load is 100 MVAR at Bus 14, the optimal locations for Location 1 and Location 2 are Bus 20 and Bus 6 with DG sizing of 1.60 MW and 3.92 MW, respectively. This implies that 1.60 MW should be installed at Bus 20, while 3.92 MW should be installed at Bus 6. On the other hand, the amount of reactive power to be dispatched by generator at Bus 2 is 68.93 MVAR, while generator at Bus 3 requires 118.88 MVAR and generator at Bus 4 requires 143.54 MVAR as highighted in the table. Apparently, the variation of Q_{d14} will result in different values of *Loc 1*, *Loc 2*, *x1*, *x2*, *x3*, P_{dgpv1} and P_{dgpv2}. These results will be beneficial to power system operators and planners. The results for other reactive power loading at Bus 14, can be referred to the same table.

B: Load Variation at Bus 16

Load variation at Bus 16 was also conducted as the second test bus in this study. When reactive power load variation was subjected to Bus 16, the same phenomenon may be experienced. Similar presentation of results is given in terms of the scatter plot during initialization process, followed by the results for the optimal locations and sizing for P_{dgpv}. The optimal sizing for ORPD at generators at Buses 2, 3 and 4 are also provided. During initialization process, considering reactive load connected to Bus 16, randomness in terms of locations i.e. *Loc 1*, *Loc 2* and sizing P_{dgpv1} and P_{dgpv2} for the DGPV and sizing for ORPD at generators at Buses 2, 3 and 4 can be seen as presented in Figure 5. The x-axis varies from 1 to 20 which indicates that we have 20 individuals for each control variable. For the initial locations denoted as *Loc 1* and *Loc 2*, the values are laid down between 1 and 26. For the locations, the values should be integer to represent load buses since we used IEEE 26-Bus RTS as the test specimen. This indicates the load buses responsible for the installation of DGPV 1 and DGPV 2, quoted in MW. These values are real numbers which represent the DGPV sizing. The values for *x1*, *x2* and *x3* are also real numbers as these values are assigned for reactive power to be dispatched by generators at Buses 2, 3 and 4.

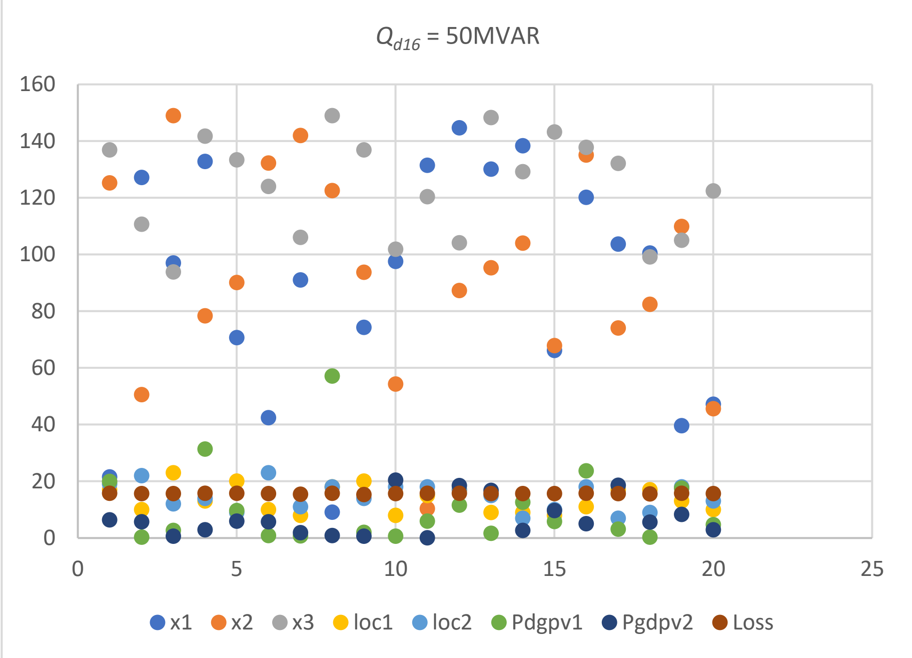

Figure 5: Initialization data at Q_{d16} = 50 MVAR.

In Figure 5, the scatter plot present the results during initialization; where the values are all random values. The values will be identical for each control variable once the solution has converged. When the solution converges, solved by the proposed IJEP we will see optimal locations and sizing for DGPV to be installed into the system, followed by the amount of reactive power to be dispatched by generators at Buses 2, 3 and 4 in the system.

Table 3: Optimal Locations and Sizing for load variation at Bus 16 using IJEP

Q_{d16} (MVAR)	Gen 1 (MW)	Gen 2 (MW)	Gen 3 (MW)	*Loc 1*	*Loc 2*	DG1 (MW)	DG2 (MW)
25	93.28	62.25	127.42	7	22	0.35	4.12
50	124.24	97.24	136.76	6	11	0.30	13.91
75	80.62	115.11	133.41	6	17	1.63	4.65
100	74.26	93.66	136.90	20	14	1.97	0.62
125	**97.03**	**148.93**	**93.77**	**23**	**12**	**2.68**	**0.62**

Table 3 tabulates the results for the optimal solution, solved using IJEP at the increasing values of Q_{d16}. Apparently, Q_{d16} was gradually increased from 25 MVAR to 125 MVAR. When the reactive load worth 125 MVAR was subjected to Bus 16 (Q_{d16}), the optimal locations for Location 1 and Location 2 are Bus 23 and Bus 12 with DG sizing of 2.68 MW and 0.62 MW, respectively. This implies that 2.68 MW should be installed to Bus 23, while 0.62 MW should be installed at Bus 12. On the other hand, the amount of reactive power to be dispatched by generator at Bus 2 is 97.03 MVAR, while generator at Bus 3 requires 148.93 MVAR and generator at Bus 4 requires 93.77 MVAR as highighted in the table. Apparently, the variation of Q_{d16} will result in different values of *Loc 1*, *Loc 2*, *x1*, *x2*, *x3*, P_{dgpv1} and P_{dgpv2}. These results will be beneficial to power system operators and planners. The results for other reactive power loading at Bus 16, can be referred to the same table.

C: Comparative Studies

The purpose of comparative studies is to evaluate the performance of the proposed IJEP over EP in terms of achieving the lowest real loss once the integrated DGPV installation and ORPD scheme isimplemented in the system. Prior to the implementatoion of ORPD-DG as the integrated compensation strategy, normal load flow was conducted as the benchmarked to calculate $Loss_{set}$. With the implementation of IJEP and EP, the loss value should be lower.

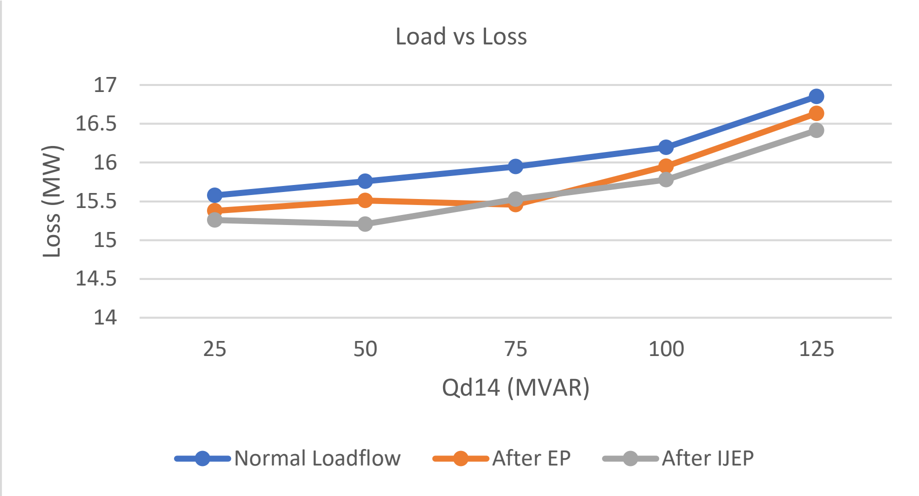

Figure 4: Loss profile with respect to load value variation at Bus 14.

Figure 4 illustrates the plot of loss profile with respect to reactive load variation at Bus 14.using all the optimization techniques in comparison to the normal load flow as the benchmarked for the loss value. IJEP managed to achieve lower loss profiles as compared to the loss profile from the normal load flow. This observation revealed that both optimization techniques have managed to achieve lower loss profile. Comparing between EP and IJEP, obviously IJEP exhibits lower loss profile over EP. This implies that IJEP is better than EP in terms of achieveing lower loss values.

Similar investigation was also conducted when reactive load variation was subjected to Bus 16, as illustrated in Figure 5. Similar phenomenon can be observed where both IJEP and EP show lower loss profiles as compared to the loss profile resulted from the normal load flow. Comparing between the loss profiles given by EP and IJEP, the loss profile by IJEP is lower than the one produced by EP. This again indicates that IJEP is superior to EP in terms of achieving the lower loss values at most of the loading condition values (on the x-axis). In terms of the numerical coparison, we can refer to Table 4 and Table 5. Table 4 tabulates the results for pre-opt and post-opt using both EP and IJEP. Pre-opt represents the pre-optimization value of loss, while post-opt represents post-optimization where ORPD and DGPV scheme isperformed to the system.

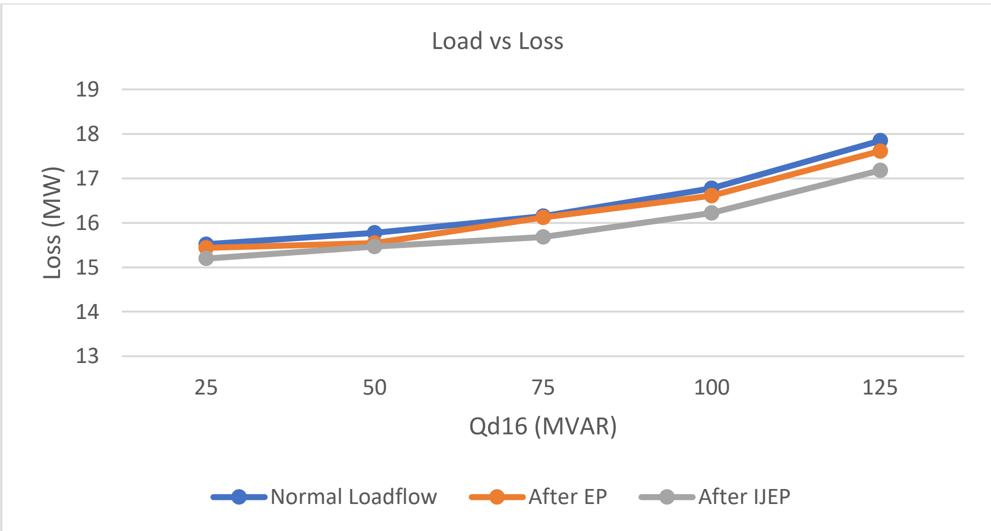

Figure 5. Loss profile with respect to load value variation at Bus 16.

From Table 4, at Q_{d14} = 100 MVAR, EP managed to reduce the total power loss from 16.19 MW to 15.95 MW, while IJEP reduced it to 15.78 MW. This is acceptably a signifcant performance for IJEP since the impact of loss reduction can lead to monetary saving to the consumer or utility. How big is the sizing is required to achieve this scenario, we can refer to previous table. For the case of reactive power load variation at Bus 16, the performance of results can be referred to Table 5. Apparently, IJEP performed well as compared to EP at all the reactive power loading. For instance, at Q_{d16} = 100 MVAR, the loss value was reduced from 16.77 MW to 16.61 , optimized using EP; while IJEP managed to achieve lower loss value worth 16.22 MW. This again demonstrates the superiority of IEP over EP.

Table 4: Results of Loss Minimization using EP and IJEP for load variation at Bus 14.

Q_{d14} (MVAR)	Pre-Opt	Post-Opt	
		EP	IJEP
25	15.58	15.38	15.26
50	15.76	15.51	15.20
75	15.95	15.46	15.53
100	16.19	15.95	15.78
125	16.85	16.63	16.41

Table 5: Results of Loss Minimization using EP and IJEP for load variation at Bus 16.

Q_{d16} (MVAR)	Pre-Opt	Post-Opt	
		EP	IJEP
25	15.52	15.44	15.19
50	15.77	15.54	15.46
75	16.15	16.12	15.68
100	16.77	16.61	16.22
125	17.85	17.61	17.18

CONCLUSION

This has presented embedded computational intelligence-based approach in synergistic optimization for integrated compensation scheme in power system transmission planning. In this study, a new optimization technique which embeds computational intelligence-based approach as a synergistic optimization approach. The new proposed technique is termed the Integrated Jaya-Evolutionary Programming (IJEP) method for optimal reactive power dispatch (ORPD) and distributed generation (DG) installation as an integrated compensation strategy (ORPD-DG); aiming to minimize power system losses. By combining the Jaya Algorithm with Evolutionary Programming, we developed a robust hybrid approach to tackle ORPD and DG installation effectively. Implemented on the IEEE 26-Bus RTS, our technique demonstrated exceptional performance in loss minimization. Simulation results revealed that while both the basic EP and IJEP methods effectively reduced system losses, IJEP significantly outperformed the basic EP. In summary, this study highlights the superior capability of IJEP in enhancing power system efficiency through loss minimization.

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REFERENCES

[1] L. Zhang, S. Li, Y. Wang, "A Review of Optimization Techniques for Reactive Power Dispatch in Power Systems," Electric Power Systems Research, vol. 176, p. 106020, 2020.

[2] M. A. Abido, "Optimal Distributed Generation Placement and Sizing in Distribution Systems: A Comprehensive Review," Renewable and Sustainable Energy Reviews, vol. 107, pp. 579-593, 2019.

[3] S. Ghosh, S. Duttagupta, A. Chowdhury, "Application of Evolutionary Algorithms in Power System Optimization: A Review," Swarm and Evolutionary Computation, vol. 53, p. 100660, 2020.

[4] S. Chakrabarti, A. Sengupta, "Optimal Allocation and Sizing of Distributed Generation: A Review," IEEE Transactions on Sustainable Energy, vol. 10, no. 3, pp. 1389-1400, 2019.

[5] X. Wang, C. Singh, R. Yadav, "Evolutionary Algorithms for Reactive Power Optimization in Power Systems: A Review," Applied Soft Computing, vol. 96, p. 106633, 2020.

[6] T. Yao, Y. Li, J. Xu, "Evolutionary Algorithms for Power System Optimization: Recent Developments and Future Directions," Energy Conversion and Management, vol. 203, p. 112199, 2020.

[7] H. Chen, J. Liu, Y. Wu, "Hybrid Evolutionary Algorithms for Multi-Objective Power System Optimization: A Review," IEEE Access, vol. 8, pp. 131858-131876, 2020.

[8] G. Deb, S. Das, "Hybridization of Evolutionary Algorithms for Power System Optimization: A Review," Expert Systems with Applications, vol. 142, p. 113106, 2020.
[9] S. Das, S. Chakraborty, K. Deb, "Nature-Inspired Algorithms for Power System Optimization: A Review," Electric Power Systems Research, vol. 189, p. 106695, 2020.
[10] K. Prasad, S. Gupta, R. Singh, "Jaya Algorithm and Its Applications in Power System Optimization: A Review," International Journal of Electrical Power & Energy Systems, vol. 128, p. 106413, 2021.
[11] S. Gupta, A. Kumar, R. Sharma, "Integrated Evolutionary Algorithms for Power System Optimization: A Review," Energies, vol. 14, no. 4, p. 1008, 2021.
[12] P. Kundur, N. Balu, "Power System Stability: A Review of Recent Developments," IEEE Transactions on Power Systems, vol. 36, no. 5, pp. 3045-3063, 2021.
[13] M. Jiang, Q. Lin, Y. Wang, "Optimal Power Flow in Power Systems: A Review of Modern Techniques," Electric Power Systems Research, vol. 192, p. 106968, 2021.
[14] N. Ahmed, R. Ali, A. Akhtar, "Review of Optimization Techniques for Power System Operation and Control," IET Generation, Transmission & Distribution, vol. 15, no. 14, pp. 2271-2282, 2021.
[15] L. Wang, X. Liu, X. Zhang, "Evolutionary Algorithms for Power System Economic Dispatch: A Comprehensive Review," IEEE Transactions on Industrial Informatics, vol. 17, no. 7, pp. 4968-4982, 2021.
[16] Patel, S. Patel, S. Singh, "Optimal Placement of Renewable Distributed Generation: A Review," Renewable Energy, vol. 171, pp. 777-788, 2021.
[17] R. Singh, A. Gupta, S. Choudhury, "Recent Advances in Reactive Power Dispatch Optimization Techniques," IET Generation, Transmission & Distribution, vol. 16, no. 1, pp. 1-13, 2022.
[18] Lee, H. Kim, S. Park, "Recent Developments in Distributed Generation: A Review," Renewable and Sustainable Energy Reviews, vol. 155, p. 110023, 2022.
[19] Mishra, R. Khadka, P. Ray, "Recent Trends in Evolutionary Algorithms for Power System Optimization: A Review," International Journal of Electrical Power & Energy Systems, vol. 134, p. 106594, 2022.