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# Mitigation Impact of Critical Contingencies in Electric Power Grid using PSO-Based Maximum Constrained Load-Shedding Technique

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## ABSTRACT

This study presents a Particle Swarm Optimization (PSO)-based scheme for optimal targeted load shedding and contingency severity assessment in the electric power grid (EPG). The IEEE 14 EPG was used as a testbed. The study identified critical branches and quantitatively evaluated the operational performance of an EPG under base case, outage without and with targeted load shedding schemes, utilizing convergence characteristics, voltage magnitudes and angles, and branch load flows as diagnostic metrics. The base case demonstrated excellent numerical stability, with convergence achieved in fewer than 5 iterations, and all bus voltages maintained within the IEEE standard range. A critical outage scenario caused severe difficulty, as evidenced by prolonged convergence (exceeding 15 iterations), a drastic voltage at Bus 1 to 0.7214pu, and overloading of Line 2 to 2.0524pu, approximately 275% of its base case loading. These conditions signified an unstable operational state, posing severe risks to system security. Implementation of targeted load shedding significantly improved system conditions: convergence iterations reduced to approximately 6, Bus 1 voltage restored to 0.9682pu, and Line 2 loading decreased to 0.5683pu. Other buses consistently maintained voltages within acceptable margins, and branch flows on non-critical lines remained insignificant across all cases. Voltage angle profiles further corroborate the systemic stress during outage and the stabilization effect post-load shedding. The proposed technique quantitatively demonstrates that selective load shedding is an effective corrective control strategy, not only restoring voltage stability but also alleviating transmission line overloading, thus enhancing the EPG's ability to maintain secure and reliable operation under severe contingency conditions.

**Keywords:** Targeted load shedding technique, PSO algorithm, Severe contingencies, Voltage profile, Load flow.

## 1. INTRODUCTION

The continuous expansion of electrical power grids (EPG), coupled with increasing penetration of intermittent loads and renewable energy sources, has intensified the demand

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for robust and adaptive load shedding strategies. Voltage instability, often triggered by faults, heavy loading, or line outages, remains a major menace to secure EPG operation. Conventional under-voltage and frequency-based load shedding methods **(Imai, 2005; Kisengeu et al., 2021)** often lack coordination and adaptability, potentially leading to unnecessary consumer outages or system collapse. In recent years, according to the study in**,** metaheuristic optimization algorithms **(Kwang and Zita, 2020)**, such as Particle Swarm Optimization (PSO) and its hybrids, have shown significant promise in intelligently allocating load curtailments and preserving system stability. Several contemporary studies have investigated the application of these optimization methods to address voltage stability and load shedding in standard benchmark systems. For instance, **(Ketabi and Fini, 2017)** proposed a PSO-based load shedding strategy that demonstrated faster convergence and effective prioritization of loads. While their work showcased the potential of PSO in such optimization tasks, it was limited by its focus solely on active power, ignoring the role of reactive power in voltage profile management. Additionally, their strategy lacked an explicit cap on total power shed, making it impractical under operational constraints where regulators often mandate thresholds**.** The study in **(Bioki et al., 2012)** advanced the problem by proposing a hybrid PSO-LP (Linear Programming) model, combining the global search power of PSO with the precision of LP. This hybrid method enabled better economic load shedding, considering costs and priorities. However, the algorithm introduced added entanglement due to the need for inter-method coordination, and the reactive power and voltage profile improvement were not directly addressed. Furthermore, integration with standard Newton-Raphson (NR) load flow models was not asserted. More recently, **(Le et al., 2023)** developed an enhanced PSO algorithm that incorporated intelligent parameter tuning and grid resilience evaluation. Their methodology accounted for fault scenarios and network robustness. Although this is a commendable enhancement, the study still fell short of enforcing strict constraints on maximum allowable shedding and reactive power considerations. Moreover, their approach assumed homogeneous load criticality, which overlooks real-world prioritization where essential loads must be preserved more than non-essential ones.

Also, **(Kisengeu et al., 2021)** developed a PSO-based optimal load shedding model for voltage stability enhancement, validated using IEEE-14 bus system. The study focused on minimizing voltage deviation by shedding loads from the most vulnerable buses. However, it did not impose any explicit operational limits on the percentage of load that could be dropped, potentially leading to excessive curtailment under terrible contingencies. Moreover, their model lacked a detailed branch-level contingency severity index (CSI), which is vital for identifying critical transmission elements during fault scenarios. Similarly, **(Tamilselvan, 2020)** proposed a hybrid PSO–Artificial Bee Colony (HPSO-ABC) algorithm to identify weak buses and optimize the amount of load to be shed. While this hybrid strategy improved voltage profiles, the objective function of the study was primarily heuristic and lacked practical system constraints such as maximum allowable load shedding or operational policies. Additionally, no visual performance metrics were provided to assess convergence speed or solution quality, which are key in real-time implementation. The study of **(Zhou et al., 2022)** adopted a neural network (NN)-based load shedding approach trained on historical contingency data for real-time execution. Although effective for real-time grid operation, their approach was highly reliant on the quality and completeness of training data, making it potentially unreliable for previously unseen fault scenarios.

Furthermore, it lacked the capability to assess system severity quantitatively during contingencies or impose strict load shedding bounds.
In another related work, **(Kiran et al., 2016)** proposed a hybrid PSO–Genetic Algorithm (HPSO-GA) approach using fast voltage stability index and apparent line power stability index as indicators. While their focus on multiple stability indices is commendable, their model did not deliver a comprehensive load shedding mechanism nor account for load prioritization or operational feasibility, limiting real-world implementation.
The abovementioned studies collectively affirm the promising relevance of soft-computing techniques for exigency containment, yet also bring to light numerous key research gaps; such as, absence of practical constraints on maximum load shedding percentages in most models; lack of a contingency severity framework to evaluate and prioritize vulnerable lines or buses; limited visualization and analysis of convergence behavior, solution robustness, and optimization traceability; and inadequate integration of real-world operational thresholds, such as maximum tolerable load curtailment levels.
The present study addresses the abovementioned gaps by proposing:

- PSO based load shedding technique that minimizes the global mismatch between available and demanded load while respecting maximum shedding constraints.
- PSO algorithm that finds the best set of line weighted factors that optimize the ability to detect and rank the most critical lines based on voltage stress.
- PSO-based algorithmic rules in investigating behavior of the electric power grid under different critical outages with and without the maximum constrained-based load shedding technique.

These enhancements position the proposed approach not only as a complementary method to existing hybrid techniques but also as a practically validated, decision-aiding tool for grid reliability and operational planning.

## 2. PROBLEM FORMULATION

This study has uncovered considerable crucial research gaps, such as the absence of practical constraints on maximum load shedding percentages in most existing models and the lack of a contingency severity concept in evaluating and prioritizing vulnerable lines or buses while investigating the performance of the EPG under critical branch outages and load shedding using PSO-based load flow analysis. This section of the paper presents formulations of these identified problems of the study.

### 2.1 Problem Formulation for the PSO Algorithm.

The PSO-based algorithmic rule was used for the determination of the metrics used in this work, which are the CSI and realistic targeted load shedding on various buses of the EPG. The algorithm was also employed to investigate the states of the EPG before, during and after critical contingencies with and without targeted load shedding on the testbed. This sub-section of the paper, therefore, presents the core tool for achieving the goal of this work.
PSO algorithm is a manner of solving problems by imitating the behaviour of a group of birds or a school of fish (**Kennedy and Eberhart, 1995; Kwang and Zita, 2020**). The algorithm is made up of a swarm of particles, each symbolizing a likely solution to the optimization problem. These particles move around the solution space, trying to get the fullest solution based on two things **(Verayiah et al., 2014; Kennedy and Eberhart, 1995; Kwang and Zita, 2020)**:

a) Personal fullest location ($pbest$): The rightest solution the particle has found hitherto for the food.
b) Global fullest location ($gbest$): The rightest solution any particle in the swarm has found for the food.

The particles adjust their location by combining their $pbest$ and the $gbest$. As time goes on, the swarm comes together as the best solution. The rate at which particles move around the solution place is governed by **(Kennedy and Eberhart, 1995; Verayiah et al., 2014, Adetona et al., 2022)**

$$v^{(m)}(t+1) = \omega * v^{(m)}(t) + c_1 * rand() * (pbest^{(m)} - x^{(m)}(t)) + c_2 * rand() * (gbest - x^{(m)}(t)) \quad (1)$$

In Eq. (1), $x^{(m)}(t)$ stands for current position of particle $m$, $\omega$ represents inertia weight, $c_1$ $and$ $c_2$ stand for the cognitive and social acquisition rates respectively, $rand()$ is a random number between 0 $and$ 1, $pbest^{(m)}$ denotes the personal rightest position of the particle $m$, and $gbest$ is the global rightest position. The current position of a particle **(Kennedy and Eberhart, 1995; Verayiah et al., 2014; Kwang and Zita, 2020, Adetona et al., 2022)** in the solution place is expressed by

$$x^{(m)}(t+1) = x^{(m)}(t) + v^{(m)}(t+1) \quad (2)$$

In Eq. (2), $v^{(m)}(t+1) =$ latest velocity of particle $m$, and $t$ is the iteration number. Each particle in the swarm represents different parameters of interest in this study to provide solutions to various problems in this study.

### 2.2 Problem Formulation for CSI based on PSO Algorithm.

One of the problems that was solved in this study was ranking the lines of EPG based on the upshot of the voltage stress on the EPG. In this work, the PSO algorithm was used to find the best set of line weighted factors ($x^{(m)}$) **(Slochanal et al., 2005; Sutha and Kamaraj, 2008; Marouani et al., 2011; Adetona et al., 2024)** that optimize the ability to detect and rank most critical lines based on voltage stress **(Gubina and Strmcnik, 1995)**. The objective is therefore to minimize the sum of the magnitudes of the weighted voltage drops, or rank lines by degree of the voltage stress they cause, and it is formulated viz:

$$\min_{x^{(m)}} f(x^{(m)}) = \sum_{k=1}^{N_l} x_k{}^{(m)} \left|V_{from,k} - V_{to.k}\right| \quad (3)$$

In Eq. (3), each particle $x^{(m)}$ is a vector and could be expressed viz., $x^{(m)} = [x_k{}^{(m)}] = [x_1{}^{(m)}, x_2{}^{(m)}, x_3{}^{(m)}, \cdots, x_{N_l}{}^{(m)}]$, where $x_k{}^{(m)}$ are optimization variables, and each of particle $m$ in the swarm denotes a weight for line $k$. Also, in Eq. (3), $N_l$ is total number of lines in the EPG, $V_{from,k}$ and $V_{to.k}$ represent voltage at the sending and receiving ends of line $k$ respectively. Eq. (3) is an objective function, and it is subject to the following constraint:

$$0 \leq x_k{}^{(m)} \leq 1 \qquad \forall k \quad (4)$$

Each of $x_k{}^{(m)}$ are updated based on Eqs. (1) and (2). It is evident from Eqs. (3) and (4) that individual $x_k{}^{(m)}$ in the swarm determines the contribution of the line $k$ to the total severity of the EPG in this work.

### 2.3 Problem Formulation of PSO-based Maximum Constraint-based Load Shedding

The outage of critical line(s) on EPG may eventually lead to total real and reactive power mismatches **(Nazir et al., 2023; Chivunga et al., 2024; Iweh et al., 2024)**. One of the ways of mitigating this problem is by using a load shedding approach **(Seyedi and Sanaye-Pasand, 2007; Xu et al., 2011; Gao et al., 2016; Choi et al., 2017; Ketabi and Hajiakbari, 2017; Kisengeu et al., 2021)**. Though many researchers have contributed to this approach, most of them did not consider the targeted load shedding technique. The objective of the proposed PSO algorithm-based selective load shedding technique is therefore to minimize the global mismatch between available and demanded load while respecting maximum shedding constraints ($\mu$), and it is formulated viz:

$$\min_{x^{(m)}} f(x^{(m)}) = \sum_{i=1}^{N_b} \left| P_{d,i}^{original} - x_i{}^{(m)} \right|, \ \min_{x_i} f(x) = \sum_{i=1}^{N_b} \left| Q_{d,i}^{original} - x_i{}^{(m)} \right| \quad (5)$$

In Eq. (5), each particle $x^{(m)}$ is a vector and could be expressed viz., $x^{(m)} = \left[ x_i{}^{(m)} \right] = \left[ x_1{}^{(m)},\ x_2{}^{(m)},\ \cdots, x_{N_b}{}^{(m)} \right]$; where $x_i{}^{(m)}$ are optimization variables, and each of particles $m$ in the swarm, denotes load adjustment at the bus $i$; therefore, $x^{(m)} = \left[ x_i{}^{(m)} \right] = [P_{d,1}^{shed},\ P_{d,2}^{shed},\ \cdots, P_{d,N_b}^{shed};\ Q_{d,1}^{shed},\ Q_{d,2}^{shed},\ \cdots, Q_{d,N_b}^{shed}]$. Also, in the equation, $P_{d,i}^{original}$ and $Q_{d,i}^{original}$ original real and reactive load demands, respectively. Eq. (5) is an objective function, and it is subject to the following constraint:

Load shedding limits: $\sum_{i \epsilon LS} P_{d,i}^{shed} \leq \mu \times P_d^{total},\ \sum_{i \epsilon LS} Q_{d,i}^{shed} \leq \mu \times Q_d^{total}$ (6)

$$0 \leq P_{d,i}^{shed} \leq P_{d,i}^{original}, 0 \leq Q_{d,i}^{shed} \leq Q_{d,i}^{original} \quad (7)$$

Update load demand after shedding:

$$P_{d,i}^{new} = P_{d,i}^{original} - P_{d,i}^{shed}, Q_{d,i}^{new} = Q_{d,i}^{original} - Q_{d,i}^{shed} \quad (8)$$

Non-negativity of power demand: $P_{d,i}^{new} \geq 0,\ Q_{d,i}^{new} \geq 0$ (9)

In Eq. (6) through Eq. (9), $P_{d,i}^{shed} Q_{d,i}^{shed}, P_d^{total}, and\ Q_d^{total}$ are real and reactive power shed at the bus $i$ and total system real and reactive power, respectively. In this study, $\mu$ in Eq. (6), takes the value of 0.15.

### 2.4 Problem Formulation for the Load Flow Analysis based on PSO Algorithm.

In this study, the NR technique was adopted for solving the nonlinear algebraic load flow equations associated with the load flow analysis before, during and after critical contingencies in the testbed. It was used because of its accuracy and fast convergence rate **(Grainger and Stevenson, 1994; Saadat, 1999; Das, 2006)**. The NR technique requires initial guesses for $V_i$ and iteratively updates them to minimize power mismatches **(Grainger**

**and Stevenson, 1994; Saadat, 1999)**. In this study, instead of relying solely on the NR method's initial guesses, PSO algorithmic rule is used to optimize initial guesses for $|V_i|$ and $\delta_i$ at PQ buses, and $P_{Gi}$ and $Q_{Gi}$ at PV buses to achieve faster and robust convergence of power flow **(Salomon et al., 2011)**. The objective of the load flow using NR technique is therefore to minimize the power mismatch to optimize $|V_i|$ and $\delta_i$ and it is formulated viz:

$$\min_{x^{(m)}} f(x^{(m)}) = \ min \sum_{i=1}^{N_b}[(\Delta P_i)^2 + (\Delta Q_i)^2] \tag{10}$$

In Eq. (10), each particle $x^{(m)}$ is a vector and could be expressed viz., $x^{(m)} = \left[x_i{}^{(m)}\right] = \left[x_1{}^{(m)},\ x_2{}^{(m)},\ x_3{}^{(m)}, \cdots, x_{N_b}{}^{(m)}\right]$; where $x_i{}^{(m)}$ are optimization variables, and each of them represents a possible bus voltage setting at bus $i$, i.e. $x^{(m)} = \left[x_i{}^{(m)}\right] = [|V_i|\angle\, \delta_i] = \left[|V_1|\angle\, \delta_1,\ |V_2|\angle\, \delta_2,\ \cdots, \left|V_{N_b}\right|\angle\, \delta_{N_b}\right]$. Also, in Eq. (10), the active and reactive power mismatches at bus $i$ are expressed as:

$$\Delta P_i = \ P_i^{spec} - P_i^{calc} \tag{11}$$

$$\Delta Q_i = \ Q_i^{spec} - Q_i^{calc} \tag{12}$$

Eq. (10) is an objective function, and it is subject to the following constraint:

Voltage magnitude limits: $\left| V_i^{min}\right| \ \le \ |V_i| \ \le |V_i^{max}|$ (13)

And the active and reactive generation limit for of each unit $i$ are given by

$$P_{spec,i}^{min} \le P_i^{spec} \le \ P_{spec,i}^{max} \qquad \forall\ spec, i\ \in \Omega_{spec,i} \tag{14}$$

$$Q_{spec,i}^{min} \le Q_i^{spec} \le \ Q_{spec,i}^{max} \qquad \forall\ spec, i\ \in \Omega_{spec,i} \tag{15}$$

Apparent power $S$ flow constraints: $\left|S_{flow}\right| \ \le S_{rated}$ (16)

In Eq. (11) through Eq. (16), $P_i^{spec},\ Q_i^{spec}, P_i^{calc}\ and\ Q_i^{calc}$ are the specified real and powers (generation minus load), and calculated real and reactive powers that are obtained from bus voltages, respectively, using (**Das, 2006**):

$$P_i = P_i^{calc} = \ |V_i|^2|Y_{ii}|cos\theta_{ii} + |V_i|\sum_{j=1}^{N_b}|V_j||Y_{ij}|cos(\theta_{ij} - \delta_i + \delta_j) \tag{17}$$

$$Q_i = Q_i^{calc} = -|V_i|^2|Y_{ii}|sin\theta_{ii} - |V_i|\sum_{j=1}^{N_b}|V_j||Y_{ij}|sin(\theta_{ij} - \delta_i + \delta_j) \tag{18}$$

In Eqs. (17) and (18), $|V_i|\angle\delta_i$ and $\left|V_j\right|\angle\delta_j$ are voltages at bus $i\ and\ j$ respectively, $\left|Y_{ij}\right|\angle\theta_{ij}$ is admittance of a line that connects buses $i$ to $j$, and, $N_b$ is the EPG's total number of buses. These two equations are formulated for each bus in the EPG, excluding the slack bus, which has specified value of $|V_i|\angle\delta_i$. From Eqs. (17) and (18), the Jacobian $J$ matrix **(Grainger and Stevenson, 1994; Saadat, 1999; Das, 2006)** for the NR method can be derived viz:

$$J = \begin{bmatrix} \frac{\partial \Delta P}{\partial V} & \frac{\partial \Delta P}{\partial \delta} \\ \frac{\partial \Delta Q}{\partial V} & \frac{\partial \Delta Q}{\partial \delta} \end{bmatrix} \quad (19)$$

where $\partial\Delta P/\partial V, \partial\Delta P/\partial\delta, \partial\Delta Q/\partial V, and\ \partial\Delta Q/\partial\delta$ are the sensitivities of real power to voltage changes, real power to angle changes reactive power to voltage changes, and reactive power to angle changes respectively. For each iteration, Eq. (19) updates the state variables using :

$$\begin{bmatrix} \Delta\delta \\ \Delta|V| \end{bmatrix} = J^{-1} \begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} \text{until } max(\Delta|P|, \Delta|Q|\,) \leq\ 10^{-6}\, pu \quad (20)$$

## 3. MODELING AND SIMULATION ANALYSIS

This study proposes the usage of PSO algorithmic rules to find the best set of line weighted factors to detect and rank the most critical lines based on voltage stress to guide SO in identifying vulnerable links. The work also proposes realistic PSO-based maximum constrained-based load shedding, to ensure practical applicability in utility operations. We also used PSO-based algorithmic rules in investigating behavior of EPG under different critical outages with and without the maximum constraint-based load shedding technique. These contributions, which have been formulated in section 2 of this paper, are herewith presented using flowchart diagrams for modeling in the MATLAB **(MathWorks, 2024)** version. The testbed that was used to investigate the performance of the EPG under critical branch outages without and with a targeted load shedding scheme using a PSO-based load flow analysis is also discussed here.

### 3.1 Testbed for Modeling.

**Fig. 1** presents the testbed used for the verification of the various methods developed in achieving the aim of this study. The testbed is an IEEE-14 EPG, a representation of a mere idea of the 1962 American EPG. It is evident from the figure that the testbed has five generators, eleven loads, fourteen buses, and twenty branches. It is characterized by excess voltage control potentiality. In this study, Bus 1 was used as the EPG's slack bus. And it is evident from **Fig. 1** that buses 2, 3, 6 and 8 are PV buses, while PQ buses are 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, and 14. The data for the testbed is obtainable at **(University of Washington, 1999)**.

### 3.2 Model for the identification of the critical branches on the Test bed.

**Fig. 2** presents the flowchart for the development of the MATLAB-MATPOWER **(Zimmerman et al., 2010; Zimmerman and Murillo-Sánchez, 2024)** script that was used for identification of the most critical branch(es); and hence studying the effect of the critical contingency conditions on the EPG with and without a selective load shedding scheme. The information obtained in subsection 2.3 of this paper was used to obtain **Fig. 2**. The inputs for the model are bus and branch data, and PSO parameter, whereas the outputs obtainable from the model are a ranked list of transmission lines based on their severities and a convergence plot showing the evolution of the best fitness in the global inputs.

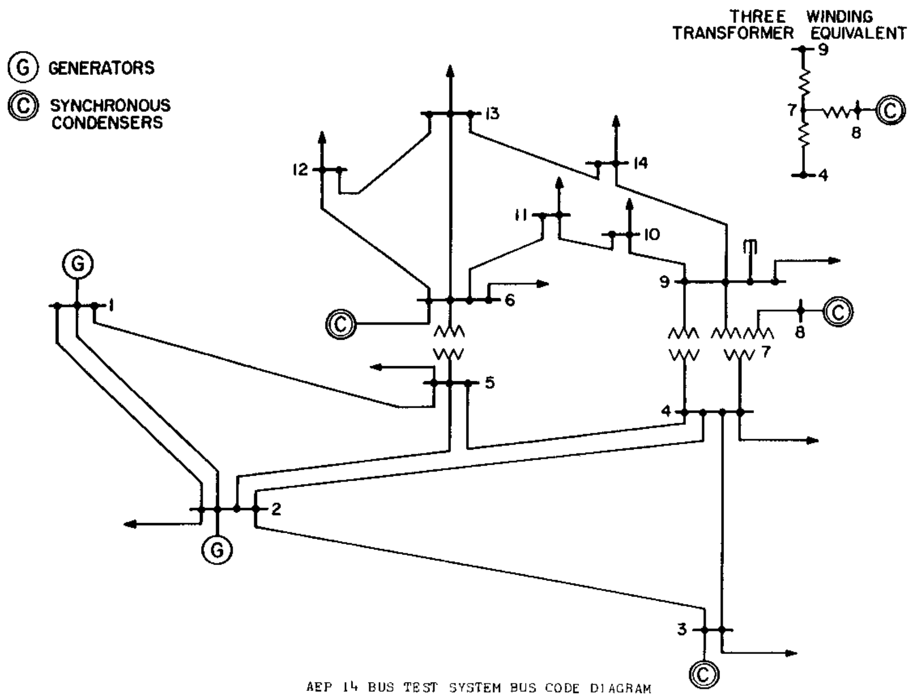



**Figure 1.** IEEE-14 bus system **(University of Washington, 1999)**

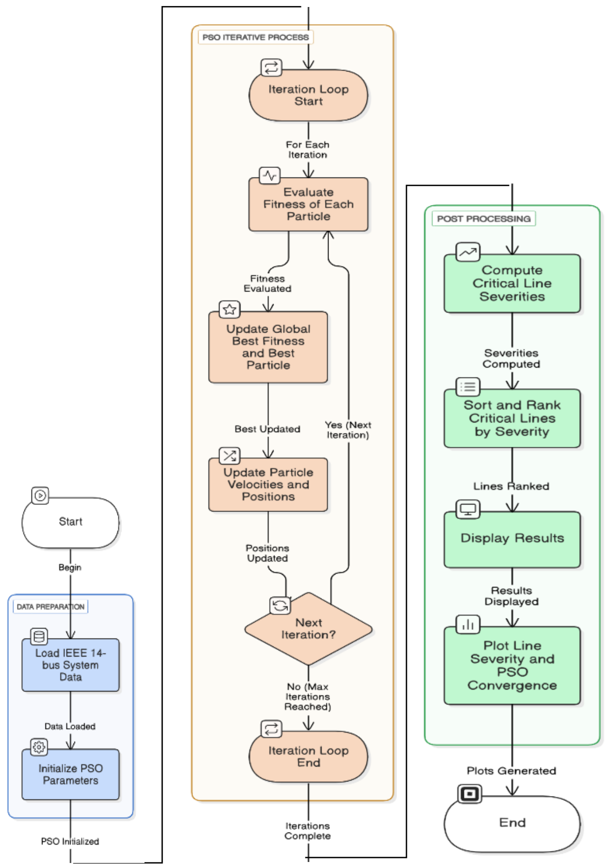



**Figure 2.** The flowchart for the implementation of the MATLAB-MATPOWER script for identifying critical branches of the EPG

### 3.3 Model for the Targeted Load Shedding of the EPG

The model for the implementation of the development of the MATLAB-MATPOWER script for PSO-based selective and targeted load shedding is presented in **Fig. 3**. The information obtained in subsection 2.4 of this paper was used to obtain **Fig. 3**. The goal of the model is to minimize the load shedding while respecting constraints (total shedding ≤ 15%). This model guides the PSO algorithm to find the optimal load flow solution while applying random load shedding to maintain system stability.

The inputs for this model are bus and branch data and PSO parameters. The outputs obtainable from this model are convergence curve, load demand before load shedding, load demand during and after targeted load shedding, and load demand shed.

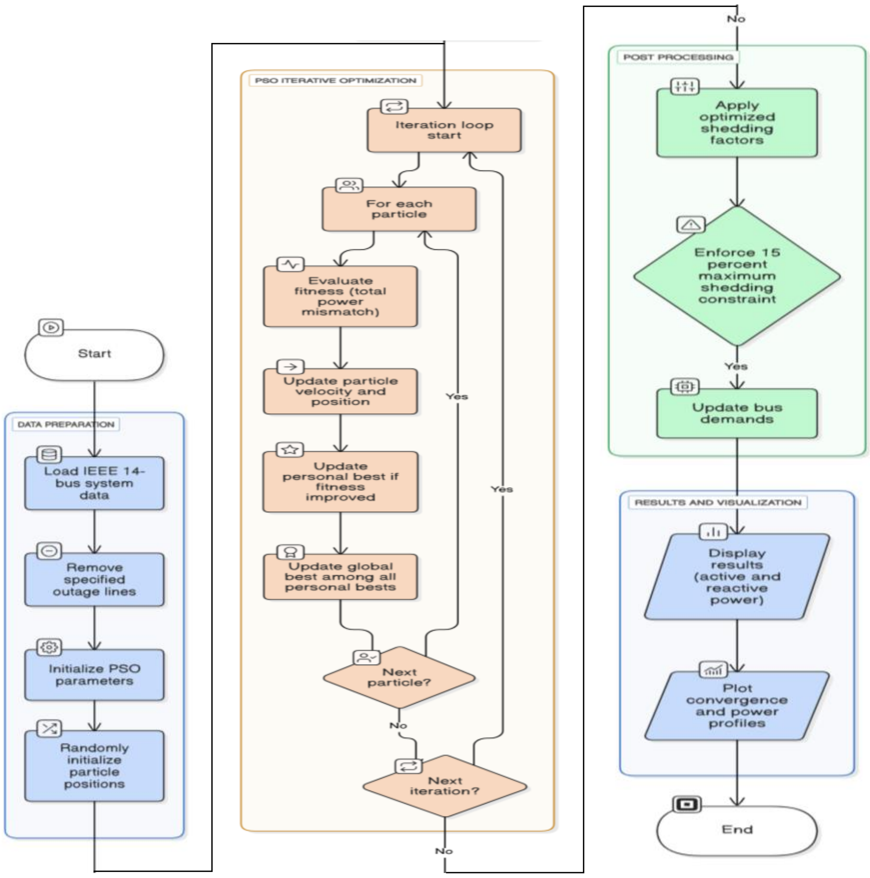



**Figure 3.** The flowchart diagram for the implementation of the MATLAB-MATPOWER program for selective and targeted PSO-based load shedding

### 3.4 Model for Studying the Pre-contingency, Contingency, and Post Conditions of the Testbed.

**Fig. 4** presents a flowchart for the implementation of the MATLAB-MATPOWER script for the PSO-based load flow using NR method. The information obtained in subsection 2.5 of this paper was used to create **Fig. 4.** The figure was used to develop the script used for studying the pre-contingency, contingency, and post conditions of the testbed. The figure is used the way it is for studying pre-contingency situation of the EPG under consideration.

To use **Fig.4** for examining contingency conditions of the testbed, the critical branches identify by the script developed from the model presented in **Fig. 2** would be outage before running the script developed through **Fig. 4**. To use **Fig.4** to study the post-contingency conditions of the testbed, apart from removing the critical branches from the grid, the results obtained from the script developed through **Fig. 3** must be implemented on **Fig. 4**; that is, all the loads identified by the script developed using **Fig. 3** would all be shed before subjecting script obtained through **Fig. 4** to the load flow analysis in the MATLAB-MATPOWER environment. In this study, we did not study the base case, outage without and with targeted load shedding separately; we integrated the three different scenarios and thereafter subjected the combined script to the load flow analysis in the MATLAB-MATPOWER environment. **Fig. 5** presents a flowchart diagram used to integrate the abovementioned scenarios.

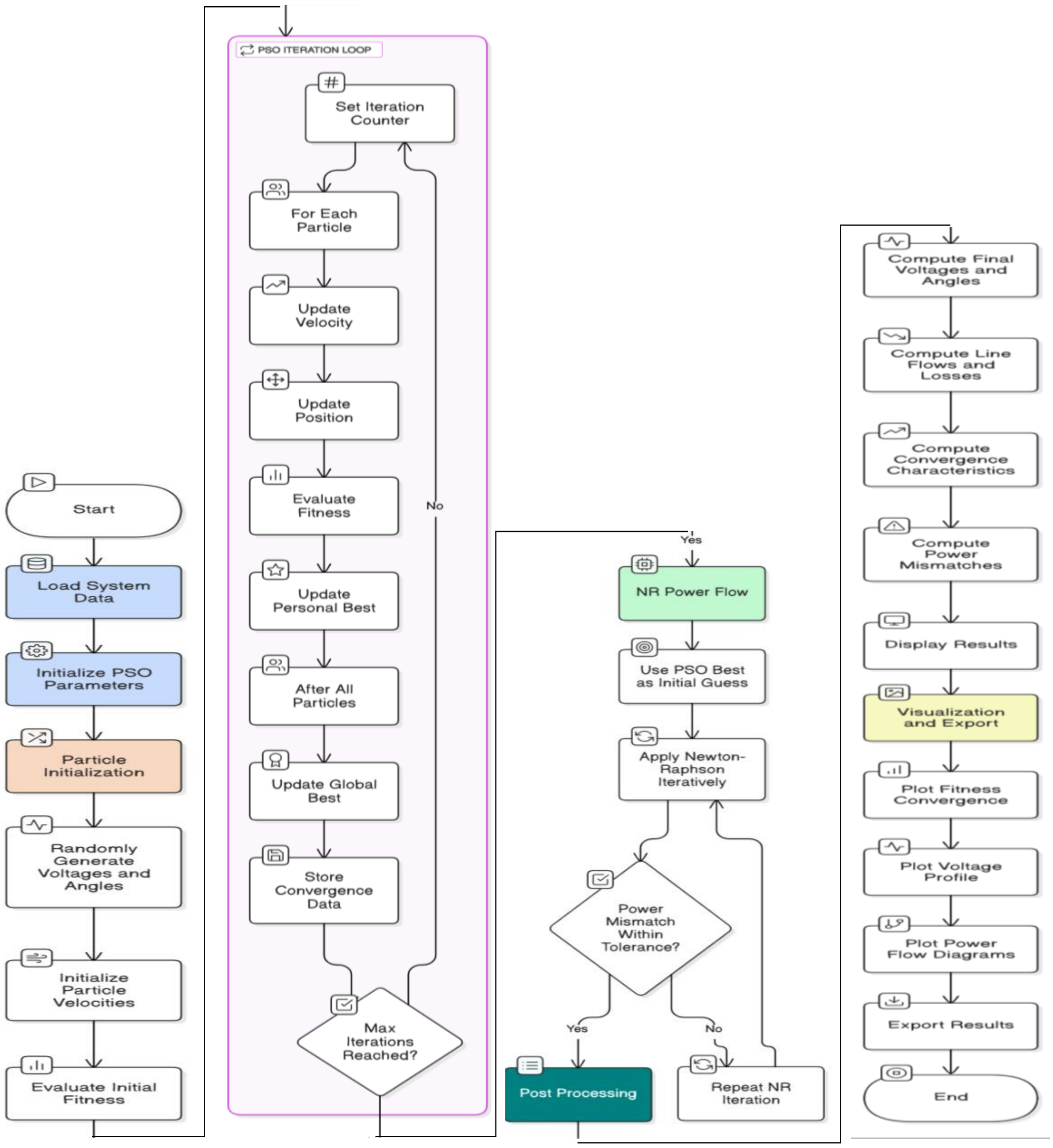



**Figure 4.** The flowchart for the implementation of the MATLAB-MATPOWER script for a PSO-based load flow using NR method

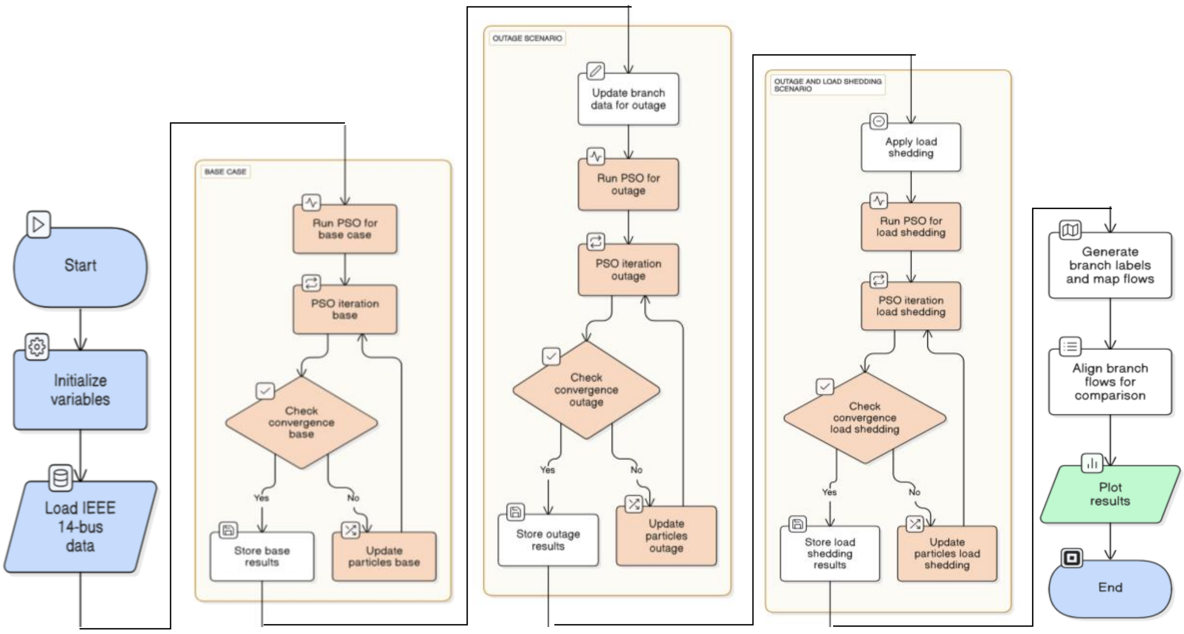



**Figure 5.** The flowchart for the implementation of the MATLAB-MATPOWER script for three different scenarios investigated in this study

## 4. RESULTS AND DISCUSSION

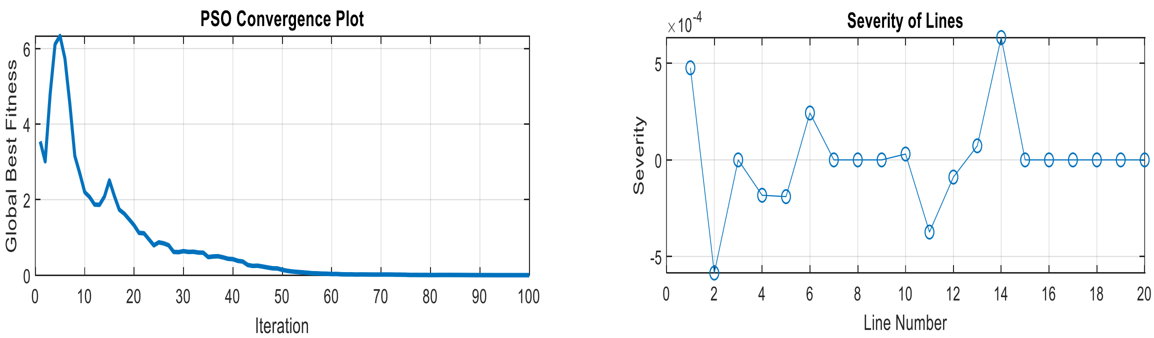
The results obtained when studying the CSI of the branches of the testbed, the loads to be shed in all the PQ buses of the testbed, and behavior of the testbed under different scenarios in the MATLAB-MATPOWER environment are presented and discussed in this area of the paper.

### 4.1 Simulation Results and Discussion

This section of the paper presents the results obtained during various simulations in the MATLAB –MATPOWER environment.

4.1.1 Simulation Results for Studying CSI

With a view to determining the severe eventualities on the testbed, the PSO-based algorithm CSI method was used in this study. The simulation results obtained in the MATLAB-MATPOWER environ are presented in **Figs. 5 (a)** and **(b)**.



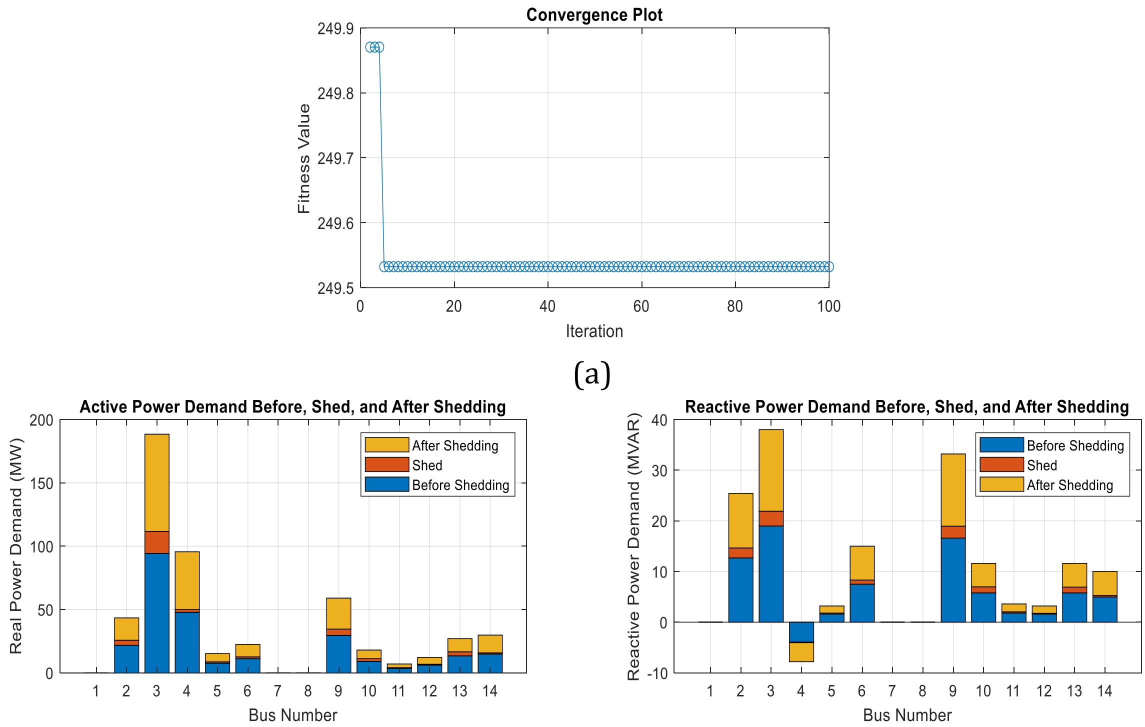

(a) (b)

**Figure 5.** Severity of the lines of the EPG

It is evident from **Fig. 5(a)** that the algorithm developed for the CSI converges rapidly, achieving a fitness value of approximately 0.5 within 25 iterations. The critical contingencies on the testbed indicated in **Fig. 5 (b)** occur at lines 1 and 14. Line 1 links buses 1 to 2; whereas line 14 links buses 7 to 8. The first result conforms with **(Malakar and Maharana, 2014)**, whereas the second result agrees with the result obtained in **(Javadi and Amraee, 2018)**. The comparisons are possible because the two studies mentioned also used the same testbed used in this study.

4.1.2 Simulation Results for Studying the Loads to be Shed in all the PQ Buses of the Grid

The results obtained when PSO-based algorithm was employed to shed loads selectively across PQ buses to prevent voltage collapse on some buses and mitigate congestion on a few lines in the EPG are presented in **Fig. 6 (a)** through **Fig. 6 (c)**.




(a)

(b) (c)

**Figure 6.** The load shedding across buses of the test bed

It is evident from **Fig. 6(a)** that the algorithm developed for the selective load shedding exercises converges rapidly, achieving a fitness value of approximately 249.532 within 5 iterations. **Fig. 6(b)** reveals that active load demands are shed on 11 buses; and it can be deduced from the figure that the total of active load demand shed was 38.8502MW. This shows that 15% of the total active load demand is shed. Also, **Fig. 6(c)** shows that reactive load demands are shed on 11 buses; and it can be deduced from the figure that the total reactive load demand shed was 11.0250 Mvar; which shows that 15% of the total reactive load demand is shed.

4.1.3 Simulation Results for Studying the Behaviour of EPG under Different Scenarios

To study the response of the EPG under consideration under varying operating conditions, **Fig. 7** presents the simulation results across convergence curves, voltage magnitudes, voltage angles, and branch flows. These plots reveal the behaviour of the testbed during the base case, the outage without and with selective and targeted load shedding scenarios.

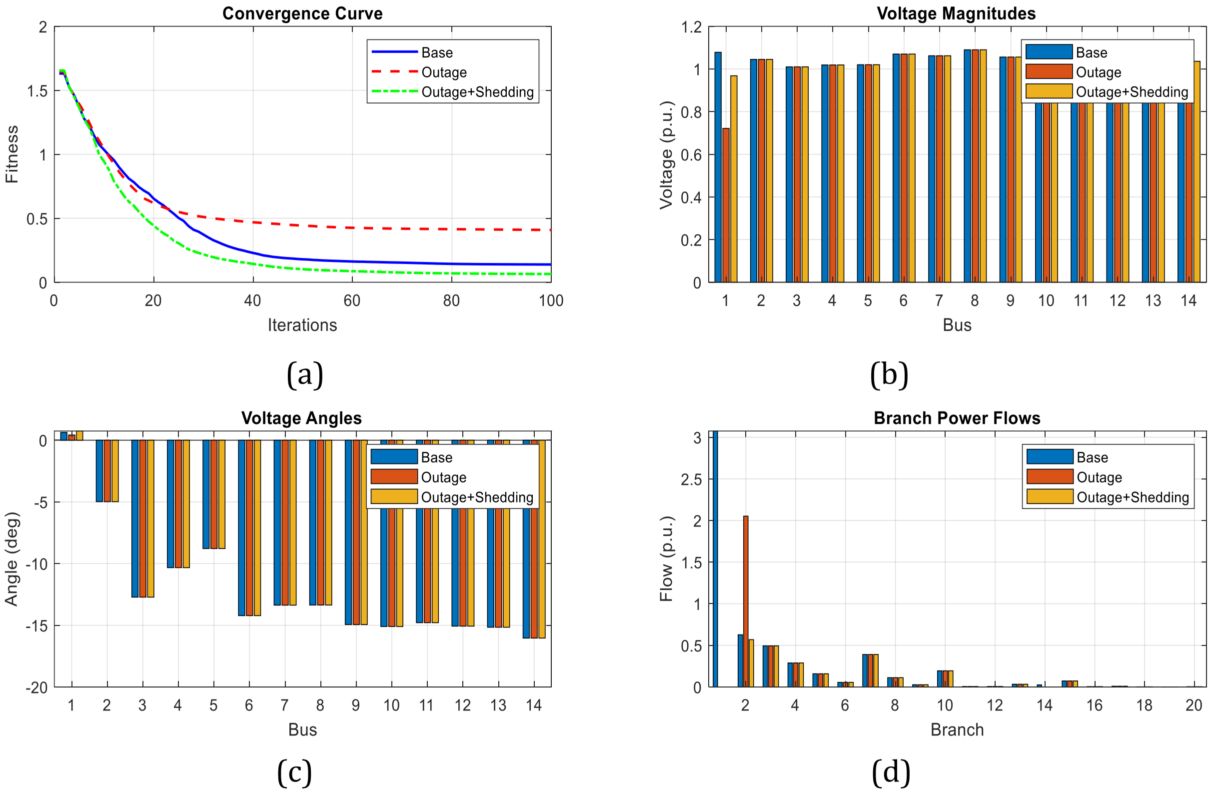



**Figure 7.** The simulation results for studying the behaviour of EPG under different scenarios

**Fig.7 (a)** presents convergence curves that show how quickly the load flow algorithm reaches a solution in each scenario. In the base case, the convergence is rapid and smooth, typically within a few iterations, indicating a well-conditioned and stable system. The algorithm takes significantly more iterations to converge in the case of the outage scenario, showing sluggish convergence behavior. This is a sign of a stressed or near-unstable system, likely due to the large voltage drop at Bus 1 and the overloading on Line 2. During the outage with the targeted load shedding, the convergence action improves drastically. The system converges faster than in the outage without load shedding case, suggesting that load shedding successfully restored system solvability and pushed the power flow solution back into a more stable region.

Voltage Magnitudes that are presented in **Fig.7 (b)** reveal the steady-state voltage magnitudes at all buses for each scenario. In the base case, magnitudes of voltage at all buses are within IEEE standard limits (0.95pu to1.05pu). Bus 1 suffers a severe voltage drop to 0.7214pu in the case of an outage without the targeted load shedding scheme, which is a major violation of voltage stability standards, signaling potential risk of voltage collapse or protection system intervention. Notably, while these disruptions were severe, voltage magnitudes at other buses remained within acceptable limits, indicating that the instability was localized but critical. During the outage and load shedding regime, voltage at Bus 1 improves to 0.9682pu, pulling it back within the acceptable range, while all other bus voltages remain within standard limits in all scenarios. This highlights that targeted load shedding has an effective corrective influence on voltage stability, especially in localized stressed areas.

**Fig. 7(c)** presents voltage angles that indicate the phase difference across the testbed and reflect the power transfer capability and stress levels of the EPG. In the Base Case, voltage angles are smoothly distributed across the buses, showing a balanced power flow. During the outage scenario, a sharp angular disparity is observed, especially near the affected area (Bus 1), indicating steep phase gradients due to the line outage and increased reactive losses. This is consistent with high power transfers and stressed network conditions. The voltage angle profile becomes more even and gradual, with reduced extremes during the outage and load shedding scenario. This smoothing suggests that load shedding reduces the stress on the system and rebalanced power flow, especially on overloaded paths.
Branch flows are presented in **Fig.7(d)**, and they show active and reactive power flow in transmission lines. In the base case, branch flows are moderate, with Line 2 carrying 0.6271pu. During the outage scenario, due to the outage of Lines 1 and 14, Line 2's flow jumps to 2.0524pu, a more than 3-fold increase, pushing it well beyond safe loading limits, indicating a potential overload or line tripping risk. In the case of outage with targeted load shedding scenario, the flow on Line 2 drops significantly to 0.5683pu, lower than the base case, suggesting that targeted-load shedding effectively relieves line congestion, and redistributed power more safely across the network. This illustrates how strategic load shedding can be an effective emergency control strategy to mitigate the impacts of contingencies and re-balance the system. There were no load flows on Lines 1 and 14 during the outage without and with targeted load shedding regime.
From all these observations, load shedding across all PQ buses with the cap is a highly effective corrective action that restores system stability, reduces voltage violations, relieves line overloads, and improves convergence behavior after an outage.

### 4.2 Validation of the Study

This section of the paper compares the results obtained in this study with the relevant studies in technical literature to validate our results.

**Table 1.** Comparison of Different Studies

| Study | Optimization Technique | Load Shedding Constraints | Contingency Assessment | Visualization Tools | Practical Applicability |
|---|---|---|---|---|---|
| **(Tamilselvan, 2020)** | HPSO-ABC | × | × | Limited | Moderate |
| **(Zhou et al., 2022)** | NN | × | × | × | √√ |
| **(Kiran et al., 2016)** | HPSO-GA | × | √ (SI) | √ | √ |
| **This Study** | PSO | √√ | √√ (CSI) | √√ | √√ |

**Table 1** shows that this study distinguishes itself by integrating a CSI for detailed branch-level analysis and enforcing practical load shedding constraints. These features collectively enhance the practical applicability and robustness of our load shedding strategy compared to the referenced studies.

## 5. CONCLUSIONS

This study showcases the resilience of the electric power grid under branch outages and targeted load shedding, emphasizing the critical role of optimization techniques in restoring system stability. By comparing three distinct scenarios, the research provides actionable insights into mitigating disruptions through demand-side strategies and enhancing convergence efficiency. Future studies could explore additional contingency measures and advanced optimization methods to further improve system reliability.

### Nomenclature

| Symbol | Description | Symbol | Description |
|---|---|---|---|
| $PSO$ | Particle Swarm Optimization | $P_i$ & $Q_i$ | Active and reactive powers injected at bus $i$ |
| $EPG$ | Electric Power Grid | $\lvert V_i \rvert$ & $\delta_i$ | Voltage magnitude and angle at bus $i$, |
| $CSI$ | Critical Severity Index | $\lvert Y_{ij} \rvert$ & $\theta_{ij}$ | Admittance magnitude and angle in line $ij$ |
| $NR$ | Newton Raphson | $J$ | Jacobian matrix |
| HPSO-ABC | Hybrid PSO Artificial Bee Colony Algorithm | $pbest^{(m)}$ & $gbest$ | The personal best location of the particle $m$, and global best location |
| HPSO-GA | Hybrid PSO Genetic Algorithm | $x^{(m)}(t)$ & $v^{(m)}(t)$ | The current location of a particle; and current rate at which particles move around the solution space |
| $NN$ | Neural Network | $\omega, c_1$ and $c_2$ | Inertia weight, cognitive and social learning rates of the particles in the swarm |

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### Credit Authorship Contribution Statement

Sunday Adetona: Methodology, writing–original draft, review & editing, Validation. Odunayo Odusanya: Methodology, & Data collection, Adeola Balogun: Writing–review & editing, Validation. Frank Okafor: Writing-review & editing.

### Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## REFERENCES

Adetona, S., John, M. and Umar, S., 2022. Optimal reactive power dispatch using improved Chaotic PSO algorithm with the Wingbeat frequency. *Acta Marisiensis. Seria Technologica.*, *19*(2). pp. 20-29, https://doi.org/10.2478/amset-2022-0013

Adetona, S.O., Olaboyin, E.B., Salawu, R.I. and Okafor, F.N., 2024. Upshot of unified power flow controller on the minimization of the severity of overloading on electric power grid. *Journal of King Saud University-Engineering Sciences*, *36*(6), pp. 400-408. https://doi.org/10.1016/j.jksues.2021.10.010

Bioki, M.H., Rashidinejad, M., Fadaeinedjad, R. and Esmaeilian, H.R., 2012, August. An application of PSO in optimal load shedding considering voltage stability. In *Global Conference on Power Control and Optimization*.

Chivunga, J.N., Longatt, F.G., Lin, Z. and Blanchard, R., 2024. Transmission line redundancy for grid resilience enhancement: The concept of Transmission Lines contributing to Energy Not Supplied (TLENS) on Malawi's transmission grid. *Energy Reports*, *12*, pp. 4670-4685. https://doi.org/10.1016/j.egyr.2024.10.047.

Choi, Y., Lim, Y. and Kim, H.M., 2017. Optimal load shedding for maximizing satisfaction in an islanded microgrid. *Energies*, *10*(1), P. 45. https://doi.org/10.3390/en10010045

Das, D., 2006, *Electrical Power Systems*, New Age International (P) Ltd, New-Delhi. India, https://books.google.com.ng/books?id=9CYS_krSvMUC

Gao, H., Chen, Y., Xu, Y. and Liu, C.C., 2016. Dynamic load shedding for an islanded microgrid with limited generation resources. *IET Generation, Transmission & Distribution*, *10*(12), pp. 2953-2961. https://doi.org/10.1049/iet-gtd.2015.1452

Grainger, J.J., and Stevenson, W.D., Jr. 1994, *Power System Analysis*, McGraw-Hill, Inc., Singapore, https://books.google.com.ng/books?id=NBIoAQAAMAAJ

Gubina, F. and Strmcnik, B., 1995. Voltage collapse proximity index determination using voltage phasors approach. *IEEE transactions on power systems*, *10*(2), pp. 788-794. https://doi.org/10.1109/59.387918

IImai, S., 2005, June. Undervoltage load shedding improving security as reasonable measure for extreme contingencies. In *IEEE Power Engineering Society General Meeting,* pp. 1754-1759. IEEE. https://doi.org/10.1109/PES.2005.1489318.

Iweh, C.D., Gyamfi, S., Effah-Donyina, E. and Tanyi, E., 2024. Analysis of contingency scenarios towards a suitable transmission pathway in the southern interconnected grid (SIG) of Cameroon. *e-Prime-Advances in Electrical Engineering, Electronics and Energy*, *7*, P. 100486. https://doi.org/10.1016/j.prime.2024.100486.

Javadi, M. and Amraee, T., 2018. Mixed integer linear formulation for undervoltage load shedding to provide voltage stability. *IET Generation, Transmission & Distribution*, *12*(9), pp. 2095-2104. https://doi.org/10.1049/iet-gtd.2017.1118

Kennedy, J. and Eberhart, R., 1995, November. Particle swarm optimization. In *Proceedings of ICNN'95-International Conference on Neural Networks*, 4, pp. 1942-1948. https://doi.org/10.1109/ICNN.1995.488968.

Ketabi, A. and Hajiakbari Fini, M., 2017. Adaptive underfrequency load shedding using particle swarm optimization algorithm. *Journal of applied research and technology*, *15*(1), pp. 54-60. https://doi.org/10.1016/j.jart.2016.12.003.

Kisengeu, S.M., Muriithi, C.M. and Nyakoe, G.N., 2021. Under voltage load shedding using hybrid ABC-PSO algorithm for voltage stability enhancement. *Heliyon*, *7*(10). https://doi.org/10.1016/j.heliyon.2021.e08138

Kiran, S.H., Dash, S.S., Subramani, C. and Pathy, S., 2016. An efficient swarm optimization technique for stability analysis in IEEE–14 Bus System. *Indian journal of Science and Technology*, *9*(13), pp. 1-6. https://doi.org/10.17485/ijst/2016/v9i13/80524.

Kwang, Y.L, and Zita A.V., 2020. *Applications of modern heuristic optimization methods in power and energy systems*, John Wiley & Sons. https:/doi.org/10.1002/9781119602286

Le, T.N., Nguyen, H.M.V., Hoang, T.T. and Nguyen, N.A., 2023. Optimizing the power system operation problem towards minimizing generation and damage costs due to load shedding. *Engineering, Technology & Applied Science Research*, *13*(5), pp. 11643-11648. https://doi.org/10.48084/etasr.6221

Malakar, S. and Maharana, M.K., 2014. Contingency assessment of electric power system by calculation of unequal priority factors for static severity indices using analytic hierarchy process. *system*, *9*, P. 13. https://www.doi.org/10.70729/IJSER15131

Marouani, I., Guesmi, T., Abdallah, H.H. and Ouali, A., 2011, March. Optimal location of multi type FACTS devices for multiple contingencies using genetic algorithms. In *Eighth International Multi-Conference on Systems, Signals & Devices*, pp. 1-7. IEEE. https://doi.org/10.5923/j.ijee.20120202.05

MathWorks, 2024. MATLAB (Version R2024b) [Software]. https://www.mathworks.com

Nazir, N., Gupta, N. and Farishta, R., 2023, November. contingency analysis in power system studies: A critical review. In *International Conference on Machine Learning, Advances in Computing, Renewable Energy and Communication*, pp. 85-95. Singapore: Springer Nature Singapore. https://doi.org/10.1007/978-981-97-5227-0_9

Saadat, H., 1999, *Power System Analysis*, New York: Mc Graw Hill, 1999.

Salomon, C.P., Coutinho, M.P., Lambert-Torres, G. and Ferreira, C., 2011, June. Hybrid particle swarm optimization with biased mutation applied to load flow computation in electrical power systems. In *International Conference in Swarm Intelligence*, pp. 595-605. Berlin, Heidelberg: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-21515-5_70

Seyedi, H. and Sanaye-Pasand, M., 2009. New centralised adaptive load-shedding algorithms to mitigate power system blackouts. *IET generation, transmission & distribution*, *3*(1), pp. 99-114. https://doi.org/10.1049/iet-gtd:20080210

Slochanal, S.M.R., Saravanan, M. and Devi, A.C., 2005, November. Application of PSO technique to find optimal settings of TCSC for static security enhancement considering installation cost. In *2005 International Power Engineering Conference*, pp. 1-394. IEEE. https://doi.org/10.1109/IPEC.2005.206940

Sutha, S. and Kamaraj, N., 2008. Optimal location of multi type facts devices for multiple contingencies using particle swarm optimization. *Electrical Engineering*, *17*, P. 18.

Tamilselvan, V., 2020. A hybrid PSO-ABC algorithm for optimal load shedding and improving voltage stability. *International Journal of Manufacturing Technology and Management*, *34*(6), pp. 577-597. https://doi.org/10.1504/IJMTM.2020.109999

University of Washington, 1999, Power Systems Test Case Archive. [Online]. Available: https://labs.ece.uw.edu/pstca/pf14/pg_tca14bus.htm

Verayiah, R., Mohamed, A., Shareef, H. and Abidin, I.Z., 2014. Under voltage load shedding scheme using meta-heuristic optimization methods. *Przegląd Elektrotechniczny*, *90*(11), pp. 162-168. https://doi.org/10.12915/pe.2014.11.43

Xu, Y., Liu, W. and Gong, J., 2011. Stable multi-agent-based load shedding algorithm for power systems. *IEEE Transactions on Power Systems*, *26*(4), pp. 2006-2014. https://doi.org/10.1109/TPWRS.2011.2120631

Zhou, Y., Park, J. and Zhu, H., 2022, July. Scalable learning for optimal load shedding under power grid emergency operations. In *2022 IEEE Power & Energy Society General Meeting (PESGM)*, pp. 1-5. IEEE. https://doi.org/10.48550/arXiv.2111.11980

Zimmerman R.D., and Murillo-Sánchez, C., 2024, MATPOWER User's Manual. [Online]. Available: http://www.pserc.cornell.edu/matpower/

Zimmerman, R.D., Murillo-Sánchez, C.E. and Thomas, R.J., 2010. MATPOWER: Steady-state operations, planning, and analysis tools for power systems research and education. *IEEE Transactions on Power Systems*, *26*(1), pp. 12-19. https://doi.org/10.1109/TPWRS.2010.2051168

# تأثير التخفيف من حالات الطوارئ الحرجة في شبكة الطاقة الكهربائية باستخدام تقنية الحد الأقصى من الحمولة المقيدة القائمة على جهاز دعم البرامج

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## الخلاصة

تقدم هذه الدراسة مخططا قائما على تحسين سرب الجسيمات من أجل التخلص الأمثل من الأحمال المستهدفة وتقييم شدة الطوارئ في شبكة الطاقة الكهربائية .تم استخدام إيبي 14 إبغ كما اختبار .حددت الدراسة الفروع الحرجة ؛ وقيمت كميا الأداء التشغيلي لمجموعة البرامج الإلكترونية تحت الحالة الأساسية ، والانقطاع بدون مخططات التخلص من الأحمال المستهدفة ومع ذلك، باستخدام خصائص التقارب، ومقادير وزوايا الجهد، وتدفقات تحميل الفروع كمقاييس تشخيصية .أظهرت الحالة الأساسية استقرارا عدديا ممتازا ، مع تحقيق التقارب في أقل من 5 تكرارات ، والحفاظ على جميع الفولتية للحافلات ضمن النطاق القياسي إيبي .تسبب سيناريو الانقطاع الحرج في صعوبة شديدة ، كما يتضح من التقارب المطول )تجاوز 15 تكرارا (، والجهد الشديد .في الحافلة من 1 إلى 0.7214 بو، والحمل الزائد للخط 2 إلى 2.0524 بو، ما يقرب من 275 ٪ من تحميل العلبة الأساسية تشير هذه الظروف إلى حالة تشغيلية غير مستقرة، مما يشكل مخاطر شديدة على أمن النظام .تنفيذ الحمل المستهدف سفك تحسن كبير في ظروف النظام :التكرار التقارب خفضت إلى ما يقرب من 6، حافلة 1 الجهد استعادة إلى 0.9682 بو، وخط تحميل انخفض إلى 0.5683 بو. حافظت الحافلات الأخرى باستمرار على الفولتية ضمن هوامش مقبولة، وظلت تدفقات 2 الفروع على الخطوط غير الحرجة غير مهمة في جميع الحالات .تؤكد ملامح زاوية الجهد بشكل أكبر الإجهاد الجهازي أثناء الانقطاع وتأثير التثبيت بعد التخلص من الحمل .توضح التقنية المقترحة من الناحية الكمية أن التخلص الانتقائي للحمل هو استراتيجية تحكم تصحيحية فعالة، ليس فقط لاستعادة استقرار الجهد ولكن أيضا لتخفيف الحمل الزائد لخط النقل، وبالتالي تعزيز .قدرة مجموعة البرامج الإلكترونية على الحفاظ على التشغيل الآمن والموثوق في ظل ظروف الطوارئ الشديدة

الكلمات المفتاحية: تسليط الحمل المستهدف، خوارزمية جهاز الأمن العام، حالات الطوارئ الشديدة، ملف تعريف الجهد تدفق الحمل