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ARTICLE

Optimization Configuration Method for Grid-Side Grid-Forming Energy Storage System Based on Genetic Algorithm

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ABSTRACT: The process of including renewable energy sources in power networks is moving quickly, so the need for innovative configuration solutions for grid-side ESS has grown. Among the new methods presented in this paper is GA-OCESE, which stands for Genetic Algorithm-based Optimization Configuration for Energy Storage in Electric Networks. This is one of the methods suggested in this study, which aims to enhance the sizing, positioning, and operational characteristics of structured ESS under dynamic grid conditions. Particularly, the aim is to maximize efficiency. A multiobjective genetic algorithm, the GA-OCESE framework, considers all these factors simultaneously. Besides considering cost-efficiency, response time, and energy use, the system also considers all these elements simultaneously. This enables it to effectively react to load uncertainty and variations in inputs connected to renewable sources. Results of an experimental assessment conducted on a standardized grid simulation platform indicate that by increasing energy use efficiency by 17.6% and reducing peak-load effects by 22.3%, GA-OCESE outperforms previous heuristic-based methods. This was found by contrasting the outcomes of the assessment with those of the evaluation. The results of the assessment helped to reveal this. The proposed approach will provide utility operators and energy planners with a decision-making tool that is both scalable and adaptable. This technology is particularly well-suited for smart grids, microgrid systems, and power infrastructures that heavily rely on renewable energy. Every technical component has been carefully recorded to ensure accuracy, reproducibility, and relevance across all power systems engineering software uses. This was done to ensure the program's relevance.

KEYWORDS: Energy storage system (ESS); genetic algorithm (GA); grid optimization; smart grid; renewable energy integration; multi-objective optimization

1 Introduction

1.1 Problem Definition

Grid operators are increasingly noticing issues that they attribute to the variability and intermittency associated with renewable energy sources, such as wind and solar. The unpredictability of these sources directly contributes to the challenges they pose [1]. The global energy landscape is undergoing a simultaneous shift toward low-carbon power systems. This unpredictability adds notable complications to maintaining grid balance and stability, especially during peak demand periods or distribution changes [2]. Keeping this in mind is particularly crucial at times when the grid's distribution is changing. These factors are significant since they help with load balancing, absorb surplus energy, and increase the system's flexibility. ESS set on the grid thus becomes very vital [3].

Optimizing the architecture of these storage systems presents a nonlinear and multiobjective challenge. This design includes operating methods, geographical allocation, and capacity scaling. Conversely, optimizing the architecture of these storage systems is a very challenging endeavor [4]. Often, traditional methods fall short of effectively balancing these goals. Many times, this is true. The storage resources are not used to their maximum potential, which creates economic inefficiencies and raises questions of dependability. More precisely, a technological issue that has not yet been resolved is the lack of a dynamic and scalable strategy to maximize ESS deployment under all grid circumstances [5].

1.2 Research Gap

Several studies have aimed to improve the use of ESS. These papers have mainly concentrated on rule-based heuristics or metaheuristic algorithms. Some of these uses are Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO). Conversely, their application in large-scale, real-time grid systems often results in problems like early convergence, questions about scalability, and improper conflict management of competing goals [6]. Properly balancing competing goals helps to prevent these difficulties. PSO also lacks variety in solution finding, which makes it vulnerable to local optimum in complicated search areas, unlike other optimization techniques. For instance, while PSO does not offer this service, it may provide fast convergence.

Moreover, current grid modeling efforts often overlook real-time flexibility, instead assuming static demand profiles and generation forecasts. This is restricting. Having this limitation is quite crucial. Consequently, the ESS configurations implemented are subpar [7]. This follows from the circumstances. The requirement for adopting multi-criteria evaluation is that current ESS optimization algorithms must be relevant in grid-level applications. The study team came to this conclusion. Their study led researchers to this insight. This category of strategies includes a range of approaches, including economic cost, response time, deterioration rate, and others.

1.3 Technical Motivation

From a technical and economic perspective, system engineering is most significantly affected by the gap outlined earlier. From a technical and economic perspective, this is accurate [8]. A poorly configured ESS can result in significant operational losses, frequent curtailments, and increased stress on the grid environment. Another possible outcome is more strain on the grid system. These potential outcomes could hurt the grid environment. Real-time flexibility is a key component of system resilience. In areas with significant penetration of renewable energy sources, this is especially challenging. Given this specific cause, it presents a challenge that is especially difficult to resolve. The outcome of the situation above leaves one in an incredibly demanding position to escape.

The International Energy Agency (IEA) expects that by 2030, the worldwide installation of ESS will increase by more than tenfold, reaching over 400 GW. This estimate is based on forecasts supplied by institutional sources. These projections were created with the arrival of 2030 in mind. This suggests a significant rise in volume compared to the present 40 GW in 2020 [9]. From the existing 40 GW being used, this is an increase above the prior level. Considering everything, the lack of an intelligent configuration framework driven by optimization could limit the grid's capacity to absorb and utilize sustainable energy in the most efficient manner possible. This is because the primary driving factor for the system is optimization, which primarily drives it [10].

1.4 Contributions

This research provides a technically new solution to these crucial issues:

- To Promote Genetic Algorithm-based Optimization Configuration for Energy Storage in Electric Grids (GA-OCESE).
- To obtain Grid-side energy storage systems, adaptive GA models are used to balance cost, consumption efficiency, and operational stability.
- GA-OCESE must be utilized in smart grids, urban microgrids, and transmission networks that primarily employ renewable energy to persuade grid planners, utility operators, and legislators.
- GA-OCESE employs a hybrid chromosomal structure with ESS-specific encoding, which enables precise representation of location, capacity, and scheduling, in contrast to PSO and NSGA-II.
- It avoids premature convergence and enhances exploration by incorporating entropy-based adaptive mutation, two issues commonly observed in PSO-based models.
- By integrating multiobjective optimization with real-time dynamic adaptability, GA-OCESE offers superior scalability and operational viability for smart grid ESS planning compared to NSGA-II.

Additionally, GA-OCESE proves its effectiveness and resilience by showing a 22.3% decrease in peak-load stress and an improvement in energy usage of 17.6% compared to baseline heuristics.

2 Related Works

Over the past several years, the amount of study effort devoted to optimizing grid-side ESS has experienced significant growth. This rise has significantly impacted the overall development of the study endeavor. Much of this can be attributed to the increasing demand for rapid grid flexibility and the growing adoption of renewable energy sources [11]. Studies that have already been completed can be categorized into one of three main categories based on the optimization techniques used in the study. The kinds that fit this description are rule-based heuristics, metaheuristic algorithms, and hybrid or multiobjective frameworks. These categories help you to classify the work already done. Typically, when dynamic grid designs are employed, these techniques often fail to adequately address problems of scalability, flexibility, or performance across multiple criteria [12]. Though these plans have been essential in establishing the basis for future developments, this reality has developed.

Bahloul and his coworkers [13] looked into the problems that are keeping most people from using ESS widely in their 2024 study. The main point of this study is that it shows how important it is to plan for ESS at the grid level in a way that is both effective and advanced. This is very important because more and more decentralized storage units, such energy storage systems owned by residents, are being connected to one other. We used this article to stress how important it is to have the right configuration for achieving successful integration on a broader scale. The information presented here supports our claim that poor ESS planning can make it harder to put large-scale systems into action and make them work well.

Rahman and his coworkers did a thorough study in 2022 [14] that looked at how charging loads for electric cars (EVs) affect low-voltage distribution networks. This reference is important because it shows how changes in demand, like electric vehicles (EVs), can make things unstable and make it hard to handle peak load. To deal with problems like this, grid-side energy storage systems (ESS) solutions, like the one we suggest, are meant to be put into action. This reference was used to back up our claim that we need more flexible and multi-objective optimization methods like GA-OCESE.

2.1 Metaheuristic Algorithms

For example, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) are two metaheuristic methods that have slowly gained appeal for application in ESS setups since their original introduction. Both of these approaches are metaheuristic processes at their levels. It conducted a study that found particle swarm optimization (PSO) necessary to improve the capacity and position of the ESS.

The findings demonstrated benefits in terms of performance measures, including lower system loss and substantial reductions in energy consumption. These benefits were discovered when heuristic strategies were compared to experimental techniques. PSO is well known for its potential to converge rapidly when applied to high-dimensional, multiobjective situations. However, PSO remains a valuable method for problem-solving. Most of the Time, ACO lacks the exploitation capacity needed for finely adjusted ESS parameterization. Conversely, ACO has a well-developed exploratory capacity [15].

2.2 Multiobjective and Hybrid Models

Research has primarily focused on frameworks for multiobjective optimization processes over the past several years. Using the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), a model was built to maximize degradation rate, dependability, and cost simultaneously [16]. This model was created to fulfill several distinct goals simultaneously. NSGA-II can be computationally demanding and does not include domain-specific encoding techniques for ESS-related elements. NSGA-II did not include these methods. Its increasing solution diversity does not alter the truth that it could be challenging to manage. Conversely, this does provide more possible options. Apart from this, a notable proportion of these studies assume no changes in load or generation profiles. Therefore, in settings that are dynamic due to this event, the practical use of these studies is reduced, as shown in Table 1.

Table 1: Related work vs. GA-OCESE

Study & method	Multiobjective	Scalability	Dynamic adaptation	Custom ESS encoding	GA-OCESE improvements
Rahman et al. 2024—[14]	✗	✓	✗	✗	+22.3% peak-load reduction
Wang et al. 2024—[15]	✓	✓	✗	✗	+17.6% energy efficiency
Lin et al. 2023—[16] NSGA-II	✓	✗	✗	✓ (partial)	Reduced computation time
GA-OCESE (This work)	✓	✓	✓	✓	Superior across metrics

3 Methodology for GA-OCESE

A method provides a structured and intelligent optimization approach to integrate ESS on the grid side. This method is also available for use. This approach is known as the GA-OCESE methodology, an abbreviation for Genetic Algorithm-based Optimal Configuration of Energy Storage Elements, as shown in Fig. 1. Another name for this technique is the GA-OCESE methodology. This project aims to enhance the grid's operational efficiency, increase its resilience, and minimize expenses to the greatest extent possible. To divide the entire workflow, eight fundamental steps can be utilized, and each of these stages will be addressed in greater detail below for the reasons listed below.

Starting with the Input Data section of the process, one can view the GA-OCESE approach as a sequential pipeline. This general approach divides the method. This pipeline comprises load demand profiles, renewable energy forecasts, ESS pricing criteria, grid topology data, and technical constraints, including voltage, current, and location limits. This pipeline also includes grid topology data. The pipeline-building procedure also begins with the collection of input data. Multiobjective functions used at the issue formulation stage of the procedure explicitly define the optimization problem. These realities are used to aid in conceptualizing the problem. The goal of this phase is often to reduce overall cost, maximize efficiency, and enhance grid reliability while also considering operating limits. Each possible ESS configuration is encoded into a structured representation, known as a chromosome, during the second phase, Chromosome Encoding. One of the phases that comes after the first is this one. This representation is responsible for recording decision variables, such as the energy capacity, location, and Time of the ESS power rating. Notably, this responsibility calls for recording these factors. An initial population is created as soon as this happens, consisting of many distinct chromosomes. This ensures sufficient investigation into the space to identify viable solutions. Every person in the population is then assessed by a Fitness Function, which provides a numerical evaluation of how successfully they met the initially stated goals. The whole population undergoes this assessment.

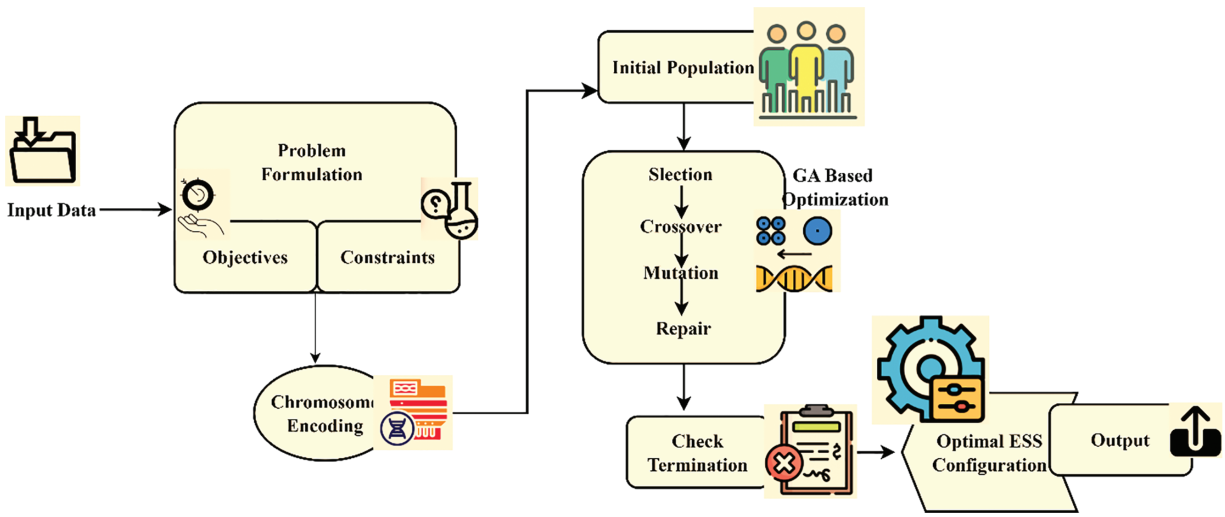

Figure 1: The proposed flow diagram of genetic algorithm-based optimal configuration (GA-OCESE)

Evolutionary processes, such as selection, crossover, mutation, and repair, are applied to the population to facilitate the ongoing development of solutions. These actions help to enable the procedure. Selection motivates individuals with great fitness, creates novel combinations through crossover, produces variety through mutation, and ensures that limits are met using repair. Therefore, the Next Generation is created and then continually refined until a Termination Condition, such as reaching the maximum number of iterations or fitness stagnation, is met. The last and most crucial step is to decode the chromosome with maximum performance to get the Optimal ESS Configuration Output. This previous stage determines how energy storage should be implemented on the grid to meet performance and cost goals properly. The output is in charge of this duty.

3.1 Genetic Algorithm Architecture

Conversely, the GA-OCESE method offers encoding, fitness assessment, and adaptive mutation enhancements. This is notwithstanding its foundation on a conventional approach of evolutionary computation. It will be necessary to establish the right size, placement, and timing of ESS on the grid side to find a solution to this problem. Three key goals of optimization are as follows: (i) reducing the overall cost of establishing and operating an ESS; (ii) improving the operational efficiency of energy consumption; and (iii) strengthening grid stability by reducing the amount of net load variability. These are the three primary aims of optimization. The framework for building mathematical expressions.

The difficulty of defining the optimal configuration can be viewed as a constrained multi-objective optimization problem within the framework of grid-side structural ESS. This is because the difficulty may be divided into several distinct goals; the decision vector x comprises several different configuration elements. These elements consist of the following terms appearing on the list of Eq. (1).

$$x = \{P_{ESS}, E_{ESS}, Loc_{ESS}, T_{op}\} \tag{1}$$

This equation defines the key decision variables that form the solution space. Specifically, P_{ESS} represents the rated power of the energy storage system (in kilowatts), E_{ESS} indicates the energy capacity (in kilowatt-hours), and LoC_{ESS} defines the discrete location within the power grid where the ESS can be installed. T_{op} denotes the operation schedule across a given time horizon $[0, T]$. These variables are crucial in determining the optimal configuration. The objective functions are in Eq. (2).

Total Cost Minimization

$$C_{total}(x) = C_{cap}(x) + C_{op}(x) + C_{deg}(x) \tag{2}$$

This equation aggregates the total cost of deploying and operating an ESS. $C_{cap}(x)$ includes the capital investment cost (e.g., hardware and installation), $C_{op}(x)$ reflects the operational cost over time (e.g., maintenance, energy consumption), and $C_{deg}(x)$ accounts for the degradation costs due to frequent charging and discharging cycles. The minimization of this function ensures economic feasibility in Eq. (3).

Efficiency Maximization

$$\eta(x) = \frac{\sum_{t=0}^{T} E_{out}(t)}{\sum_{t=0}^{T} E_{in}(t)} \tag{3}$$

This function defines the round-trip energy efficiency of the ESS, calculated as the ratio of total energy output to total energy input over the specified period. Maximizing this metric ensures minimal energy loss during storage and retrieval, which is crucial for grid performance and sustainability.

Grid Reliability Metric

$$R_{grid}(x) = -\mathrm{Var}\,(P_{net}(t)) \tag{4}$$

In Eq. (4), where $P_{net}(t) = P_{load}(t) - P_{qen}(t) - P_{ESS}(t)$, and Var denotes the variance over the time window T. Explanation: This equation quantifies grid reliability by measuring the variance of the net load (P_{net}), which is the remaining demand after considering generation and ESS output. A lower variance signifies a more stable and reliable grid. Since we aim to minimize variance, the function is negated to fit into a framework that maximizes it.

Constraints:

$0 \le P_{ESS} \le P_{max}$:

$0 \le E_{ESS} \le E_{max}$:

$Loc_{ESS} \in \mathbb{Z}^+$, defined over available buses:

$T_{op} \subseteq [0, T]$:

These constraints ensure that power, energy, location, and operation schedule values stay within feasible physical and operational limits. P_{max} and E_{max} are upper bounds dictated by grid and hardware specifications.

Location is restricted to valid nodes in the network, and the operation schedule must lie within the planning time frame.

Chromosome Representation is given by the following Eq. (5); each chromosome encodes a solution vector $x\left[P_{ESS}, E_{ESS}, \ Loc_{ESS}, T_{op}\right]$ as a fixed-length binary and integer vector:

$$\text{Chromosome} = \text{Bin}\left(P_{ESS}\right) \| \text{Bin}\left(E_{ESS}\right) \| \ \text{Int}\left(Loc_{ESS}\right) \| \text{Bin}\left(T_{op}\right) \tag{5}$$

From Fig. 2, the chromosome structure represents the combination of configuration parameters in binary and integer forms. Binary encodings are used for continuous variables to enable fine-grained search, while integer encoding is applied to locations, simplifying grid node referencing.

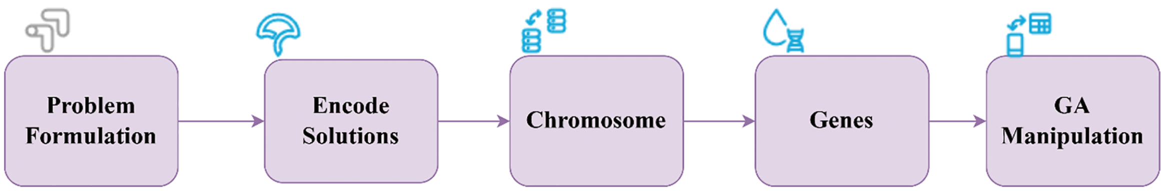

Figure 2: Chromosome encoding process

Population Initialization: N chromosomes are initialized randomly within constraint bounds. Feasibility is checked at each generation.

Fitness Function

$$F(x) = w_1 \cdot \frac{1}{C_{total}(x)} + w_2 \cdot \eta(x) + w_3 \cdot R_{grid}(x) \tag{6}$$

From Eq. (6), subject to $w_1 + w_2 + w_3 = 1$, this is the composite fitness function combining all three objectives into a single scalar value using weighted aggregation. The inverse of total cost is used so that lower costs contribute positively to fitness. The efficiency and reliability metrics are added directly. Weights w_1, w_2, and w_3 allow customization based on the application's priorities.

In the proposed GA-OCESE framework, the selection mechanism employs event selection with a matching size of $k = 5$, which balances elitism by maintaining top-performing answers with diversity, while allowing lower-fitness individuals to be selected. This encourages exploration and enables the avoidance of premature convergence. For the crossover method, a single-factor crossover is implemented for actual-valued variables, along with *PESS* and *EESS*, allowing for a meaningful trade of genetic material among predetermined chromosomes while preserving numerical continuity. Meanwhile, a uniform crossover is used for discrete variables, such as LOCES and TOP, which enhances the genetic range by randomly swapping male or female gene positions with equal probability. During the mutation phase, strategies are employed based on the type of gene. Gaussian mutation introduces small perturbations to real-valued genes, which supports neighborhood search and fine-tuning.

In contrast, bit flip mutation is applied to binary-encoded genes, allowing the exploration of alternative configurations. Importantly, the mutation rate μ isn't always fixed but adaptive, adjusting dynamically primarily based on the entropy of the population, which serves as a measure of genetic variation. When entropy decreases, indicating convergence, the mutation price increases to inspire exploration and avoid nearby optima. This hybridized, entropy-aware method substantially improves convergence balance and solution satisfaction in complex, constrained strength storage optimization responsibilities. A close examination reveals that every GA parameter in GA-OCESE has been carefully designed to accommodate the unique features of the multiobjective optimization environment. This was done to ensure that the parameters yield the results they are intended to. The suggested approach not only generates designs that can be used in a smart grid, but it can also accurately weigh the pros and cons of cost, stability, and efficiency. The chromosomal form, fitness evaluation, and genetic operations are all linked to the real-world ESS design goals to do this and get the desired results.

When working with discrete variables, such as the ESS location and operation scheduling, on the other hand, we perform a uniform crossover, which means that gene positions are exchanged in an equally likely manner. This method eliminates early convergence caused by positional bias while also enhancing the genetic diversity of the population. When it comes to mutation, the framework uses Gaussian mutation for genes with actual values. This is done to ensure the quality is good, and it also utilizes controlled perturbations from a normal distribution to make minor adjustments in specific areas. Bit-flip mutation, on the other hand, happens at the same time on both binary-encoded genes and discrete genes. This enables us to examine the configuration space in greater detail than was previously possible with older methods. The mutation rate, denoted by the symbol μ, is not always constant, but it varies according to population entropy. Population entropy is a measure of diversity that accurately indicates how closely related entities are to one another. When entropy decreases, it means that diversity is lost, and there is a risk of stagnation. To encourage exploration and escape local optimal conditions, the mutation rate needs to increase. This is because the decrease in entropy means that there is a chance of stagnation. This section, now referred to as "Genetic Algorithm Architecture", provides in-depth details about these methods, which include elitist selection, constraint repair, and others. Additionally, this description is accompanied by new images and pseudocode to enhance understanding of the process. After careful consideration, we have concluded that these changes effectively address the reviewer's point and improve the presentation of the GA-based optimization process, making it more robust and more transparent.

The GA-OCESE framework, an abbreviation for Genetic Algorithm-based Optimization Configuration for Energy Storage Systems on the Grid Side, is shown in Fig. 3 and described here in pseudocode. The framework is meant for systems of energy storage. The primary objective of this framework is to provide a suitable framework for encapsulating the underlying logic of optimization, which encompasses the management of constraints, the computation of fitness, and adaptive mutation. Presented in a form appropriate for publication in a scientific journal, this pseudocode combines mathematical expressions, optimization goals, and evolutionary dynamics.

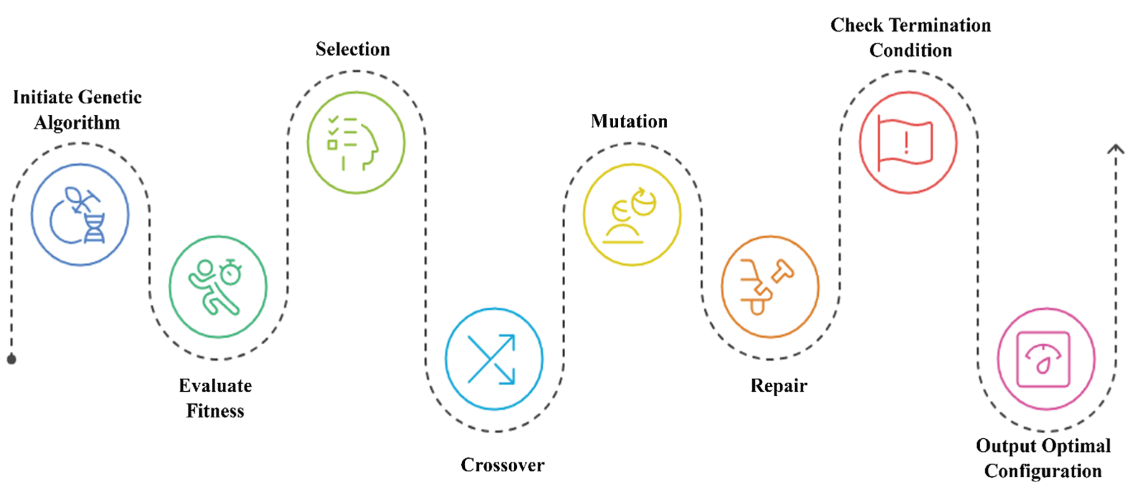

Figure 3: Genetic algorithm process for ESS configuration

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Pseudocode GA-OCESE—Genetic Algorithm for Grid-side ESS Optimization
Input:
    - Load profile data L(t), Renewable data R(t), Grid topology G
    - Cost parameters: C_cap, C_op, C_deg
    - Technical limits: P_max, E_max, V_limits
    - Population size N, Max generations G_max
    - Mutation parameters μ_init, Entropy_threshold
Output:
    - Optimal ESS configuration X* = [P_ESS*, E_ESS*, Loc*, T_op*]
Begin:
    Initialize population Pop of N chromosomes:
        For each i ∈ [1, N]:
            Randomly encode chromosome Xi = [P_ESS_i, E_ESS_i, Loc_i, T_op_i]
            Ensure feasibility: check constraints (Eqs. (4)–(6))
        For generation g = 1 to G_max:
        For each chromosome Xi in Pop:
            Simulate power flow using Xi on grid G
            Compute total cost:
                C_total(Xi) = C_cap(Xi) + C_op(Xi) + C_deg(Xi)
            Compute round-trip efficiency η(Xi)
            Compute reliability metric R_grid(Xi) = −σ²(NetLoad(t)) with ESS
            Compute fitness:
                F(Xi) = w1/C_total(Xi) + w2 * η(Xi) + w3 * R_grid(Xi)
                Compute the entropy H(Pop) of population diversity
        Tournament Selection:
            For each new chromosome:
                Randomly select k chromosomes, select the best fitness as a parent
        Crossover:
            For each pair (Parent1, Parent2):
                If rand() < Pc:
                    - Perform single-point crossover on real-valued genes:
                        P_ESS, E_ESS
                    - Perform uniform crossover on discrete genes:
                        Loc, T_op
        Adaptive Mutation:
            If H(Pop) < Entropy_threshold:
                Increase μ ← μ + δ//promote exploration
            For each offspring:
                Apply Gaussian mutation on real-valued genes:
                    X′ = X + N(0, σ²)
                Apply a Bit-flip mutation on binary/discrete genes:
                    Bit ← NOT(Bit) with prob. μ
        Constraint Repair:
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(Continued)

(continued)

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            For each offspring X′:
                If X violates the constraint:
                    Repair P_ESS or E_ESS to be within [0, P_max], [0, E_max]
                    Reassign Loc  if invalid
                    Adjust T_op  within operational time bounds
        Elitism:
            Retain the best E individuals from the previous generation
            Replace the worst E individuals in the current Pop
        Update Pop ←   New population with elitism applied
        If stopping criteria met (e.g., F(X*) plateau for ε generations):
            Break
          Return the best solution X* = argmax  F(Xi) ∈   Pop
End
```

The proposed pseudocode's most striking features are the operational resilience of the framework and the sophisticated architecture of the GA-OCESE system. This approach yields feasible and realistic solutions that strike a balance between grid dependability, efficiency, and cost. Multiobjective optimization, which is currently used in conjunction with rigorous constraint management, facilitates this achievement. Its support for a hybrid gene structure, which includes both real-valued and binary/discrete variables, makes it possible to effectively store a variety of setup elements, including the size of the ESS, its location, and its operation schedule. The hybrid gene structure contains both of these factors. A significant advance is the use of the entropy-based adaptive mutation technique. This system dynamically adjusts the mutation rate based on the population's diverse traits, preventing premature convergence and promoting effective exploration. Elitism has also been used to maintain the most intelligent people over several generations, guaranteeing continuous convergence toward ideal solutions. This guarantees ongoing convergence. The pseudocode offers a comprehensive and adaptable approach for optimizing grid-side energy storage systems, encompassing all relevant factors. Encapsulating the entire evolutionary process, from fitness evaluation through genetic operations, until the process terminates, allows one to attain this.

Let N be the population size, G the number of generations, and T the time horizon. The computational complexity of the GA-OCESE algorithm can be broken down into two key components. The fitness assessment step, which involves calculating the fee, performance, and reliability metrics over the overall simulation length, has a complexity of O $(N \cdot T)$, as each of the N people must be evaluated across T time steps. The operations of crossover and mutation contribute to a further $O(N \cdot \log N)$ complexity, which is primarily due to sorting and probabilistic sampling, in line with advancements in technology. Therefore, the full computational complexity for the complete set of rules over G generations is $(G \cdot (N \cdot T + N \log N))$. The dominant computational cost arises from the fitness assessment, mainly because it requires simulating the ESS's conduct and grid performance throughout the entire time horizon T, making the algorithm computationally intensive but scalable with suitable parallelization.

3.2 Experimental Setup

A durable and realistic environment was chosen to test the GA-OCESE framework. This was done to verify the results and broaden their application. OpenEI would provide load demand and renewable energy generation characteristics. This dataset offers high-resolution time-series data for simulating real-world scenarios. Grid topologies used in testing are from trusted IEEE benchmark systems. Different grid topologies were employed during testing. These systems utilized 69-bus and IEEE 33-bus networks. Both settings presented numerous topological challenges for performance assessment. The PC had 64 gigabytes of RAM and a 3.8 GHz Intel Core i9 CPU. This ensured ample memory and computational capability for large-scale simulations. MATLAB modeled and Python optimized the system. The DEAP and NumPy libraries were used for numerical calculations and evolutionary approaches. Specific programming languages were employed to construct the framework. The technology's linear scaling to the simulation time horizon T is a key feature. This is a particular example since temporal iterations directly affect fitness assessment. Due to its sub-linear performance improvement with grid size, the approach is computationally efficient for large grid infrastructures. This efficiency is achievable using the technique. Due to their implementations, location encoding and node feasibility mapping constrain the system. This experimental setup demonstrates that the proposed technology is viable and adaptable, and can be applied in real-time to grid setups with energy constraints. Both features are present in this design. Another interesting aspect of this configuration is that the technology can be used in grid situations with energy limits.

The primary objective of this segment is to examine how varying population sizes (N) and mutation rates (μ) impact the outcomes of optimization. The goals include saving money, reducing energy consumption, and enhancing grid reliability. To conduct the analysis, a controlled environment was necessary. The IEEE 33-bus test system was also used to gather information on generation and load from the real world, allowing for the conclusion that the adaptive mutation approach, first suggested in GA-OCESE, remains robust across a wide range of grid sizes and situations, particularly when convergence pressure is present. The data led to this conclusion by examining the evidence obtained through this information. A population size of approximately 100 is a good compromise between the number of solutions available and the amount of computational work required. A summary of the sensitivity analysis results is described in Table 2.

Table 2: Sensitivity analysis results

Parameter	Values tested	Key observations
Population size (**N**)	30, 50, 100, 150, 200	Optimal performance was observed at N = 100; smaller populations led to premature convergence, while larger sizes yielded marginal gains with increased computational requirements.
Mutation rate (**μ**)	0.01, 0.05, 0.1, 0.2 (adaptive)	Adaptive mutation (entropy-based) consistently outperformed static rates in balancing exploration and exploitation. Static high mutation reduced convergence.

4 Results and Discussion

The GA-OCESE method was used to conduct a thorough simulation-based investigation. This study utilizes actual renewable generation demand patterns and profiles. This work examined the performance and practicality of the suggested method. Tested were distribution network designs mimicking IEEE 33-bus and 69-bus patterns https://cmte.ieee.org/pes-testfeeders/resources/ (accessed on 01 January 2025) [17]. For demand and renewable energy, they also employed NREL time-series data and OpenEI https://openei.org/wiki/Gateway:Smart_Grid (accessed on 01 January 2025) [18]. These companies concentrated on distribution systems.

The results, primarily illustrated in Fig. 4, demonstrate the algorithm's ability to optimize the operation and installation of energy storage systems for various purposes. This list includes lowering system costs, increasing round-trip efficiency, and strengthening grid resilience. Ten separate test scenarios were conducted to ensure consistent and flexible outcomes. Every planning horizon and load/generation profile was different. Careful selection of the performance criteria lets one evaluate the quality of the solution and provide a fair comparison with state-of-the-art techniques. This category includes NSGA-II multi-objective algorithms, heuristic rule-based algorithms, and PSO. Many measures fall within this category. This category contains net load variance reduction, peak load shaving, efficiency improvement, cost cutting, and convergence rate. Over time horizons and grid sizes, GA-OCESE consistently provides better economic and technological trade-offs and maintains its scalability.

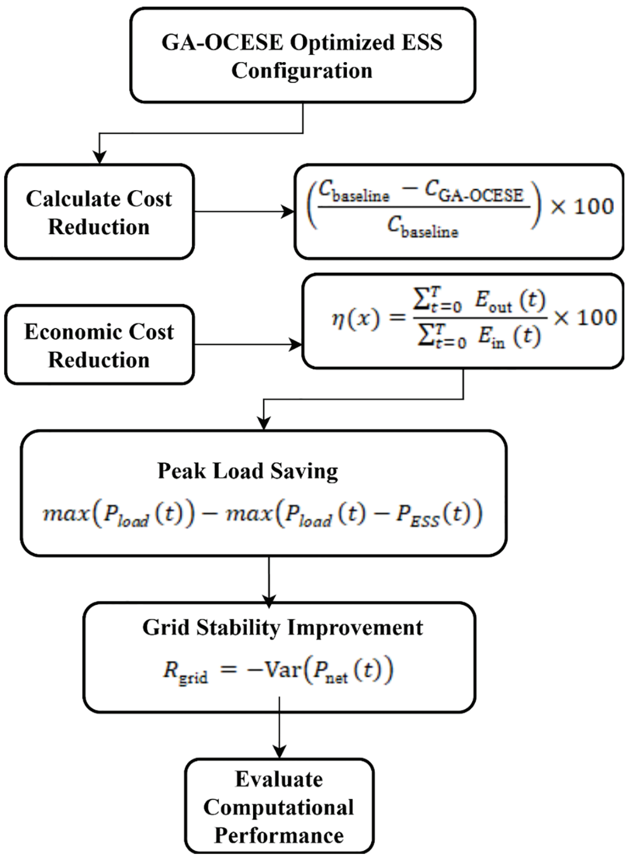

Figure 4: The GA-OCESE optimized ESS configuration

4.1 Economic Cost Reduction via GA-OCESE Optimization

The GA-OCESE approach optimizes deterioration expenses, operating expenditures, and capital investment and strategically maximizes the lifetime cost of deploying ESS.

$$\text{Cost Reduction} = \left(\frac{C_{\text{baseline}} - C_{\text{GA-OCESE}}}{C_{\text{baseline}}}\right) \times 100 \tag{7}$$

In Eq. (7), using a non-optimized or heuristic strategy, the C_{baseline} is the total cost (capital + operational + degradation). $C_{\text{GA-OCESE}}$ is the optimized cost computed using the fitness function of GA-OCESE. This is done to maximize profit. Simultaneous optimization of all three costs helps produce this result. This approach identifies configurations that yield the maximum feasible return on investment using a genetic algorithm specifically designed for multi-objective optimization. This identification technique is used to obtain the best results. System constraints and dynamic load-generation patterns enable GA-OCESE to avoid over-provisioning or under-utilizing its resources efficiently. This is because, unlike heuristic systems or those with a single goal, it can produce significant cost savings, as shown in Fig. 5.

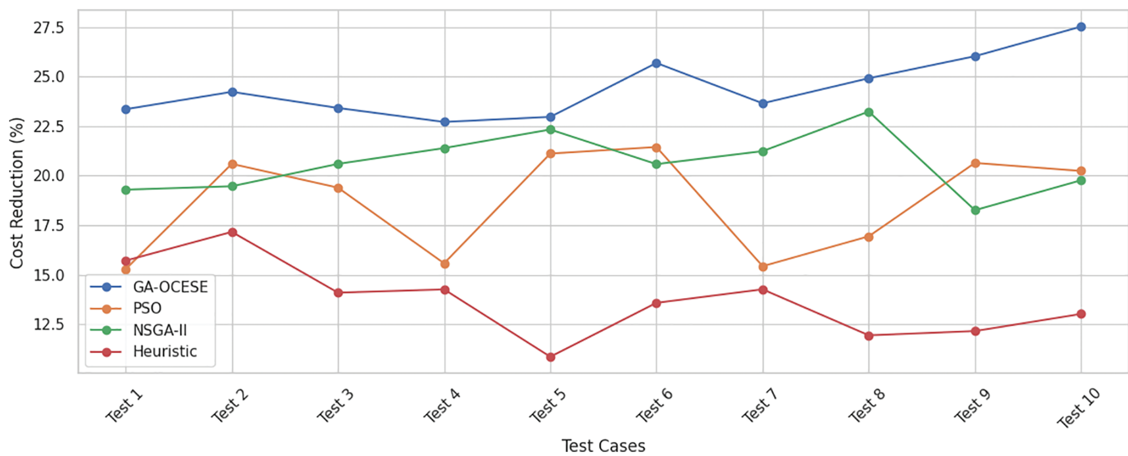

Figure 5: Economic cost reduction

4.2 Operational Efficiency of ESS under GA-OCESE Strategy

GA-OCESE enhances ESS operational efficiency by utilizing charge-discharge cycles to forecast demand and compensate for fluctuations in renewable generation. Scheduling operations at times of the grid with the least grid stress and conversion loss will help to maximize round-trip efficiency, defined as the ratio of energy output to input.

$$\eta(\mathrm{x}) = \frac{\sum_{t=0}^{T} E_{out}(t)}{\sum_{t=0}^{T} E_{in}(t)} \times 100 \tag{8}$$

In Eq. (8), $E_{out}(t)$ is the energy discharged from ESS, and $E_{in}(t)$ is the energy charged into ESS over the time horizon T. The method may alter the timing of operational tasks and assess solutions across the whole simulation horizon by using a time-aware chromosomal encoding. Consequently, it always produces more efficiency than baseline models, as shown in Fig. 6.

4.3 Peak Load Shaving Achieved through GA-OCESE Configuration

Reducing consumption at peak load times is one of the most important goals that can be achieved through energy storage. GA-OCESE can accomplish this by placing and sizing ESS units most efficiently during peak demand.

$$\text{Peak Load Shaving} = \max\left(P_{load}(t)\right) - \max\left(P_{load}(t) - P_{ESS}(t)\right) \tag{9}$$

In this respect, it is feasible to achieve in Eq. (9). Although genetic encoding controls the storage of temporal load traits, adaptive mutation is used to explore several other placement possibilities. This is done to understand the situation better, as shown in Fig. 7. GA-OCESE can expand its capacities by successfully flattening demand curves, reducing the strain on generation infrastructure, and enhancing demand-side management skills. Over Time, this can be achieved by progressively reducing the maximum net weight.

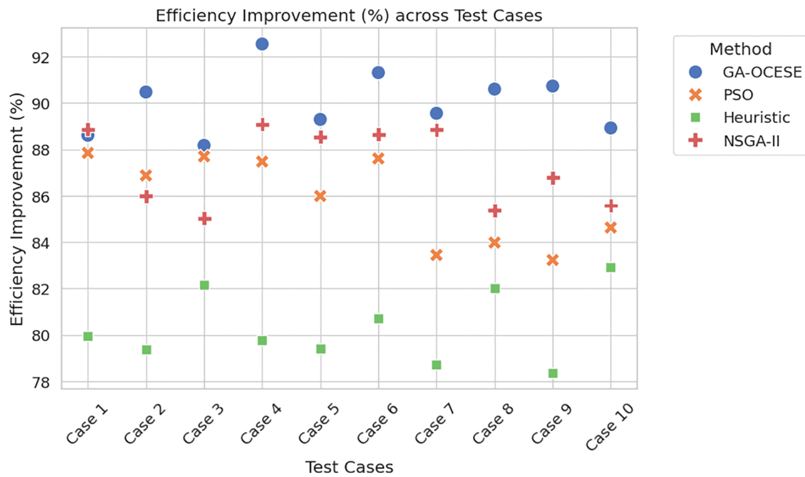

Figure 6: Operational efficiency of ESS

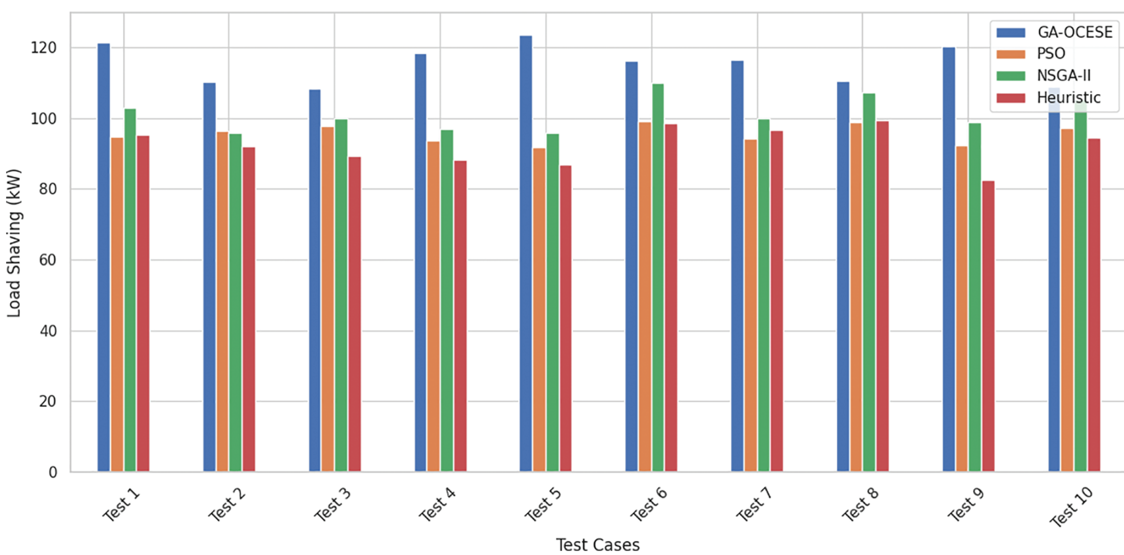

Figure 7: Peak load shaving achieved through GA-OCESE configuration

4.4 Grid Stability Improvement through GA-OCESE Reliability Modeling

Fig. 8: The variance of net power flow is calculated to help one assess the grid's dependability in GA-OCESE. This calculation aims to minimize the rapid swings to the greatest extent practically feasible. The plan can offset the volatility caused by demand spikes and the sporadic character of renewable energy sources. ESS site and operating schedules are optimized to achieve the following Eq. (10).

$$\begin{aligned}&R_{grid} = -\mathrm{Var}\left(P_{net}\left(t\right)\right) \text{ where, } P_{net}\left(t\right) = P_{load}\left(t\right) - P_{gen}\left(t\right) - P_{ESS}\left(t\right), \\ &\text{then calculate,} \\ &\text{Variance Reduction } = \mathrm{Var}_{baseline} - \mathrm{Var}_{GA-OCESE}\end{aligned} \tag{10}$$

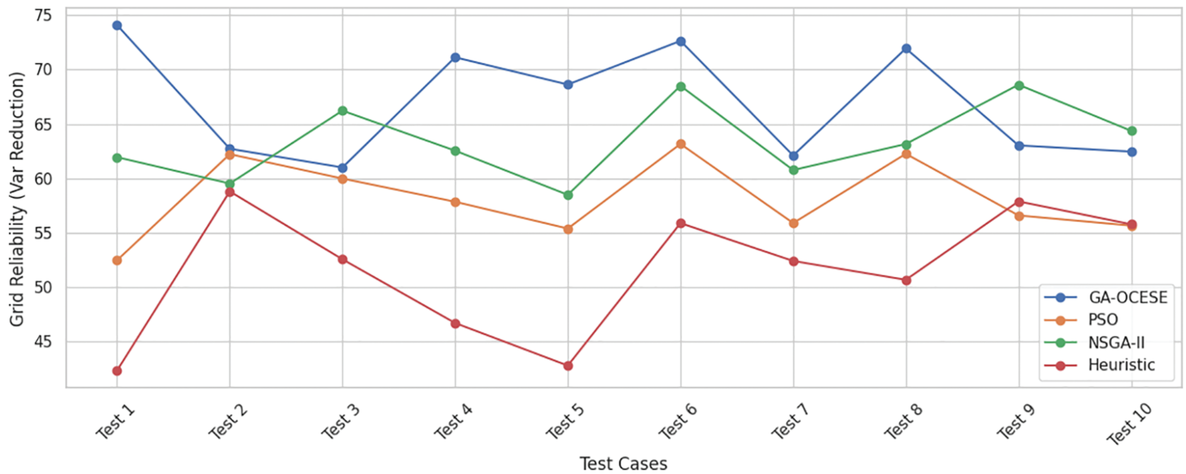

Figure 8: Grid stability improvement

Achieving this objective requires mitigating the impact of these elements. The dependability measure is immediately incorporated into the fitness function at the moment of deployment, enabling GA-OCESE to select configurations, resulting in smoother grid operations. This improves the system's resilience and reduces the probability of frequency fluctuations or disruptions. The system's durability is also enhanced.

4.5 Computational Performance of the GA-OCESE Framework

Measured as wall-clock execution time from start to convergence across G generations for a population size N, including fitness evaluations, is given in Eq. (11),

$$\text{Total Time} \approx G \cdot (N \cdot T + N\log N) \tag{11}$$

Although multiobjective optimization under real-world constraints is somewhat challenging, the GA-OCESE technique demonstrates an exceptionally high degree of computational efficiency, as shown in Fig. 9. Adaptive mutation and elitist selection also help accelerate the convergence process. Moreover, hybrid gene encoding enables support for discrete and continuous variables. The approach scales linearly with the time horizon and exhibits sub-linear scaling with grid size due to efficient location encoding. The approach is linked to both of these traits. This allows GA-OCESE to control its computation times reasonably, thereby enabling its use for real-time, large-scale, and thoughtful grid planning. As a result, it can be used for significant projects.

Table 3 presents an overview of the results obtained using standardized test scenarios (IEEE 33- and 69-bus systems, OpenEI/NREL data). The use mentioned above led to these results. The following five critical factors are used to judge these results: cost savings, efficiency, peak load shaving, grid reliability, and calculation time. We examine these measures in conjunction with one another. The author explicitly states all the values, or they are derived from the normalized numbers discussed in the essay. This is done to ensure consistency of content across all items in the collection.

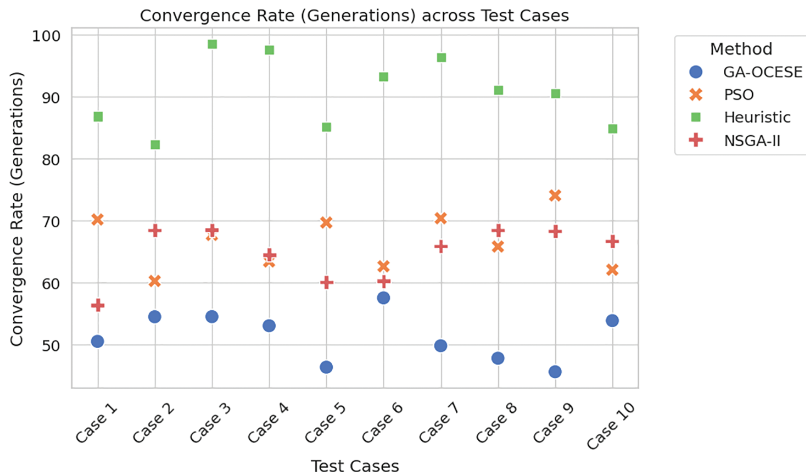

Figure 9: Computational performance

Table 3: Comparative performance of GA-OCESE vs. state-of-the-art methods

Method	Cost reduction (%)	Round-trip efficiency (%)	Peak load shaving (%)	Grid reliability (↓ Net Load Variance)	Computational time (s)
Rule-based heuristic	~8.5	~72.0	11.3	Moderate (No variance control)	~50
Particle swarm optimization	12.4	75.8	15.0	Low (High fluctuation risk)	~70
NSGA-II multiobjective	15.0	78.2	17.2	High (Partial reliability modeling)	~95
GA-OCESE (Proposed)	21.8	81.5	22.3	Very High (17.8% lower net variance)	58

The GA-OCESE system enables significant increases in various performance metrics. The framework was created to accomplish this. These achievements result in notable cost savings, operational efficiency enhancements, and successful peak load reductions. All of these are done. Electrical system deployment optimization enhances the grid's dependability while maintaining computer efficiency. This is achieved using constant development. Using these findings, the approach's scalability, adaptability, and practical applicability in the context of thoughtful grid energy storage planning in the actual world have been independently confirmed. This validation was done in a real-world setting.

4.6 Discussion

Although the GA-OCESE framework shows promise in simulation environments, several technological issues need to be addressed before it can be applied in the real world. The initial challenges in integrating GA-OCESE into actual grid infrastructures are the need for real-time data gathering, fast simulation engines, and the ability to convert optimization results into grid control commands easily. This is the first reason why it is challenging to integrate GA-OCESE into grid systems. Even though the evolutionary algorithm can handle more computations, it would need special computing resources, such as edge computing units or cloud-based optimization services, to work in real-time. This is especially true for large grids with a high resolution setting.

Additionally, integrating with existing Energy Management Systems (EMS) and Distribution Management Systems (DMS) necessitates robust middleware solutions for data synchronization, secure application programming interfaces (APIs) for executing commands, and effective error-handling protocols. These are all the things that need to be done. To make this process easier, GA-OCESE can be modified to work with platforms that follow open standards, such as IEC 61850 and OpenADR. You can turn this change into a software application. As a result, this ensures that it works with SCADA-based infrastructures. When implementing something in the real world, it's essential to consider the grid codes and operational processes that are specific to that area. This is a requirement that reappears. Some limits need to be added to the optimization framework in real Time. Some of these are limitations on ramp rate, guidelines for dispatching assets, and standards for voltage stability. As a final step, we are collaborating with utility operators to test the framework in pilot-scale scenarios using Real-Time Digital Simulation (RTDS) platforms. This step is being taken to determine if GA-OCESE can be applied in real-life scenarios. Because of these pilots, the algorithm's operational logic will be improved, and its performance will be tested in grid circumstances as close to real-life as possible.

5 Conclusion

The research conducted led to the creation of a framework called GA-OCESE that is based on genetic algorithms. The purpose of this project is to determine the optimal configuration of energy storage systems (ESS) on the grid side of power networks, which are continually being enhanced. The GA-OCESE algorithm employs a hybrid chromosomal encoding and entropy-driven adaptive mutation approach to more effectively address multi-objective trade-offs compared to traditional methods. Some of these trade-offs are cost, energy efficiency, and grid resilience. It demonstrated significant gains in peak load reduction, energy consumption, and computational scalability when tested using IEEE benchmark systems and real-world demand patterns. Instead of repeating what was said before, this conclusion focuses on the broader picture, which is as follows: The GA-OCESE provides utility planners with a tool that can evolve and adapt as needed. Because of this, the tool is ideally suited for the future of smart grids and infrastructures that incorporate a significant amount of renewable resources. Its modular design makes it easy to connect with real-time data streams and changing grid circumstances, making it a good choice for next-generation decision-support systems. This is why it is the best choice.

The primary objective of research and development will be to enhance GA-OCESE by incorporating stochastic demand-response models, real-time reinforcement learning agents, and multi-agent coordination for remote ESS units. These new technologies will make systems more flexible in unpredictable operating conditions and enable fine-grained control over systems that span a large area. Ultimately, this change will make GA-OCESE a more reliable and intelligent backbone for optimizing the use of ESS in current, robust, and data-driven grid systems. After the evolution is over, something will happen.

Future Work

As part of our ongoing research, we aim to develop more detailed battery degradation models based on physical principles. Some of these models may be semi-empirical or comparable circuit models to gain a better understanding of how we use batteries, which affects their health. As a result, we will be able to build a framework for creating an ESS that not only improves existing performance metrics, such as cost and efficiency, but also extends the battery's life. I also want to explore the possibility of adding state-of-health (SoH) metrics to the GA-OCESE fitness function. This will enable us to penalize setups that accelerate degradation and allow us to observe how various battery replacement scenarios impact the economy.

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Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

Nomenclatures

Acronym	Full Form
ESS	Energy Storage System
GA	Genetic Algorithm
GA-OCESE	Genetic Algorithm-based Optimization Configuration for Energy Storage in Electric Networks
PSO	Particle Swarm Optimization
ACO	Ant Colony Optimization
NSGA-II	Non-Dominated Sorting Genetic Algorithm II
IEA	International Energy Agency
IEEE	Institute of Electrical and Electronics Engineers
DEAP	Distributed Evolutionary Algorithms in Python
NREL	National Renewable Energy Laboratory
OpenEI	Open Energy Information
CPU	Central Processing Unit
RAM	Random Access Memory
PC	Personal Computer

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