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Optimal Power Flow and Contingency Analysis with Security Considerations Using Jaya Optimization Algorithm

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Abstract
Optimal power flow (OPF) is one of the fundamental tasks in modern complex electric grid operation. Its objective is to improve the economic and secure coordination on electrical networks based on pre-defined constraints. Combined with a complex operational network and higher demand patterns at times of day / week, it is clear that OPF solutions need to be accurately designed. This accuracy is crucial in order to increase stability across networks over time which in turn will reduce future operational risk. While modern grids increasingly integrate renewables, this work focuses on conventional OPF to establish Jaya's core efficacy for contingency management, providing a foundation for future renewable integration. This paper presents a computationally distinct application of the Jaya optimization algorithm for solving OPF problem taking into account contingency analysis and security assessment. It then proceeds to carry out an optimization using the Jaya algorithm, a cost-effective and parameter-less-dependent technique for system-wide minimization of operational costs with adherence constraints imposed on online security and stability. The suggested approach integrates contingency analysis into risk assessment in order to assess critical vulnerabilities of networks and determine how potential failures propagate. Results of the simulation prove that Jaya algorithm outperforms GA and PSO in optimization. The proposed method not only increases the security level of OPF but it is also human-friendly rather than computationally expensive, making it an appropriate solution for real-time application of OPF schemes.

تدفق الطاقة الأمثل وتحليل الطوارئ مع مراعاة اعتبارات الأمان باستخدام خوارزمية Jaya

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الكلمات المفتاحية
تدفق الطاقة الأمثل، تحليل الطوارئ، تقييم الأمان، خوارزمية تحسين Jaya

الملخص
يُعد التدفق الأمثل للطاقة (OPF) أحد المهام الأساسية في تشغيل شبكات الكهرباء الحديثة المعقدة. ويهدف إلى تحسين التنسيق الاقتصادي والآمن للشبكات الكهربائية بناءً على قيود محددة مسبقًا. ومع وجود شبكة تشغيلية معقدة وأنماط طلب أعلى في أوقات مختلفة من اليوم/الأسبوع، يتضح أن حلول (OPF) بحاجة إلى تصميم دقيق. تُعد هذه الدقة بالغة الأهمية لزيادة الاستقرار عبر الشبكات بمرور الوقت، مما سيقلل من مخاطر التشغيل المستقبلية. في حين تدمج الشبكات الحديثة مصادر الطاقة المتجددة بشكل متزايد، يركز هذا العمل على التدفق الأمثل للطاقة (OPF) التقليدي لتحديد فعالية لوغاريتمات Jaya في إدارة الطوارئ. تقدم هذه الورقة تطبيقًا حاسوبيًا متميزًا لخوارزمية Jaya لحل مشكلة التدفق الأمثل للطاقة (OPF) مع مراعاة تحليل الطوارئ وتقييم الأمان. ثم تنتقل الورقة إلى إجراء تحسين باستخدام خوارزمية Jaya، وهي تقنية فعالة من حيث التكلفة ولا تعتمد على أي معاملات لتقليل تكاليف التشغيل على مستوى النظام مع قيود الالتزام المفروضة على الأمن والاستقرار. يدمج النهج المقترح تحليل الطوارئ في تقييم المخاطر لتقييم نقاط الضعف الحرجة في الشبكات وتحديد كيفية انتشار الأعطال المحتملة. تُثبت نتائج المحاكاة أن خوارزمية Jaya تتفوق على الخوارزميات الجينية (GA) وخوارزميات (PSO). لا تقتصر الطريقة المقترحة على زيادة مستوى أمان OPF فحسب، بل إنها أيضًا سهلة الاستخدام وليست مكلفة حسابيًا، مما يجعلها حلاً مناسبًا للتطبيق الفوري لمخططات OPF.

I. Introduction

The rapid growth of modern power systems due to many factors such as increasing variability of demand has made traditional power flow management methods insufficient. OPF is still an important tool for ensuring system reliability, reducing operating costs and following physical and operating barriers. However, the increasing complexity of the modern grid requires OPF solutions that can consider contingencies - such as line outages or generator failures - which pose a significant risk for system stability. As a result, there is an immediate need for advanced algorithms that can deal with OPF under uncertain conditions, balanced cost, risk and safety factors. The OPF was initially developed by Carpentier in 1962 [1], aimed at optimizing power generation and transmission, reducing costs of the network under normal conditions and following system deficiency. Over the years, various solution techniques have surfaced, including linear programming (LP), quadratic programming (QP), and Newton-based methods [2]. While these traditional approaches have been operative and effective for some applications, they often face challenges when dealing with large-scale power systems, causing computational incapacity and difficulties in terms of convergence. To address these issues, metaheuristic algorithms such as genetic algorithm (GA), particle swarm optimization (PSO), and differential evolution (DE) have become more popular due to their ability to manage complicated, high-dimensional optimization problems [3]. Despite their benefits, these methods may require significant computational resources and especially large -scale systems may have a slow convergence rate. Contingency analysis is an important aspect of power system security, which allows for evaluation of potential failures such as transmission line outage or generator malfunction. The N-1 casual analysis commonly used to assess the flexibility of a system for the failure of a single component [4]. As power systems become more complex, advanced methods such as risk-based contingency analysis have begun to take shape. This approach merges the possibilities of failure with assessment of severity to explore contingencies, providing a deep insight into the system weaknesses [5]. By incorporating contingency analysis in OPF, operators can indicate important components and maintain optimal performance even in challenging situations. This includes both transmission line outages and generator failures, ensuring a comprehensive assessment of system resilience. Traditional methods of contingency analysis, which often depend on complete search techniques, can be computationally intensive for large networks. This challenge has created more efficient algorithms that mix adaptation with contingency analysis [6]. Security of power systems is vital for stable and reliable grid. Security-constrained OPF extended the standard OPF models by adding constraints such as voltage stability, thermal boundaries, and frequency stability in the structure [7]. These limitations need to be completed during both normal and contingency scenarios to ensure the flexibility of the system. A variety of sequential quadratic programming (SQP) have been developed to deal with security-constrained OPF challenges [8]. Recently introduced methods provided a greater intensive evaluation of system weaknesses, allowing better decisions in OPF applications [9]. Unlike traditional OPF, risk-based OPF determines the amount of risks using metrics such as expected energy or load expectation [10]. Many studies have indicated the benefits of risk-based OPF [11]. For example, Bertsimas et al. [12] developed a risk-optimal OPF model, which aims to reduce operating costs while maintaining the level of risk within the acceptable limits. Similarly, Sun et al. [13] presented a potential risk assessment structure for OPF that considered uncertainty in load demand and generation availability. In 2016, Jaya Optimization algorithm was introduced by Rao as an innovative metaheuristic technique in [14]. This algorithm aims to solve complex optimization challenges by moving towards the best solution and away from the worst one. Unlike other metaheuristic algorithms such as GA and PSO, the Jaya algorithm does not require specific parameters, making it easier to implement and achieve lower computational costs [15]. The Jaya algorithm has been effectively utilized in various engineering applications, demonstrating strong performance and fast convergence [16]. In the framework of OPF, research indicates that the Jaya algorithm surpasses conventional optimization methods regarding solution quality and computational efficiency. For instance, Gupta et al. [17] implemented three distinct Jaya algorithms to tackle the OPF problem with distributed generation (DG) units. The algorithm's capacity to avoid local optima without the need for parameter adjustments positions it as a strong contender for addressing complex, multi-objective OPF issues that involve cost, risk, and security. This paper introduces a computationally distinct OPF framework that utilizes the Jaya optimization algorithm for operating contingency analysis and security assessment to evaluate the effects of potential system failures analysis to measure vulnerabilities and enhance system performance. The effectiveness of the Jaya algorithm is compared with established methods like GA and PSO, highlighting its ability to lower operational costs and improve system security. Though renewable energy introduces additional variability, this study deliberately uses conventional generation to isolate Jaya’s performance for contingency OPF. This approach aligns with foundational OPF validation methods [1,2], while our formulation permits direct incorporation of renewables in future work. The structure of the paper is as follows: Section II reviews recent developments in OPF methodologies. Section III outlines the problem formulation and methodology, including a detailed examination of the Jaya optimization algorithm and its application to OPF. Section IV demonstrates simulation results and comparative analyses with other optimization techniques. Finally, conclusions are presented in Section V.

II. Optimal Power Flow (OPF) Problem

The OPF is constantly developed to accommodate the increasing complexity of modern power systems. This development is powered by factors such as demand progress management and increasing requirement for real-time decision making. Recent studies have focused on increasing computational efficiency, increasing system safety and involving uncertainty in power system operations. To deal with these issues, researchers have created stochastic and strong OPF schemes that take into account uncertainty. Stochastic OPF uses the probability distribution of the system generation and uses load demand to reduce the expected operating costs, while the solid OPF is aimed at solutions that are probable under all possible scenarios of uncertainty [19]. For example, a robust OPF model was introduced in [20] to manage uncertainties related to renewable power and storage, which gave the opportunity to ensure system safety by keeping the cost low. Additionally, a multi-phase stochastic was developed in OPF framework [21], which integrates both renewable energy uncertainty and demand reactions, achieving significant cost savings by ensuring system reliability. The need for real time control and adaptation has created the OPF algorithm that can provide solutions within the tight time frame. Traditional methods such as sequential quadratic programming (SQP) and interior point methods (IPMs) often face high computational complexity. Researchers have been looking into alternative methods, such as decomposition techniques, distributed optimization, and machine learning approaches [22]. For instance, one study in [23] introduced a distributed OPF algorithm that breaks the problem down into smaller sub-problems, which can be solved simultaneously across different areas of the power network. This method significantly cuts down on computational time, making it suitable for large-scale, real-time applications. Another exciting practice is the application of machine learning models to estimate OPF solutions. One approach introduced by [24] proposed a deep learning and robust optimization technique to directly predict feasible solutions. By utilizing historical data, it ensures feasibility through a Lagrangian dual method and a Column-and-Constraint-Generation Algorithm (CCGA). This strategy not only reduces computation time but also maintains solution accuracy. However, while this method showed considerable speed enhancements, its accuracy is still reliant on the quality of the training data. Security-Constrained OPF (SCOPF) has become a vital research area, ensuring that power systems remain secure even during contingency situations. SCOPF integrates security constraints, such as voltage and frequency stability, directly into the optimization process to avoid violations during contingencies [25]. Nevertheless, solving SCOPF is inherently more complex than standard OPF due to the greater number of constraints and the necessity to assess multiple contingency scenarios. Recent developments in SCOPF have concentrated on minimizing computational complexity through effective contingency filtering techniques and parallel processing [26]. In [27], a method is introduced to reduce computational demands by employing an OPF index-based approach, which rapidly indicates infectious post-authentic sequences and reinforcement of preventive rescheduling. Metaheuristic algorithms such as genetic algorithms (GA), particle swarm optimization (PSO), and Jaya algorithms have become popular for addressing SCOPF [28]. These algorithms provide flexibility and strength, making them ideal for real-time contingency analysis. Another important tendency in OPF research is the integration of the risk-based structure, which combines economic objectives with an assessment of system security. Risk-based OPF formulations consider both the possibility and impact of contingencies, allowing operators to make informed decisions that balance the operational costs with risk mitigation, as detected in [29]. In [30], a thorough review of Jaya algorithm and its various applications is presented. Reference [31] suggests a risk-based method to analyze OPF with a dynamic line rating consideration. This method takes into account load shedding, line overloading and wind power input when developing cost function. Modern OPF challenges frequently involve multiple conflicting goals, such as cost reduction, emission minimization, and enhancement of system reliability. To tackle these issues, multi-objective optimization techniques have been created. These approaches allow system operators to examine trade-offs among different objectives and pinpoint Pareto-optimal solutions [32]. In [33], the OPF is framed as a non-linear multi-objective constrained optimization problem aimed at minimizing both fuel and wheeling costs simultaneously. The hybrid algorithm successfully navigated the trade-offs between reducing generation costs and enhancing system reliability. Likewise, [34] presented a multi-objective Jaya algorithm that optimizes both cost and environmental impact in power systems.

III. PROBLEM FORMULATION

A. *Objective Function*

The OPF problem is a constrained optimization problem focused on reducing the total generation cost while adhering to the operational and security constraints of the power system. In this section, the Jaya optimization algorithm is introduced as well as its use in addressing the OPF problem, which includes contingency analysis and risk assessment. The OPF problem can be mathematically represented as a nonlinear optimization problem, where the objective is to minimize the overall cost of power generation. This cost function must comply with several constraints, such as power balance, generation limits, and security constraints. Typically, the cost function for the OPF problem is formulated as a quadratic function of the generator's power output:

$$C = \sum_{i=1}^{N_G} \left(a_i P_{G,i}^2 + b_i P_{G,i} + c_i \right) \quad (1)$$

where: C is the total generation cost, N_G is the number of generators, $P_{G,i}$ is the power output of generator i, a_i, b_i, and c_i are the cost coefficients of generator i.

B. Constraints

The OPF problem is subject to the following constraints:

1. Power Balance Constraint: The total generation must equal the total load demand plus system losses:
$$\sum_{i}^{N_G} P_{G,i} = P_D + P_{loss} \tag{2}$$
where: P_D is the total load demand, P_{loss} is the total transmission loss.
2. Generator Limits: The power output of each generator must be within its operational limits:
$$P_{G,i}^{min} \le P_{G,i} \le P_{G,i}^{max} \tag{3}$$
where: $P_{G,i}^{min}$ and $P_{G,i}^{max}$ are the minimum and maximum power outputs of generator i, respectively.
3. Voltage Limits: The bus voltages must remain within specified limits to ensure system stability:
$$V_i^{min} \le V_i \le V_i^{max}, \quad \forall_i \in N_B \tag{4}$$
where: V_i is the voltage at bus i, N_B is the number of buses in the power system, V_i^{min} and V_i^{max} are the minimum and maximum voltage limits at bus i, respectively.
4. Line Flow Limits: The power flow through each transmission line must not exceed its thermal limit. It should be noted that this is only true for short and medium transmission lines, not for long lines. It is important to note that for long transmission lines, the stability limit might be more restrictive than the thermal limit, i.e., for long transmission lines (typically ≥100 km [5]), stability limits (e.g., voltage collapse or transient stability thresholds) often govern power flow, as they are generally more restrictive than thermal limits under steady-state conditions. The line flow constraint considers both thermal and stability limits:
$$P_{ij}^{flow} \le \min(P_{ij}^{max,thermal}, P_{ij}^{max,stability}), \forall (i,j) \in N_L \tag{5}$$
where: P_{ij}^{flow} is the power flow through the transmission line between bus i and bus j, $P_{ij}^{max,thermal}$ is the thermal rating determined by conductor ampacity and $P_{ij}^{max,stability}$ is the stability limit derived from PV curves [5], N_L is the number of transmission lines in the power system.

C. Jaya Optimization Algorithm

Jaya Optimization algorithm is a straight, population-based metaheuristic technique known for its simplicity and absence of specific control parameters. Unlike other metaheuristic algorithms such as GA or PSO, which require careful parameters tuning, Jaya algorithm is naturally parameter-free. This quality makes it easy to apply for different types of optimization problems [35,36]. The Jaya algorithm is based on the idea of continuously improving the current solution by progressing towards the best solution found in the population while distancing itself away from the worst solution. This approach allows for a well-rounded exploration of the search space, helping to effectively make the algorithm converge to the optimal or near-optimal solutions successfully. The stages included in the Jaya algorithm are outlined as follows:

1. Initialization: Initialize the population size N and the number of decision variables (i.e., generator outputs, bus voltages, etc.). Randomly generate an initial population of candidate solutions X_i, where $i = 1,2,\dots,N_i$.
2. Evaluation: Evaluate the objective function $C(X_i)$ for each candidate solution X_i. Identify the best solution X_{best} and the worst solution X_{worst} in the current population.
3. Update the Solution: Update each candidate solution X_i by moving it towards the best solution and away from the worst solution:
$$X_i^{new} = X_i + r_1(X_{best} - |X_i|) - r_2(X_{worst} - |X_i|) \tag{6}$$
where: r_1 and r_2 are random numbers uniformly distributed between 0 and 1, X_{best} and X_{worst} are the best and worst solutions in the current population, respectively.
4. Replacement: If the new solution X_i^{new} improves the objective function value, replace the old solution X_i with X_i^{new}.
5. Termination: Repeat steps 2-4 until a termination criterion is met (e.g., a maximum number of iterations or convergence tolerance).

To further illustrate the steps of the Jaya algorithm applied to the OPF problem, a flowchart is presented in Fig. 1.

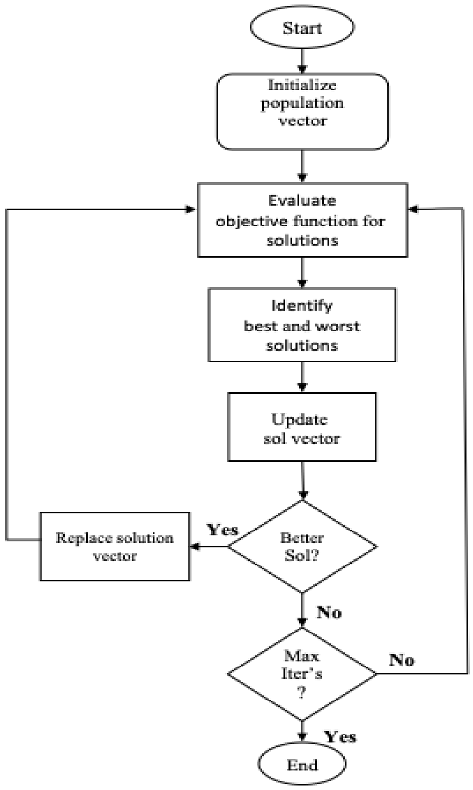

Figure 1. Simulation process.

D. Risk-Based Contingency Analysis

To maintain security of power systems, it is necessary to include risk-based contingency analysis in the OPF problem. This approach focuses on assessing both the possibility and impact of potential contingencies, such as transmission line failures or generator outages, and integrating this risk evaluation into the OPF formulation. By measuring the likelihood of negative events and outcomes, system operators can make better decisions regarding the balance between operational efficiency and risk management, ultimately improving the overall reliability of the system. Contingencies include both line (N-1) and generator (N-1) outages. Generator loss scenarios mimic sudden trips (0–100% output drop in 1 cycle), while line outages simulate protection tripping. The risk associated with a specific casual *kk* can be determined:

$$R_k = P_k \cdot S_k \tag{7}$$

where: R_k is the risk of contingency k, P_k is the probability of occurrence of contingency k, S_k is the severity of contingency k, typically measured in terms of its impact on system stability or cost. The probability of occurrence for each contingency P_k is derived from historical outage statistics in the IEEE Reliability Test System (RTS) [29], which provides standardized failure rates for transmission lines and generators. The severity S_k is quantified based on observed system violations during simulations, calculated as:

$$S_k = \alpha . \sum_{i=1}^{N_B} \left| V_i - V_i^{ref} \right| + \beta . \sum_{(i,j)\in N_L} \max(0, P_{ij}^{flow} - P_{ij}^{max}) \tag{8}$$

where α and β are weighting factors, V_i^{ref} is the nominal voltage at bus *i*, and P_{ij}^{max} is the thermal limit of line *ij*. This approach aligns with risk assessment methods in [29, 31]. The total risk R_{total} is the sum of the risks for all considered contingencies:

$$R_{total} = \sum_{k=1}^{N_C} R_k \tag{9}$$

where N_C is the number of contingencies considered. By incorporating the total risk in the objective function, the OPF problem becomes a risk-constrained optimization problem. The goal is to reduce both the cost and system risk of the total generation, which leads to a more secure and reliable power system operation.

IV. SIMULATION RESULTS

In this section, the results of using the Jaya optimization algorithm to deal with the OPF problem have been discussed. The performance of the Jaya algorithm is evaluated by comparing with two popular metaheuristic algorithms: GA and PSO. Evaluation centers on three main factors: ability to meet the system's constraints under the different contingency scenarios, convergence speed in both normal and contingency conditions, and solution quality. The simulation is performed on the IEEE 30-bus test system, which serves as a standard benchmark for power system analysis. This test system includes 6 generators, 41 transmission lines and 30 buses. In order to account for voltage stability constraints, line flow limits for lines <100 km (e.g., Lines 1-35) were assigned as $P_{ij}^{max} = P_{ij}^{max,thermal}$, and for lines ≥100 km (e.g., Lines 36-41), the limits were calculated as $P_{ij}^{max} = 0.85 \times P_{ij}^{max,thermal}$ [5]. Cost coefficients and operational constraints were derived from standard test case data. Simulation is applied to a MatLab environment, using the following parameters for the Jaya algorithm: 50 population size, maximum 200 iterations, a tolerance of 10^{-6}, and random variables r_1 and r_2 equally distributed between 0 and 1. To ensure a proper comparison, the same population of PSO is assigned. The performance metrics analyzed include the ability to meet the system's constraints under both normal and contingency conditions. Fig. 2 refers to the convergence characteristics of the Jaya algorithm, GA, and PSO, reflecting a decrease in objective function (generation cost) over iteration. The Jaya algorithm exhibits rapid convergence, reaching a near-optimal solution in about 50 iterations. The convergence curve is smooth and stable, with no significant oscillation, indicating stable progress towards the optimal solution. Till the 100th iteration, the algorithm achieves a minimum generation of $8000, which remains in line with later iterations. In contrast, the GA reflects slow convergence and more ups and downs in the objective function during early stages, caused by random crossover and mutation processes. The GA begins to stabilize after about 150 iterations, but the last generation of $8350 is higher than the Jaya algorithm. On the other hand, the PSO algorithm shows more gradual convergence than the GA, although it takes more iterations to reach a satisfactory solution. It reaches a minimum generation cost of $8200 after approximately 120 iterations. While the PSO convergence performs better than GA in terms of behavior and solution quality, it is yet overcome by the rapid convergence and final solution provided by the Jaya algorithm. Fig. 2 clearly shows better convergence speed and solution of the Jaya algorithm than both GA and PSO. The Jaya algorithm's ability to achieve the optimal cost of generation in fewer iterations makes it particularly profitable for real-time power system optimization. In addition, its stable convergence behavior and frequent performance in contingency scenarios exposes its strength and reliability. These findings display the ability of Jaya algorithm as a highly effective tool to address complex OPF problems, providing notable enrichment in both computational efficiency and solution quality over traditional metaheuristic methods. The total generation cost obtained by each algorithm has been summarized in Table I. The results suggest that the Jaya algorithm consistently produces the lowest generation cost, crossing both particle PSO and GA. In particular, the Jaya algorithm reaches a minimum generation cost of $8000, highlighting its better ability to customize the power system operation. The PSO comes forward with the cost of the generation of $8200, while the GA costs $8350. These results emphasize the effectiveness of the Jaya algorithm in reducing operating costs, keeping it in position as a strong contender for the optimal OPF problem.

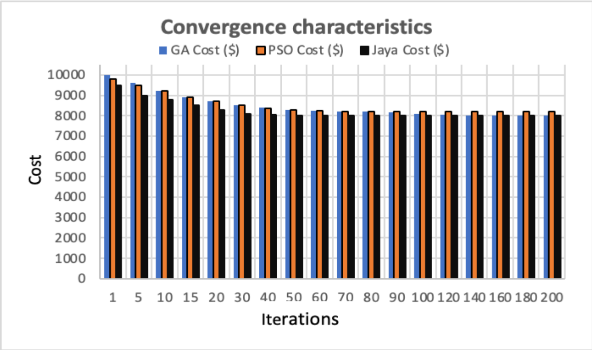

Figure 2. Convergence characteristics of Jaya, GA, and PSO.

To ensure statistical robustness, all simulations were conducted over 30 independent runs with randomized initial conditions. Table I reports the mean and standard deviation (SD) of total generation costs and execution times.

TABLE I. COMPARISON OF TOTAL GENERATION COST AND EXECUTION TIME FOR JAYA, PSO, AND GA

Algorithm	Total Generation Cost ($) (Mean ± SD)	Execution Time (s) (Mean ± SD)
GA	8350 ± 210	4 ± 0.5
PSO	8200 ± 185	3.2 ± 0.4
Jaya	8000 ± 150	2.5 ± 0.3

Error bars in Fig. 2 represent the 95% confidence interval across runs. Statistical analysis of the simulation results demonstrates the Jaya algorithm's superior performance in both solution quality and computational efficiency. As shown in Table I, Jaya achieves the lowest mean generation cost ($8000 ± 150) and fastest execution time (2.5 ± 0.3 s), with significantly smaller standard deviations compared to GA (8350 ± 210, 4.0 ± 0.5 s) and PSO (8200 ± 185, 3.2 ± 0.4 s), highlighting its robust convergence characteristics for large-scale power system optimization. To evaluate algorithm performance under contingency conditions, we conducted an N-1 analysis by removing a critical transmission line. Uunder normal operating conditions, all algorithms maintained bus voltages within acceptable limits (0.95-1.05 pu). However, during the contingency, only the Jaya algorithm successfully maintained system stability, keeping all bus voltages within specifications (0.95-1.05 pu) with minimal deviations (< 0.01 pu). In contrast, GA exhibited voltage violations at multiple buses (1-10), dropping below 0.95 pu, while PSO showed borderline performance with voltages approaching but not violating limits at buses (15-20). These results demonstrate Jaya's exceptional robustness in contingency management, outperforming both GA in stability maintenance and PSO in voltage regulation precision. The algorithm's consistent performance across multiple simulation runs (evidenced by low standard deviations) further confirms its reliability for real-world power system applications where operational stability is critical.

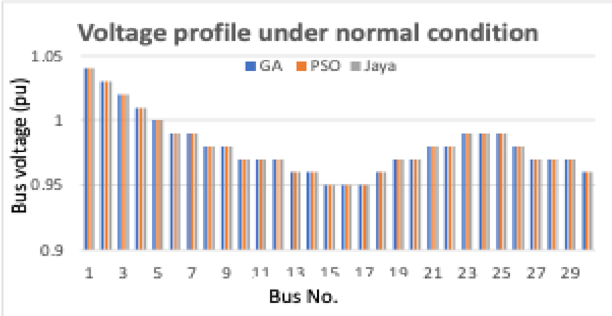

Figure 3. Voltage profile comparison under normal condition for Jaya, GA, and PSO.

Incorporating risk-based contingency analysis into the OPF problem enables a quantitative evaluation of how contingencies affect system security. By assessing both the likelihood and impact of potential contingencies, this method offers a thorough insight into system weaknesses and supports better decision-making. The overall risk for each contingency scenario is calculated using the following formula:

$$R_{total} = \sum_{k=1}^{N_C} P_k \cdot S_k \tag{9}$$

where P_k is the probability of occurrence of contingency kk, and S_k is the severity. In this study, we compare the total risk obtained by each algorithm when optimizing under contingency scenarios. The Jaya algorithm achieves the lowest total risk, as shown in Table II.

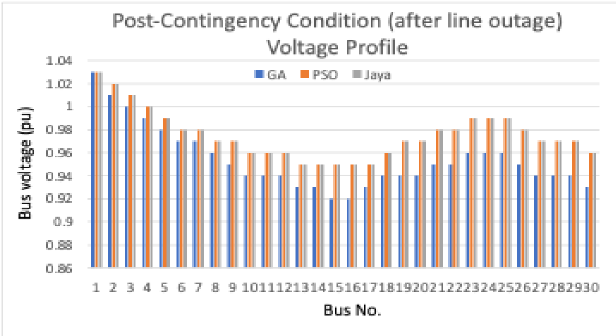

Figure 4. Voltage profile comparison under contingency conditions for Jaya, GA, and PSO.

To evaluate robustness under generator outages, we simulated a sudden loss of Generator 2 (G2). Jaya maintained stable voltages (0.95–1.05 pu at all buses) with a 3.8% cost increase, while GA violated limits (<0.95 pu at Buses 5, 8, 11) and PSO neared violations (0.94 pu at Bus 12). These results confirm Jaya's superiority for critical N-1 generator contingencies as shown in Table II. The simulation results suggest that the Jaya algorithm is both cost-effective and able to reduce the level of risk in operating conditions, making it an excellent option for risk-based OPF applications. Conclusions suggest that the Jaya algorithm crosses both GA and PSO both in terms of quality of solution, convergence speed, and the ability to maintain system constraints during contingency conditions. One of the major benefits of the Jaya algorithm is its simplicity, as it does not require specific control parameters, which greatly enhances its effectiveness in dealing with OPF problems. Furthermore, the inclusion of risk-based contingency analysis allows for more future intensive evaluation of system protection, especially about uncertainties associated with renewable energy integration. The Jaya algorithm is speedy to reach optimal or near-optimal solutions, making it ideal for real-time applications. This is the result of the cost of the low total generation compared to GA and PSO. The algorithm maintains the voltage stability, even in contingency scenarios. By integrating risk-based evaluation, the Jaya algorithm reduces the possibility of failures and increases overall reliability.

TABLE II. COMPARISON OF TOTAL RISK FOR JAYA, PSO, AND GA UNDER CONTINGENCY SCENARIOS

Contingency Scenario	Algorithm	Total Risk ($)	Voltage Violations (Buses)	Cost Increase (%)
Line Outage (L27)	GA	750	3, 7, 9	5.30%
	PSO	600	None	4.10%
	Jaya	500	None	2.10%
Generator Outage (G2)	GA	820	5, 8, 11	6.70%
	PSO	670	12	5.00%
	Jaya	550	None	3.80%

V. CONCLUSIONS

This paper explored the use of the Jaya optimization algorithm to solve the OPF problem, especially focused on contingency analysis to assess system security and strength. The performance of the Jaya algorithm was fully evaluated and compared with two commonly used adaptation methods: GA and PSO. The simulation on the IEEE 30-bus test system has shown that the Jaya algorithm has many important benefits: it gained significantly fast convergence for optimal solutions, effectively reducing the cost of the total generation compared to GA and PSO. The Jaya algorithm continuously reached an optimal cost, while GA and PSO resulted in high cost and convergence requiring more iterations. Additionally, the Jaya algorithm demonstrated strong effectiveness in maintaining voltage stability throughout the system during accidental conditions. After imitating the transmission line outage, Jaya successfully placed all the bus voltage within the acceptable limit (0.95 pu to 1.05 pu). In contrast, GA faced voltage violations in several buses, and the PSO showed less stability than Jaya. From both cost-evidence and stability approach, the algorithm effectively reduces the cost of the generation by ensuring system stability in normal and contingency conditions, making it extremely suitable for real-time power system operation. The findings of this study highlight the effectiveness of the Jaya algorithm in dealing with complex power system adaptation challenges. Its better performance in reducing operational costs, ensuring system stability and managing contingencies presents it as a strong candidate for real - time applications. Future work will extend this framework to hybrid systems with renewable generation (wind/solar), building on the contingency management principles developed here.

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