Optimal Resilience Enhancement Strategy for Power Systems Using Multi-Objective Evolutionary Algorithm

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***Abstract*— The increasing frequency and severity of natural extreme events have significantly impacted the resilience of electric power delivery, highlighting the critical need for investing in more resilient power systems. One effective strategy for enhancing power system resilience is the reinforcement of transmission lines that connect critical nodes within the grid. This study proposes a comprehensive framework aimed at maximizing system resilience by strategically selecting the optimal transmission lines for reinforcement. The approach integrates both technical and economic considerations, seeking to minimize the investment costs associated with line reinforcement while ensuring the stability and reliability of the power system. The optimization problem is formulated as a multi-objective optimization problem, which is solved using the Non-dominated Sorting Genetic Algorithm (NSGA-II) to balance the conflicting resilience and cost objectives. Additionally, the framework accounts for constraints such as the available investment budget, making it a practical tool for decision-makers in the planning and development of resilient power infrastructure.**

Keywords—optimal resilience enhancement, line reinforcement, multi-objective optimization, evolutionary algorithm

I. INTRODUCTION

The recent increase in low-frequency but high-impact extreme events, such as windstorms, wildfires, and severe weather events, has highlighted the critical need for highly resilient power systems. These events can cause severe damage to the power infrastructure, leading to widespread and prolonged power outages, which can have devastating consequences for communities, businesses, and essential services [1]. While power utilities typically prepare for failures in one or two system components (known as N-1 or N-2 contingency planning), extreme events can indeed lead to massive power system failures that exceed these preparedness levels. Hurricane Sandy in the United States which lead to N-90 contingency and the 2008 ice disaster in southern China where 36000 transmission lines has been damaged serve as stark examples of such situations. Such events highlight the urgent need to expand resilience planning to address scenarios exceeding N-1 or N-2 contingencies. This expansion should involve reinforcing critical infrastructure, improving the load survivability [2], [3].

Power system resilience refers to the ability of an electrical power infrastructure to withstand and recover from disruptions, such as natural disasters, equipment failures, or cyberattacks, while minimizing downtime and maintaining the reliable delivery of electricity to customers. Resilience encompasses the capacity to absorb shocks, adapt to changing conditions, and rapidly restore power services to prevent or mitigate the impact of disruptions on communities, businesses, and critical services, ensuring the continued functionality and stability of the electrical grid even in the face of adverse events.

II. LITERATURE REVIEW

Quantifying power system resilience is essential for assessing and improving the ability of an electrical grid to withstand and recover from disruptions. Several methods and metrics are used to measure power system resilience. One widely adopted and highly effective method for assessing and visualizing the resilience of power systems is through the use of what is known as the "resilience trapezoid." This concept offers a comprehensive depiction of the various states that critical infrastructure, such as power systems, can undergo during an event, along with the transition between these states. To quantify the resilience of power systems, numerous indices have been created, including the "modified Resilience Index (RICD)" and the "quantitative resilience metric framework ΦΛΕΠ." These metrics provide valuable tools for evaluating power system resilience [4], [5]. Resilience can be quantified by estimating the economic impact of power outages. This involves evaluating the financial losses incurred by businesses, the cost of emergency response and recovery efforts, and the overall economic consequences of extended power disruptions. These assessments help utilities understand the financial implications of grid resilience and prioritize investments accordingly [6].

After evaluating the resilience of the power system, extensive research efforts have been devoted to improving its resilience. One highly effective strategy for enhancing power system resilience involves reinforcing the transmission lines to increase the resistance of system components to extreme weather conditions [7], [8]. In [9], two deterministic single-group approximation solutions were introduced to address the enhancement of post-disaster restoration performance through line reinforcement. Additionally, in [10], a study focused on improving system resilience by addressing transmission line reinforcement planning in the context of high penetration injection of probabilistic power flows from renewable energy sources. Furthermore, in [11], a robust optimal line reinforcement approach was proposed, leveraging multi-temporary microgrids to mitigate the impacts of worst-case N-k contingencies. Another resilience enhancement optimization model was proposed in [12]. The method integrates both line reinforcement and the strategic placement of emergency generators for maximum system resilience.

While traditional methods such as dynamic programming and heuristic approaches have been employed to solve

2024 IEEE Sustainable Power and Energy Conference (iSPEC) | 979-8-3503-9507-5/24/$31.00 ©2024 IEEE | DOI: 10.1109/ISPEC59716.2024.10892417

resilience optimization problems, they often face significant limitations. Dynamic programming, although capable of providing optimal solutions, is computationally intensive, particularly for large-scale, multi-objective problems. This leads to scalability issues as the size and complexity of the power grid grow. Heuristic methods, on the other hand, are faster and more computationally efficient but may converge to suboptimal solutions and lack the flexibility to handle the conflicting objectives that arise in power system resilience planning.

This paper's primary aim is to enhance the power system's resilience, focusing on the resistance of the system against wind storms. The study entails optimizing the reinforcement of the system's transmission lines, taking into account factors such as failure probabilities and the associated costs of reinforcement. This strategic reinforcement not only enhances the system's ability to withstand extreme events but also does so at a minimal cost, leading to savings in outage and restoration expenses for the electricity company.

The contribution of this study can be summarized as:

A. Maximize the utility's profit:

The decision on reinforcing power lines will be done to maximize the electricity company profits. This investment will save the costs of power outages caused by the extreme events and the restoration processes. Additionally, the investment cost will be minimized by optimizing the selection of lines to be reinforced. This upgrades the optimization problem to a multi-objective optimization.

B. Utilization of evolutionary multi-objective optimization algorithms

The study will employ evolutionary multi-objective optimization algorithms to simultaneously address the dual objectives of fortifying the power system's resilience by enhancing its ability to withstand unforeseen challenges at minimum cost. These advanced algorithms enable the consideration of multiple, often conflicting, objectives inherent in power system optimization, ensuring a comprehensive and nuanced approach. By exploring a diverse solution space and generating Pareto-optimal solutions, the algorithms facilitate the development of robust strategies that balance resilience and expenses. Their adaptability to changing conditions and integration with simulation models enhance the practical applicability of the identified solutions. Ultimately, the study seeks to provide decision-makers with a transparent and informed decision-making process, empowering them to navigate the intricate landscape of power system resilience effectively.

III. Problem Formulation

A. Resilience quantification

With the aim to enhance the resilience, the first step is always to mathematically model and quantify the resilience of power systems. The resilience trapezoid is considered to be the best representation of the system's response during extreme events as shown in figure 1. The resilience of power system is then represented by the area of the difference between the ideal system behavior and the actual one during extreme events. This metric can also be approximated to the total amount of load shedding happening during disasters.

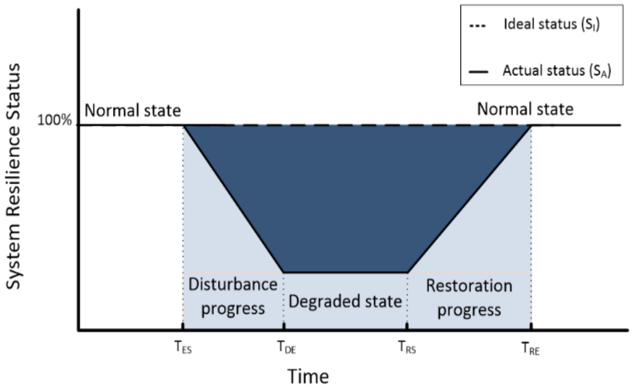

Fig. 1. Resilience trapezoid curve

$$R^* = \int_{T_{ES}}^{T_{RE}} S_I - S_A \approx \sum_{t\in \mathrm{T}} \sum_{i\in\Omega_N} w_i \cdot pc_{it} \quad (1)$$

where S_I and S_A represent the ideal and actual resilience statue curves of the systems as illustrated in Fig. 1, T_{ES} denotes the time when the extreme event starts, while T_{RE} marks the end of the restoration process when the system returns to its normal state, w_i is the weight associated with the load connected to bus i which enables us to distingush and prioritize critical loads in the sytsem, pc_{it} is the amount of shedded load in bus i during time t. This mathematical representation allows for a quantitative assessment of power system resilience, enabling the identification and prioritization of critical loads to improve overall system robustness during extreme events.

B. Investment cost

Investing in the resilience of a power system involves considering the costs associated with reinforcing existing infrastructure. Reinforcing the power grid involves upgrading and strengthening the existing transmission and distribution lines to withstand extreme events. The investment cost for reinforcement includes expenses related to materials, labor, engineering, and potential land acquisition. For simplicity, we will assume that the cost to reinforce all lines is the same.

Therefore, the reinforcement cost of system lines can be calculated by:

$$C_L = \sum_{ij\in\Omega_L} c^L \cdot h_{ij} \quad (2)$$

where: C_L is the line reinforcement cost, c^L stands for the reinforcement cost for one line, and h_{ij} is a binary variable indicating whether distribution line ij is reinforced (1 - reinforced, 0 - not reinforced).

C. Extreme event modelling

Natural extreme events can have significant and detrimental impacts on power systems, disrupting the generation, transmission, and distribution of electrical energy. The specific effects of any extreme event depend on its type, intensity, duration and the distance from the power infrastructure. Wind-based natural disasters can be modelled using the modified Rankine vortex model as follows:

$$v = \begin{cases} v_{max}\sqrt{\dfrac{r}{R_{w,max}}}\ , r \le R_{w,max} \\ v_{max}\sqrt{\dfrac{R_{w,max}}{r}}\ , r \ge R_{w,max} \end{cases} \quad (3)$$

where v is the effective wind speed on the transmission line, v_{max} is the maximum wind speed, r is the distance from the line to the center of the event, $R_{w,max}$ is the maximum radius of the wind.

Based on the obtained effective wind speed of each line, the failure probability of each line can be computed using the following formula:

$$p_{ij} = \begin{cases} 0, \quad 0 \le v_{ij} < v_l \\ e^{\frac{0.60931(V_{ij}-v_l)}{v_l}} - 1, \quad v_l \le v_{ij} \le 2v_l \\ 1\ , \quad v_{ij} > 2v_l \end{cases} \quad (4)$$

where p_{ij} is the failure probability of the transmission line connecting buses i and j, V_{ij} represents the wind speed affecting the line between buses i and j., v_l is the maximum wind speed the line can tolerate.

The expression specifies that the distribution line is considered safe if the wind speed is below the designed wind speed (v_l). When the wind speed exceeds 2 times the designed wind speed ($2v_l$), the line is assumed to be damaged. For wind speeds between v_l and $2v_l$, the failure probability is modeled using an exponential function. This formulation allows for the quantification of the likelihood of distribution line failure under different wind speed conditions, providing a basis for assessing the resilience of the power distribution system to extreme weather events.

D. *Objective Function*

1) Resilience enhancement

The objective function of the proposed model is to improve the resilience of system by minimizing the resilience index R^*:

$$\mathbf{Min} \sum_{s \in S} \sum_{i \in \Omega_N} p(s) \cdot D(s)\, \omega_i \cdot pc_{i,s} \quad (5)$$

where $p(s)$ is the probability of scenario s, $D(s)$ is the duration of the extreme event of scenario s, ω_i is the weight of load i, while $pc_{i,s}$ is the amount of shedded load at bus i in scenario s.

2) Investment cost reduction

The second objective aims to minimize the investment cost associated with the reinforcement of lines. The goal is to optimize the selection of lines to be reinforced, considering factors such as the cost of materials, labor, engineering, and maintenance. This objective can be formulated as:

$$\mathbf{Min} \sum_{s \in S} C_L \quad (6)$$

By minimizing the overall investment cost, the objective seeks an economically efficient solution that achieves the desired level of resilience for the power distribution system in the face of natural disasters and extreme weather events. The optimization process involves finding a balance between enhanced resilience of the system and the costs associated with reinforcing infrastructure to ensure a cost-effective and resilient power system.

E. *Constraints*

The model take into account the cost of line reinforcement as well as the available investment budget by applying the following constraints:

$$C_L \le C_{inv} \quad (7)$$

$$u_{ij,s} = h_{ij} + z_{ij,s} - h_{ij} \cdot z_{ij,s}\ ;\forall ij,s \quad (8)$$

C_{inv} indicates the total investment budget for PDS planning, $z_{ij,s}$ is a binary variable representing whether line ij is attacked by a disaster in scenario s (0 - attacked, 1 - not attacked), $u_{ij,s}$ denotes a binary variable for the final status of the line (0 - damaged, 1 - not damaged). Constraint (7) constrains the investment budget of PDS.

Constraint (8) denotes that the final status of the line is determined by reinforcement and disruption. The model considers that the reinforced lines will not be damaged during the extreme weather event [18]. In other words, if line ij is reinforced ($h_{ij} = 1$), then $u_{ij,s} = 1$. In contrast, $u_{ij,s} = z_{ij,s}$ when line ij is not reinforced ($h_{ij} = 0$).

Additionally, the model ensures stable operation of the system by applying the following constraints:

$$\sum_{j \in \Omega_N} pf_{ji,s} + pg_{i,s} + pc_{i,s} = \sum_{j \in \Omega_N} pf_{ij,s} + pd_i \ ;\forall i,s \quad (9)$$

$$\sum_{j \in \Omega_N} qf_{ji,s} + qg_{i,s} + qc_{i,s} = \sum_{j \in \Omega_N} qf_{ij,s} + qd_i \ ;\forall i,s \quad (10)$$

$$V_{i,s} - V_{j,s} \le M \cdot (1 - u_{ij,s}) + 2 \cdot (r_{i,j} \cdot pf_{ij,s} + x_{ij} \cdot qf_{ij,s})\ ;\forall i,j,s \quad (11)$$

$$V_{i,s} - V_{j,s} \ge M \cdot (u_{ij,s} - 1) + 2 \cdot (r_{i,j} \cdot pf_{ij,s} + x_{ij} \cdot qf_{ij,s})\ ;\forall i,j,s \quad (12)$$

$$V_i^{min} \le V_{i,s} \le V_i^{max} \quad ;\forall i,s \quad (13)$$

$$-u_{ij,s} \cdot P_{ij}^{min} \le pf_{ij,s} \le u_{ij,s} \cdot P_{ij}^{max} \quad ;\forall ij,t, \quad (14)$$

$$-u_{ij,s} \cdot Q_{ij}^{min} \le qf_{ij,s} \le u_{ij,s} \cdot Q_{ij}^{max} \ ;\forall ij,s \quad (15)$$

$$0 \le pg_{i,s} \le PG_i^{max} \quad ;\forall i,s \quad (16)$$

$$0 \le qg_{i,s} \le QG_i^{max} \quad ;\forall i,s \quad (17)$$

$$0 \le pc_{i,s} \le pd_i \quad ;\forall i,s \quad (18)$$

$$0 \le qc_{i,s} \le qd_i \quad ;\forall i,s \quad (19)$$

where the variables $pg_{i,s}$ and $qg_{i,s}$ represent the active and reactive power of bus i in scenario s, while $pf_{ji,s}$ and $qf_{ji,s}$ signify the active and reactive power flow from bus i to j in scenario s. Additionally, $pc_{i,s}$ and $qc_{i,s}$ denote the active and reactive load shedding of bus i in scenario s, and pd_i and qd_i indicate the active and reactive power demand supplied by bus i. The squared voltage magnitude of bus i in scenario s is denoted by $V_{i,s}$, and M is introduced as a large positive number. Further, V_i^{max} and V_i^{min} signify the square of the maximum and minimum voltage magnitude of bus i, while P_{ij}^{max} and P_{ij}^{min} represent the maximum and minimum active power flow of line ij. Additionally, Q_{ij}^{max} and Q_{ij}^{min} indicate the maximum and minimum reactive power flow of line ij, and PG_i^{max} and QG_i^{max} indicate the maximum active and reactive power output of the substation at bus i.

The set of constraints encompasses various aspects. Constraints (9)-(10) intricately describe the power balance at bus i. Utilizing the linearized DistFlow model, constraints (11)-(12) delineate linear voltage constraints employing the big M method. The safe range of nodal voltages is defined by constraint (13). Furthermore, constraints (14)-(15) confine the capacity of power flow, while constraints (16)-(17) pertain to the active and reactive power output of substations. Load shedding is explicitly governed by constraints (18)-(19). Collectively, these constraints provide a comprehensive framework for modeling and analyzing the intricate power dynamics within the specified system.

IV. METHODOLOGY

The framework for enhancing resilience includes a strategy comprising the planning of line reinforcement to mitigate the adverse impacts of extreme weather events. The evolutionary optimization algorithm is based on generating diverse individual solutions and comparing their fitness to each objective. Initially, system data are initialized and gathered including components coordinated locations and wind durability. Subsequently, the Monte Carlo Method

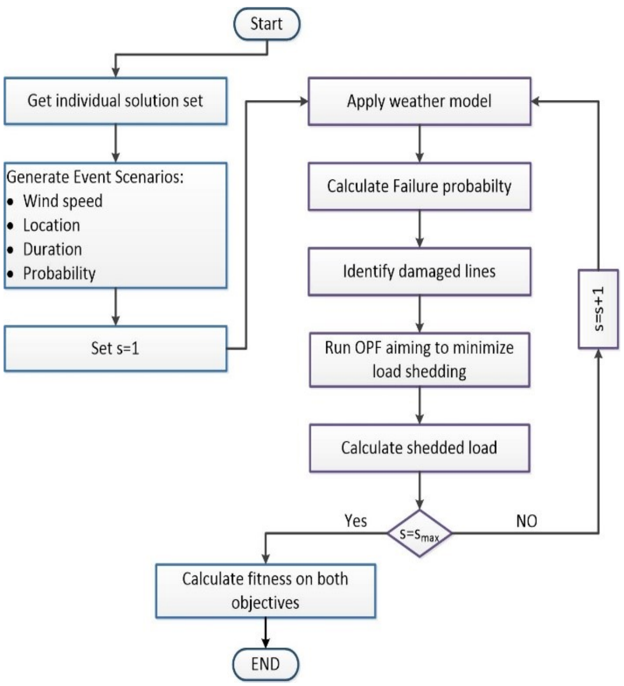

Fig. 2. Resilience assesment framwork

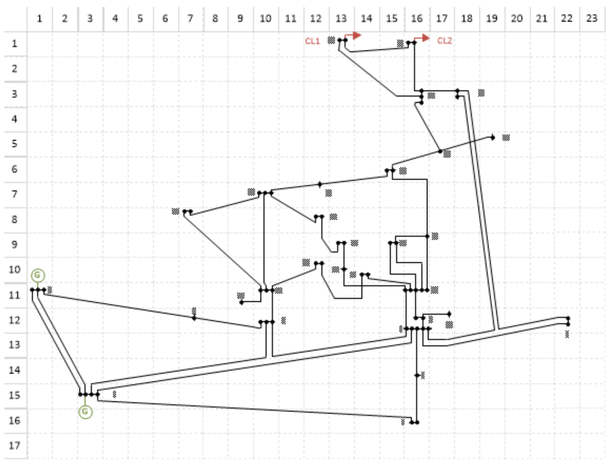

Fig. 3. Coordinated view of the IEEE 30 bus test system

(MCM) is employed to generate sets of windstorm events with different attacked locations, severity, and durations. Then, weather data is fed into the extreme weather event model to determine the failure probability of each line. Using these failure probabilities, the damaged lines are identified by comparing their failure probability with uniformly distributed random number. Once applying the modification to the system structure, optimal power flow analysis is applied with the objective of minimizing the forced outages required. The final step is to sum up the amount of load shedding required in each scenario and calculate the two objectives as illustrated in Fig. 2. Having the fitness values of all generated individuals, the evolutionary optimization algorithm can determine the optimal set of lines to be reinforced for maximum system resilience and minimum investment cost.

V. CASE STUDY

For verification and comparison purposes, the proposed resilience enhancement optimization scheme was applied on the IEEE-30 bus system. The genetic algorithm (GA) was utilized in this case study to solve the optimization problem.

A. Test system

The study investigates an optimal strategy using the IEEE-30 bus test system, implemented through simulation in MATLAB. Fig 3 illustrates a Coordinated view of the IEEE 30-bus test system to determine the location of the windstorm and identify the attached lines. Critical load buses (29 and 30), representing entities like hospitals and governments, are selected. The critical load is assigned a weight of 100, while the noncritical load is given a weight of 1. The total investment budget is assumed to be \$30,000, with a line reinforcement cost of \$4,000 per line.

The power system is assumed to be affected by a windstorm impacting one square area of the grid's coordinated location system as illustrated in Fig. 3. Using MCM, 10000 windstorm scenarios with different attacked location, severity (wind speed), and duration are generated. Line reinforcement is identified as the most effective strategy for enhancing system resilience.

B. Single objective optimization

For comparison purposes, the optimization problem is framed as a single-objective problem with the primary goal of enhancing the resilience of the power system. This problem is subject to constraints such as an investment budget and

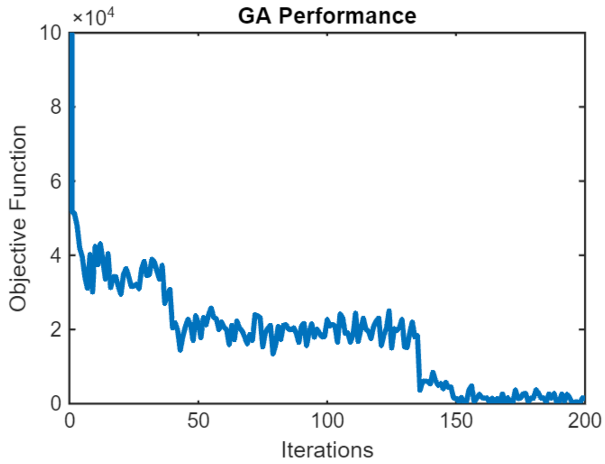

Fig. 4. GA performance for single-objective case

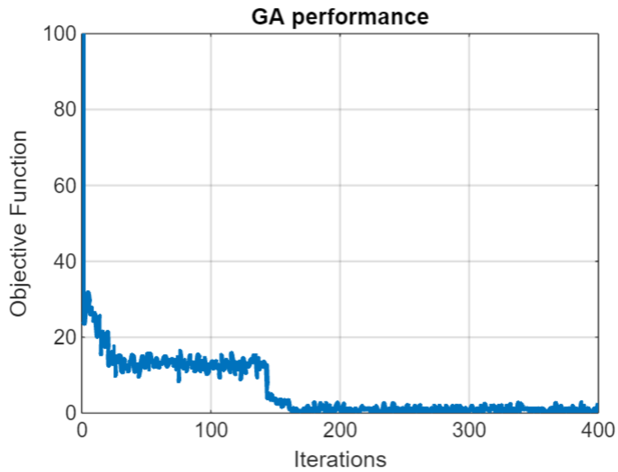

Fig. 5. GA performance for weighted-sum multi-objective case

operational limits within the power system. The objective is to find an optimal set of lines to be reinforced that maximize resilience while adhering to the specified constraints. These constraints include the available investment budget, which ensures that the proposed solution remains financially feasible, and adherence to power system operation limits, which guarantees that the resilience improvements do not compromise the normal functioning of the power grid.

Table 1 provides a comprehensive summary of the optimal choices for reinforcing transmission lines, the average resilience index (objective 1), and the investment cost for reinforcing the selected lines (objective 2). Simultaneously, Fig. 4 visually represents performance of the GA optimization by illustrating the decrease in the resilience index of the power system along the generations of the GA. The outcomes depicted in the table and graph underscore the significant impact that the selection of reinforced lines has on the overall system response to windstorms. This information serves to elucidate the nuanced effects of strategic decisions on system resilience, offering valuable insights into the interplay between reinforcement strategies and the power system's ability to withstand and recover from extreme events.

TABLE 1. SINGLE-OBJECTIVE RESULTS

Reinforced lines	Average resilience index (MWh)	Line reinforcement cost
25-27, 28-27, 27-29, 27-30, 29-30, 8-28, 6-28	1493	$28,000

C. *Weighted-sum multi-objective optimization*

In this case, the optimization problem will have both objectives aiming to maximize the system resilience by reducing load shedding and to minimize the investment cost associated with reinforcing the transmission lines. The objective function is modelled by adding the two objectives in (4) and (5) after normalization. In this case, both objectives are given equal weight. Table 2 shows the results of the optimization problem by listing the optimal choices of the transmission lines to be reinforced, the average resilience index after applying these enhancements, and the associated cost of this investment. In addition, Fig. 5 shows the performance of GA optimization by indicating the decrease in the value of objective function along the iterations of the algorithm.

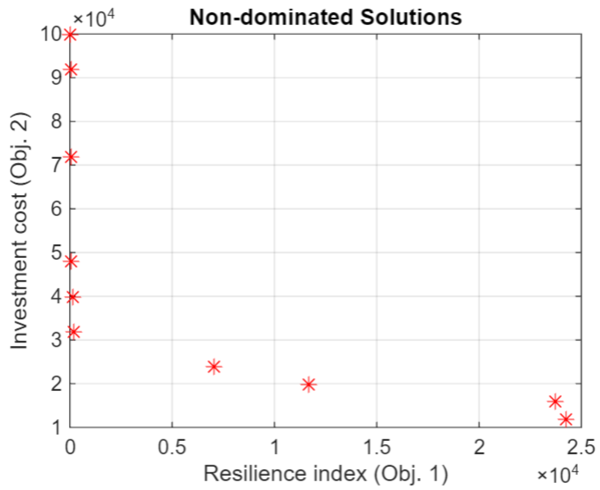

Fig. 6. NSGA-II results for the multi-objective case

TABLE 2. WEIGHTED-SUM MULTI-OBJECTIVE RESULTS

Reinforced lines	Average resilience index (MWh)	Line reinforcement cost
25-27, 28-27, 27-29, 27-30, 29-30, 8-28, 6-28	1458	$28,000

D. *Non-dominated sorting genetic algorithm multi-objective optimization*

In this section, the application of multi-objective optimization focuses on addressing the dual goals of enhancing power system resilience and minimizing investment costs. The objective is to identify an optimal set of transmission lines for reinforcement to maximize resilience while minimizing investment expenses within specified constraints. These constraints encompass the available investment budget to ensure financial feasibility and adherence to power system operation limits, safeguarding the normal functioning of the grid. Fig. 6 visually illustrates the Pareto front of the optimization problem which contains all the non-dominated optimal solutions. Each solution has its fitness value for each objective function. In this case and to equally consider both objectives, solution 8 was selected to be the optimal solution to this problem. Table 3 presents a summary of optimal choices for reinforced lines associated with this optimal solution as well as its corresponding values of average resilience index and investment cost.

TABLE 3. MULTI-OBJECTIVE RESULTS

Reinforced lines	Average resilience index (MWh)	Line reinforcement cost
28-27, 27-29, 27-30, 8-28, 6-28	11750	$20,000

The results highlight the substantial impact of line reinforcement selection on the overall system response to extreme events, offering valuable insights into the nuanced relationship between reinforcement strategies and the power system's ability to withstand and recover from such events. Additionally, the multi-objective approach yields a lower resilience and number of recommended reinforced lines, emphasizing its effectiveness in minimizing total investment costs.

VI. CONCLUSION

To enhance the resilience of the power system in the face of extreme weather events, an optimal strategy for line reinforcement is presented in this study. The identification of damaged lines set is facilitated by a combination of an extreme weather event model and the MCM. Subsequently, the planning strategy for line reinforcement is derived using the power system resilience enhancement model. The outcomes of this study serve as valuable references for utility companies, aiding them in formulating resilience enhancement strategies within specified budget constraints. This approach not only fortifies the power system against extreme weather events but also provides utilities with practical insights for effective decision-making in resilience planning.

ACKNOWLEDGMENT

H. Binqadhi and M. Almuhaini would like to acknowledge the support of King Fahd University of Petroleum and Minerals (KFUPM), Dhahran, Saudi Arabia, and would like to express their profound gratitude to King Abdullah City for Atomic and Renewable Energy (K.A.CARE) for their financial support in accomplishing this work. A. Bineshaq would like to acknowledge the research support provided by The Renewable Energy Technical Incubator (RETI) funded by the National Industrial Development and Logistics Program (NIDLP) under the Interdisciplinary Research Center for Sustainable Energy Systems (IRC-SES) at King Fahd University of Petroleum & Minerals, through Project No. CREP2522.

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