

Enhancing Power System Resilience Through Optimized Load-Shedding Strategies

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ARTICLE INFO	ABSTRACT
Article history: Received 4 November 2024 Received in revised form 17 November 2024 Accepted 2 December 2024 Available online 20 December 2024	Electric power systems are critical to modern life, supporting essential services and economic activities. However, these systems are increasingly vulnerable to natural disasters such as hurricanes, which can severely damage infrastructure and disrupt power supply. The growing intensity and frequency of these events, driven by climate change, highlight the urgent need to enhance power system resilience. Load shedding is a vital mitigation strategy used to balance the supply and demand during extreme events, ensuring system stability and resilience which preventing widespread outages. Despite its importance, existing studies primarily focus on immediate impacts, with limited exploration of optimal load-shedding strategies to minimize power losses and enhanced resilience. This study introduces the Integrated Clonal Squirrel Search Evolutionary Programming (ICSSEP), a novel hybrid optimization technique that integrates Clonal Selection Optimization (CSO) and the Squirrel Search Algorithm (SSA) into the Evolutionary Programming (EP) algorithm. The ICSSEP algorithm addresses the limitations of traditional optimization methods, such as entrapment in local optima, by improving accuracy and efficiency. Using the IEEE 57-Bus Reliability Test System (RTS), the proposed method determines the optimal locations and sizes for load-shedding to minimize power losses and enhance system resilience. Two scenarios simulating hurricane impacts were analysed, focusing on line outages and their effects on system performance. The ICSSEP-based load-shedding strategy was applied, and pre- and post-load-shedding resilience indices were calculated. Results demonstrated significant improvements in resilience and substantial reductions in power losses across all scenarios and reactive power demands. For instance, at Bus 33 with a reactive power demand of 15 MVAr, power losses were reduced by 14.17% in Scenario
	effectively enhances the power system resilience and minimizes transmission losses,
Keywords:	proving to be a robust tool for mitigating the adverse impacts of extreme events. Its adaptability to varying operational conditions makes it a promising solution for modern
Load shedding; resilience; IEEE 57-Bus	power systems. Future research should explore its application to larger networks and dynamic environments to further validate its scalability and effectiveness.
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https://doi.org/10.37934/ sijese.4.1.19

1. Introduction

Electric power systems play a vital role in modern society by enabling critical services, supporting industries, and facilitating daily activities [1-7]. However, these systems face increasing risks from natural disasters such as hurricanes, floods, and earthquakes, which can severely damage infrastructure, interrupt supply chains, and cause widespread power outages. With climate change intensifying the frequency and severity of these events, it has become essential for power systems to not only mitigate the likelihood of failures but also demonstrate the ability to adapt and recover quickly when disruptions occur. This capacity, known as resilience, refers to a power system's ability to endure, adjust to, and recover from disturbances, ensuring reliable electricity delivery as reported in [3,5,8-11]. To enhance power system resilience, various strategies have been adopted by previous research, including the integration of distributed generation (DG), the deployment of microgrids, the application of advanced optimization methods as addressed in [12-16]. These approaches aim to reduce the impacts of disruptions, ensure continuity in electricity supply, and support sustainable energy systems in an increasingly uncertain environment [17,18].

Load shedding is a critical strategy in power systems designed to balance the supply and demand during periods of extreme stress, ensuring system stability and resilience which in turn preventing widespread outages. It is a controlled process of disconnecting non-essential loads to maintain the integrity of the grid when power generation falls short of demand or when the system faces operational challenges, such as equipment failures, natural disasters, or cyberattacks [19-21]. The implementation of load-shedding strategies is increasingly vital as modern power systems become more vulnerable to extreme events caused by climate change, such as hurricanes and floods, which can disrupt infrastructure and cause significant system losses. Additionally, hybrid multi-source energy systems have been optimized to consider grid load shedding, enhancing their adaptability to supply shortages and improving grid reliability [22]. Optimization algorithms, such as the Crow Search Algorithm with Lampinen's criterion, have further improved load-shedding strategies by accounting for voltage stability and system dynamics, thereby reducing system losses and enhancing grid resilience [23].

As power systems evolve to incorporate renewable energy sources and distributed generation, the challenges of balancing supply and demand become increasingly complex. Load shedding, when optimized with advanced computational techniques, not only mitigates any immediate threats to system stability but also enhances the overall resilience of the grid. This study builds upon these advancements, focusing on developing an efficient load-shedding framework that minimizes power losses and enhances system performance during disruptive events. This paper introduces a novel optimization technique, the Integrated Clonal Squirrel Search Evolutionary Programming (ICSSEP), which combines the strengths of Clonal Selection Optimization (CSO) and the Squirrel Search Algorithm (SSA) within the Evolutionary Programming (EP) framework. ICSSEP overcomes the limitations of traditional CSO, SSA, and EP methods by enhancing optimization accuracy [24,25]. It is applied to the IEEE 57-Bus RTS to determine the optimal locations and sizes for load-shedding, with the goal of minimizing power losses and improving system resilience. The effectiveness of ICSSEP is evaluated by analyzing its ability to reduce power losses through an optimal load-shedding strategy. This study identifies the most effective load-shedding locations and capacities to enhance system performance following disruptive events.

2. Methodology

2.1 Problem Formulation

Power systems must withstand a wide range of unpredictable events, including natural disasters such as floods, tsunamis, hurricanes, and earthquakes, as well as human-induced threats like vandalism and cyberattacks. This study focuses on hurricanes as the primary disruptive event, with an emphasis on evaluating the fragility of transmission towers under varying wind speeds. Simulations are conducted based on the Saffir-Simpson Hurricane Wind Scale, developed by the National Hurricane Centre (NHC) [26], to analyse the effects of sustained wind speeds across different hurricane categories. The study specifically examines Category 1 and Category 2 hurricanes, providing a practical baseline for understanding the impact of moderate wind speeds on power system resilience.

Figure 1 illustrates the hurricane patterns and the regions affected within the test systems. Specifically, it highlights the hurricane impact zones and patterns for the IEEE 57-Bus RTS. To reflect the characteristics of real-world transmission systems, which often span multiple geographic regions, the IEEE 57-Bus RTS is divided into two distinct areas for analysis. The IEEE 57-Bus RTS is organized into two distinct regions, as shown in Figure 1.



Fig. 1. Impact of hurricanes on the IEEE 57-Bus RTS: zones and patterns

The buses are distributed across various operational areas within the network, enabling sectionalized monitoring and testing. This structure facilitates independent management and analysis of each region, which is essential for conducting resilience studies and optimization efforts.

The area-wise allocation of buses allows for targeted interventions and detailed evaluation of specific sections, enhancing the precision and effectiveness of the test system analysis. Two scenarios, namely Scenario 1 and Scenario 2, have been designed to simulate the hurricane patterns on the IEEE 57-Bus RTS. The simulations analyse the impact of hurricanes, leading to line outages within the system. To mitigate these effects, load-shedding measures are implemented as a corrective action to improve system performance following the event and the resilience index is then calculated.

The resilience of a power system during an extreme event is primarily indicated by the changes in system performance following the event. It can be quantified as the inverse of the performance loss experienced by the system due to the event [27]. The resilience can be mathematically represented by;

$$Resilience = \frac{1}{Loss}$$
(1)

where Loss can be represented by;

$$Loss = \frac{Q_0 - Q_{min}}{Q_{min}} \tag{2}$$

Performance loss is quantified as the largest deviation from the system's normal operating level, where Q_0 represents the system's normal performance, and Q_{min} denotes its lowest performance level during an extreme event. The resilience of a power system is demonstrated by the variations in system performance as the event progresses. In this study, optimization techniques are employed to determine the optimal location and size of load-shedding, ensuring that the objective function is achieved. The objective function (*O.F.*) aims to minimize the total power loss within the system and is mathematically represented by Eq. (3);

$$O.F.=Minimize \ \sum_{i=1}^{n} P_{loss}, i$$
(3)

2.2 Proposed Technique

The proposed ICSSEP technique integrates elements of CSO and SSA into the main EP algorithm, forming a hybrid approach that addresses the limitations of traditional EP and SSA methods, particularly their tendency to become trapped in local optima. Figure 2 depicts the general research flow for evaluating and optimizing power system resilience using the proposed ICSSEP-based loadshedding strategy. The flowchart is divided into two main stages: pre-load-shedding and post-loadshedding, with iterative steps to assess and enhance system performance. In the pre-load-shedding stage, the process begins with running a load flow analysis to calculate power losses under normal operating conditions (Loss_{set}), establishing a baseline for comparison. This is followed by running a load flow analysis after the occurrence of disruptive events (Lossout), such as outages or hurricanes, to quantify the initial impact on the system. Using these data, the system's resilience (R1) is calculated, reflecting its ability to withstand and recover from the disruption. The post-load-shedding stage involves applying the ICSSEP algorithm to identify the optimal locations and capacities for load shedding. The load flow analysis is then performed again with the optimized load-shedding strategy, and the system's resilience (R2) is recalculated to evaluate the effectiveness of the optimization process. The process includes a decision-making step to determine whether the system's performance has improved (i.e., reduced losses or enhanced resilience) after applying ICSSEP. If no improvement is observed, the procedure iterates back to the ICSSEP optimization step for further refinement. If improvement is achieved, the final step involves conducting a comparative analysis of the pre-load-shedding (*R1*) and post-load-shedding (*R2*) results to quantify the gains achieved through the optimization process. This structured approach ensures a comprehensive evaluation of the ICSSEP algorithm's ability to enhance power system resilience, providing a systematic methodology for mitigating the impacts of disruptive events and improving system reliability. The study can be presented in the pictorial representation in the form of flowchart as in Figure 2.



Fig. 2. Flowchart of general research flow

3. Results

The proposed Integrated Clonal Squirrel Search-Evolutionary Algorithm (ICSSEP) was implemented on the IEEE 57-Bus RTS to assess its effectiveness in optimizing load-shedding strategies. The algorithm's performance was analysed in terms of its ability to reduce power losses by determining the optimal size and location of buses for load-shedding implementation. To validate the impact of this approach, a comparative analysis was carried out, presenting the results for both before and after the application of the load-shedding technique. This comparison underscores the potential of ICSSEP in enhancing system resilience and minimizing transmission losses. Table 1 presents the loss values of the IEEE 57-Bus RTS system before any outages or events. The table provides a detailed breakdown of power losses (in MW) for buses 31, 32, and 33 under varying reactive power demands (Q_d) ranging from 5 MVAr to 15 MVAr. For each bus, the corresponding loss

values ($Loss_{set}$) are reported, illustrating how the system's losses are influenced by changes in reactive power demand. For instance, at Bus 31, the $Loss_{set}$ values are 28.464 MW, 29.220 MW, and 30.565 MW corresponding to Q_d values of 5 MVAr, 10 MVAr, and 15 MVAr, respectively. This data establishes the baseline performance of the system, serving as a reference for evaluating the impact of subsequent events or optimization techniques such as load-shedding.

Table 1									
Loss values of IEEE 57-Bus RTS before outage and events									
Bus	31			32			33		
<i>Q</i> _d (MVAr)	5	10	15	5	10	15	5	10	15
Loss _{Set} (MW)	28.464	29.220	30.565	28.667	29.424	30.661	28.557	29.298	30.548

Table 2 presents the numerical results of Scenario 1. The table provides data for buses 31, 32, and 33, with varying reactive power demands (Q_d) of 5 MVAr, 10 MVAr, and 15 MVAr. In Scenario 1, the Loss_{Out} values range from 32.850 MW to 42.753 MW when the Q_d is varied at Bus 31, 33.254 MW to 39.148 MW at Bus 32, and 33.031 MW to 37.997 MW at Bus 33. This table highlights the variations in power losses under different outage scenarios and demonstrates the influence of increasing reactive power demand (Q_d) on system performance. These results provide critical insights into the system's behaviour under stressed conditions, forming the basis for evaluating mitigation strategies such as load-shedding.

Table 2									
Numerical results of Scenario 1									
Bus	31			32			33		
Q _d (MVAr)	5	10	15	5	10	15	5	10	15
Loss _{Out} (MW)	32.850	34.413	42.753	33.254	34.836	39.148	33.031	34.512	37.997
Loss _{LS} (MW)	29.485	31.231	32.215	29.997	31.852	32.541	31.254	32.514	32.614
R1	6.488	5.627	2.508	6.250	5.437	3.613	6.382	5.618	4.101
R2	8.762	9.816	3.057	9.213	10.676	4.926	17.587	16.271	6.059
Loc ₁	8	21	21	10	5	9	10	8	15
Loc ₂	5	5	5	8	9	5	13	5	7
Loc₃	6	13	13	7	12	13	5	21	6
Pd1	65.75	74.44	107.10	31.97	112.40	59.57	70.28	46.98	37.51
Pd_2	150.54	167.95	75.69	61.78	139.98	140.67	44.10	133.32	51.34
Pd₃	57.48	29.35	48.95	73.51	63.58	39.55	150.83	51.21	50.49
Qd1	98.60	34.71	26.10	41.47	139.84	75.43	157.97	64.35	15.83
Qd_2	27.42	119.45	13.25	99.12	26.89	90.27	61.78	41.47	34.71
Qd₃	46.36	181.46	43.97	73.51	63.58	39.55	83.89	41.94	111.52

34.71 MVAr, and 111.52 MVAr, respectively. The results underline the importance of precise loadshedding strategies to achieve significant reductions in power losses and enhanced system resiliency, particularly under varying reactive power demands and outage scenarios.

Table 3 provides the numerical results for Scenario 2, illustrating the significant impact of system disturbances on power losses. Similar to Scenario 1, the loss values after outages and events are substantially higher than those recorded before the events. This trend underscores the critical need for effective mitigation strategies to minimize losses and enhance system resilience. For example, at Bus 31 with Qd = 15 MVAr, the total system loss is reduced from 47.340 MW (Loss_{Out}) before loadshedding to 29.865 MW (LossLS) after implementing load-shedding. Correspondingly, the resilience index improves from 1.508 (R1) to 1.709 (R2). The optimized locations for load-shedding are identified as buses 12, 38, and 45. At these locations, the real power to be shed amounts to 182.488 MW, 145.798 MW, and 95.595 MW, respectively, while the reactive power to be shed is 118.862 MVAr, 31.255 MVAr, and 78.300 MVAr, respectively. These results emphasize the critical role of carefully designed load-shedding strategies in significantly reducing power losses and improving system resilience. By addressing varying reactive power demands and outage scenarios, such strategies ensure a robust response to system disturbances.

Numerical results of scenario 2									
Bus	31			32			33		
Q _d (MVAr)	5	10	15	5	10	15	5	10	15
Loss _{Out} (MW)	47.340	49.466	54.694	47.768	49.812	55.062	47.522	49.560	53.901
Loss _{LS} (MW)	29.865	31.852	32.562	30.254	31.251	31.025	32.506	32.514	32.245
R1	1.508	1.443	1.267	1.501	1.443	1.257	1.506	1.446	1.308
R2	1.709	1.808	1.471	1.727	1.684	1.291	2.165	1.907	1.489
Loc ₁	12	50	55	28	15	18	55	10	23
Loc ₂	38	32	38	22	44	15	17	35	13
Loc₃	45	18	10	51	29	38	23	29	6
Pd_1	182.488	39.196	36.890	26.829	153.821	65.058	86.594	67.111	112.642
Pd_2	145.798	27.421	114.213	113.513	63.377	29.615	156.014	57.688	135.319
Pd₃	95.595	82.315	89.899	88.119	51.737	72.519	58.361	48.602	72.968
Qd1	118.862	69.047	87.516	52.406	42.131	33.064	65.839	36.239	32.789
Qd ₂	31.255	27.855	1173.967	115.905	95.845	184.404	30.678	27.530	75.100
Qd₃	78.300	41.972	33.589	82.609	33.782	81.098	99.646	64.848	104.482

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4. Conclusions

This paper has presented enhancing power system resilience through optimized load-shedding strategies. This study introduces the Integrated Clonal Squirrel Search-Evolutionary Algorithm (ICSSEP) as an effective optimization strategy for load-shedding in power systems, with performance evaluated using the IEEE 57-Bus RTS dataset. The analysis demonstrated ICSSEP's ability to identify optimal load-shedding locations and capacities, effectively reducing power losses and improving resilience. Pre-event and post-event simulations highlighted the impact of outages on system performance, revealing significant increases in power losses after events. Notably, ICSSEP optimization achieved substantial loss reductions across all scenarios and buses, with pronounced improvements under high reactive power demands (Q_d) . On the other hand, this study demonstrates that ICSSEP-based load-shedding is a powerful optimization tool for enhancing power system

resilience and minimizing transmission losses. Its ability to adapt to varying outage conditions and operational stresses positions it as a reliable approach for improving the reliability and efficiency of modern power systems. Future research could explore its application to larger power networks and dynamic operating environments to further validate its scalability and effectiveness.

Acknowledgement

The authors would like to acknowledge the Universiti Teknologi MARA (UiTM) Shah Alam, Selangor, Malaysia. This research was not funded by any grant.

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