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Application of the JAYA Algorithm for Optimal Power Flow and RES uncertainty with Distributed Generation on the IEEE 30-Bus System

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ABSTRACT- Because they are intermittent and stochastic, Renewable Energy Sources (RES) like wind and solar add a great deal of uncertainty to power systems when integrated. Particularly in large-scale systems like the 220kV IEEE 30-Bus network, these uncertainties make grid stability maintenance challenging. This paper introduces a framework that uses JAYA optimization to reduce the effects of RES uncertainty on grid performance. Power flow, voltage stability, and reactive power support are optimized in variable RES generation situations using the JAYA algorithm, which is renowned for its robust convergence qualities and its simplicity. To keep the system stable, the suggested method makes real-time adjustments to control parameters such reactive power compensators, tap-changing transformers, and generator outputs. When compared to conventional optimization methods, the JAYA algorithm considerably improves voltage profile, decreases power losses, and increases system dependability in simulations run on the IEEE 30-Bus system with high-penetration renewable energy sources added. In view of the increasing impact of renewable energy sources, this study emphasizes the possibility of intelligent metaheuristic algorithms to facilitate robust and stable grid operation. In terms of identifying high-quality, optimally viable solutions, the numerical results demonstrate that the proposed JAYA Optimization outperforms all prior published-results over a range of objective functions with total generation cost reduced values of 747.16 ₹/h according to the data. In addition, the proposed algorithm's superiority then BSA approach.

Keywords: Optimal power flow, Jaya algorithm, Generation cost, Power losses, Voltage stability enhancement, Distributed generation.

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1. INTRODUCTION

When it comes to running an electric power network, optimal power flow (OPF) solutions are vital [1,2]. In spite of several limitations, this intelligent power flow uses optimization algorithms to govern the power grid in the most efficient way possible [3,4]. The OPF problem has been tackled by a number of classical optimization techniques, such as non-linear systems [5,6], the Newton algorithm [7], quadratic programming [8], and decomposition algorithms [9]. In [10], the deterministic (traditional) optimization techniques that were previously used are reviewed in detail. Problems with these approaches include their sensitivity to initial search sites, their incapacity to handle non-differentiable objective functions, and their tendency to get stuck in local optima (that is insecure convergence qualities). Despite this, there are situations when these methods can find the globally optimal solution. On top of that, a worldwide answer is not guaranteed by these algorithms. Therefore, alternate approaches to the aforementioned problems must be suggested [11-14].

A growing number of researchers are turning to optimization methods inspired by nature to tackle OPF challenges, thanks to the exponential growth of computing power in the last several years. Some stochastic optimization methods for OPF issues [15-17]. Variants of OPF are solved using non-deterministic search (stochastic search) techniques, which are reviewed in [18-21]. Without getting caught up in local optima, these algorithms find global solutions to various nonlinear OPF problems more efficiently. The rapid and concurrent evaluation of numerous points in the solution space allows for this benefit to be realized. They are well-suited for optimization problems on a grand scale because to their simplicity of implementation and universal applicability. These methods handle discrete and integer variables. Despite their benefits, population-based optimization algorithms all require algorithm-specific regulating parameters that, if not calibrated correctly, increase computational effort (*i.e.*, convergence property) or result in a suboptimal solution.

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This work introduces the Jaya method to solve OPF problems to advance the discipline. The Jaya-based OPF solution approach is the most important addition. We also add DG's effect to the OPF problem. The proposed OPF formulation includes extra state variables. The package comprises transformer tap settings, active power generation outputs, generation node voltage magnitudes, reactive power injection into shunt capacitors, and DG power generation. In this study, we maximize voltage stability, real power loss, and generating cost individually. This study also discusses the ideal mesh network location of distributed generation (DG) nodes, taking into account generation cost and loss sensitivity to active and reactive power injection.

Jaya is tested, validated, and demonstrated using the modified IEEE 30-bus. This article continues: The geometric formulation of OPF concerns that accounts for the DG effect is introduced in *section 1*. Related work is briefly described in *section 2*. *Section 3* applies the Jaya algorithm to OPF. *Section 4* analyzes and compares the results to different algorithms. Jaya algorithm implementation results are in *Section 6*. The *figure 1* shows the standard IEEE-30 Bus Test system for case studies.

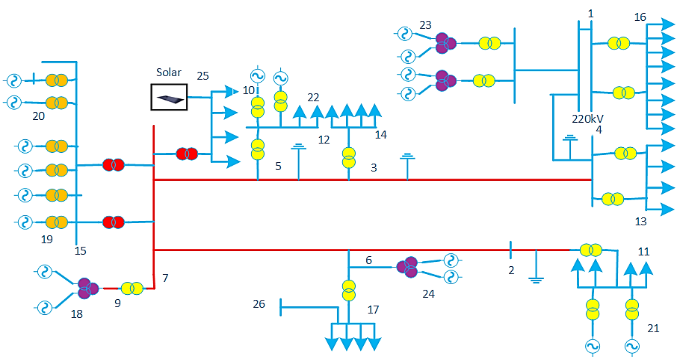

Figure 1. IEEE 30-bus test system

2. RELATED WORK

2.1.Optimal Power Flow Problem Formulation

Generally, the OPF problem can be formulated as follows [1]:

$$min \;\; J(x,u) \tag{1}$$

Subject to:

$$g(x,u)=0 \tag{2}$$

$$h(x,u)\le 0 \tag{3}$$

$$u\in U \tag{4}$$

since the objective function to minimize is denoted by J. x is the dependent variable vector that includes generation reactive power outputs Q_G, load bus voltages V_L, slack bus power P_{G1}, and transmission line loadings S_l. This leads us to the following expression for vector x:

$$\boldsymbol{x}^T=[P_{G1},\;V_{L1}\ldots V_{LNL},Q_{G1}\ldots Q_{GNG},S_{l1}\ldots S_{lNTL}] \tag{5}$$

In this context, NL refers to the number of load buses, NG to the number of generators, and N_{TL} to the number of transmission lines. u is a vector of control variables that contains things like shunt VAR compensations Q_C, transformer tap settings T, voltages V_G (not including the slack bus P_{G1}), and active power outputs P_G (not including the slack bus P_{G1}). That being said, u can be expressed as:

$$u^T=[P_{G2}\ldots P_{GNG},V_{G1}\ldots V_{GNG},T_1\ldots T_{NT},Q_{C1}\ldots Q_{CNC}] \tag{6}$$

where NT is the number of regulating transformers and NC is the number of VAR compensators.

2.2. Equality Constraints

The equality constraints *eq. (2)* are the typical nonlinear power flow equations.

$$P_{Gi}-P_{Di}-V_i\sum_{j=1}^{NB}V_j\left(G_{ij}\cos\delta_{ij}+B_{ij}\sin\delta_{ij}\right)=0 \tag{7}$$

$$Q_{Gi}-Q_{Di}-V_i\sum_{j=1}^{NB}V_j\left(G_{ij}\sin\delta_{ij}-B_{ij}\cos\delta_{ij}\right)=0 \tag{8}$$

$i=1$ to N_B, P_D and Q_D represent load active and reactive powers, δ_{ij} represents voltage angle between busses, and Gij and Bij represent real and imaginary bus admittance matrix terms for the i^{th} row and j^{th} column.

2.3. Inequality Constraints

Limits on the size of the load bus voltage, the generator's reactive power output, and the branch flow are all examples of functional operating restrictions that fall within the category of equality constraints.

$$V_{Li}^{min}{}_{Li}^{max}\text{, where } i=1,\ldots,N_L \tag{9}$$

$$Q_{Gi}^{min}{}_{Gi}^{max}\text{, where } i=1,\ldots,N_G \tag{10}$$

$$S_{li}\le S_{li}^{max}\text{, where } i=1,\ldots,N_{TL} \tag{11}$$

The problem's feasibility region is defined by constraints, which include limits on the following control variables: maximum active power output of the generator, maximum voltage magnitude on the generator bus, maximum tap setting on the transformer, and maximum shunt VAR correction.

$$P_{Gi}^{min}{}_{Gi}^{max}\text{, where i}=1,\ldots,\text{NG} \tag{12}$$

$$V_{Gi}^{min}{}_{Gi}^{max}\text{, where } i=1,\ldots,\text{NG} \tag{13}$$

$$T_i^{min}{}_i^{max}\text{, where } i=1,\ldots,\text{NT} \tag{14}$$

$$Q_{Ci}^{min}{}_{Ci}^{max}\;W\text{here}=1,\ldots,\text{NC} \tag{15}$$

2.4.Objective Function

The objective function can vary. The OPFGUI (optimal Power Flow Graphical user Interface) program includes six cases with different objectives, such as minimizing fuel cost, power loss, voltage deviation, simultaneous minimizing of fuel cost and power loss, and simultaneous minimizing of fuel cost, power loss, and voltage deviation. The Minimization of Fuel Cost (*Fcost*) is the generator cost characteristics *f* is a quadratic function of power output P_G. J minimizes fuel expense for all generators.

$$J(x,u) = Fcost(x,u) = \sum_{i=1}^{NG} f_i(P_{Gi}) = \sum_{i=1}^{NG} (a_i + b_i P_{Gi} + c_i P_{Gi}^2) \quad (16)$$

c_i, b_i, and a_i are the i^{th} generator's cost coefficients. Cost coefficients ai, bi, and ci are expressed in units of ₹/h, ₹/MWh, and ₹/MW²h, respectively, for P_{Gi} in MW. The Minimization of Real Power Loss (*Ploss*) is given by

Here, we can see the form of the objective function *eq. (1)*:

$$J(x,u) = Ploss(x,u) = \sum_{L=1}^{NTL} P_{loss,L} \quad (17)$$

in which N_{TL} is the total number of transmission lines and P_{loss}, L is the actual power loss at line L.

The Minimization of Voltage Deviation (V_D) is Bus voltage is a highly significant and vital indicator of service quality and safety [2]. Here, reducing V_{Ds}, or voltage deviations, on the load bus, is the target:

$$J(x,u) = VD(x,u) = \sum_{i=1}^{NL} |V_i - V_i^{ref}| \quad (18)$$

The i^{th} bus's reference voltage magnitude, V_i^{ref}, is typically set to 1 p.u., where N_L is the number of load buses.

The Minimization of F_{cost} *and* P_{loss} takes a stab at minimizing the system's fuel cost and actual power loss. The suggested method optimizes both of these conflicting goals at the same time. To prevent one goal from becoming too dominant, the objective function strikes a balance between them. One such formulation of the revised objective function is

$$J(x,u) = Fcost(x,u) + w_{Ploss} \cdot Ploss(x,u) \quad (19)$$

where w_{Ploss} is the user-specified weighting factor for the real power loss and P_{loss} is the overall real power loss of the system.

The Minimization of Voltage Deviation may be to minimize the total cost of generation's fuel, but the voltage profile might not be up to snuff. For this reason, we are considering a dual aim function here: reducing fuel costs while simultaneously improving the voltage profile by keeping the load bus voltage as close to 1.0 p.u. as possible. One way to express the objective function is as

$$J(x,u) = Fcost(x,u) + w_V \cdot VD(x,u) \quad (20)$$

where w_V weights voltage deviation.

Minimization of Fcost, Ploss and V_D is given by

$$J(x,u) = Fcost(x,u) + w_{Ploss} \cdot Ploss(x,u) + w_V \cdot VD(x,u) \quad (21)$$

Finally Expanded Objective Function is that control variables are self-constrained. A quadratic penalty term for inequality constraints on the dependent variables P_{G1}, V_L, Q_G, and S_l is introduced to the objective function [2]. Now the enlarged objective function to minimize is

$$J_p = J + \lambda_P \left(P_{G1} - P_{G1}^{lim}\right)^2 + \lambda_V \sum_{i=1}^{NL} \left(V_{Li} - V_{Li}^{lim}\right)^2 + \lambda_Q \sum_{i=1}^{NG} \left(Q_{Gi} - Q_{Gi}^{lim}\right)^2 + \lambda_S \sum_{i=1}^{NTL} \left(S_{li} - S_{li}^{lim}\right)^2 \quad (22)$$

where λ_P, λ_V, λ_Q and λ_S are defined as penalty factors.

Figure 2 represents the flow diagram of maximization Process which include all parameters such as Power flow model, Optimization and Control.

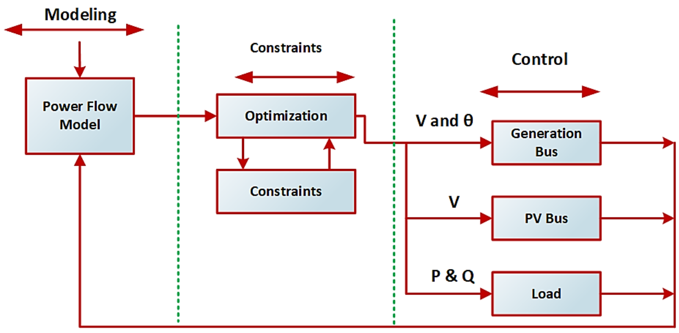

Figure 2. The flow of maximization process

3. RENEWABLE ENERGY PENETRATION

Increasing the amount of renewable energy in the grid is the primary goal of optimisation, as this is demonstrated below.

Three synchronous power plants are linked to this system at buses 1, 2, and 8. At buses 1 and 2, the sixth-order model generators are attached to the automated voltage regulator (AVR) and solar PV system is constructed at an equal distance from each bus. The integration of a solar photovoltaic generator at bus 13 *via* transformer and bus 16 can be modelled by connecting a synchronous generator to bus 11 *via* bus 17 in order to mimic the power generation from RES.

Figure 4 shows the solar model's connection to the IEEE 30-bus system in a simplified form.

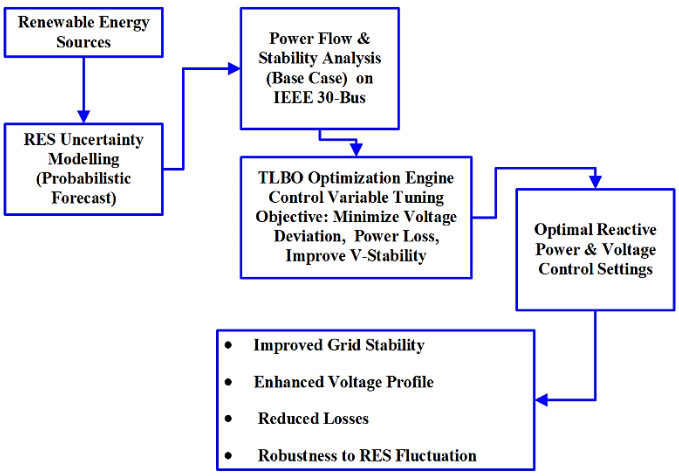

Figure 3. Flow diagram of Proposed Work

International Journal of
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Research Article | Volume 14, Issue 1| Pages 146-153 |e-ISSN: 2347-470X

4. BACKTRACKING SEARCH OPTIMIZATION ALGORITHM (BSA)

Civicioglu created BSA for stochastic searches [20]. Research on simpler, more efficient search algorithms with fewer control parameters impacted BSA's development. BSA's structure can be understood by dividing its functions into initiation, mutation and crossover.

The population *P* is randomly assigned to the control variable's lower and higher boundaries under BSA. BSA determines search direction using Selection-I's historical population oldP. An experiment population BSA mutation creates mutant from *P* and *oldP*. BSA develops a trial population that benefits from earlier generations using the search-direction matrix's historical population. The last trial population is BSA crossover *T*. Mutant indicates the experimental population's initial value after mutation. Two steps comprise crossover. First, an N-by-N binary integer-valued map is created for each group of *T* people using relevant *P* people. Greedy selection updates Ti with superior fitness values than *Pi* to *Pi*. When the fitness value of the best individual in *P* (Pbest) is higher than the global minimum value provided by BSA, the global minimizer is adjusted to reflect Pbest and the global minimum value is set to it.

5. JAYA ALGORITHM

Jaya, a population-based optimization method invented [22], may handle optimization problems with or without constraints. Jaya controls the number of generations (G_n) and population size (m), which indicate the total iterations and candidate solutions, respectively. This differs from population-based heuristic algorithms that use algorithm-specific parameters. This method's optimization technique requires iteratively improving less-than-ideal solutions [22–25]. Basic Jaya method is a straightforward optimization approach because it has one phase. *Figure 3* shows the Jaya technique diagram.

5.1. Jaya Algorithm to OPF Problem

The following sections detail the proposed approach of solving the OPF problem using the Jaya algorithm:

Step 1: Branch, active and reactive power load, and generating unit information must be entered. Set the starting values for producing bus voltage, photovoltaic bus active power production, distributed generators' real power output (if applicable), shunt compensators' reactive power injection, and regulating transformer tap settings.

Step 2: Start status load dispatch. Use *equations (1), (3)*, and *(4)* to calculate the initial condition objective functions: minimizing generating costs, lowering real power losses, and enhancing voltage stability.

Step 3: figure out where to put the distributed generators according to how active power loss and generation cost are affected by injecting reactive and active power, using the formulas that follow:

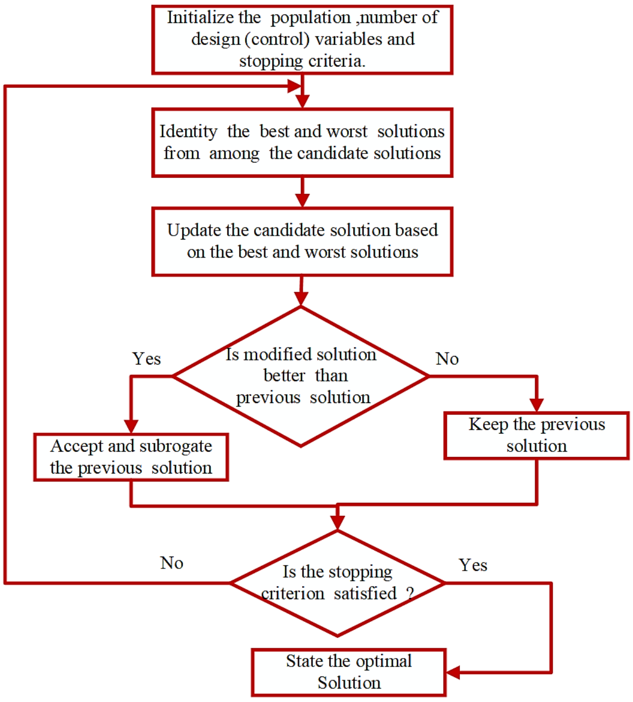

Figure 4. Jaya algorithm Flowchart

6. RESULTS AND DISCUSSION

An evaluation is performed utilizing the IEEE-30 bus system benchmark test case in MATLAB software to assess the efficacy of the developed method. This paper presents and discusses an arithmetic result for the IEEE 30 bus system. The system comprises six generators, including a slack bus, resulting in five real power generation variables, six generator bus voltage magnitudes, and four transformer tap locations as control variables. The system's basic MVA is 100 MVA.

The BSA and JAYA algorithms are effective for addressing the OPF problem in power systems, but with one equivalence and one dissimilarity constraint. The IEEE 30 Indian utility system serves as the test system, and the outcomes of the aforementioned problem are presented in the table below. The JAYA algorithm performs favorably in comparison to BSA. The JAYA algorithm yields superior outcomes relative to alternative algorithms. The technique yields a smaller number of residents compared to other algorithms, and the merging process significantly impacts PSO, GWO, and BSA; yet, JAYA demonstrates superior outcomes.

The cost co-efficient used for the simulation is given in the *table1*.

Table 1. Generator Cost Constants for OPF

S. No	Bus No	$P_{min}(MW$	$P_{max}(MW$	α(₹/hr)	β(₹/MWhr)	γ(₹/MW²hr)
1	1	70	185	0	1.5	0.0043
2	2	30	75	0	0.85	0.0155
3	5	25	55	0	0.9	0.0445
4	8	20	48	0	2.05	0.0043
5	11	20	50	0	1.95	0.025
6	13	18	60	0	1.95	0.013

Research Article | Volume 14, Issue 1| Pages 146-153 |e-ISSN: 2347-470X

Table 2 provides the limits for the dependent and control variables. The limitations correspond to the individual variable's unit values.

Table 2. Limits on Additional Control and Dependent Parameters

Types of Variables	Description	Lower Limit (PU)	Upper Limit (PU)
Control	Transformer Tap Position	0.90	1.10
Control	PV bus voltage	0.95	1.05
Dependent	PQ bus voltage	0.95	1.05

JAYA has five real power generators (PG), six generator bus voltages (V_G), and four transformer tap positions. The solution space population starts with 100 iterations. This population evolves iteratively to find the global optimum response. It is predicted to develop up to 200 times. This approach uses to be determined using the OPF's quadratic cost function and modified for the next generation. Use a 0.9 absorption coefficient and a 1.0 starting attractiveness β_0. The randomization vector (εi) ranges from 0 to 0.5, while the coefficient (α) is 0 to 1. This study uses 0. 2.

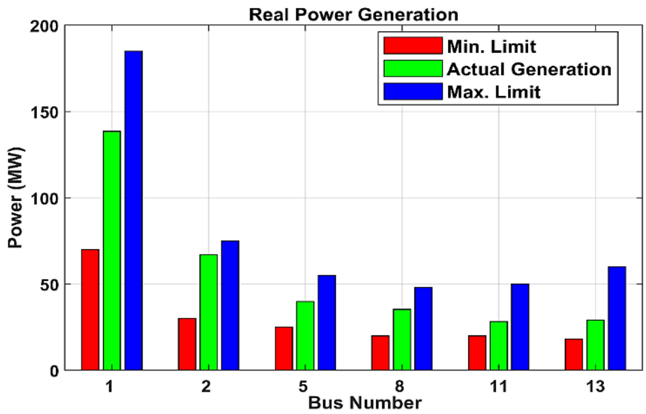

Figure 5. Real Power Generation of all Generators using JAYA

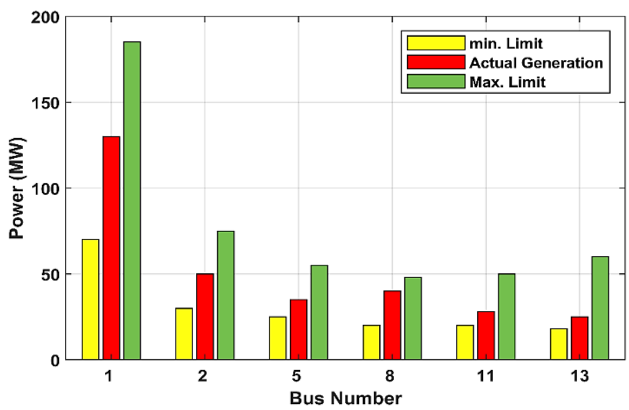

Figure 6. Real Power Generation of all Generators using BSA

Figure 5 depicts Real Power generation of all generators using JAYA. It is evident from *figure 6*. that the generation falls within the permitted limits. In comparison to the other generators, the fifth generator contributes less and the slack generator contributes more to the actual power generation. The minimal limit of generators five and six is almost reached. There is 337.94MW of real power generated overall. Figure 7. displays the dependent variables for load bus voltages and the voltage control variables for generator bus voltages. All voltages are within acceptable bounds. A higher generator bus voltage, limited to a maximum of 1.06 pu, will result in a better overall voltage profile and less loss in the system. Figure 8. depicts Voltage magnitude(pu) variation with BSA and JAYA. The four transformers in the power system under consideration have a minimum tap position limit of 0.90 pu and a maximum limit of 1.10pu. All transformer tap positions are within the bounds, as seen in *figure 9*. *Figure 10* and *figure 11* represent the results of Tap Value(pu) of Transformers and Total Active Power losses (pu) with Base case and Optimal solution.

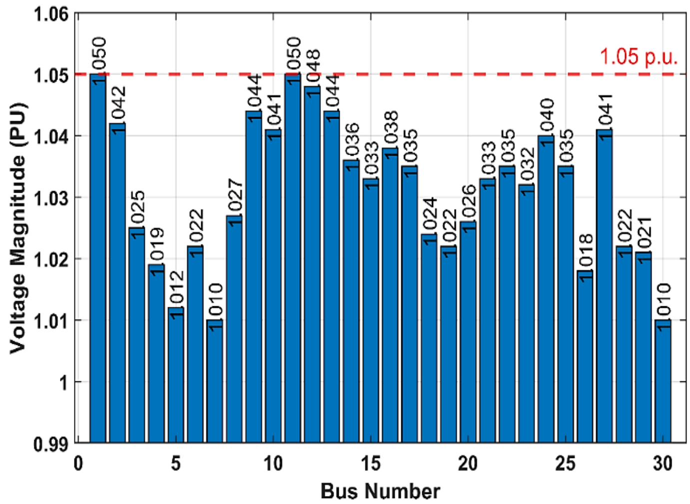

Figure 7. Voltage Profile of 30 buses

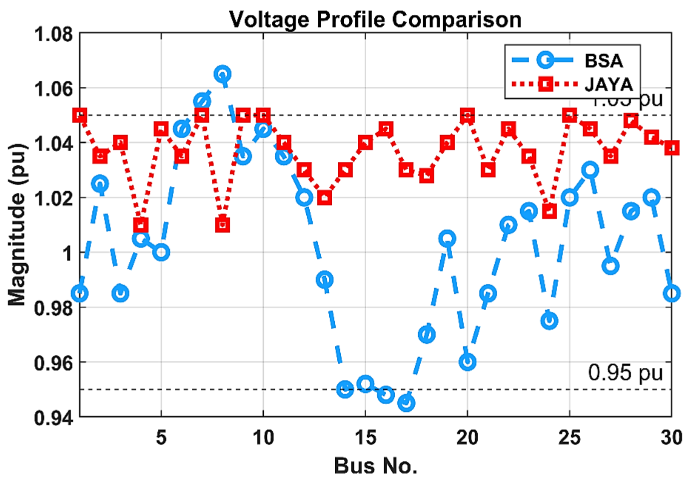

Figure 8. Voltage magnitude(pu) variation with BSA and JAYA

Research Article | Volume 14, Issue 1| Pages 146-153 |e-ISSN: 2347-470X

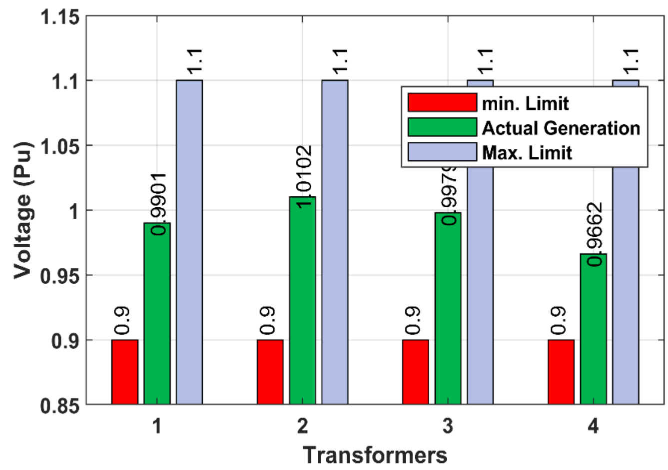

Figure 9. Transformer tap positions

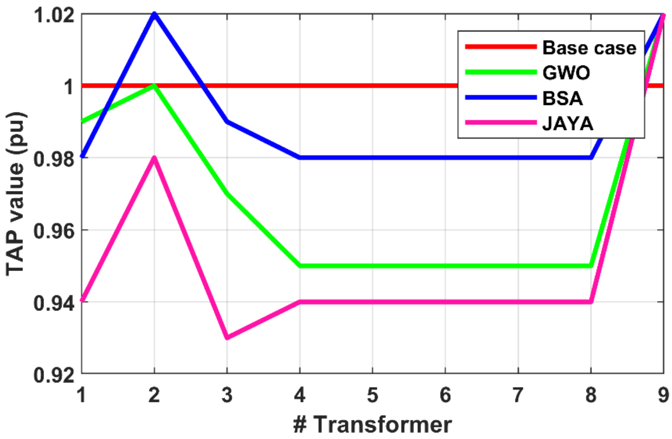

Figure 10. Tap Value(pu) of Transformers

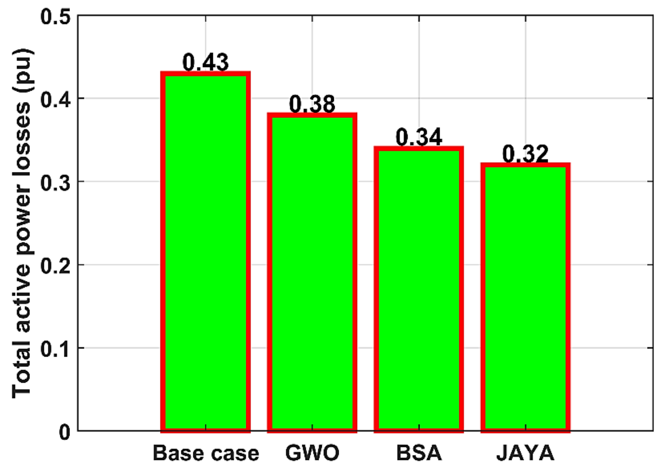

Figure 11. Total Active Power losses (pu) with Base case and Optimal solution

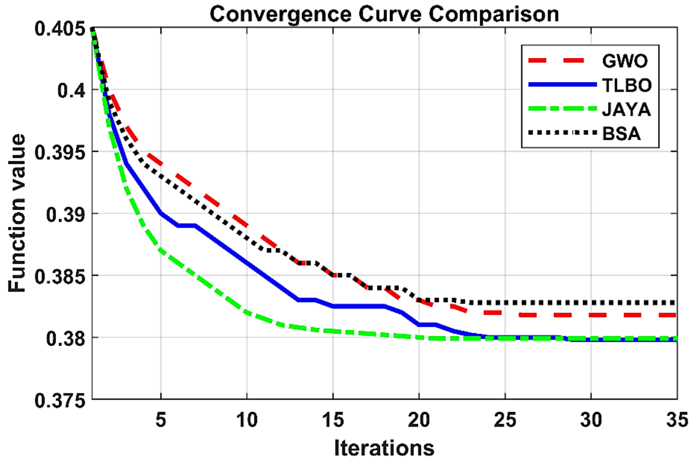

Figure 12.Convergence Curve

It is evident that the JAYA algorithm converges faster and achieves a lower objective function value compared to TLBO, and GWO, demonstrating superior optimization capability. According to *table 3*, the generating pattern's true power loss is 53.549 MW, and its generating cost is 726.96 ₹/hr. *Figure 12* depict the Performance Analysis of all parameters with JAYA and BSA and Comparison Analysis with JAYA and BSA of Voltage and transformer Tap Positions,

Table 3. Comparison Table of OPF Result of Jaya and BSA

Control Variables	JAYA	BSA
P_{g1} (MW)	138.4965	131.023
P_{g2} (MW)	66.9354	49.1802
P_{g3} (MW)	39.8851	35.4221
P_{g4} (MW)	35.3344	39.5964
P_{g5} (MW)	28.2348	28.6546
P_{g6} (MW)	29.0629	24.8181
V_{g1} (pu)	1.0384	1.0440
V_{g2} (pu)	1.0250	1.0231
V_{g3} (pu)	0.9976	1.0064
V_{g4} (pu)	1.0011	1.0052
V_{g5} (pu)	1.0801	1.0537
V_{g6} (pu)	1.0309	1.0012
T_1 (pu)	0.9901	1.0697
T_2 (pu)	1.0102	1.1017
T_3 (pu)	0.9979	0.9678
T_4 (pu)	0.9562	0.9694
Tot. Gen. (MW)	337.9491	308.6944
Demand	284.4	284.4
Loss (MW)	6.549	6.9944
Time (s)	101.238	171.6830
Cost (₹/hr)	**726.96**	**747.16**

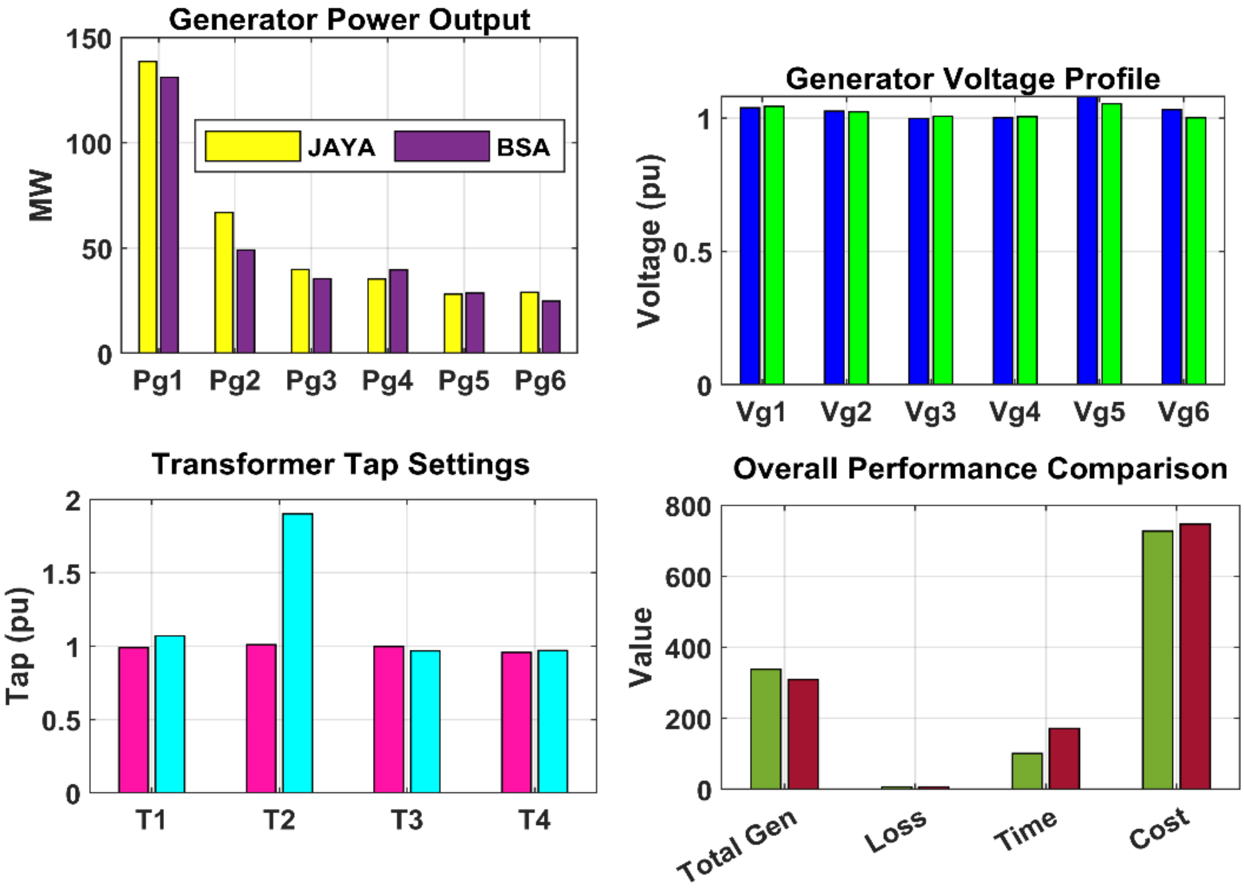

Figure 13. Performance Analysis with JAYA and BSA

7. CONCLUSIONS

The MATLAB-based JAYA algorithm was created to address the OPF issue in the power grid. The innovative and efficient Jaya algorithm was used to resolve OPF issues in the study. This research shows that the JAYA optimization algorithm can successfully handle the problems caused by RES uncertainties in a high-voltage 220kV IEEE 30-Bus system. The suggested method decreases power losses, improves voltage profiles, and increases system stability under different renewable production scenarios by optimizing reactive power devices, voltage levels, and generator outputs. Based on the findings, JAYA is a great tool for optimizing power systems in real time since it is parameter-free and has robust convergence. Contributing to the development of smart and sustainable power systems, this work demonstrates the promise of intelligent optimization methods for facilitating the safe and dependable integration of renewable energy into the grid. The established technique could be applied to enormous power systems and real-time power systems in India as part of future expanded study. The JAYA algorithms have shown to be superior to the BSA algorithms.

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Conflicts of Interest: The authors declare no conflict of interest

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