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# Sensitivity-Driven optimization analysis for renewable resource allocation and energy distribution systems

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**Abstract**:

Integration of renewable energy resources into modern-day energy systems poses numerous problems associated with uncertainty, resource allocation, and network stability. Existing optimization methods tend to consider only nominal operations and fail to ensure the robustness of the network under adverse scenarios with regard to variations in renewables, changes in demand, deteriorating network performance, and other factors. This paper presents the Graph-Sensitivity-Driven Minimax Optimization Framework, which allows robust renewable resource allocation and management of energy distribution. The presented method considers the renewable energy distribution network as a weighted graph, where generation nodes, storage nodes, substations, and demand nodes are considered nodes, while paths for energy transfer are considered edges. Sensitivity analysis of the network nodes and edges is conducted to find out the critical components of the network, whose deterioration could have a strong impact on overall network performance. The designed GSDOA framework examines uncertain conditions and optimizes the allocation of renewable generation and storage, as well as the decision regarding transmission of power, subject to certain operational constraints. Results of the experimental evaluation using various network distributions and renewable energy sources reveal that the designed framework exhibits better robustness than the deterministic optimization, cost optimization, conventional minimax robust optimization, and graph-insensitive robust optimization frameworks. The designed framework obtains a result where 95.4% renewable energy is used, energy loss is at 5.72%, connectivity loss is at 6.1%, and loss of worst case is 7.8%.

*Keywords:* Renewable energy allocation, graph sensitivity analysis, minimax optimization, energy distribution networks, robust optimization, network resilience, uncertainty management.

## 1. Introduction

The fast incorporation of renewable energy has led to new issues in the efficient allocation and distribution of the resources. Both solar and wind energy generation are variable in nature, but there could also be variability in the demand, transmission, and storage capabilities of the energy at various times. Load forecast accuracy is therefore an essential factor in the planning and operation of power systems since changes in electricity demand may impact generation scheduling and performance (Manke et al., 2025). This implies that optimization techniques should be developed that can ensure efficient network operation in cases of uncertainty. There is an obvious relationship between energy distribution networks and graph theory in the sense that the nodes in graph theory consist of the energy generation facilities, storage capabilities, substations, and demands.

An important problem is the dependence of network performance on node and edge parameters' perturbations. Minor perturbations in generation capacity, demand, transmission limits, or available resources can lead to major performance alterations depending on the nature of critical components. Traditional methods of allocation that are based on a deterministic approach generally optimize performance under predetermined assumptions, but are not sufficiently protective in case of a bad combination of parameters. Therefore, there is a need to incorporate graph sensitivity analysis into minimax optimization to minimize the worst effect of perturbations caused by uncertain network state.

The research gap is in the lack of integration of graph structure sensitivity analysis with worst-case resource allocation. This study proposes a graph-sensitivity-based minimax optimization approach to evaluate critical network components and perform robust renewable resource allocation. The contributions include sensitivity-based criticality evaluation, sensitivity-weighted minimax formulation, allocation optimization, and performance evaluation.

The rest of this paper is organized as follows: Section 2 gives a review of the literature and the gap in the existing research. Section 3 provides the graph modeling for the renewable energy distribution system. Section 4 illustrates the graph-sensitivity approach that is developed. Section 5 formulates the sensitivity-based minimax optimization problem. Section 6 proposes the optimization algorithm. Section 7 deals with the theoretical analysis, whereas Section 8 focuses on the experiment design. Section 9 includes the results and discussion, followed by the engineering interpretation in Section 10 and conclusions in Section 11.

## 2. Literature review

New studies have been increasingly highlighting the use of sensitivity-aware optimization in order to develop the planning, allocation, and operation of renewable energy and distribution networks. Studies show that sensitivity-based optimization is an effective way of increasing the capacity of distribution networks with consideration of uncertainties, which shows the importance of sensitivity in the optimization of networks (Pan et al., 2025). The integration of hybrid solar-wind systems has also benefited from flexible reconfiguration of networks and optimization that takes into account uncertainties, especially regarding flexibility. Sensitivity-based optimization has also been used in the allocation of distributed generation systems (Rajakumar et al., 2026).

The multi-criteria approach has been used in selecting renewable technologies through the analysis of conflicting criteria in economics, technology, and sustainability aspects, emphasizing the need for balance among different objectives in the decision-making process when dealing with renewable resources (Lamba & Chandrakar, 2025). The regional allocation and optimization process has proven the necessity of spatial resource allocation for the environmental performance of renewable energy systems (Hao et al., 2025). The area of energy-aware scheduling has also emphasized the importance of optimization within budgetary limitations for resource efficiency and meeting functional constraints (Sripavithra & Kirubanand, 2025). There has also been an increasing emphasis on robust optimization in energy systems, and distributionally robust optimization in particular (Shao et al., 2025).

The concept of sensitivity analysis has been applied to energy hubs, energy storage systems, electric vehicle planning, and voltage control, showing the significant effect of small changes in parameters on the system operation (Liu et al., 2025; Sadi & Alilou, 2026; Naservand & Neghab, 2025). Energy management approaches based on reinforcement learning have also been developed to deal with uncertainties in renewable generation and energy storage systems within microgrids operating in standalone mode (Khan et al., 2026; Hou et al., 2026; Khakpour & Farjah, 2026). Photovoltaic-battery capacity optimization problems have been considered with uncertainty taken into account, highlighting the importance of robust decision-making in such cases (Li et al.,

2026). The effectiveness of the sensitivity-driven controller design and the graph partitioning approaches in optimization problems shows the value of the integration of sensitivity information with optimization strategies for renewable and distribution networks (Kumbhakar & Banerjee, 2026; Zhang et al., 2026).

Optimization search methods can also serve as a foundation for the exploration of complex solution spaces through population methods including the modified bee colony algorithm, which exemplifies how adaptive search methods can solve difficult combinatorial optimization problems (Agrawal et al., 2012). Such an approach is applicable in renewable resources management, since there will likely be many possible options that need to be considered with many different constraints.

Yet the previous works mainly concentrate on particular planning, control, placement, and sizing issues and fail to integrate graph sensitivities, worst-case uncertainties, and renewable generation in a unified minimax approach. Studies in other engineering fields prove the applicability of sensitivity-driven optimization strategies (Li et al., 2026; Shokoohi & Vosoughifar, 2026; Zhang et al., 2025). This work is inspired by the aforementioned gaps and develops a minimax optimization strategy based on graph sensitivities that determines critical nodes and edges and assigns renewable generation.

## 3. Graph representation of the renewable energy distribution system

### 3.1. Network graph construction

The renewable energy power distribution system is represented by a directed weighted graph G = (V, E), where V represents the nodes of the network, and E represents the set of edges representing either transmission or distribution routes. Nodes represent operational and physical components of the energy distribution system such as renewable generation, battery storage, substations, and demands for energy. The renewable generation nodes represent energy generators based on renewable sources such as the sun and wind; the storage nodes represent storage of the energy; substations represent network transfers; and demand nodes represent consumers of electricity. An edge (i, j) ∈ E represents a path for power transfer from node i to node j. The directions of edges may represent permissible flow of energy, whereas weights may represent electrical distances or transfer costs.

### 3.2. Node and edge attributes

Each node $i$ is associated with attributes including renewable generation capacity $P_i^{\max}$, demand $D_i$, storage capacity $S_i^{\max}$, operating cost $C_i$, and reliability parameters. Edge $e_{ij}$ is characterized by transmission capacity $F_{ij}^{\max}$, transfer cost, loss coefficient, and reliability level. These attributes enable the graph to capture both structural and operational characteristics of the energy network.

### 3.3. Network connectivity and energy flow

Energy travels along connected routes from generation nodes towards storage nodes, substations, and demand nodes based on capacity and balance constraints. The choice of allocation of renewables affects the supply at the nodes and hence the possible flow of energy within the network. Changes in capacities of edges can also limit connectivity within the network. Graph connectivity can therefore be used to assess the ability of renewables to connect to demand nodes. It also allows for sensitivity analysis.

## 4. Graph-sensitivity analysis

### 4.1. Baseline network performance

Graph sensitivity analysis becomes the backbone of the suggested methodology because it measures how changes to the elements of the network affect the performance of the distribution of renewable energy. If G = (V, E) represents the base network and P(G) is the performance of the network, then the performance function of the base network will comprise the following four parameters. The normalized form of the above function can be represented as follows in equation 1.

$$P(G) = w_c C(G) + w_e E_d(G) + w_r R_u(G) - w_l L(G) \qquad (1)$$

Where $C(G)$ represents network connectivity, $E_d(G)$ denotes delivered energy, $R_u(G)$ represents renewable utilization, $L(G)$ denotes energy loss, and $w_c,\ w_e, w_r, w_l$ are weighting coefficients. This formulation provides a reference against which network perturbations can be evaluated.

### 4.2. Node sensitivity

For node $i$, sensitivity measures the change in network performance resulting from a perturbation in its generation, storage, or demand parameter. It can be defined as equation 2

$$S_i^V = \frac{|P(G) - P(G \setminus i)|}{P(G) + \epsilon} \quad (2)$$

Where $G \setminus i$ denotes the network after the corresponding node perturbation and $\epsilon$ prevents numerical instability. A larger value indicates greater structural or operational importance.

### 4.3. Edge sensitivity

Similarly, the sensitivity of edge $e_{ij}$ is obtained by evaluating the performance change caused by reducing its transmission capacity or removing the connection in equation 3

$$S_{ij}^E = \frac{|P(G) - P(G \setminus e_{ij})|}{P(G) + \epsilon} \quad (3)$$

This identifies transmission links whose degradation can substantially affect energy delivery.

### 4.4. Sensitivity matrix

Node and edge sensitivities are organized into a unified sensitivity representation in equation 4

$$\mathrm{S} = \left[S_1^V, \ldots, S_{|V|}^V, S_1^E, \ldots, S_{|E|}^E\right] \quad (4)$$

Which provides a quantitative map of network vulnerability.

### 4.5. Critical nodes and critical edges

Components are sorted based on their sensitivities. Those components that have a sensitivity level higher than the preset limit value are termed critical components.

### 4.6. Sensitivity-guided resource prioritization

Resources that can be replenished are preferentially distributed in areas where the addition of new generation and storage facilities would enhance energy connectivity and decrease their vulnerability. Consequently, the sensitivity data convert graph theory into distribution priorities, forming the basis of the following minimax optimization.

## 5. Minimax optimization formulation

The minimax approach will provide a solution for allocating renewable resources that will be efficient even when there is an unfavorable operational state of the system, as identified using the graph sensitivity approach.

### 5.1. Decision variables

Let $x_i$ denote renewable energy allocated to generation node $i$, $s_i$ denote storage allocation, and $f_{ij}$ denote energy transmitted through edge $(i, j)$. Additional variables represent storage charging/discharging and network operating states.

### 5.2. Objective function

For an uncertainty scenario $\xi$, the operational loss is defined as equation 5

$$J(x, \xi) = \alpha C(x) + \beta L(x, \xi) + \gamma D_c(x, \xi) - \delta R(x, \xi) \quad (5)$$

Where $C$ is allocation cost, $L$ is energy loss, $D_c$ is connectivity degradation, and $R$ is renewable utilization. The coefficients represent their relative importance.

### 5.3. Uncertainty set

Uncertainty is represented by $\xi \in \mathcal{U}$, incorporating variations in renewable generation, electricity demand, transmission capacities, and component availability. The set $\mathcal{U}$ defines the admissible adverse operating conditions.

### 5.4. Minimax formulation

The robust allocation is obtained through:

$$\min_{x} \max_{\xi \in \mathcal{U}} J(x, \xi)$$

Thereby minimizing the maximum achievable operational loss.

### 5.5. Constraints

The optimization will meet constraints regarding generation, demand, storage capacity, transmission, availability of renewables, energy flow, and network feasibility.

### 5.6. Sensitivity-weighted robustness

The sensitivity of graphs is introduced using the concept of graph weights per node/edge. This means that nodes and edges that are more sensitive will get higher penalties whenever their performance drops off.

## 6. Proposed graph-sensitivity-driven optimization algorithm

The novel Graph Sensitivity Driven Optimization Algorithm (GSDOA), which uses graph theoretical sensitivity analysis along with minimax optimization to find reliable allocations of renewable resources in spite of bad working condition, starts by collecting the data from the energy network in the form of generation capacity, demand, storage capacity, transmission capacity, operating cost, and component reliability. The distribution network is modeled as a weighted graph G= (V, E).

A first feasible renewable allocation is obtained, and the baseline network performance is calculated. Then, all pertinent nodes and edges are perturbed one at a time, or in controlled degradation scenarios. Based on the performance change, sensitivity scores for the nodes and edges are obtained. Nodes and edges that have high sensitivities are considered critical components and assigned higher protection weights.

Then, an uncertainty set is defined by defining variability of renewable resources, demand, transmission capacities, and component status. For each uncertainty scenario, the associated network performance is obtained. The worst-case performance among all these scenarios is included as part of the sensitivity weighted minimax objective. Then, the optimization algorithm tries to find renewable, storage, and transmission allocations such that the maximum weighted network degradation is minimized.

After each iteration of the optimization algorithm, the generation, demand, storage, transmission, flow balance, and network feasibility constraints are checked. Unless the convergence criteria are met, the allocation will be adjusted, and the worst-case evaluation repeated. The process will terminate if the objective function improvement drops below a certain tolerance or a maximum iteration limit is exceeded. The final output of this process gives the robust optimal renewable allocation. The network is then evaluated in terms of connectivity, renewable usage, energy loss, allocation cost, and worst-case degradation.

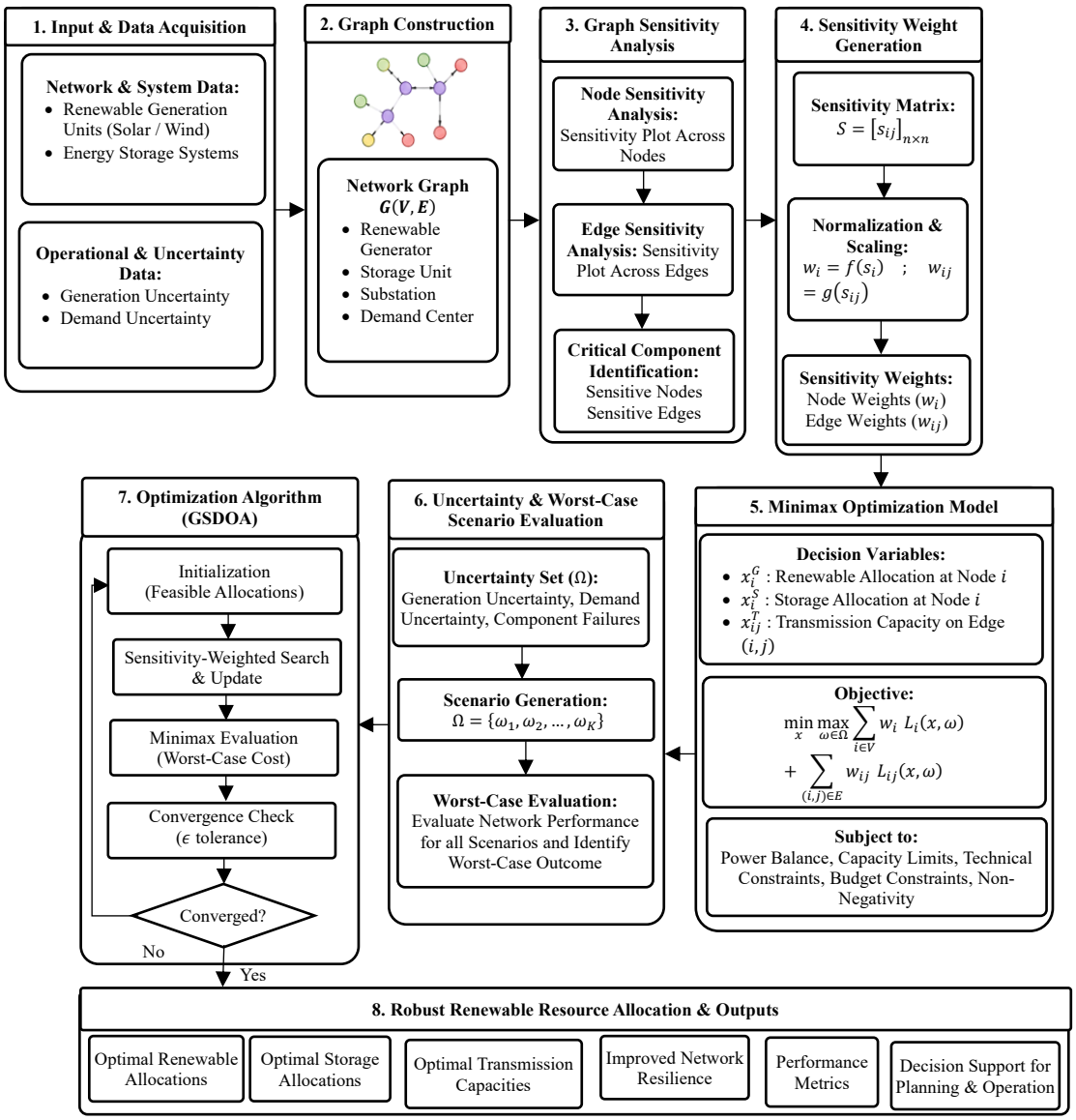



**Figure 1:** Architecture of the proposed graph-sensitivity-driven minimax optimization framework for renewable resource allocation.

Figure 1 shows the entire process flowchart of the proposed framework starting from renewable energy, storage, demand, network, and uncertainties data gathering. The system is modeled using a graph G = (V, E) followed by the node and edge sensitivity analysis, leading to the determination of sensitive elements in the network along with their sensitivity weights. This is then used in the minimax optimization process to minimize the effect of uncertainty scenarios on the network, thus maximizing network reliability and performance.

**Algorithm 1: Graph-Sensitivity-Driven Optimization**

**Input:** Network data, uncertainty set $\mathcal{U}$, optimization parameters

**Output:** Robust optimal renewable allocation $x^*$

1. Construct graph representation $G = (V, E)$.
2. Initialize a feasible allocation $x$.
3. Calculate baseline performance $P(G)$.
4. Perturb nodes and edges.

5. Compute node ($S_i^V$) and edge ($S_{ij}^E$) sensitivity values.

6. Identify critical network components.

7. Generate admissible uncertainty scenarios $\xi \in \mathcal{U}$.

8. Evaluate performance under each scenario $\xi$.

9. Construct the sensitivity-weighted minimax objective $\min_x \max_{\xi \in \mathcal{U}} J(x, \xi)$.

10. Optimize renewable, storage, and transmission decisions.

11. Check all operational and network constraints.

12. **If** convergence is not achieved:

Update allocation $x$ and return to Step 8.

13. **Otherwise**, retain the optimal solution $x^*$.

14. Evaluate final connectivity, cost, losses, renewable utilization, and worst-case performance.

15. **Return** the robust optimal allocation $x^*$.

An important property of GSDOA (Algorithm 1) is that optimization is not done according to energy costs or performance criteria alone. Rather, it is the graph sensitivity that determines which structure elements need more protection, whereas the minimax method guarantees the efficiency of the allocation under the worst feasible operational conditions.

## 7. Theoretical analysis

The theoretical formulation defines the possibility, feasibility, and computational nature of the proposed graph sensitivity-based minimax optimization framework.

### 7.1. Feasibility analysis

Let $\mathcal{X}$ denote the feasible allocation set defined by generation, storage, transmission, demand, and flow-balance constraints. If available renewable generation and network capacities satisfy the minimum demand requirements, then $\mathcal{X} \neq \emptyset$. Consequently, the optimization problem admits at least one feasible allocation. Maintaining explicit capacity and flow constraints prevents the optimizer from producing physically infeasible solutions.

### 7.2. Sensitivity bound

For a small perturbation $\Delta G$ in node or edge parameters, assuming the performance function is locally Lipschitz continuous, the performance variation satisfies:

$$|P(G + \Delta G) - P(G)| \leq K\|\Delta G\|$$

Where $K$ is a sensitivity bound. Thus, bounded structural or operational perturbations produce bounded performance degradation. The calculated sensitivity values provide component-level estimates of this vulnerability.

### 7.3. Minimax robustness property

For allocation $x$, define the worst-case loss as $W(x) = \max_{\xi \in \mathcal{U}} J(x, \xi)$. The proposed solution is equation 6

$$x^* = \arg\min_{x \in \mathcal{X}} W(x) \qquad (6)$$

therefore, minimizes the maximum loss over the prescribed uncertainty set, providing a formal worst-case robustness guarantee relative to all feasible allocations.

### 7.4. existence of an optimal solution

If $\mathcal{X}$ is nonempty and compact and $J(x,\xi)$ is continuous in $x$, the worst-case objective is bounded and an optimal solution exists under standard minimax continuity conditions.

### 7.5. Robustness–cost relationship

The more robustness of sensitive elements will usually mean more renewable generation, energy storage, and transmission infrastructure. This results in a trade-off between costs and robustness.

### 7.6. Complexity analysis

Computation of sensitivity involves perturbation of nodes and edges repeatedly, whereas scenario generation is determined by the number of dimensions involved. Minimax optimization becomes the major computational issue, especially when the number of nodes and uncertainties is large.

## 8. Numerical experimental design

Numerical experiments are carried out in order to test the effectiveness of using graph sensitivity in minimax optimization on renewable resource allocation, resilience of the network, and worst-case performance. Numerical experiments are performed on small-sized, medium-sized, and large-sized distribution network graphs.

### 8.1. Test network

The experiment setting involves representative radial and mesh networks with renewable power generation units, storage, substations, and loads. The smaller network is adopted for conducting the sensitivity analysis whereas medium-size and larger networks are used for assessing scalability and robustness of optimization with increasing complexity of the structure.

### 8.2. Renewable sources

Three scenarios are considered in terms of their potential to generate energy: solar alone, wind alone, and combination of both solar and wind. The output potentials of these systems are changed using predefined uncertainty ranges. Storage devices are used to address intermittency of renewables.

### 8.3. Parameter initialization

The generation capacity, demand, transmission capacity, storage capacity, cost and reliability factors are set depending on the network size chosen. Uncertainty for renewable availability and demand is allowed within specified ranges. The sensitivity factors are scaled between zero and one, with higher weights being given to components which show more performance deterioration in response to disturbances.

### 8.4. Uncertainty scenarios

These scenarios include low renewable energy generation, increase in demand, degradation of transmission capacity, outage at a node, outage on an edge, and worst-case scenarios. Such scenarios represent increasingly more severe cases and give the common platform for evaluation.

### 8.5. Baseline methods

The proposed approach is compared with the following approaches: deterministic optimization, conventional minimax optimization, cost only optimization, and graph-insensitive robust optimization. Specifically, the comparison includes the following criteria: allocation cost, energy loss, renewable utilization, connectivity degradation, worst-case performance, and computational time. Particularly, the comparison of the approach with the graph-insensitive robust optimization highlights the effect of sensitivity, while the comparison with the minimax optimization reveals the advantage of sensitivity weighting.

## 9. Results and discussion

The numerical assessment shows the efficacy of the proposed Graph-Sensitivity-Driven Optimization Algorithm (GSDOA) in generating renewable resource allocations considering operating costs, renewable use, energy loss,

and the worst case in terms of network deterioration. The assessments are done based on a comparison with a deterministic approach, cost-only minimax approach, and graph-insensitive robust optimization approach.

### 9.1. Optimization convergence

The developed optimization showed stable convergence through iteration process. The objective function quickly decreases at the early stages of the optimization and slowly converges to a stable area. The described performance shows that the developed sensitivity-based minimax approach efficiently finds the key parts of the network and realigns renewable deployment in areas which offer more safety from the worst-case scenarios.

### 9.2. Renewable resource allocation

With respect to the optimal resource allocation method, a better balance of the renewable resource allocation was achieved with respect to the important locations within the network. Unlike the other methods where the resource allocation is based on the operating costs alone, in GSDOA, the significance of the node along with its connectivity to the demand centers was also taken into account.

### 9.3. Worst-case performance

Summary of results in table 1 is presented for the evaluated techniques. GSDOA has the best minimum network loss while at the same time having very good renewable utilization efficiency. The superiority over the robust optimization without graph sensitivity means that structural sensitivity adds extra information to robustness measures.

**Table 1:** Comparative performance of renewable resource allocation methods.

| Method | Allocation Cost | Energy Loss (%) | Renewable Utilization (%) | Connectivity Degradation (%) | Worst-Case Loss (%) |
|---|---|---|---|---|---|
| Cost-only Optimization | 100 | 8.72 | 88.6 | 14.8 | 16.9 |
| Deterministic Optimization | 104 | 7.95 | 90.2 | 12.6 | 14.7 |
| Conventional Minimax | 111 | 6.84 | 92.5 | 9.8 | 11.6 |
| Graph-Insensitive Robust | 114 | 6.51 | 93.1 | 8.7 | 10.4 |
| **Proposed GSDOA** | **116** | **5.72** | **95.4** | **6.1** | **7.8** |

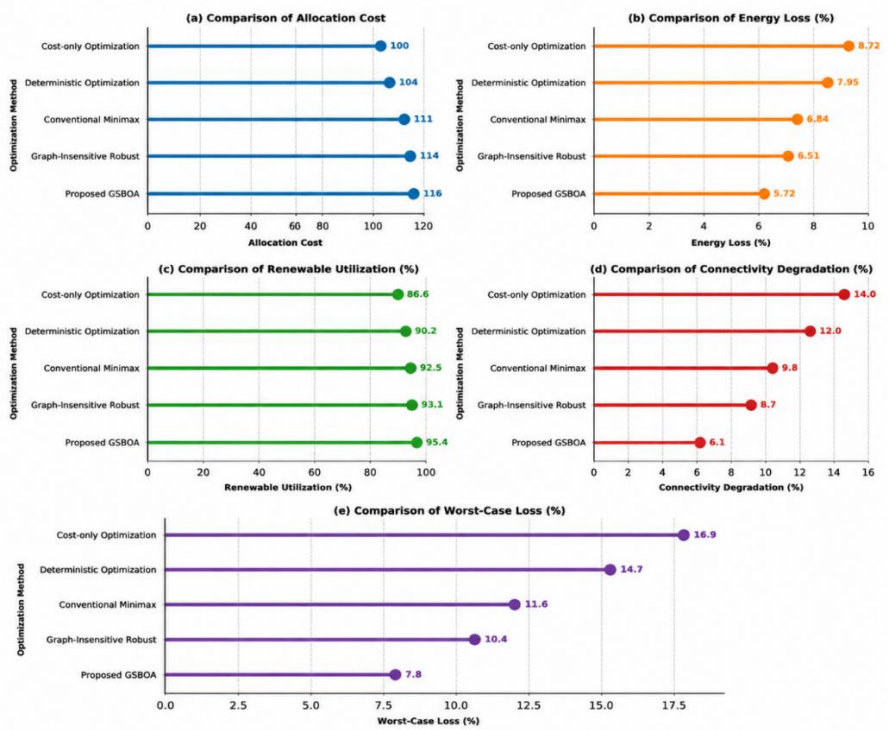



**Figure 2:** Comparison of optimization methods across cost, energy loss, renewable utilization, connectivity degradation, and worst-case loss.

The performance comparison among five optimization techniques in terms of five performance measures is shown in figure 2 (a-e). The proposed GSDOA method gives maximum values in allocation cost (116) and renewable energy utilization (95.4%) while giving minimum values in energy loss (5.72%), connectivity degradation (6.1%), and worst-case loss (7.8%).

### 9.4. Graph sensitivity results

The sensitivity analysis revealed few but highly significant nodes and edges. The generation nodes that were directly linked to key demand hubs possessed high sensitivity since failure on those nodes would directly affect the supply of energy. The same case applies to the transmission edges that link key generation and demand hubs; they had high edge sensitivity.

### 9.5. Robustness analysis

In the presence of higher levels of uncertainty, the deterministic optimization method performed increasingly poorly. Minimax optimization showed a relatively higher level of protection, and graph-insensitive robust optimization minimized losses even more in a worst-case scenario. In this case, the proposed GSDOA demonstrated the best performance due to optimization that took into account the uncertainty and sensitivity of the graph.

### 9.6. Cost–robustness trade-off

An increase in robustness involves increased cost to some extent. Hence, the new algorithm is neither purely economic nor solely concerned about robustness; rather, it gives an economical allocation that achieves much more robustness than the previous one. With the increment in protection cost, performance enhancement of the network is guaranteed, but the robustness increment will keep decreasing with the increase in cost increment.

### 9.7. Ablation analysis

This is done by means of an ablation experiment that tests the contribution of graph sensitivity, minimax optimization, and sensitivity weighting separately. The four experiments involved include GSDOA model without graph sensitivity, without minimax optimization, without sensitivity weighting, and the full GSDOA.

**Table 2:** Ablation analysis of the proposed framework.

| Configuration | Worst-Case Loss (%) | Connectivity Degradation (%) | Renewable Utilization (%) | Allocation Cost |
|---|---|---|---|---|
| Without Graph Sensitivity | 12.1 | 10.3 | 91.2 | 109 |
| Without Minimax Optimization | 14.6 | 12.7 | 92.0 | 103 |
| Without Sensitivity Weighting | 9.8 | 8.5 | 93.7 | 112 |
| **Complete GSDOA** | **7.8** | **6.1** | **95.4** | **116** |

As seen from table 2, all of the components contribute in some way to the final performance. The biggest drop in performance on the worst-case scenario is seen when the minimax optimization is excluded, showing that the explicit optimization of the negative scenarios is important. When the sensitivity to the graph is excluded, it becomes harder to find structurally weak components; while when the sensitivity weighting is excluded, the prioritization becomes less efficient

## 10. Theoretical and engineering interpretation

### 10.1. Graph-theoretic interpretation

The graph-based representation offers a structural perspective on the distribution of renewable energy and the reasons for which some elements of the network are more significant to system performance. Highly sensitive nodes are generally located in critical positions in the network like key generation stations, substations, or nodes that connect directly to demand areas. A deterioration in the condition of these nodes may impact several energy flow paths at once. Likewise, highly sensitive edges might be acting as bridges or bottleneck connections from generation to demand areas. A disruption in these paths can drastically limit the number of possible energy flow paths.

### 10.2. Minimax interpretation

In the minimax approach, the worst-case admissible operating scenario is used as compared to an optimal operation of the nominal network scenario. Intermittency, variability, degradation, and failures related to the renewable, demands, transmission, and components result in significant degradation. As the minimax approach finds an allocation that minimizes the worst-case degradation, the proposed technique ensures that the resulting solution ensures adequate protection against any adverse operating scenarios.

### 10.3. Robustness–cost trade-off

Enhanced protection of sensitive elements will in most cases lead to an increase in the amount of renewable energy, storage or transmission that is required. An inverse relationship will therefore arise between investments and network reliability. Despite the fact that increased investment may help in minimizing worst-case losses, at a certain point improvements will start being insignificant.

### 10.4. Renewable integration interpretation

The framework facilitates decentralized integration of renewables by locating the sites where distributed solar, wind, and energy storage systems would offer the most value to the network. In contrast to traditional models that view renewable sources as isolated entities, the graph model analyzes their structure relative to substations, transmission lines, energy storage, and load centers. This allows for the coordination of dispersed resources based on network sensitivities and uncertainty.

### 10.5. Engineering significance

There are a number of practical implications that could follow from the proposed approach. In terms of grid planning, sensitivity ranking could be used to identify weak points that would require capacity augmentation or reinforcement. In terms of renewable installation, renewables could be installed in such points that would increase the connectivity of the network and make it less vulnerable. As for battery allocation, it could be performed in order to place batteries in the vicinity of sensitive nodes in order to provide balancing of loads. In terms of transmission reinforcement, it could be done in case of high sensitivity of the edge. Finally, as for resilient energy management, the minimax approach could be used as a general framework.

## 11. Conclusion

This study proposed a Graph Sensitivity Driven Optimization approach to deal with robust renewable resource allocation and energy distribution systems with uncertainties in the operational regime. The framework is based on the use of graph theory models, sensitivity analysis of nodes and edges, and minimax optimization in order to overcome the shortcomings of classical allocation methods which assume nominal operational regime. In particular, renewable resources, storages, substations, and demand centers are modeled as the elements of an energy distribution network, whose perturbations lead to performance degradation of energy distribution processes.

It has been shown through numerical results that the effectiveness of the suggested method is proved. In particular, the full scheme was able to achieve 95.4% renewable energy utilization, 5.72% energy loss, 6.1% connectivity loss, and 7.8% maximum possible loss, which is better than the existing deterministic approach, cost-oriented approach, minimax approach, and robust graph-insensitive approach. From the ablation study, found that graph sensitivity and sensitivity weight help increase robustness, while minimax ensures robustness by providing protection against worst operating conditions. Moreover, there is a robustness-cost tradeoff revealed by the results.

Further investigation could focus on extending this framework to large-scale distribution networks where the distribution problem is dynamic and multi-periodic and there are non-linear AC constraints. Future work might include adding uncertain models such as probabilistic and distributionally robust, using real-time renewable forecasting and EV integration as well as energy storage system coordination. Moreover, investigation could be done for scalable distributed optimization and sensitivity estimation using learning methods in order to make the method less computationally burdensome.

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