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OPTIMIZED DISTRIBUTION NETWORK RECONFIGURATION USING HYBRID OPF AND GRAPH THEORY TECHNIQUES

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Abstract. *The proposed work aims to assess the reduction in power losses and better voltage profiles in network reconfiguration through a hybrid approach that combines Optimal Power Flow (OPF) and graph theory for static power source. The layout of a distribution network can be modified by opening or closing ties and sectionalizing. The OPF is conducted on the IEEE 30-node system using optimization methodologies such as the Interior Point Method, Sequential Quadratic Programming, and Active Set methods. Feasible radial topologies are obtained through Prim's Maximal Spanning Tree algorithm, using the parameters obtained through the OPF methodologies. This approach eliminates the need for a tedious mesh check for an IEEE 30-node system. To validate the proposed methodology, the results were compared with those of the Social Spider Optimization (SSO), Edmonds' Maximal Spanning Tree algorithm, and Kruskal's maximal spanning tree algorithm. Simulation results for the IEEE 30-node model confirm the effectiveness of Prim's Maximal Spanning Tree algorithm, particularly when OPF is conducted using the Interior Point Method. Results shows that Prim's maximal spanning tree- based interior point methods outperformed the other methods with 0.71938 p.u. active power loss, 2.0062 p.u. reactive power loss voltage stability index of 0.1457 p.u., showing strong resilience against voltage fluctuations. The study is carried out using MATLAB software (2020 version) and MATLAB–based Power System Analysis Toolbox (PSAT) for programming and analysis.*

Key words: *Network reconfiguration, Prim's Maximal Spanning Tree, Interior Point Method, Graph theory*

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Acronyms

Abbreviations

OPF	Optimal Power Flow
DNRC	Distributed Network Reconfiguration
ACO	Ant Colony Optimization
GA	Genetic Algorithm
BPSO	Binary Particle Swarm Optimization
DN	Distribution Network
DG	Distributed Generation
SQP	Sequential Quadratic Programming
IPM	Interior Point Method
MST	Maximal Spanning Tree
SSO	Social Spider Optimization
SFS	Stochastic Fractal Search
NR	Network Reconfiguration
PSO	Particle Swarm Optimization
WGA	Wild Goats Algorithm
DSR	Distribution System Reconfiguration
RRA	Runner Root Algorithm
VSI	Voltage Stability Index
ISSA	Improved Salp Swarm Algorithm
PGS	Plant Growth Simulation
RDN	Radial Distribution Network
JSA	Jellyfish Search Algorithm

Elements

P_{Loss}	The active power loss
$V_{u,} V_v$	The bus voltages at node *u* and *v* respectively
$\theta_{u,} \theta_v$	Phase angle of voltage at bus *u* and *v* respectively
$MinP_{LOSS}$	Objective function on minimization of active power loss
P_{Gu}	The generator generates real power at node *u*
P_{Du}	The active power load demand at node *u*
g_{uv}	Series conductance of line in '*u-v*' consideration of a π model
b_{uv}	Series susceptance of line in '*u-v*' consideration of a π model
V^{nin}, V^{max}	Limit on the magnitude of voltage
b_{shuv}	Shunt susceptance of line in '*u-v*' consideration of a π model
I^b_{uv}	Current moving through branch *b* between node *u* and *v*

1. INTRODUCTION

Reconfiguring the network is an effective strategy for decreasing power losses and improving voltage stability. This reconfiguration involves strategic positioning of the switches throughout the system to alter the network topology. By operating sectionalizing and tie switches, the topological layout undergoes changes, ultimately leading to an improved voltage profile through loss reduction. Network reconfiguration is crucial for power-distribution systems. This process entails adjusting the topology of the distribution network by manipulating switches to optimize performance. Optimal network reconfiguration helps minimize power losses, optimize voltage profiles, and enhance system reliability. Given the increasing amount of energy used at any time and the increasing incorporation of green energy sources, the necessity for efficient power distribution has become more pronounced. Network reconfiguration serves as a key mechanism for adapting the distribution system to evolving conditions, ensuring overall stability, and maximizing efficiency within the power grid. Achieving an optimal solution for distribution network reconfiguration is a formidable challenge owing to its significant computational complexity.

The Hybrid OPF-Graph Theory approach introduced in this study offers a unique and innovative solution for Distribution Network Reconfiguration by combining the strengths of both the methodologies. Combining Optimal Power Flow (OPF) and Graph Theory ensures efficient power distribution by minimizing losses, enhancing voltage stability, and adding a crucial layer of topological analysis, thereby facilitating the modeling of distribution networks. The hybrid method exhibits greater scalability and flexibility, making it applicable to larger and more complex networks that face real-world challenges. The combination of OPF and Graph Theory improves computational efficiency by accelerating the reconfiguration process, making it a highly efficient approach compared to traditional distribution network reconfiguration methods.

The hybrid approach combining Prim's Maximal Spanning Tree algorithm-based interior point method, was evaluated on the IEEE-30 bus system to identify the optimal path that minimizes reactive and active power loss while enhancing voltage levels. To validate the effectiveness of this methodology its performance was compared with other techniques such as Edmonds' Maximal Spanning Tree algorithm, Prim's maximal spanning tree algorithm-based active set methods, Prim's maximal spanning tree algorithm-based sequential Quadratic Programming, Kruskal's Maximal Spanning Tree algorithm, and Social Spider Optimization (SSO).

Numerous studies have been conducted in this regard. In paper [1], a new hybrid optimization technique combining modified Particle Swarm Optimization (PSO) based on the population of moving particles and Genetic Algorithm (GA) based on the principle of natural selection and genetics, with consideration of environmental issues, was used to reduce power losses in the transmission grid and enhance voltage stability. Paper [2] describe n alternative approach to reduce active and reactive power losses in radial distribution systems by applying a combination of the golden flower algorithm to evaluate reconfiguration issues. In paper [3], the hybrid approach combining the Marine Predator Algorithm (MPrA) and Jellyfish Search Algorithm (JSA) was used to decrease energy losses while enhancing voltage profiles and the net profit, crucially influenced by reactive and active power injections. Paper [4], introduced the Chaotic Stochastic Fractal Search Algorithm (CSFSA) method to tackle the reconfiguration problem, focusing on reducing losses and enhancing voltage stability in distribution systems. Paper [5] aims to reduce active power losses and enhance system reliability by introducing multi-criteria optimal and simultaneous allocation strategy. In paper [6], Improved Salp Swarm Algorithm (ISSA) was employed to solve the network reconfiguration problem. Paper [7] introduced a two-stage stochastic optimization algorithm to mitigate the influence of curtailing wind power on network losses. In paper [8], a differential hybrid Petri net model employing an event-triggered strategy characterizes the logical relations of reconfiguration based on voltage alerts within a cloud-edge collaborative architecture. Papers [9-11] described how to reduce the real power loss, and all the challenges associated with distribution network reconfiguration are addressed by employing a minimum spanning tree algorithm, which uses graph theory to generate feasible radial topologies. In paper [12-13], an optimization technique was developed to mitigate the emission of generated flicker by improving the power quality of the network, considering the voltage flicker levels, voltage profiles, and traditional power loss objectives for distribution network reconfiguration. Furthermore, the performance of distribution systems is enhanced by the concurrent deployment of DG, sectionalized switches, and network reconfiguration. In paper [14], a New Antlion Optimizer (ALO) algorithm was used to minimize losses and enhance power quality indices. Paper [15,16] introduced the runner root algorithm (RRA) to tackle the distribution network reconfiguration (NR) problem focusing on minimizing active power loss and enhance the reliability of the distribution network. In paper [17], an enhanced binary Particle Swarm Optimization incorporating a novel sigmoid function was employed to eliminate power loss during distribution system reconfiguration. Paper [18] employs the Multi-objective Cuckoo Search algorithm to enhance the voltage magnitude and minimize active power loss. In paper [19], a harmony search algorithm was used to enhance the voltage stability and active power loss minimization by considering network reconfiguration. In paper [20], the exchange market algorithm (EMA) and wild goat algorithm (WGA) were implemented in combination to improve both the accuracy and speed of reconfiguration. In paper [21], a meta-heuristic optimization algorithm called Slime Mould Algorithm (SMA) was used to identify the optimal allocation (locate and size) of the PVDG units into RDN for mitigating the power losses, enhance the RDN system voltage profiles and improve the overcurrent protection system. Papers [22, 23] detail the reliability improvement of radial distribution system with network reconfiguration and DGs placement and provide the solution to solved the network reconfiguration challenges. Papers [24, 25] introduced a hybrid approach combining Plant Growth Simulation (PGS) algorithm and Particle Swarm Optimization (PSO) to evaluate network reconfiguration issues in Radial Distribution Network (RDN). Paper [26] utilized Ant Colony Optimization (ACO) to address the challenges of distribution network reconfiguration, focusing on minimizing loss and stabilizing the load within a complex framework. The optimal allocation of capacitors in the distribution network provides results in reduced loss and enhances the voltage profile by reactive power compensation. Paper [27] uses General Algebraic Modeling System (GAMS) software to evaluate voltage deviations and active power loss minimization at each node of the network. Paper [28] introduced Distribution system reconfiguration (DSR) as a well-established method for loss reduction that operates sectionalized and tie switches in a distribution network [28]. Paper [29] integrates the hybrid method combining Grasshopper Optimization Algorithm (GOA) with Cuckoo Search (CS) methods to optimize both the position and size of DG units to reduce power losses in the distribution system. In paper [30, 31], Particle Swarm Optimization (PSO) was formulated to solve the issue of network reconfiguration subject to the following constraints: (a) radial network topology, (b) voltage limits, and (c) active and reactive power balances. In paper [32, 33] the graph theory was used to obtain the radial optimal network, which aims to effectively reconfigure the interconnected network into a radial system by optimizing its operational characteristics. Paper [34] describe the reconfiguration process involving adjusting the tie lines and dividing the sections. In the updated grid topology, its addresses the problem of optimal scheduling for Distributed Energy Resources to mitigate the cumulative costs associated with dispatchable distributed energy resource operations and to reduce the load. Ultimately, the optimal topology, which reduces the overall cost, was chosen from among all the radial topologies. In paper [35], the distribution system reconfiguration (DSR) was commonly used to solve the issues of Network Reconfiguration. In paper [36], Social Spider Optimization (SSO) was employed to concurrently reconfigure the network and enhance the voltage stability and minimize power loss of the distribution network. Paper [37] introduces a Genetic Algorithm to optimize the Distribution Network Reconfiguration to minimize both investment costs and active power losses. Paper [38] discussed the strategies, such as Dijkstra's Shortest Path and Prim's Minimal Spanning tree algorithm, to achieve optimal radial networks. Simulations confirmed the effectiveness of graph theory in optimizing network reconfigurations. Paper [39] addresses the minimal spanning tree problem in discrete optimization, acknowledging the limitations of traditional approaches, and introducing contemporary logarithmically efficient algorithms. Focusing on the radiality constraints, the proposed algorithm minimizes power losses while satisfying the voltage constraints. The method iteratively selects and eliminates branch based on the degree, simplifies the algorithm, and enhances its applicability to various science and engineering problems. A demonstration with a 14-node example illustrated the effectiveness of this strategy in optimizing spanning-tree configurations. Paper [40] addresses the issue of fluctuating voltage profiles in distribution systems owing to changes in distributed renewable generation. A novel network reconfiguration model was introduced to mitigate voltage volatility by minimizing network loss and controlling the voltage volatility indices using switched-capacitor banks. The formulation incorporates a new index for measuring the voltage volatility at each bus. The results indicate an effective reduction in network loss and enhanced voltage regulation, offering potential cost savings compared with relying solely on power electronic controllers in high renewable penetration scenarios. In paper [41], a two-phase optimization approach using the firefly algorithm for optimal network reconfiguration (NR) in an Electrical Distribution Network was used to reduce power loss and improve voltage. The paper [42] introduces a hybrid approach that integrates heuristics and genetic algorithms for optimal Distribution Network Reconfiguration. The algorithm successfully minimizes power losses and the network loading index while preserving a radial configuration with the capability to balance the voltage profiles. Paper [43,44] introduced a stochastic fractal search (SFS) algorithm to solve the issues of network reconfiguration. The findings emphasize that SFS is an effective approach for evaluating the issues of network reconfiguration with the incorporation of DGs. This study establishes a multi-division model and proposes a graph-theory-based algorithm for feeder-to-feeder reconstruction. Additionally, a JA-BE-JA optimization technique was introduced to further optimize the distribution network reconfiguration, showing robustness and a 10.68% reduction in network loss compared with traditional methods. The results highlight the potential for improved performance and efficiency in large-scale distribution-network reconstruction. Paper [45] highlights the use of digital devices to improve operational efficiency. The goal is to minimize outage time and provide cost-effective energy restoration for most consumers. Paper [46] introduces an approach for solving distribution system reconfiguration issues using particle swarm optimization (PSO) and graph theory. The results highlight the effectiveness of the proposed Particle Swarm Optimization-based method in determining optimal solutions for

Distribution Network Reconfiguration. Paper [47] addressed the Distribution Network Reconfiguration Problem by combining branch exchange heuristics with cluster analysis and evolutionary metaheuristics. Case studies have demonstrated the efficiency of this approach in finding configurations with reduced power and energy losses with a minimum number of power flow executions. In paper [48], a reconfiguration–load–shedding coordination optimization scheme was introduced to enhance the power system frequency stability. The hybrid approach that combines a minimum spanning tree algorithm with an enhanced genetic algorithm was employed to improve efficiency. The robustness of the proposed method in reducing the cost of loss and the number of outage users was validated using the IEEE 33 bus system. Paper [49] presents a strategy to restore faulted areas in a distribution network following abnormal events with the aim of increasing connected loads while minimizing switching operations and adhering to technical operational constraints. The testing of case studies confirmed the effectiveness of the proposed restoration strategy, showing its potential for addressing electrical and mechanical failures in distribution networks [49]. In paper [50], the distributed generator (DG) was integrated in a radial distribution system (RDS) to change the single power source to multiple power sources and bidirectional load flow which enhances the system reliability and reduces system power losses.

The study of the presented works lies in implementation of hybrid approach that integrates Optimal Power Flow (OPF) through Interior Point Method with graph theory methodology to improve the efficiency of network reconfiguration in distribution networks. Unlike traditional methods, which often require complex cycle detection, this approach employs Prim's Maximal Spanning Tree algorithm to optimize the process.

The initial approach for optimizing the IEEE 30-bus system involves employing various optimization techniques, including the Interior Point Method, Sequential Quadratic Programming (SQP), and the Active Set Method, to achieve optimal power flow. These methodologies are employed to enhance the efficiency and performance of the distribution network by ensuring that the power flow is optimized under given operational constraints. Using these optimization techniques, a cost matrix for the system is calculated, yielding the set of optimized parameters for voltage and phase angles. These parameters are then used to convert the meshed network of IEEE-30 bus system into an optimal radial configuration using Prim's maximal spanning tree and ensuring, that no nodes are left isolated while effectively minimizing the losses and ensuring voltage stability of the system.

Furthermore, the methodology was validated through a comparative analysis with other spanning tree algorithms (Edmonds and Kruskal) and Social Spider Optimization. Prim's Maximal-Spanning Tree-based Interior Point Method results in a voltage stability index that enhances the stability of the reconfigured radial network. Using the optimized data obtained through OPF, Prim's algorithm achieved an optimal radial topology for the IEEE 30-bus system. The performance of Prim's maximal spanning tree-based interior point method was compared with Prim's Maximal Spanning Tree (MST) algorithm-based sequential Quadratic Programming, Prim's Maximal Spanning Tree (MST) algorithm-based active set methods, Edmonds' maximal spanning tree algorithm [32], Kruskal's maximal spanning tree algorithm [32], and Social Spider Optimization (SSO) [36]. The obtained outcome emphasizes on the superior performance of Prim's maximal spanning tree-based Interior Point Method in network reconfiguration, effectively optimizing the radial topology of the network while minimizing power losses and enhancing voltage stability index.

Section 2 outlines the objectives of the proposed methodology, focusing on mitigating the power losses. An optimal power flow is performed using the Interior Point Method, incorporating a well-defined objective function subject to the constraints of real and reactive power injection as defined in Eq. 5 and Eq. 6. Section 3 explains the overall proposed methodology, integrating a hybrid approach combining the Interior Point Method and Prim's Maximal Spanning Tree to enhance the efficiency and performance of the distribution network. Section 4 presents the findings and validates the efficiency of the proposed approach. Finally, Section 5 provides a conclusive summary. This refined method offers an effective and efficient solution for achieving an optimized loss-minimized radial network configuration.

2. Problem Definition

2.1. Objective Function and Constraints

The goal of the power flow equation methodology, which is susceptible to limitations in equity and inequality, is to minimize the total real power loss. This statement is framed in Eq. (1) and Eq. (2):

$$\text{Minimize: } x(u,v) \tag{1}$$

$$\text{Subject to: } y(u,v)$$

$$z(u,v) \tag{2}$$

where, eq. (1) and eq. (2) define the framing of the objective function, equality, and inequality limitations respectively. u and v denote the state and control variables, respectively.

The system has a meshed configuration, but it is expected to run radially with minimal loss. All lines are assumed to have sectionalizing or tie switches for network reconfiguration. The objective function defined in eq. (3) is as follows:

$$MinP_{Loss} = \sum\nolimits_{v\in N(u)} g_{uv}(V_u^2 + V_v^2 - 2V_uV_v\cos(\theta_u - \theta_v)) = P_{Gu} - P_{Du} \tag{3}$$

Where;

P_{Loss}: Active power loss

V_u and V_v: The bus voltages at u and v respectively

θ_u and θ_v: The Phase angles of voltage at buses u and v, respectively.

Active power (P) is consumed by resistive elements along the distribution lines, leading to I^2R losses that reduce the overall efficiency of power delivery and limit the amount of usable power at the load end. These losses are caused by the resistance of conductors along the distribution lines, where electrical energy is converted into heat. As the current increases, the magnitude of these losses increases, which can degrade the voltage profile and impose thermal stress on conductors and associated equipment. Therefore, through distribution network reconfiguration, this loss can be minimized by choosing the best path for the power flow, which results in increased efficiency and ensures system reliability. Reactive power (Q), on the other hand, is associated with the energy exchange in inductive and capacitive components within the system. Although reactive power does not perform real work, it is essential for voltage regulation, supporting power transfer, and maintaining stable operation of the power system. Effective management of reactive power is crucial for voltage stability and system performance [51].

For every candidate topology, the number of branches in the distribution system graph must be consistently equivalent to the total number of linked buses, excluding one, to ensure the network is radial. m_b is the overall number of branches for graph depiction of a distribution system comprising of open switches. n_c is the number of linked buses with a route to the parent node in the distribution system topology.

$$m_b = n_c - 1 \tag{4}$$

The constraint of actual power injection is explained in eq. (5)

$$P_{Gu} - P_{Du} = \sum_{v \in N(u)} a_{uv} \left| g_{uv} V_u^2 - V_u V_v (g_{uv} \cos(\theta_u - \theta_v) + b_{uv} \sin(\theta_u - \theta_v)) \right| \tag{5}$$

Where;

P_{Gu}: The generator generates real power at the node u - v

P_{Du}: The active power load demand at the node u - v

g_{uv}: Series conductance of line in u - v considering π model.

b_{uv}: Series susceptance of line in u - v considering π model.

The constraint of reactive power injection is explained in eq. (6)

$$Q_{Gu} - Q_{Du} = \sum_{v \in N(u)} a_{uv} \left| -(b_{uv} + b_{shuv} / 2) V_u^2 + V_u V_v (b_{uv} \cos(\theta_u - \theta_v)) \right| \tag{6}$$

b_{shuv}: Shunt susceptance of line u - v in consideration of a π model

Current movement via branches 'b' must be satisfied within their efficiency limits, as proposed in Eq. (7) to maintain the systems security.

$$\left| I_{uv}^b \right| \le I_{uv}^b, max \tag{7}$$

I_{uv}^b = current moving through branch '*b'* between node u and v.

The magnitude of the voltages of individual bus must be ensured within the stated limits, as prescribed, to maintain the dependability and power quality of the network.

$$V^{min} \le V_u \le V^{max}, u = 1, 2, \ldots, N_{bus} \tag{8}$$

Eq. (8) represents the limit of the voltage magnitude for N_{bus}.

For the IEEE 30 bus system, the bus and line data are generated with constant generation and consumption, ensuring a simplified analysis that primarily examines the impact of network reconfiguration on power losses, voltage profiles, and voltage stability indices. This assumption eliminates variability from fluctuating load and generation conditions, allowing for a clearer assessment of reconfiguration effects on distribution system performance.

3. DEFINITION OF THE PROPOSED APPROACH

3.1. Voltage Stability Index

The stability index is an indicator in distribution network which are used to indicate the stability of a power distribution network. It is referred as a voltage stability index (VSI) It helps identifying the critical nodes or branches where voltage may drop significantly, indicating a potential for voltage instability. Consider a single line diagram as shown in figure 1.

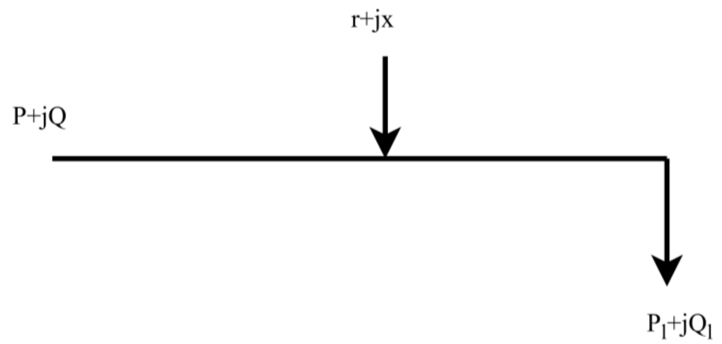


Fig. 1 Single line diagram of power system

From Fig. 1, the real and reactive power equations have been derived [33] as

$$P = r(P^2 + Q^2) / (V^2 + P_l) \tag{9}$$

$$Q = x(P^2 + Q^2) / (V^2 + Q_l) \tag{10}$$

Where;

P: injection of real power
Q: injection of reactive power
r: resistance of line
x: reactance of line
P_l: real load
Q_l: reactive load
V: voltage

From eqns.9 and 10, we can eliminate the $(P^2 + Q^2) / V^2$ terms by rearranging the equations and dividing them, thus obtaining

$$x(P - P_l) = r(Q - Q_l) \tag{11}$$

On rearranging eqn.11, and eliminating Q in eqn.9, a quadratic equation in terms of P is obtained

$$(r^2 + x^2)P^2 - (2x^2 P_l - 2rxQ_l + r)P + (x^2 P_l + r^2 Q_l^2 - 2rxP_l Q_l + rP_l) = 0 \tag{12}$$

The voltage at the sending end is the reference voltage, and its magnitude is kept constant, and in this case V^2.

Hence, from eqn.12,

$$P = \frac{2x^2 P_1 - 2rxQ_1 + r}{2(r^2 + x^2)} - \frac{\left[(2x^2 P_1 - 2rxQ_1 + r^2) - 4(r^2 + x^2) * (x^2 P_1^2 + r^2 Q_1^2 - 2rxP_1 Q_1 + rP_1)\right]^{\frac{1}{2}}}{2(r^2 + x^2)} \tag{13a}$$

Similarly, for reactive power Q, owing to the symmetry of the equations, we can derive the reactive power equation as,

$$Q = \frac{2r^2 Q_1 - 2rxP_1 + x}{2(r^2 + x^2)} - \frac{\left[(2x^2 P_1 - 2rxQ_1 + r^2) - 4(r^2 + x^2) * (x^2 P_1^2 + r^2 Q_1^2 - 2rxP_1 Q_1 + rP_1)\right]^{\frac{1}{2}}}{2(r^2 + x^2)} \tag{13b}$$

The above equations are quadratic in form and, for P and Q to have real roots, hence

$$(2x^2P_1 - 2rxQ_1 + r)^2 - 4(r^2 + x^2) * (x^2P_1^2 + r^2Q_1^2 - 2rxP_1Q_1 + rP_1) > 0 \quad (14)$$

Which, on simplification, can be reduced to

$$4(xP_l - rQ_L)^2 + xQ_l + rP_l < 1 \quad (15)$$

Hence, for the reduced network

$$VSI = 4 * \left(((X_{eqv} * P_{leqv}) - (R_{eqv} * Q_{leqv}))^2 + (X_{eqv} * Q_{leqv}) + (R_{eqv} * P_{leqv}) \right) \quad (16)$$

Where;

P_{leqv}: the total (equivalent) real loads
Q_{leqv}: the total (equivalent) reactive loads
R_{eqv}: the equivalent resistance
X_{eqv}: equivalent reactance

The value of the voltage stability index ranging between 0 to 1. If the value approaching 0 it determined that each node and branch voltages are stable which signifies the system are stable. On the other hand, if the value approaches 1 the system become unstable and likely to be collapse [33].

3.2. Maximal Spanning Tree (MST)

MST is a type of spanning tree within a weighted graph that aims to maximize the sum of the branch weights while still connecting all nodes without forming cycles. While determining the maximum spanning tree, the weight of all the branch of a spanning tree is maximized. The branches denote the distribution lines or conductors that connect two different nodes in the network. Each branch carries electric current from one node to another, allowing the flow of power across the network.

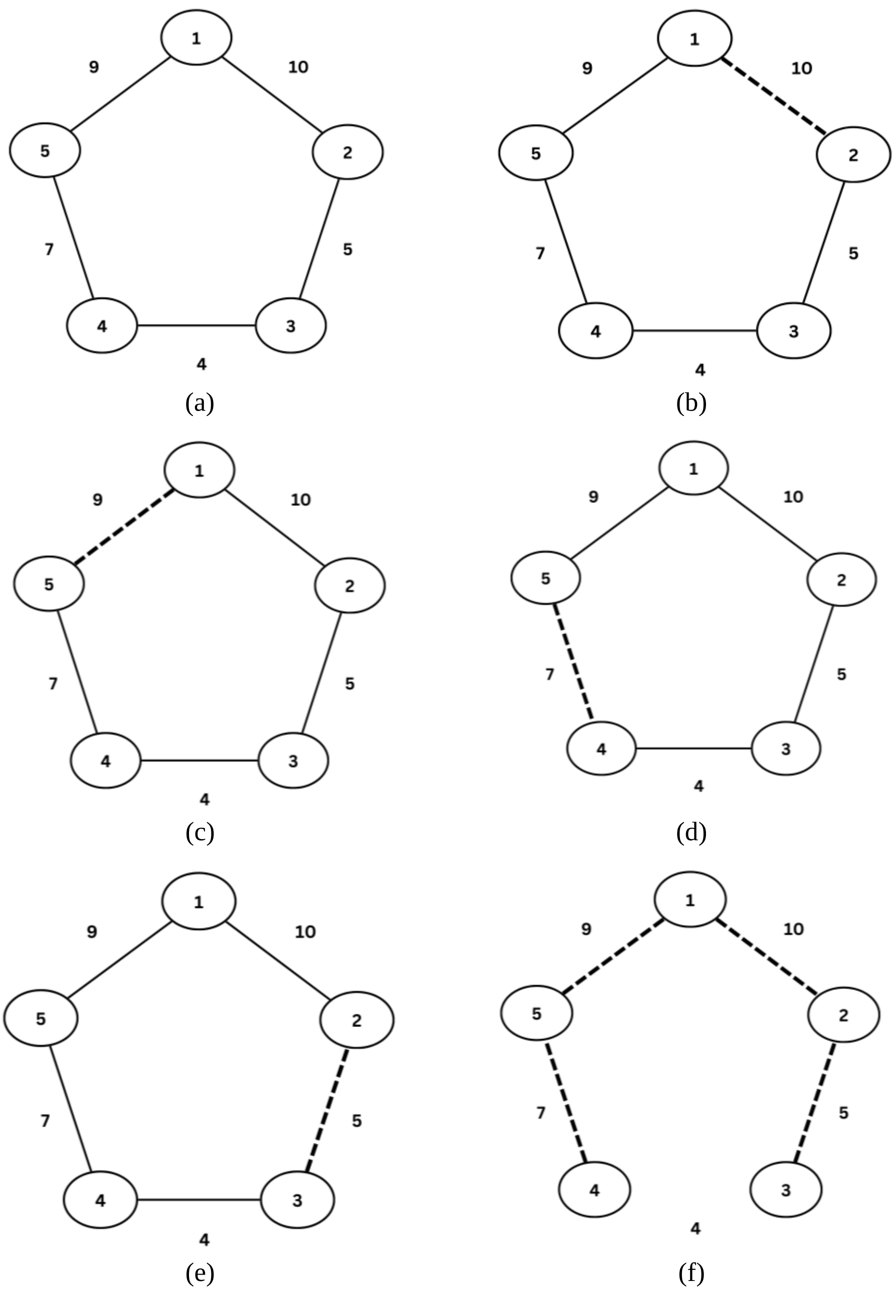
The load carrying capability of the feeder lines also called the Weight of the branch of each feeder lines can be determined by using the relation:

$$\sum_{i=1}^{N_C} LB_N = \frac{V_u V_v}{X_{uv}} \sin(\theta_u - \theta_v) \quad (17)$$

Where;
V_u: Voltages at node u
V_v: Voltages at node v
X_{uv}: Reactance between node u and v
θ_u, θ_v: Phase angle at node u and v.

3.3. Prim's Maximal Spanning Tree

Prim's Maximal Spanning Tree is obtained by connecting all nodes in a spanning tree. The technique begins by selecting an arbitrary starting node and the tree grows by connecting it to another node with the highest weight link. The process involves determining the node with the highest weight, marking unvisited nodes as visited, and updating the weights of the nearby unvisited nodes. Iterations are performed to update the weights, ensuring that the value of each node reflects the weight of the branches connecting it and is higher than the previous branch.



(a) (b) (c) (d) (e) (f)

Fig. 2(a-f) Network reconfiguration using Prim's Maximal Spanning Tree

Fig. 2(a) shows a weighted graph. Node '1' was selected randomly. It searches for the branch with the maximum weight to form a tree. Fig. 2(b) depicts the connection of the branch, '1-2,' marking node '2,' as visited. Fig. 2(c) portrays the connection of the branch, '1-5' consisting of a weight '9,' and marking the node '5' visited. Fig. 2(d) portrays the connection of the branch, '5-4', marking the node '4' visited, resulting in the formation of a tree. The following adjacent node, '2,' is visited, and branch '2-3' is connected, as depicted in Fig. 2(e). Fig. 2(f) shows the maximum spanning tree deduced from the graph (Fig. 2(a)).

Pseudo Code for Prim's Maximal Spanning Tree:

1. Initialize variables for Prim's algorithm.
   T=Zero-Matrix (m-1,3) %Matrix to store MST branch (first node, second node, cost)
   C = [1] %Starting node for Prim's algorithm
   C_N= All Nodes - [1] %List of nodes excluding the starting node
2. For k from 2 to m
   Initialize min = infinity
   For each node i in C
   For each node j in C_N,
   If V_MAT (i, j) < min
   Update min to V_MAT (i, j)
3. Set s = i, e = j, counter = index of j in C_N %% s=start node e=end node counter=node to remove
4. Add node e to C
5. Remove node at position counter from C_N
6. Insert [s, e, min] to T (start node, end node, and branch weight)

3.4. Interior Point Method (IPM)

Linear standard programming problems were solved using the interior-point method. The general representation of the objective function and constraints is elucidated in eqn. 18 and 19, respectively, for the applied optimization technique. The constraints outlined in eqn. 19 must be satisfied to derive the objective function described in eqn. 18. The minimized value of the objective function obtained through optimization must adhere to the constraints specified in eqn. 19, ensuring that it lies within the feasible region, as indicated in eqn. 20.

$$\text{Minimize } g(y_{mx1}) = B^T y_{mx1} \tag{18}$$

$$\text{Subject to } C_{ymx1} = a_{nx1},\ a \geq 0,\ y \geq 0 \tag{19}$$

Eqn. 18 represents the minimization of the objective function subjected to the constraints given in eqn. 19. Given the cost factor $B \in R^n$, m are linear equality constraints denoted by a matrix $C \in R^{m*n}$ and a vector $b \in R^m$.

The Feasible region F_r is defined as,

$$F_r = \{y \mid C_y = a, y \geq 0\} \tag{20}$$

The eqn. 20 represents the set of all possible points that satisfy the constraints given in eqn. 19 of the optimization problem.

The procedures for implementation of the Interior Point Method are:

- **Procedure 1**: The iterative process is started by identifying an initial workable point solution, ensuring that the interior point resides within the feasible region outlined in eqn. 20.

- **Procedure 2**: A new viable interior point is generated with a reduced value for the objective function.
- **Procedure 3**: Verifying the optimality of selected points. If point is not optimal, return to Step 2 and repeat the process.

4. RESULT AND DISCUSSION OF THE SUGGESTED METHODOLOGY

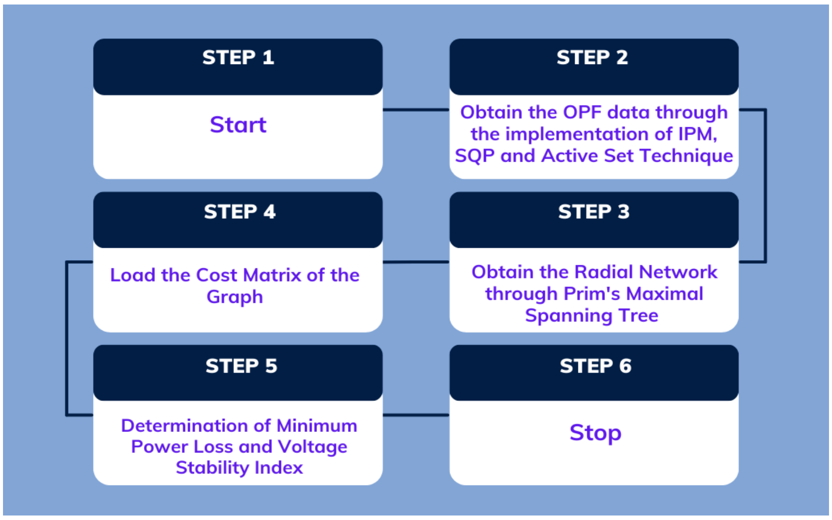


Fig. 3 Flowchart depicting the proposed methodology

Fig. 3 shows the flowchart outlining the proposed method. To assess the optimal voltage magnitudes and angles for all buses in different test system scenarios, we conducted a load flow analysis using interior point, sequential quadratic programming, and active set methods. The optimized voltage magnitudes and phase angles were determined using the above methods, while considering the specified objective function and constraints for the IEEE 30-node system. The constraints were assessed based on observations of the load-flow problem. Data obtained from the OPF were used to determine the maximum power limit. Prim's maximal Algorithm can be used for an '*N*' node network to determine the optimal radial network. Branch cost values were employed when creating the optimum radial network to ensure the most directed spanning tree. In the present study, for a network '*N'* node $N \times N$ size, a load-bearing capability matrix was generated for N_c nodes based on Eq. (17). Now for a feeder that connects *'u'*, *'v'*, and node, the element of adjacency matrix can be represented by a_{uv}, if there is no connectivity, then $a_{uv} = 0$. The illustration of the cost matrix for Fig. 2(a) has been explained in Table 1.

The cost of the sides, which are not interconnected, are depicted as follows: $a_{11} = a_{13} = a_{14} = a_{22} = a_{24} = a_{25} = a_{31} = a_{33} = a_{35} = a_{41} = a_{42} = a_{44} = a_{52} = a_{53} = a_{55} = 0$. The cost of sides interconnecting the pairs of nodes is given as, $a_{12} = a_{15} = a_{21} = a_{23} = a_{32} = a_{34} = a_{43} = a_{45} = a_{51} = a_{54} = 1$.

In this research, the components of the cost matrix are derived using computational load power flow evaluation, which is accomplished using the Interior Point Method, SQP and Active Set Method to evaluate the system power flow of the target function. Prim's Maximal Spanning Tree is used to construct the radial network using the adjacency matrix produced by the cost function, wherein a search for a radial system with feeders with greater load-carrying capability is performed. After ascertaining the load-carrying capability and power distribution among all feeder lines, anyone with lower load-carrying ability was excluded. Consequently, in the proposed methodology, feeders with lower weight-carrying capabilities are placed outside the operation and feeders with higher load-carrying capabilities are selected while unlocking the sectionalizing switches. The system's power demands both reactive and active power are 126.20 MVAR and 283.40 MW, respectively. For a 30-node system, the load-carrying capability matrix or cost matrix size was 30X30, and was calculated using Eq. 17. The optimal load flow problem converges by implementing IPM, resulting in optimized voltages and phase values for the proposed methodology. In the present work, 30-node systems are considered as test systems, as shown in Fig. 4, with one sectionalizing series.

Table 1 Illustration of cost matrix feeder for Fig.1(a)

	node 1	node 2	node 3	node 4	node 5
node 1	0	1	0	0	1
node 2	1	0	1	0	0
node 3	0	1	0	1	0
node 4	0	0	1	0	1
node 5	1	0	0	1	0

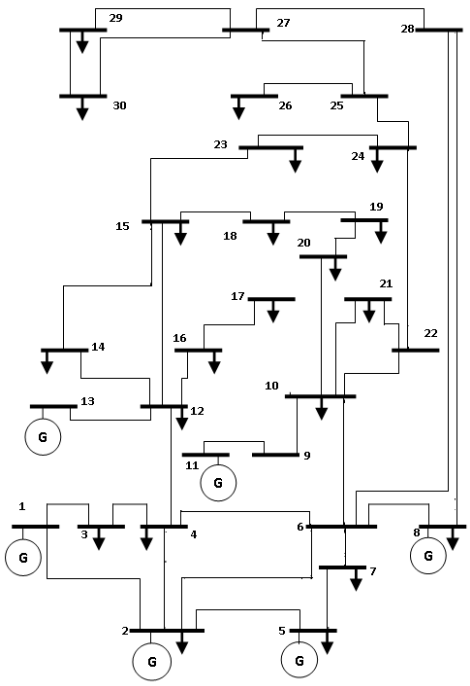


Fig. 4 30-node system

Each feeder is switched on and off sequentially ranging $\sum_{j=1}^{41} Sw_j$ as depicted in Table 2.

Table 2 Switch configuration data for the IEEE 30-Bus System

Start Bus	Terminate Bus	Switch
1	2	Sw_1
2	3	Sw_2
2	4	Sw_3
3	4	Sw_4
2	5	Sw_5
2	6	Sw_6
4	6	Sw_7
5	7	Sw_8
6	7	Sw_9
6	8	Sw_{10}
6	9	Sw_{11}
6	10	Sw_{12}
9	11	Sw_{13}
9	10	Sw_{14}
4	12	Sw_{15}
12	13	Sw_{16}
12	14	Sw_{17}
12	15	Sw_{18}
12	16	Sw_{19}
14	15	Sw_{20}
16	17	Sw_{21}
15	18	Sw_{22}
18	19	Sw_{23}
19	20	Sw_{24}
10	20	Sw_{25}
10	17	Sw_{26}
10	21	Sw_{27}
10	22	Sw_{28}
21	22	Sw_{29}
15	23	Sw_{30}
22	24	Sw_{31}
23	24	Sw_{32}
24	25	Sw_{33}
25	26	Sw_{34}
25	27	Sw_{35}
28	27	Sw_{36}
27	29	Sw_{37}
27	30	Sw_{38}
29	30	Sw_{39}
8	28	Sw_{40}
6	28	Sw_{41}

4.1. Case 1: Implementation of Prim's Maximal Spanning Tree -based Interior Point Method

The maximal spanning tree-based Interior Point Method was used to optimize power distribution networks by minimizing power losses and enhancing voltage stability. This approach combines the Interior Point Method (IPM), effective for large-scale linear optimization, with Prim’s algorithm tailored for Maximal Spanning Tree to maximize the weighted sum of network connections and prioritize efficient pathways. In this setup, the cost-matrix calculation identifies the optimized paths, resulting in real and reactive power losses of 2.0062 p.u. and 0.71938 p.u., respectively. The optimized network achieves a VSI of 0.1457 p.u., showing strong resilience against voltage fluctuations. The optimal configuration, shown in Fig. 5, connects all essential nodes in a cycle-free radial network, as depicted in Fig. 6, enhancing the stability and efficiency of the network. The presented framework proves valuable in power systems research, supporting modern grid stability and efficient power delivery. p.u. stands for Per Unit. It is a normalized value used in power systems to express electrical quantities such as voltage, current, power, impedance, etc. in a dimensionless form. It is defined as a ratio of actual value in any unit to the base value of the same unit.

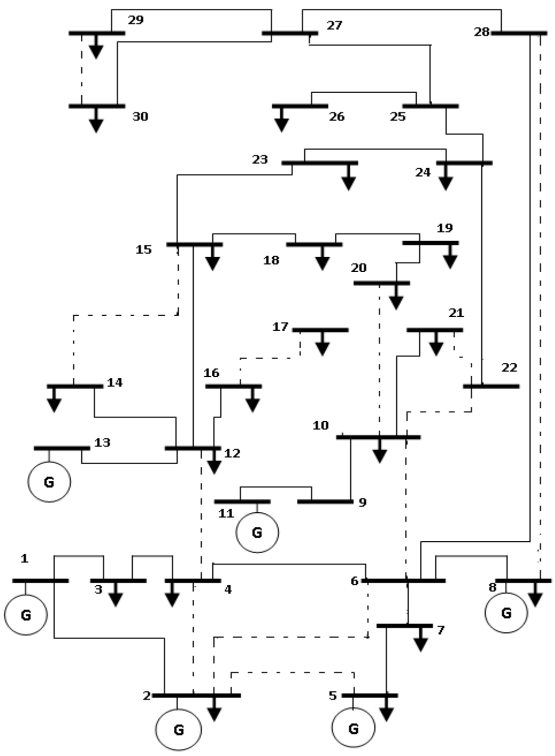


Fig. 5 Optimal configuration of Prim’s Maximal Spanning Tree through implementing Interior Point Method

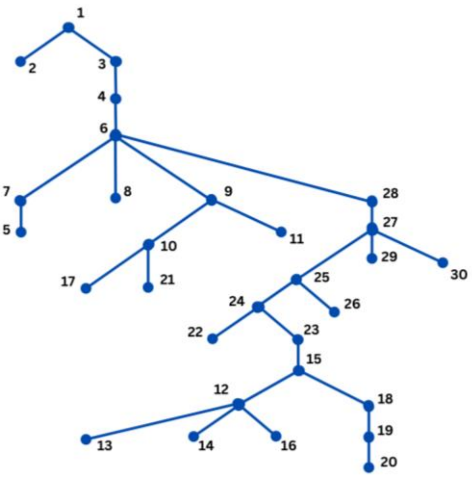


Fig. 6 Graphical configuration of Prim's Maximal Spanning Tree by applying the Interior Point Method

4.2. Case 2: Implementing sequential quadratic programming method based on Prim's Maximal Spanning Tree

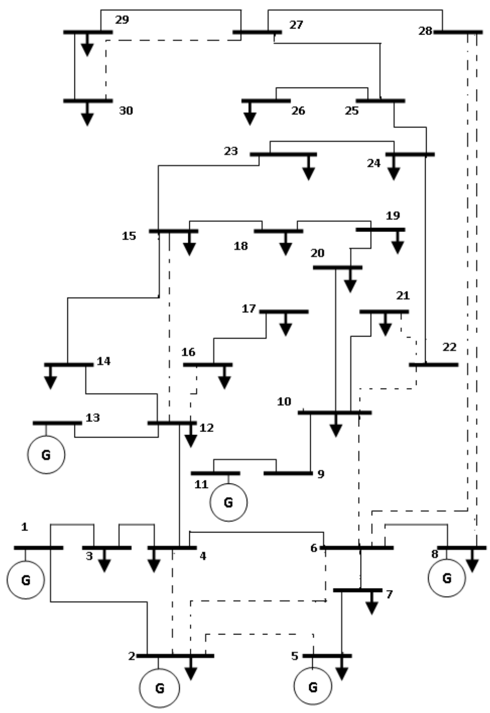


Fig. 7 Optimal configuration of Prim's Maximal Spanning Tree through implementing SQP

In this case, the load flow analysis was performed using sequential quadratic programming (SQP). The SQP method optimizes the voltage and phase angle data, ensuring compliance with the power-balanced constraints. Using Prim's maximal spanning tree, we derived an optimized radial network with minimal power loss by employing the cost matrix formulated with the optimized voltage and phase angles.

The reactive and active power losses achieved through Prim's Maximal Spanning Tree -based SQP were 2.9068 and 0.7617 p.u., respectively. The optimum VSI is 0.1572 p.u. The optimal configuration of Prim's Maximal Spanning Tree tree-based SQP is illustrated in Fig. 7. Fig. 8 shows the graphical topology of Prim's Maximal Spanning Tree -based SQP.

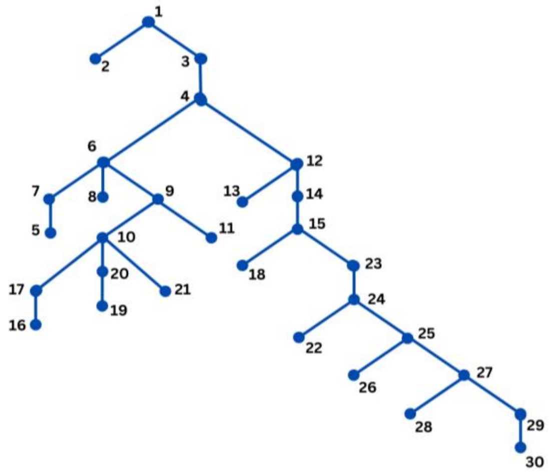


Fig. 8 Graphical configuration of Prim's Maximal Spanning Tree through implementing SQP

4.3. Case 3: Implementation of Prim's MST-based Active-Set Method

Another optimization methodology, the active-set method, was employed to address the load flow problem and successfully converged. Prim's Maximal Spanning Tree algorithm determined the optimal radial path for the IEEE 30-node system using the active-set optimization approach while satisfying the power balance constraints. The resulting active and reactive power losses are 0.72731 p. u. and 2.8586 p. u., respectively, obtained using optimized data through Prim's maximal spanning tree-based Active Set Method. The obtained VSI was 0.1635 p.u. The optimal configuration obtained through Prim's maximal spanning tree-based Active Set Method of the IEEE 30-node system is shown in Fig. 9. Fig. 10 illustrates a graphical representation of Prim's maximal spanning tree-based Active Set Method.

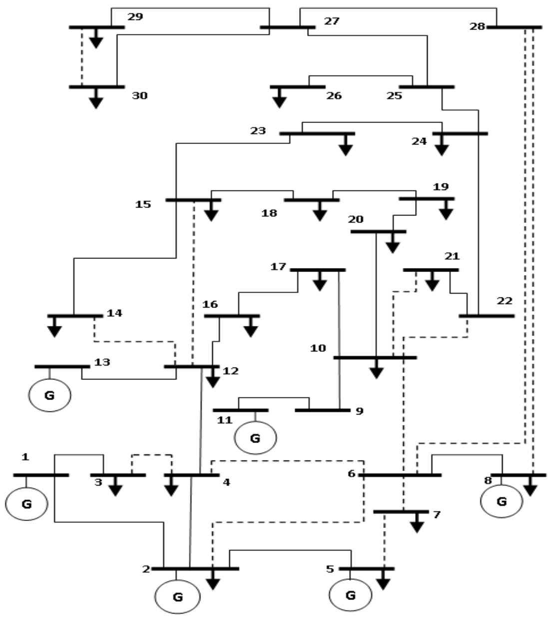


Fig. 9 Optimal configuration of Prim's Maximal Spanning Tree through the implementation of Active Set

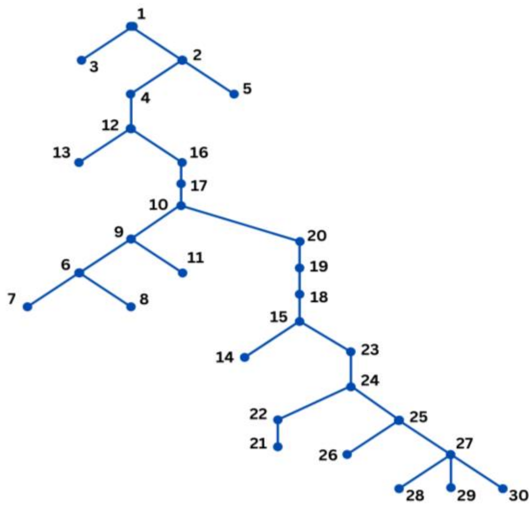


Fig. 10 Graphical configuration of Prim's Maximal Spanning Tree through the implementation of Active Set

4.4. Comparison of the Proposed Methodologies

Table 1 lists the switch configuration data for an IEEE 30-node system. Various case studies were conducted to evaluate the robustness and effectiveness of the proposed algorithm, and Prim's Maximal Spanning Tree-based Interior Point Method was compared with other techniques, as detailed in Table 3 and illustrated in Fig. 11 through a comparative chart.

Table 3 Comparative results for Prim's Maximal Spanning Tree utilizing Optimization Techniques on the IEEE 30-bus system for Active Power Loss, Reactive Power, and Voltage Stability Index

Radial Layout	Switches that are in the open position	Active Power Loss (p.u.)	Reactive Power Loss(p.u.)	Voltage Stability Index(p.u.)
1(Prim's maximal spanning tree-based Interior Point Method)	S40, S39, S29, S28, S25, S21, S20, S15, S12, S6, S5, S3	0.71938	2.0062	0.1457
2(Prim's maximal spanning tree-based SQP)	S41, S40, S38, S29, S28, S23, S19, S18, S12, S6, S5, S3	0.7617	2.9068	0.1572
3(Prim's maximal spanning tree-based Active Set)	S41, S40, S39, S28, S27, S18, S17, S12, S8, S7, S6, S4	0.72731	2.8586	0.1635
4(Kruskal's maximal spanning tree) [32]	S40, S39, S35, S31, S29, S26, S24, S20, S12, S8, S3	1.099	2.244	0.2821
5(Edmonds' Algorithm) [32]	S40, S39, S3, S31, S29, S26, S24, S20, S12, S8, S6, S3	1.0484	2.0065	0.1685
6(SSO) [36]	S41, S39, S32, S24, S27, S14, S19, S6, S5, S3	1.6	2.3201	0.2063

Prim's maximal spanning tree-based Interior Point Method outperformed all other configurations in terms of efficiency and stability, as shown in Table 4. Layout 1 shows lower losses, with an active power loss of 0.71938 p.u., as depicted in Table 3, compared to other methodologies. Layout 1 achieves the reactive power loss of 2.0062 p.u., which is lower than the values observed in other methodologies. Layout 1 achieved the highest stability among the other layouts, with a voltage stability index of 0.1457 p.u. A voltage stability index closes to zero indicates the highest level of stability in the system, enhancing the system's reliability by making the network less prone to voltage collapse, thus reducing the risk of a blackout. As depicted in Table 4, 5.88% higher of active power loss compared to Layout 1, meaning Layout 2 has nearly 6% more active power loss than Layout 1 and 44.89% for reactive power loss, indicating almost 45% more reactive power loss and 7.89% less stable as compared to Layout 1 for IEEE-30 bus system. For Layout 3, the active power loss was 1.10% higher than that for Layout 1. The reactive power loss is 42.49% higher compared to Layout 1, approximately 42% more, and the system is 12.22% less stable than Prim's maximal spanning tree-based Interior Point Method (Layout 1). The active power loss for layout 4 was 52.77% higher, showing a significant increase in power loss (i.e., over 50%). The active power loss for Layout 4 was 11.85% higher than that of Layout 1, indicating a nearly 12% increase in reactive power loss. Additionally, it was 93.62% higher, indicating a significant decrease in stability compared to Layout 1. Layout 4 exhibits a 45.74% higher active power loss, nearly 46% more compared to Layout 1. It also shows a 0.01% higher reactive power loss and is 15.65% less stable (approximately 16%) than

Layout 1, as shown in Table 4. In contrast, Layout 5 demonstrates a 122.41% higher active power loss, a 15.65% increase in reactive power loss, and a 41.59% reduction in voltage stability, indicating significantly lower performance compared to Layout 1.

These percentages illustrate that Layout 1 achieves the lowest active and reactive power loss and optimal voltage stability. Other layouts have increased losses and decreased stability, with Layout 6 showing the highest active power loss at over 122% more than Layout 1. Table 3 presents a comparative analysis of various techniques in terms of real and reactive power loss minimization (in p.u.) and the voltage stability index (in p.u.). Based on these findings, Prim's maximal spanning tree-based Interior Point Method outperforms other methods in minimizing power loss and enhancing voltage stability.

Table 4 Comparative results for Prim's Maximal Spanning Tree -based Interior Point Method outperforming other methods in minimizing power loss and enhancing voltage stability

Layout	Prim's Maximal Spanning Tree based Interior Point Method (Layout 1)			
	Methodologies	Percentage increase in Active Power Loss	Percentage increase in Reactive Power Loss	Relative Percentage change in Voltage Stability Index
2	Prim's Maximal Spanning Tree - based SQP	5.88%	44.89%	7.89%
3	Prim's Maximal Spanning Tree - based Active Set	1.10%	42.49%	12.22%
4	Kruskal's Maximal Spanning Tree [32]	52.77%	11.85%	93.62%
5	Edmonds' Algorithm [32]	45.74%	0.01%	15.65%
6	SSO [36]	122.41%	15.65%	41.59%

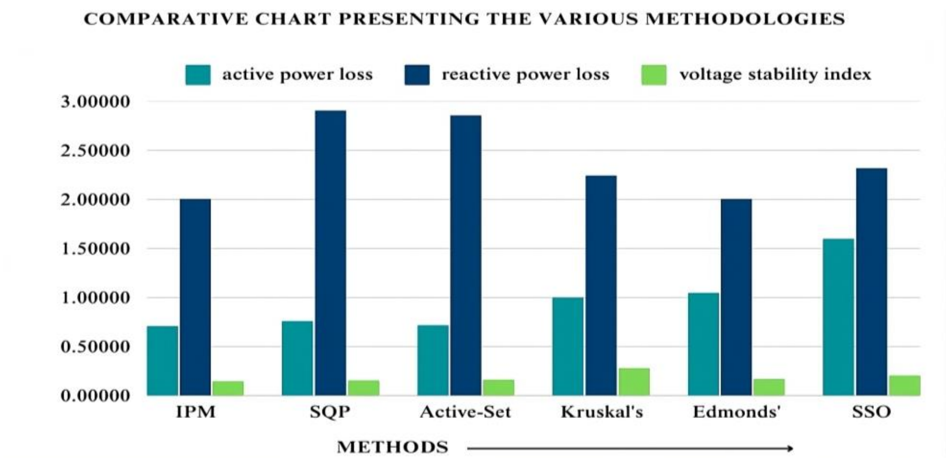


Fig. 11 Comparative chart presenting the various methodologies implemented

In Fig. 11, a comparative chart presents the performance of Prim's Maximal Spanning Tree method against various optimization techniques employed for load flow analysis, specifically the Interior Point Method, Sequential Quadratic Programming (SQP), and Active-Set Method. For a comprehensive comparison, Kruskal's spanning tree [32], Edmonds' Algorithm [32], and Social Spider Optimization (SSO) [36] are also included.

The integration of Prim's Maximal Spanning Tree algorithm with the Interior Point Method (IPM) has shown exceptional effectiveness in optimizing distribution network configurations. It surpasses other methods, such as Prim’s Maximal Spanning Tree (MST) algorithm-based sequential Quadratic Programming, and Prim’s Maximal Spanning Tree (MST) algorithm-based active set methods, Edmonds’, and Kruskal’s Maximal Spanning Tree algorithms, as well as Social Spider Optimization, in key performance such as minimizing power losses and enhancing voltage stability. The combination of these algorithms ensures the creation of an optimal radial network, marked by a minimized voltage stability index and reduced power losses, as clearly depicted in Fig. 11, emphasizing the significant improvements in network efficiency and demonstrating its ability to stabilize and optimize the efficiency of distribution systems.

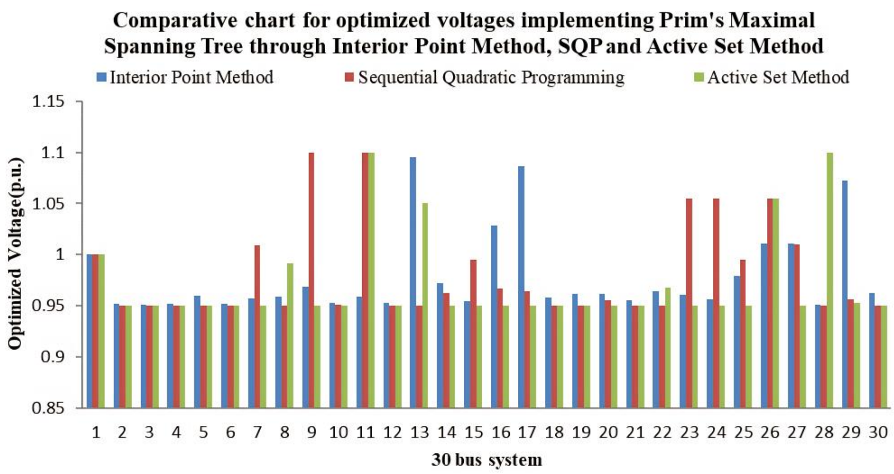


Fig. 12 Comparative analysis for optimized voltages implementing Prim's Maximal Spanning Tree using the Interior Point Method, SQP and Active Set Method.

Fig. 12 illustrates a comparative analysis of optimized voltage profiles achieved using three distinct optimization techniques—Prim’s Maximal Spanning Tree -based Interior Point Method**,** Sequential Quadratic Programming (SQP)**,** and the Active Set Method, applied to the load flow problem for the IEEE 30-bus system. Each optimization approach uses a radial configuration through Prim’s Maximal Spanning Tree framework, tailored to enhance network performance. The chart visually contrasts the optimized voltages attained by these methodologies, providing a clear depiction of their effectiveness in voltage optimization for a complex bus system. The comparative analysis in Fig. 12 underscores the variations in voltage performance among the techniques, highlighting the potential of each method to achieve reliable and stable voltage levels across the network.

5. Conclusion and Future Work

5.1. Conclusion

The proposed hybrid approach, which combines Optimal Power Flow (OPF) techniques and graph theory, optimizes the IEEE 30-bus system. By employing methodologies such as the Interior Point Method, Sequential Quadratic Programming, and the Active Set Method, the presented work shows a significant reduction in active and reactive power losses and, enhances the voltage profiles in the reconfigured network. Using Prim's Maximal Spanning Tree algorithm combined with OPF not only optimizes achieving a feasible radial topology but also eliminates the complexities associated with the mesh structure. This study compares the performance of the proposed method, that is, Prim's Maximal Spanning Tree-based Interior Point Method, with other techniques such as Prim's Maximal Spanning Tree algorithm-based Sequential Quadratic Programming, and Prim's Maximal Spanning Tree algorithm-based active set methods, Edmonds' Maximal Spanning Tree, Kruskal's Maximal Spanning Tree, and Social Spider Optimization. The results presented in Table 4 demonstrate that Prim's Maximal Spanning Tree-based Interior Point Method outperformed all the other configurations regarding efficiency and stability. The proposed methodology (Layout 1) shows significantly lower power losses and a better voltage stability index as depicted in Table 4. Specifically, Prim's Maximal Spanning Tree-based SQP has 5.88% higher active power loss when compared with the proposed methodology, 44.89% more reactive power loss, and 7.89% higher voltage stability index than Prim's Maximal Spanning Tree-based Interior Point Method. Prim's Maximal Spanning Tree-based Active Set is 1.10% higher in active power loss, 42.49% higher in reactive power loss, and 12.22% higher in voltage stability index compared to the proposed methodology. The active power for Edmonds' Algorithm was 52.77% higher, showing a significant increase in power loss (over 50%), 11.85% higher in reactive power loss, and 93.62% higher in voltage stability index, almost doubling, which indicates that it is much less stable. For SSO, 122.41% higher than the active power loss, 15.65% higher in reactive loss, and 41.59% higher in voltage stability than Prim's Maximal Spanning Tree-based Interior Point Method. Based on the analysis, Prim's Maximal Spanning Tree-based Interior Point Method demonstrates superior performance compared to other techniques, in terms of power losses and enhances the overall efficiency and performance of the distribution network.

5.2. Future Work

Future research will aim to improve the computational performance of the proposed model by applying it to larger bus systems, such as the IEEE 57-Bus system or IEEE 118- Bus systems. Furthermore, more sophisticated metaheuristic techniques will be integrated with advanced graph theory methods to manage larger bus systems and address more complex distribution network, ultimately enhancing voltage stability and overall system performance while minimizing both active and reactive power losses. The proposed methodology can be extended to scenarios with time-varying generation and consumption, incorporation of renewable energy and battery energy system which will be considered in future work to further enhance the practical applicability of the approach.

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