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Renewable energy optimization in isolated microgrids: A Python-based tool for cost-effective solutions using genetic algorithms

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ABSTRACT

Isolated areas often rely on diesel generators for electricity production, which is associated with high costs and environmental impacts. Microgrids (MG) that integrate renewable energy and storage offer a more sustainable alternative. To support the techno-economic planning of such systems, this paper presents a modular Python-based tool for evaluating renewable energy penetration in isolated hybrid microgrids through single- or bi-objective optimization using genetic algorithms (GA). The tool combines a rule-based dispatch simulator with a GA optimizer and supports both hourly and minute-resolution data. It enables users to assess and optimize key performance indicators such as diesel consumption and Levelized Cost of Energy (LCOE). Applied to a real case study in Nunavik, Quebec, the tool evaluates five scenarios including wind integration and storage. Results indicate that optimized scenarios can reduce diesel consumption by up to 87% and the LCOE by up to 58% relative to diesel-only configurations. The proposed tool provides a flexible and practical framework for assessing and optimizing renewable integration in isolated MGs.

1. Introduction

The transition toward low-carbon energy systems has intensified efforts to integrate renewable energy sources into power systems, driven by environmental concerns, economic pressures, and policy objectives. While many regions benefit from interconnected grids, remote and isolated communities continue to rely primarily on diesel generators due to their reliability and ease of deployment. However, diesel-based generation is associated with high operating costs, fuel logistics challenges, and significant greenhouse gas emissions.

In Canada, although renewable energy, mainly hydropower, accounts for nearly 60% of national electricity production [1], many northern and remote communities remain disconnected from the main grid and depend almost entirely on diesel generation. This context has motivated increasing interest in isolated microgrids (MGs) that integrate renewable energy sources and energy storage systems as a pathway to reduce diesel consumption and environmental impact [2].

Microgrids are commonly defined as localized electrical systems that include distributed energy resources (DER), storage, and loads, capable of operating either grid-connected or in islanded mode [3,4]. In isolated operation, maintaining the balance between generation and demand is particularly challenging due to the variability of renewable sources such as wind and solar, and the limited flexibility of conventional generation units [5].

Energy Management Systems (EMS) are vital for maintaining the generation-load balance and achieving operational and economic objectives in microgrids. In this work, the term EMS refers to the overall management system, while specific decision logics are referred to as control or dispatch strategies. EMS approaches are commonly classified as rule-based, optimization-based, hybrid, adaptive, demand-side management, resilience-focused, or community-oriented strategies. Rule-based strategies rely on predefined control logic and are widely used due to their simplicity and robustness [6–8]. Optimization-based approaches use mathematical programming or metaheuristics to schedule system operation under technical and economic constraints [9–11]. Hybrid strategies combine both philosophies to balance computational efficiency and operational realism [12].

Although a large body of literature addresses EMS design and renewable integration in microgrids, several limitations remain. Many studies focus on simplified system structures, single diesel generator configurations, or long-term planning without explicitly addressing

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multi-generator coordination, spinning reserve management, or sub-hourly operation. In addition, numerous tools emphasize theoretical optimality but offer limited transparency or adaptability for real-world planning and engineering applications.

This work addresses these gaps by presenting a modular, Python-based planning tool that integrates a rule-based EMS with a genetic algorithm (GA) optimizer. Rather than introducing a new optimization algorithm, the contribution lies in the system-level integration of: (i) efficiency-based dispatch of multiple diesel generators, (ii) explicit spinning reserve management combining diesel units, renewables, and storage, (iii) compatibility with hourly and minute-scale simulation, and (iv) a modular architecture that supports single- and bi-objective optimization. This positioning emphasizes practical applicability, transparency, and flexibility for techno-economic planning of isolated microgrids.

Several works focus primarily on techno-economic sizing and penetration optimization of renewable components. For instance, Thomas et al. [13] and Ma et al. [14] assess feasibility under different dispatch strategies, while Kiptoo [15] analyzes system-wide costs across a spectrum of renewable penetration scenarios. Other authors explore system-specific configurations, such as Hamilton et al. [16], who emphasize wind-storage synergies and load-side management, and Michael et al. [17], who target low-load diesel (LLD) operation to reduce fuel use. Despite the diversity of targets, a recurring objective across these studies is maximizing renewable share. Notably, Zhou et al. [18] achieve over 100% PV penetration and 85% utilization through high-resolution simulations, though without addressing DG coordination in detail. Cleantechnol et al. [19] and Nasr et al. [20] report significant renewable contributions using EMS and optimization tools, while Belboul et al. [21] introduce a novel swarm algorithm, underscoring the growing interest in advanced metaheuristics.

A second cluster of works focuses on dispatch strategy development. For example, Zhou et al. [18] compare optimized and rule-based dispatch at minute resolution, an uncommon but relevant feature for realistic MG operation. Other studies, such as Khirennas et al. [22] and Lambert and Hassani [23], develop models for DG coordination, but primarily through Mixed-Integer Linear Programming (MILP) formulations with ideal assumptions. Although promising, these strategies often lack applicability to multi-DG real-world systems, particularly where control simplicity and computational speed are essential.

The economic dispatch and unit commitment literature is extensive but reveals similar trade-offs. Studies like Rezaee et al. [24] and Hou et al. [25] emphasize optimization under uncertainty and introduce AI-based scheduling, but often focus on single-objective cost minimization. Others, including Xu et al. [26] and Ishraque et al. [27], adopt richer performance indicators such as reliability, emissions, or user satisfaction. Still, most rely on simplified representations of microgrid behavior or limited temporal detail, which can reduce their applicability to EMS deployment.

Several studies also examine unit commitment under hybrid strategies. For instance, Ishraque et al. [28] assess multiple rule-based strategies, while Kutaiba et al. [29] introduce hybrid fuzzy-Grey Wolf Optmizer (GWO) methods for storage sizing. Yet, as with dispatch, these works often operate under assumptions of single DG, rarely addressing the challenge of managing multiple heterogeneous diesel units simultaneously.

An often-overlooked aspect in MG operation is spinning reserve. While some efforts address this explicitly, e.g., through Battery Energy Storage Systems (BESS)-based reserve management [30], wind integration schemes [31], or cooperative multi-source control [32], many other studies either ignore reserve requirements or handle them indirectly by over-sizing generators or storage, which limits their practical relevance.

Beyond conventional optimization frameworks, and as mentioned earlier, several studies have focused specifically on the application of metaheuristic techniques to address the multi-objective optimization of hybrid microgrids. Fonseca et al. [33] proposed a comprehensive framework for sizing PV-diesel hybrid systems in isolated networks, combining Mixture Design of Experiments (MDOE), Normal Boundary Intersection (NBI), and super-efficiency Data Envelopment Analysis (DEA). This integrated approach supports decision-making by generating equidistant Pareto front solutions and selecting the optimal configuration based on performance. However, limitations arise from the exclusion of demand and solar generation variability in the uncertainty modeling and from the impact of high battery costs on the final Levelized Cost of Energy (LCOE). Bouchekara et al. [34] addressed similar challenges by proposing an Improved Multi-Objective Evolutionary Algorithm based on Decomposition (IMOEAD) that explicitly accounts for battery degradation and load uncertainty, offering a wide Pareto front of technically feasible solutions. Although the study excels in modeling practical constraints, it relies on simplified representations of load variability and does not fully exploit the computational advantages of the decomposition strategy.

Other contributions emphasize system resilience and algorithmic performance. Borghei and Ghassemi [35] introduced a multi-objective MILP model targeting critical load support and reduced dispatchable generation capacity, innovatively integrating switching operations for future microgrid configurations. Güven et al. [36] proposed a hybrid Firefly-Particle Swarm Optimization (PSO) algorithm that outperformed traditional methods such as Genetic Algorithm (GA), and PSO, achieving 100% renewable penetration and zero emissions in their case study, although the scenario's specificity may limit its generalization. Goel and Yadav developed a hybrid optimizer for combined economic and emission dispatch, demonstrating improved convergence but requiring penalty-weight tuning due to the conversion of multi-objective problems into single-objective formulations. Riou et al. [37] tackled microgrid reliability by introducing a tri-dimensional Pareto front (renewable integration, cost, and reliability) using Non-dominated Sorting Genetic Algorithm II (NSGA-II), highlighting the trade-offs involved when aiming for 100% renewable penetration. Finally, Nallolla et al. [38] provided a comprehensive review of multi-objective algorithms, reinforcing the importance of balancing cost, emissions, and renewable fraction, while also acknowledging the lack of implementation frameworks in existing literature.

Table 1 provides a detailed comparison of representative works, synthesizing their EMS strategies, optimization models, MG configurations, and control assumptions.

Taken together, the literature confirms the centrality of EMS in isolated MG performance, but also reveals several gaps. While existing approaches are useful for theoretical modeling or long-term planning, few offer practical, adaptive, and scalable EMS solutions suited for real-world deployment, particularly in multi-DG configurations. The present work addresses these limitations by introducing a modular, Python-based tool that combines rule-based EMS with a GA optimizer, capable of handling minute-resolution data and spinning reserve management, while enabling both single- and multi-objective analysis.

The main contributions of this work, addressing the aforementioned challenges and limitations, are as follows:

Contributions of this work

- Implementation of a rule-based EMS that ensures energy balance while prioritizing renewables.
- Integration of a DG dispatch strategy based on generator efficiency.
- Compatibility with multiple time resolutions and scalable to various MG configurations.
- Bi-objective optimization (LCOE and diesel consumption) with sensitivity analysis for improved GA performance.
- Python-based structure allowing transparency and user-level customization.

Table 1
Summary of key characteristics and approaches in MG energy systems across various studies.

Ref	Year	Location	Connectivity	Energy system	Optimization model	Optimized variables	Rule based strategy	Software	Spinning reserve
[17]	2020	Australia	Off-grid	DG (1), PVS, WT, BESS, LLD, FDL	Economic dispatch	Total cost (DG+BESS+FDL)	Priority dispatch renewable	MATLAB	No
[18]	2020	Australia	Off-grid	DG (6), PVS, BESS	GA	Total cost (fuel, maintenance, degradation)	Priority dispatch renewable, net load and SOC based, DG dispatch	MATLAB	Yes
[39]	2021	Saudi Arabia	Off-grid	DG (1), PVS, WT, BESS, Biomass '	Giza Pyramids construction algorithm, Algorithm of Artificial Electric Field (AEFA), GreyWolf Optimizer (GWO)	Total cost, NPC, LCOE	Priority dispatch renewable, SOC based DG dispatch	HOMER	No
[20]	2020	CIGRE (Test grid)	Off-grid	DG (1), PVS, WT, ESS	Mixed-Integer Linear Programming (MILP)	Unit commitment for daily operational cost minimization, spinning reserve optimization, robustness optimization	Unit commitment, model predictive control (MPC)	GAMS - CPLEX	Yes
[19]	2021	Vietnam	Off-grid	DG (1), PVS, BESS	Homer economic optimization for components sizing	NPC, LCOE	Not mentioned	HOMER	No
[40]	2023	Spain	Off-grid	PVS, hydrogen chain (Onsite electrolysis, gaseous vessels, fuel cells), backup generation (Microturbine - MT)	Nested max–min optimization framework, Constraint- and-column generation algorithm (C&CGA), MILP	Operative cost under uncertainty conditions	Not mentioned	MATLAB, Gurobi	No
[27]	2021	Bangladesh (My-mensingh,Rajshahi, Rangpur, Sylhet)	Off-grid	DG (1), PVS, WT, BESS	Homer economic optimization for components sizing	NPC, LCOE	Load following (LF), Cycle charging (CC), Generator order (GO), Combined dispatch (CD), Homer predictive strategy (PS)	HOMER MATLAB/Simulink	No
[41]	2021	Australia (Mines DeGrussa, Greenfield Queensland, Greenfield South Australia)	Off-grid	DG (6), PVS, BESS	Homer economic optimization for components sizing	NPC (CAPEX, OPEX), LCOE	LF, CC	HOMER	Not handled directly, DG are oversized in order to surpass the demand
[23]	2023	Generic model (Canada)	Off-grid	DG (3)	MILP (For real time optimization)	Operative costs (fuel, penalization for On/Off operations, Power out of boundaries, frequent starts)	No	PuLP (Python), CPLEX, Gurobi, Cbc	Not handled directly, DG are oversized in order to surpass the demand
[42]	2023	Algeria	Off-grid	DG (1), PVS, WT, BESS	Homer economic optimization for components sizing	NPC, LCOE, CO_2 emissions, and fuel consumption	No	HOMER	No
[43]	2023	IEEE RTS-96 test system integration (Saudi Arabia)	On-grid	PVS, WT, ESS, conventional (Coal, nuclear, hydro)	Mixed integer quadratically constrained programming (MIQCP)	Total operative cost (Conventional sources production cost, start up and shut down costs, wind and solar curtailment)	No	GAMS, CPLEX	No
[44]	2023	Ecuador	Off-grid	DG (1), PVS, BESS	Fuzzy logic controller (FLC) parameters optimized with Particle Swarm Optimization (PSO) and Cuckoo Search (CS)	Parameters of membership functions for overall cost minimization	A set of several rules for the unit dispatch is given for the FLC parameters	MATLAB, Typhoon HIL Control Center	Not handled directly, but diesel emergency starts, detailed forecast for load and operation, and other measures are included
[45]	2022	Generic model	On-grid/Off-grid	DG (1), PVS, WT, BESS, MT, FC, cogeneration units (CHP)	GA, Artificial Bee Colony (ABC)	Optimal power flow, total cost minimization	No	Not specified	Not handled directly
[46]	2022	Not specified (Italy)	Off-grid	DG (1), PVS, WT, BESS, MT	MILP, lineal programming (LP), economic dispatch, Markov process, Autoregressive Moving Average (ARMA)	Total operative cost	No	Not specified	Yes, for DG and MT (At least three times the statistic deviation of the specified demand). Additional conditions included in optimization restrictions
[24]	2020	Not specified	Off-grid	DG (4), 2 non specified renewable generators, reducible load	PSO, GWO	Total operative cost through generation and demand curtailment optimization	No	Not specified	No
[25]	2022	China	Off-grid	DG (2), PVS, WT, BESS, modifiable load, electric vehicles	Multi objective economic dispatch, Extreme Learning Machine (ELM), eXtreme Gradient Boosting (XGBoost), LP, MILP, MSPO	Total operative cost, renewable participation, reliability of the system	Partial or immersed in a firs stage of dispatch, based on net load.	MATLAB and Python	Not handled directly for diesel, but traded off with accurate generation forecasting
[28]	2021	Bangladesh (Barishal, Chattogram)	Off-grid	DG (1), PVS, WT, BESS	Homer economic optimization for components sizing and analysis of frequency and voltage responses in Matlab	NPC, LCOE, CO_2 emissions	GO, CC, LF, PS, CD	HOMER, MATLAB	Not handled directly
[26]	2020	Not specified (China)	On-grid/Off-Grid	PVS, WT, BESS, gas turbine, FC	PSO	Total operative costs (considering renewable uncertainty and client satisfaction)	Not entirely. Instead, logic rules for charge/discharge of battery, load transfer or electricity sell are related to the optimization process	Not specified	Yes
[13]	2016	Greece (Agios Efstratios Island)	Off-grid	DG (5), PVS, WT, BESS, dump load, boiler	Homer economic optimization for components sizing	NPC, LCOE	LF, CC	HOMER	Yes, as a percentage of load and percentages of renewable generation
[14]	2022	Persian Gulf (Larak, Failaka, Lavan)	Off-grid	DG (1), PVS, WT, BESS, Hydrokinetic turbines (HKT)	Homer economic optimization for components sizing	NPC, LCOE,	LF, CC	HOMER	Not handled directly
[16]	2018	Australia (King Island, Flinders Island, Rottnest Island)	Off-grid	DG (5), PVS, WT, BESS, resistance bank, flywheel based DG (2), LLD (2), resistance bank	Not properly, instead analysis of diverse renewable sources, rationalizing energy storage and application of LLD	Reduction of system complexity, use of proven technologies, optimization of diesel efficiency	Not explicitly described	HOMER	Nod handled directly, but managed with components like the flywheel
[15]	2020	Kenya	Off-grid	DG (2), PVS, WT, BESS, pumped thermal energy storage (PTES)	MILP	Total cost of the MG (CAPEX, OPEX, DSM associated)	In parallel with optimization.	MATLAB	No

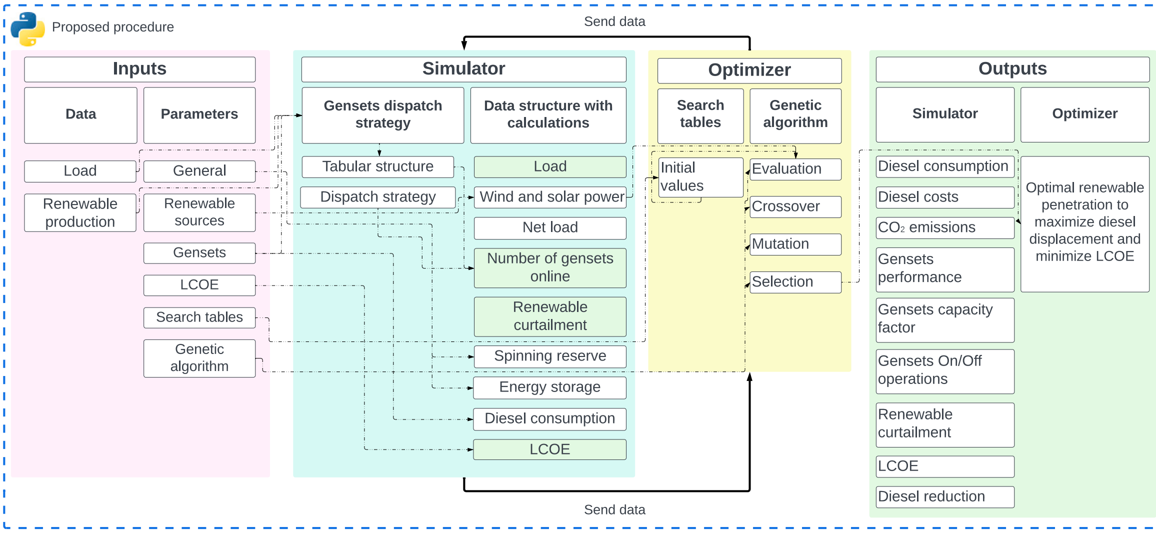


Fig. 1. General diagram of the proposed procedure.

The remainder of this paper is organized as follows. Section 2 presents the methodology, including the dispatch strategy, EMS principles, and optimization framework. Section 3 discusses the validation approach, while Section 4 presents the case study, scenarios, and optimization results. The final section concludes the study.

2. Methodology and numerical formulations

The proposed tool comprises four main modules: input data and parameters, the DG dispatch routine, the dispatch simulator, and the optimizer. Although the DG dispatch could be described as part of the simulator, it is presented separately here to clarify the dispatch logic and its role within the overall workflow.

The tool reads time-stamped input data for electrical load and renewable generation and uses user-defined parameters to configure the simulation. The dispatch simulator then computes energy flows and performance indicators (e.g., diesel consumption and levelized cost of energy, LCOE) for different levels of renewable penetration. These outputs can subsequently be analyzed and used within the optimization stage.

The optimizer module uses a GA to explore candidate design variables based on simulator outputs. At each iteration, candidate solutions are evaluated by running the dispatch simulator, and the GA updates the population through selection, crossover, and mutation. The process continues until a stopping criterion is met (e.g., a maximum number of generations or convergence of fitness values).

Because the initial design space can be large, the tool includes a preliminary screening step that generates search tables to restrict candidate ranges and improve optimization efficiency. These tables are produced through a structured parameter sweep that identifies feasible regions and trends in objective values as key decision variables are varied within predefined bounds.

The proposed framework is intended for techno-economic planning and comparative analysis rather than real-time operational control. Accordingly, detailed network constraints, ramp-rate limits, and dynamic stability models are not included. These assumptions are consistent with many planning-oriented tools and allow efficient evaluation of multiple scenarios and design configurations.

Fig. 1 illustrates the overall procedure in four global stages leading to the development of the tool.

To improve readability, the main text focuses on the energy management logic and modeling assumptions, while implementation-level pseudocode is provided in Appendix.

2.1. Input data and parameters

This section outlines the information and settings that a user must provide when initiating the analysis, tailored to their needs or specifications.

2.1.1. Input data

The input data consist of time-stamped time series that may be provided at hourly or minute resolution. The simulation is performed using the native time step of the input series. Required inputs include the electrical load and renewable generation profiles (wind and/or solar), provided as text files.

The tool does not automatically retrieve meteorological data. Users must provide time-series inputs for load and renewable generation (wind and/or solar). These inputs may be obtained from measurements or external databases (e.g., ERA5, NASA POWER, PVGIS), but data acquisition is performed outside the tool.

2.1.2. Parameters

In addition to the input data, several parameters must be configured to execute the calculations effectively.

Table 2 summarizes the main parameter categories and their roles in the simulation and optimization framework.

The "General" category includes parameters for calculations in the simulator, "Renewable" covers technical aspects of renewable elements, and "Gensets" refers to those for DG. "LCOE" parameters specify cost values, while "Search tables" define the search space limits. GA parameters set the type of optimization and the specific GA settings for each case.

2.2. Description of the simulator

The simulator consists of two main stages: the dispatch strategy, which determines the DG required to meet the load, and the data structure, which collects and organizes the calculated values of the variables related to power flows within the MG. These calculations follow the framework designed for an isolated hybrid system, as shown in Fig. 2.

The simulator is capable of performing a range of calculations that can be included in the results if needed.

For clarity and conciseness, the simulator calculations are described under six categories: genset dispatch strategy, wind and solar power, spinning reserve, capacity factor, energy storage, and performance and diesel consumption.

Table 2
Overview of input parameter categories used for microgrid modeling, simulation, and optimization.

Category	Description
General	Parameters associated with various calculations in the code, such as input spinning reserve requirement, battery spinning reserve, accepted renewable spinning reserve, average load, among others.
Renewable sources	Values concerning wind turbine size, number of turbines, non-integrated wind power, battery spinning reserve, battery size, and initial state of charge (SOC), among others.
Gensets	Key information about gensets, including nominal capacities of generators, minimum and maximum operating percentages relative to their nominal capacity, minimum number of online gensets, and information for calculating diesel consumption based on capacity factor and performance, among others.
LCOE calculations	Parameters related to installation and maintenance costs for wind, solar, and storage resources, as well as gensets. Additionally, costs of CO_2 production, diesel price, project lifetime, discount rate, and grant percentage, among others.
Search tables	Values determining the search space, such as setting the LCOE to be minimized based on wind resource penetration percentage, upper and lower thresholds for that percentage, and time step for exploration.
GA	The GA can conduct bi-objective optimization, allowing the setting of weights for each objective and defining lower and upper thresholds for varying variables to attain optimality. Essential GA parameters include initial population size, number of individuals chosen for the next generation, and probabilities of crossover and mutation, among others.

Table 3
Diesel genset combinations used in the simulations, with equivalent rated capacity and minimum and maximum operating limits.

Indicator	Generator combination	Rated (kW)	Min (kW)	Max (kW)
0	–	0	0.0	0.0
1	{g1: 560}	560	168.0	504.0
2	{g2: 855}	855	256.5	769.5
3	{g1: 560, g2: 855}	1415	424.5	1273.5
4	{g2: 855, g3: 855}	1710	513.0	1539.0
5	{g1: 560, g2: 855, g3: 855}	2270	681.0	2043.0
6	{g2: 855, g3: 855, g4: 855}	2565	769.5	2308.5
7	{g1: 560, g2: 855, g3: 855, g4: 855}	3125	937.5	2812.5

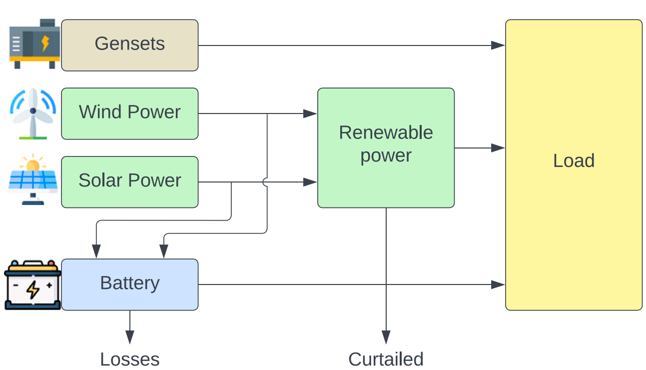


Fig. 2. General diagram of the considered hybrid system.

2.2.1. *Gensets dispatch strategy*

The genset dispatch strategy involves two main components. The first component describes how generator information is organized in a tabular structure. The second component outlines the decision-making process for dispatching individual gensets or genset groups based on the operational conditions at each time step.

(1) Tabular structure for gensets
The tool accommodates an arbitrary number of gensets with identical or heterogeneous rated capacities and constructs non-redundant combinations that can be selected to meet demand. Generator rated powers are read from the input parameters and sorted in ascending order. Unique identifiers are assigned to each genset, and all feasible combinations are generated while avoiding duplicates that arise when units share the same rating. Once the combinations are generated, the genset information is organized in a tabular format, including an identifier for each combination, the generator names, their equivalent rated powers, and the minimum and maximum power for each genset. For example, if the input vector consists of four generators with rated capacities of 560 kW, 855 kW, 855 kW, and 855 kW, respectively, the resulting tabular structure would resemble Table 3.
The values in the "Rated" column correspond to the sum of nominal generator capacities. The "Min" and "Max" values are obtained by applying the minimum and maximum operating fractions specified in the input parameters (30% and 90% in this example). Combinations with identical aggregate capacity are reported once to avoid redundancy.

(2) Dispatch strategy

Given the variable number of gensets and the automatic tabular organization described earlier, generator dispatch must also be automated, regardless of the number of generators or the length of the tabular structure.

The dispatch strategy is based on an efficiency criterion. If a single generator cannot meet the load, the next one with a higher rated capacity is selected to cover it. If this is still insufficient, multiple generators will operate together to supply the load. Consequently, the choice of the appropriate generator group from Table 3 is made according to this efficiency-based criterion. In this case, the lower threshold is set to be 30%, based on typical operational efficiency limits of diesel generators, where prolonged operation at low loads can lead to fuel inefficiency and increased maintenance. However, it remains a configurable input parameter and can be adjusted depending on the study case. It is worth mentioning that using multiple diesel generators of varying sizes offers operational advantages over a single large unit or identical units. As highlighted by Cardenas et al. [47], such configurations can reduce generator cycling, minimize dumped load during transitions, and improve load-matching efficiency. These benefits are particularly relevant in isolated microgrids with highly variable demand, as they allow for more flexible and efficient generator dispatch while avoiding prolonged operation under low-load conditions.

When minute-resolution inputs are used, minimum run-time constraints are enforced to avoid unrealistic cycling of generator commitment. For example, if the load varies abruptly, a generator that has been active for less than an hour may not be switched off immediately. The key dispatch strategy considerations in this scenario are summarized as follows:

- Dispatch is determined by selecting a genset (or genset combination) whose operating range (“Min”–“Max”) can meet the net load.
- The simulator runs at the native time step of the input series. For hourly inputs, generator commitment may change at each step; for minute-resolution inputs, a minimum one-hour run time is enforced before shutdown.
- Gensets can be in three states: Off, On (supplying load), or Running (online without supplying load, providing spinning reserve). A shutdown is permitted only after the minimum run time is satisfied.
- The simulator records the committed genset combination and computes the instantaneous operating ratio (capacity factor) used for fuel consumption estimation.

For readability, the detailed pseudocode of the genset dispatch routine and the associated capacity factor calculation are provided in Appendix.

In Algorithm A.1, the term “parameters” refers to the parameters discussed earlier, while “data_frame” represents a tabular structure that stores input data for load and renewable resources in columns. The rows in this structure correspond to values for each time step. As calculations proceed (as detailed in subsequent sections), additional columns, such as those for the capacity factor of the generators, their state, and the spinning reserve, are progressively added. “dataframe_generators” refers to the tabular structure for gensets, and “column_name” denotes the column containing the load used to determine generator dispatch.

The strategy automatically evaluates the load values for each time step against the predefined boundaries for each genset or set of gensets. These boundaries are automatically determined on the basis of the number of generators and the values in the input parameters specific to the investigated design configuration. Algorithm A.1 generates several outputs: “index_gen_on” serves as an identifier referencing the set of generators operating at each time step, which is crucial for subsequent calculations. “Counters” records time-step information, tracking how long each generator has been running, whether loaded or in parallel. “Generators_state_indicator” communicates the state of each genset or set of gensets at each time step (On, Off, Running). The “Capacity_factor” is calculated for each genset or set of gensets to determine fuel consumption and associated costs. The capacity factor (CF) for each time step is computed using Eq. (1), where $load(t)$ represents the load value and $rated(t)$ denotes the rated power of a genset or the sum of rated powers when multiple gensets operate.

$$CF(t) = \frac{load(t)}{rated(t)} \tag{1}$$

In this work, the term “capacity factor” is used at each time step to represent the instantaneous operating ratio of a generator relative to its rated capacity, mainly for fuel consumption estimation. This should not be confused with the annual capacity factor commonly used in renewable energy assessment, which is defined over long-term operation.

In addition to this algorithm, another is developed specifically to track the spinning reserve attributable to gensets. This aims to incorporate information about the available power and fuel costs associated with such scenarios into the tabular structure of the calculations.

2.2.2. Data structure with calculations

The simulation data structure forms the core of the methodology and implements the rule-based EMS. The EMS prioritizes renewable utilization while maintaining diesel generators within an efficient operating range (30%–90% of rated capacity, configurable).

Fig. 1 illustrates how all the calculations in the simulator are organized into a data structure composed of rows and columns. This structure facilitates the determination of the power flows within the isolated MG. Each column represents a calculated variable, while each row corresponds to the variable’s value at a specific time step, which means that the number of rows equals the time steps over the simulation period.

The first column contains the load, followed by columns for wind and solar resources. Then additional variables are computed from these inputs. As shown in Fig. 1, variables such as “Load”, “Generators online”, and “LCOE” are color-coded to match the outputs section, indicating that all variables in the data structure can be accessed as results. A list of variables important for explaining the actual EMS is presented in Table 4.

Based on these definitions, the operational principles of the MG are explained in the following, ensuring that the balance of power between the generation sources, storage systems, and load is maintained properly.

Before proceeding, it is important to clarify that the net load and the renewable curtailment are calculated using Eqs. (2) and (3), respectively:

$$net\_load = load - renewable\_contribution \tag{2}$$

$$renewable\_curtailment = renewable\_total - renewable\_contribution \tag{3}$$

Another key feature to consider is an input parameter known as the minimum number of generators online, which specifies the minimum number of generators required to remain operational to meet the load. If this value is set to zero, all generators can be turned off, provided that renewable sources are sufficient to meet the demand. Otherwise, the load is served primarily by this minimum number of generators, with additional generators activated as the load increases.

Table 4
Key calculated variables used to describe the rule-based energy management system within the simulation data structure.

Variable	Description
Load	Electrical demand profile applied at each simulation time step.
Wind and solar power	Renewable power input profiles derived from wind and solar resources.
Total renewable power	Aggregate power produced by all renewable generation sources.
Renewable contribution	Portion of renewable power directly supplying the load.
Renewable energy curtailment	Renewable power not utilized due to operational or system constraints.
Net load	Residual load to be supplied by diesel generators after renewable contribution.
Generators online	Number of diesel generators required to meet the net load at a given time step.
Spinning reserve	Power margin available from diesel generators, renewable sources, or storage systems to compensate for short-term load or generation fluctuations.

(1) Calculation of the net load
The net load at each time step is determined based on the following conditions:

- If the load is below the minimum operating power of the minimum-number-of-online gensets (e.g., 30% of their rated capacity), the net load is set equal to the total load. Because the minimum-online constraint may not correspond to the smallest unit, an alternative genset combination may be selected to supply the net load.
- If, after accounting for renewable energy, the remaining uncovered portion of the load is greater than or equal to the minimum starting power of the minimum number of online generators, this portion becomes the net load to be supplied by additional generators.
- If neither of the above conditions is met, the net load is set to the minimum starting power of the minimum number of online generators. In this scenario, the generator operates at no load, corresponding to 30% of its nominal capacity. If the minimum number of online generators is zero, the net load will also be zero.

The step-by-step pseudocode used to compute the net load according to the above conditions is provided in Algorithm A.2 (Appendix).

(2) Calculation of the number of generators online
This variable represents the number of generators responsible for covering the net load. The number is determined according to the following conditions:

- If the net load is less than the minimum starting power of the minimum number of online generators, a new combination of generators is selected to cover the load. This is because the minimum number of online generators may not correspond to the smallest generator, as noted above.
- If the net load exceeds the minimum starting power of the minimum number of online generators, the larger value is chosen between the minimum number and a new combination of generators capable of covering the net load. In this case, the generators initially selected are supplemented with others, if necessary, to meet the demand.

The strategy for determining the appropriate combination of generators aims to maximize efficiency. Generators with different nominal capacities are selected to ensure that they operate within their efficient range. This strategy also respects the minimum operating time constraint: a generator must run for at least one hour before shutting down. If a shutdown is requested before this time is reached, the generator will continue to operate without load or resume load as needed.
When referring to the selection of a new combination of generators, this involves applying or calling the dispatch strategy for the generators discussed earlier. In addition, the capacity factor at which the generators operate is included in the data structure when calculating a new combination of generators.

(3) Calculation of additional renewable curtailment
Eq. (3) shows that the portion of renewable power remaining after covering the load must be curtailed. DG cover the part of the load that is not met when renewable is insufficient. However, in some cases, this net load may be too low to keep the generators within their efficient operating range. In such situations, the renewable contribution must be reduced to increase the net load covered by the generators. This reduction is referred to as the "additional curtailment" and is added to the renewable curtailment, which is the difference between the total available renewable power and the actual amount used to cover the load. The conditions for determining additional curtailment are as follows.

- If the net load is less than the minimum starting power of the minimum number of online generators, additional curtailment is zero.
- If no generators are in operation, additional curtailment is zero.
- If the capacity factor of the generator or group of online generators is less than 30%, the additional curtailment will be the minimum of:
  - The renewable power contribution to the load (to avoid excessive curtailment).
  - The percentage required to bring the generator to 30% of its nominal capacity, calculated as follows:

$$additional\_curtailment = 30\% - CF \times \text{Generators rated power} \tag{4}$$

The algorithmic procedure used to compute the additional renewable curtailment is detailed in Algorithm A.3 in Appendix.

(4) Update of system variables
After applying the above conditions, it is expected that the values for net load, renewable contribution, curtailment, and generator capacity factor will need to be recalculated.

- New net load: The sum of the initial net load and the portion of the load that is no longer covered by renewable energy due to curtailment.
- New renewable contribution: The difference between the total load and the new net load.
- New curtailment value: The total renewable generation minus the new renewable contribution.
- New capacity factor: The total net load covered by the generators divided by their nominal power.

(5) Spinning reserve calculations
Three main variables are considered in the spinning reserve calculations, as described below:

- Spinning reserve available from DG: This refers to the power that operating DG can deliver immediately after supplying the load. It is calculated as the difference between the nominal power of an online DG and the net load that it covers (after adjustment). In our case, the total spinning reserve also includes a portion supplied by a battery bank.

- Required spinning reserve: This is the amount of power that DG must be able to deliver in case of fluctuations in the renewable portion of the load. The goal is to maintain the stability of the MG. To calculate it, the maximum value is selected between:
  - The contribution of each wind turbine to the total renewable generation, or
  - A percentage of the required spinning reserve relative to the total available renewable.

  This value is reduced by any excess renewable energy contribution that can be used as part of the spinning reserve. This contribution, expressed as a percentage, can be set as an input value. In this study, if the value is zero, all the spinning reserve comes exclusively from DG, without considering renewable. If the value is non-zero, the available renewable energy is calculated by subtracting the portion of renewable energy that already covers the load.
- Missing spinning reserve: If the required spinning reserve exceeds the available reserve, the difference is considered to be missing spinning reserve. In this case, an additional DG must be activated, selecting the most efficient combination.
  Once a new generator is started, the total spinning reserve is recalculated by subtracting the net load covered by the active generators from their total capacity, then adding the battery reserve.
  The situation is reassessed to check whether the additional generator is sufficient to cover the spinning reserve deficit by calculating the difference between the required reserve and the new total reserve.

The algorithmic procedure used to assess spinning reserve requirements and update generator commitment is detailed in Algorithm A.4 in Appendix.

(6) Further adjustments to system variables
When a generator is started to cover the missing spinning reserve, it may operate outside its efficiency range. In such cases, it is necessary to recalculate the renewable curtailment to ensure that the generator returns to its efficient operating range. Thus, it also means recalculating the net load, total renewable generation, and total supplied load. The total supplied load corresponds to the sum of the renewable contributions that cover the load and the net load. At this point, the total value must match the initial load, confirming that the MG is stable in terms of power balance.
After these adjustments, all relevant variables are recalculated to determine the total curtailment (i.e., the total renewable generation minus the renewable contribution) and to calculate the load reduction, defined as the difference between the initial load and the net load covered by the generators after adjusting for renewable curtailment.

(7) Energy storage
The management of energy storage is analyzed during the charging and discharging processes of the batteries.
For the battery charging process, when there is renewable curtailment (i.e., excess renewable energy), the charging power is determined as the minimum of the following three values:

- The curtailment value of renewable energy (i.e., the excess energy available at a specific time step).
- The difference between the total battery capacity and its SOC in the previous time step.
- The maximum charging power of the battery, determined by its nominal capacity in MW.

Regarding the battery discharging process, it is activated when curtailment equals zero, meaning there is no excess renewable energy. In this case, batteries are used to cover the load that DG cannot provide. The discharge power is calculated as the minimum of the following:

- The maximum discharge rate of the battery, determined by its nominal capacity in MW.
- The available energy, which depends on the SOC of the battery in the previous time step.
- The value of the net load not covered by the DG. If the energy in the battery is greater than the net load to be covered, the discharge power corresponds to the net load that needs to be supplied. If the energy in the battery is less than the net load, the discharge power will be the remaining amount that the generators can cover, operating at 30% of their nominal capacity to ensure efficiency.

The battery SOC at each time step is updated from the previous SOC by adding charging energy and subtracting discharging energy over the corresponding time step.
The algorithmic procedure used to manage battery charging, discharging, and state-of-charge evolution is detailed in Algorithm A.5 in Appendix.

(8) Adjustments after batteries are included.
When batteries are put into operation, the variables for net load, net renewable, curtailment, and total supplied load are recalculated as follows.

- The new net load corresponds to the net load after considering renewables, minus the battery discharge.
- The renewable contribution is the sum of the renewable input and the power discharged from the battery.
- The total supplied load is the sum of the net load and the renewable contribution.
- The total curtailment is calculated as the curtailment without batteries, minus the battery charging power.

(9) Performance and diesel consumption
The final stage involves assessing the performance and diesel consumption of the gensets, with and without the contribution of renewable sources. The performance of the genset is evaluated using linear regression to relate the capacity factor of the genset to its average yield. The average yield data for various capacity factors must be available in advance to perform this regression. Diesel consumption (L/h) is calculated by dividing the load supplied by the generators (kW) by the efficiency of the generator (kWh/L). Thus, for each hourly time step, consumption is expressed in liters. For intervals in minutes, the consumption is automatically adjusted to liters based on the specific duration of each time step. This ensures that diesel usage is accurately measured in relation to the performance of the gensets.
For completeness, the algorithmic procedures used to interpolate genset performance and compute diesel consumption are detailed in Algorithms A.6 and A.7 in Appendix.
Although not all variables are detailed here, the user can choose which ones to display. The variables listed in the outputs section are specific to this study case, but the result variables are not limited to those alone.
For clarity and conciseness, detailed pseudocode and algorithmic implementations supporting the dispatch strategy, spinning reserve management, renewable curtailment logic, and storage

operation are provided in Appendix. The main methodology section focuses on the conceptual structure and engineering logic of the proposed energy management system, while the appendix allows interested readers to examine the full computational details without interrupting the flow of the manuscript.

2.3. Description of the optimizer

The optimization stage evaluates objective values through simulation rather than using a closed-form analytical objective function. The simulator is used to explore variable values that maximize or minimize specific outcomes, such as reducing diesel consumption or minimizing the LCOE. Given the broad search space, a heuristic optimization approach is chosen. Although heuristic methods do not guarantee optimal solutions, they efficiently find acceptable solutions within reasonable time frames, making them well-suited for complex problems. Specifically, a GA, a metaheuristic inspired by natural selection and part of evolutionary algorithms, is utilized [48].

To narrow down the search space, search tables are introduced as part of this algorithm. Before detailed analysis of the GA, a brief description of the tables is provided in the following, with additional related information discussed in the results, particularly in Section 4.1.2.

2.3.1. Search tables

The tables generated by the algorithm serve as effective tools for identifying the most efficient combinations of renewable energy sources, battery storage sizes, and the proportion of wind energy in the mix. These tables are based on the optimized parameters and the defined optimization criteria.

By varying these parameters, the algorithm can explore a wide range of potential solutions. The GA iteratively refines a population of candidate solutions, guiding them toward an optimal configuration.

The LCOE tables provide a straightforward method for pinpointing areas with the most favorable costs. These tables typically employ color coding to highlight the most cost-effective, or "optimal", values in a lighter color, while darker shades represent less desirable or "non-optimal" values. This visual aid allows quick identification of the best-performing scenarios in economic terms. In simpler scenarios, the LCOE tables alone might suffice to determine an optimal solution. However, GA offers a robust optimization method in more complex cases or when further refinement is needed.

2.3.2. Genetic algorithm

The GA begins by initializing a population of candidate solutions. Each is evaluated on the basis of a fitness function. Selection is performed using the NSGA-II algorithm, which is widely used for multi-objective optimization. Crossover combines segments of the parent chromosomes to create offspring, while mutation introduces random changes to maintain genetic diversity. Less fit individuals are replaced by new offspring, producing successive generations. This process continues until a stopping criterion is met, such as a maximum number of generations or convergence of solutions [45].

In the GA implemented, each individual is defined by three attributes: installed renewable energy capacity, percentage of wind energy, and battery size. The fitness function aims to minimize LCOE while maximizing the reduction in fuel consumption. The optimal solutions are identified from the first Pareto front, representing trade-offs between economic and environmental objectives.

The GA is implemented using the DEAP evolutionary computation framework, which provides operators for initializing populations, evaluating fitness, and applying crossover, mutation, and NSGA-II selection.

The toolbox includes the following.

- Individual characteristics
- Functions for random generation of the initial population
- The evaluation or fitness function
- Crossover, mutation, and selection functions

The GA is executed using a standard $(\mu + \lambda)$ evolutionary strategy implementation provided by the DEAP framework. The following components make up this algorithm:

- Initial population: An individual function is created for each characteristic, responsible for generating a random value within a specified range.
- Mutation function: Randomly adjusts the values of an individual's genes according to specified mutation rates and strengths, ensuring that values remain within certain limits. If a randomly generated number is below the mutation rate, a random value drawn from a Gaussian distribution is added.
- Crossover function: Facilitates exchange between genes or characteristics of individuals. This function takes two individuals, calculates a delta factor for the crossover, and performs the crossover by adjusting the elements accordingly.
- Selection function: Within the toolbox, the operation is registered as "select" utilizing "tools.selNSGA2", a function provided by the DEAP library implementing a selection operator. Specifically, it refers to the NSGA-II (Non-dominated Sorting Genetic Algorithm II) algorithm, widely used for addressing multi-objective optimization problems within evolutionary algorithms.

The optimization stage is implemented using the DEAP evolutionary computation framework. Decision variables include installed renewable capacity, wind–solar energy share, and battery size. These variables are constrained within user-defined minimum and maximum bounds and discretized using predefined step sizes to reflect engineering design granularity.

The fitness function combines normalized techno-economic objectives, including levelized cost of energy and diesel consumption reduction, through user-defined weighting factors. Candidate solutions are evaluated by running the full dispatch simulator, ensuring that technical feasibility is assessed at each evaluation.

As a stochastic method, the genetic algorithm does not guarantee mathematically global optimal solutions. Convergence behavior is monitored by recording the average, minimum, and maximum fitness values at each generation, which are reported through convergence curves presented in the Results section. These indicators allow verification that the population stabilizes toward high-quality solutions. The algorithm also supports checkpointing, enabling long optimization runs to be paused and resumed.

2.4. Description of the outputs

The outputs after performing a study using the tool proposed here can be interpreted as outputs from the simulator and outputs from the optimizer. Both of them and a brief description of each are presented in Table 5. As mentioned above, the variables listed in this table are specific to this study case, but the result variables are not limited to those only.

2.5. Description of the Python implementation

The Python implementation for the proposed procedure is organized in folders that simultaneously group several modules with the functions that carry out every single operation and calculation in the code. A description of that organization is presented in Table 6 for the reader who may be interested in implementing the proposed method.

The implementation was developed in collaboration with an industrial partner and is subject to confidentiality and intellectual property agreements. Therefore, the full source code cannot be publicly released at this stage. To ensure transparency and reproducibility, the manuscript provides detailed descriptions of the algorithmic logic, equations, and pseudo-code, as well as explicit definitions of inputs and outputs, enabling independent reproduction of the modeling assumptions and computational workflow at a conceptual level.

Table 5
Summary of simulator- and optimizer-derived output variables for the case study.

Output source	Variable description	Units
Simulator	Diesel consumption: Fuel consumed by the diesel generators at each simulation time step.	L, kL
	Diesel cost: Cost associated with diesel fuel consumption at each simulation time step.	CAD, kCAD
	CO_2 emissions: Carbon dioxide emissions resulting from diesel generator operation.	t
	Generator efficiency: Electrical energy produced relative to fuel consumption.	kWh/L
	Generator capacity factor: Ratio of actual electrical output to the maximum possible output.	%
	Generator on/off operations: Number of start-up and shutdown events of diesel generators.	Dimensionless
	Renewable curtailment: Amount of renewable energy not utilized due to operational constraints.	GWh
	LCOE: Levelized cost of electricity calculated over the simulation period.	cents/kWh
Optimizer	Renewable and storage capacities selected by the optimization procedure, together with the associated wind penetration and diesel displacement relative to the reference configuration (for the selected objective(s)).	MW (renewables), MWh (storage), % (wind), % (diesel displacement)

Table 6
Main components of the Python-based simulation and optimization framework and their functional roles.

Folder/File	Module or file	Description
Main	–	Handles execution flow, including reading input parameters and data, performing sensitivity analyses, or running the genetic algorithm–based optimization.
	input_load.txt	Text file containing the microgrid electrical load profile.
	input_solar_power.txt	Text file containing solar photovoltaic power production data.
Input	input_wind_power.txt	Text file containing wind turbine power production data.
	import_functions.py	Python module responsible for importing and preprocessing input data.
	parameter.json	JSON file containing input parameters required for the simulation and optimization procedures.
	gensets_data.py	Python module that structures diesel generator information, including identification indices, generator combinations, and associated minimum and maximum operating limits.
Hybrid Power	calculation_function.py	Python module containing functions used to compute operational quantities such as generator dispatch and capacity factors.
	simulator.py	Python module implementing the rule-based energy management system and computing performance indicators, including LCOE.
	tables_optimizer.py	Python module used to perform sensitivity analyses in order to reduce the optimization search space.
	optimizer.py	Python module implementing the genetic algorithm–based optimization and interfacing with simulator outputs to evaluate candidate solutions.

2.6. Simulation and modeling assumptions

Before applying the tool to the case study, the main assumptions made during simulation and optimization are presented in this section.

The simulation assumes complete input data, provided in .txt format at either hourly or minute-level resolution depending on the case study. No additional preprocessing is performed within the tool unless externally implemented or customized by the user. The model expects consistent time steps and aligned data across all input variables.

The system includes multiple diesel generators of varying rated capacities, reflecting typical configurations in remote microgrids. Generator dispatch is handled using an efficiency-based criterion, selecting the smallest generator (or combination of generators) capable of meeting the load above a minimum operating threshold (commonly 30%), which is configurable. Operational constraints such as ramp rates and minimum run time are not considered in this paper, as simulations were conducted with hourly resolution. However, the tool includes functionality for enforcing minimum run time at minute-level resolution.

Renewable generation includes wind and optionally solar, with the total renewable share fixed per scenario. In the case study presented here, 100% of the renewable component corresponds to wind due to the location-specific resource availability. Renewable curtailment is only applied when necessary, for example, when storage is full or when maintaining diesel generator efficiency, and is not enforced as a fixed cap. The battery model assumes constant round-trip efficiency, and dispatch logic prioritizes renewable energy to meet the load, followed by storage discharge, and lastly diesel generation.

The tool's two-layer architecture, comprising a rule-based simulator and a genetic algorithm optimizer, enables modular development and flexible configuration. Optimization parameters, including population size and number of generations, were internally tuned to balance convergence quality and computational speed for the study scale. The model does not include detailed network modeling (e.g., power flow, voltage, or frequency analysis) and is intended for techno-economic planning rather than real-time control.

2.7. Applicability and adaptation

To apply the proposed tool in other locations, users need to prepare site-specific input data, including hourly or sub-hourly load profiles, wind generation time series, and the technical and economic characteristics of the system components. These can come from local measurements, utilities, or public databases—for example, ERA5 or NASA POWER for wind data, PVGIS for solar, and NREL to estimate solar production. Load profiles can be estimated from historical data or based on reference curves adjusted to local context. Once the data is formatted to match the tool's requirements, the simulation and optimization can be run. This process allows the framework to be applied to different regions and supports preliminary assessments and comparative studies.

3. Validation of the proposed method

As discussed in the Introduction, many microgrid techno-economic studies evaluate EMS performance using hourly time steps. Hourly resolution is appropriate for planning analyses based on available resource and load datasets, whereas sub-hourly resolution is typically required for detailed operational control studies and for capturing fast transients in load and renewable generation.

In the present case study, the available load and wind datasets for Nunavik are provided at hourly resolution; therefore, the results reported in Section 4 are based on hourly simulations. Verification of the proposed implementation was performed through cross-checks against previously developed internal simulation workflows used by the authors for similar planning analyses, as well as through consistency tests across temporal resolutions. Hourly input series were temporally upsampled to minute resolution, and additional tests were conducted using minute-resolution wind profiles and perturbed load trajectories. Agreement was assessed using annual aggregated indicators (e.g., energy balance, diesel consumption, and key operational quantities) and qualitative comparison of temporal trends when the same underlying profiles were evaluated at different time steps. Although formal error metrics and external benchmarks are not reported, the observed consistency across implementations and time resolutions supports the numerical correctness of the simulator for techno-economic planning analyses.

Internal numerical consistency was further verified through feasibility checks implemented directly within the dispatch routine. At each time step, a power-balance residual is computed as the difference between total load and total served power, both before and after storage integration. This allows verification that generation and demand remain balanced within a prescribed numerical tolerance over the full simulation horizon.

Operational constraints are also systematically enforced, including battery state-of-charge bounds, generator minimum and maximum loading limits, and spinning reserve requirements. Generator commitment and loading are determined through the dispatch routine, and any uncovered load is explicitly tracked if technical limits are reached. Spinning reserve is computed at each time step, and reserve deficits trigger the commitment of additional generator capacity. Battery charging, discharging, and state-of-charge evolution are integrated into the net-load calculation to maintain physical consistency between dispatched power, storage operation, and fuel consumption.

4. Results

This section presents the results obtained by applying the proposed framework to an isolated hybrid microgrid located in Nunavik (Quebec, Canada).

4.1. Study case

The isolated hybrid system under investigation is located on a northern territory of 330 people in the province of Quebec, Canada (61° 2′ 47′′ north, 69° 38′ 1′′ west). The system has an average electrical load of 0.521 MW and includes 3.02 MW of installed renewable power provided by a single operational wind turbine. Furthermore, the system has a battery storage capacity of 0.9 MWh and two DG, labeled g1 and g2, whose characteristics are detailed in Table 3. The comprehensive information on the system is presented in Table 7.

The capabilities of the algorithm are assessed through an annual analysis of key variables related to renewable energy curtailment and DG. These variables include diesel consumption, fuel cost, CO_2 emissions, generator performance, capacity factor, and generators on/off cycle.

To evaluate these variables, two groups of scenarios are defined. The first group focuses on testing the simulator with three different levels of renewable energy penetration. The second group evaluates both the simulator and the optimizer, considering one and two optimization objectives. The proposed scenarios are summarized in Table 8.

The input parameters used for the optimization in Scenarios S2.1 and S2.2 are summarized in Table 9. The genetic algorithm hyperparameters adopted in this case study were selected following internal testing to ensure stable convergence while maintaining reasonable computation times. All parameters are user-configurable and can be adjusted according to problem complexity.

Furthermore, Table 10 presents the capital and operating costs, along with maintenance costs, associated with the various components used in economic analysis to calculate the LCOE. All costs are expressed in Canadian dollars ($). It is important to note that the information in Tables 7 and 10, as well as the discount rate of 4% and the project life cycle of 25 years, are provided by Hatch. Furthermore, the equivalent

Table 7
Main parameters and component characteristics of the isolated hybrid microgrid considered in the case study.

Component	Parameter	Value
Gensets	Minimum operating percentage	30%
	Maximum operating percentage	90%
	Rated power	g1 = 560 kW, g2 = 855 kW
	Diesel price	2 CAD/L
Battery	Battery energy capacity	0.9 MWh
	Initial state of charge (SOC)	50%
	Auxiliary load	20 kW/MWh
	Spinning reserve contribution	0.9 MW
Wind turbine	Number of turbines	1
	Rated power	3.02 MW
General	CO_2 emission factor	2.5 kg/L
	CO_2 cost	0.05 CAD/kg
	Discount rate	4%
	Project lifetime	25 years

Table 8
Definition of simulation and optimization scenarios considered in the case study.

Identifier	Scenario type	Description
S1.1	No renewable integration	Diesel generators operate as the sole supply source.
S1.2	Wind integration (3 MW)	Wind turbine operates with diesel generators providing backup supply.
S1.3	Wind (3 MW) and battery integration (0.9 MWh)	Wind turbine operates in combination with a battery energy storage system and backup diesel generators.
S2.1	Single-objective optimization (LCOE minimization)	Optimization of wind capacity, total renewable capacity, and battery energy capacity with the objective of minimizing LCOE.
S2.2	Bi-objective optimization (LCOE minimization and diesel displacement)	Optimization of wind capacity, total renewable capacity, and battery energy capacity considering LCOE minimization and diesel displacement reduction.

CO_2 emissions per liter of fuel, the cost of CO_2, and the fuel price are set at 2.5 kg/l, 0.05 $/kg, and 2 $/l, respectively.

Fig. 3 presents the yearly variation of the total load (Fig. 3(a)) and the production of wind power (Fig. 3(b)) for the selected location. In both figures, the green and red continuous lines represent the monthly average values. The time step for these profiles is one hour.

Fig. 3(a) illustrates that power demand increases during winter, probably due to heating equipment, with peak values reaching 800 kW and an average of around 600 kW in January. In contrast, during summer, as the heating demand decreases, the load profile drops to a low of 350 kW, with an average of 400 kW in July. In addition, Fig. 3(b) shows that net normalized wind production remains relatively steady throughout the year, averaging approximately 1000 kW, which corresponds to a turbine capacity factor of approximately 33%. April stands out as the month with the highest production, reaching around 1250 kW. Although the wind speed graph is not shown here, data indicate that the average wind speed in April is 9.3 m/s, significantly higher than the annual average of 8.8 m/s for this location. Net wind production is calculated as gross production minus losses and is normalized relative to the turbine's rated capacity.

4.1.1. LCOE formulation and considerations description

The LCOE assesses the cost per unit of energy produced by the MG. The LCOE calculation considers various factors, including initial capital costs, operating and maintenance expenses, the estimated life expectancy of the MG, and the total electricity generated during that period. The standard simplified formula for calculating the LCOE is as follows:

$$\mathrm{LCOE} = \frac{C_{\mathrm{cap}} + \sum_{t=1}^{T} \frac{C_{\mathrm{op},t} + C_{\mathrm{fuel},t} + C_{\mathrm{CO_2},t}}{(1+r)^t}}{\sum_{t=1}^{T} \frac{E_t}{(1+r)^t}} \tag{5}$$

Where C_{cap} and $C_{\mathrm{op},t}$ represent the capital expenditure (CAPEX) and the annual operating and maintenance costs (OPEX) in year t, respectively. These costs account for all system components, including renewable sources, diesel generators, and storage systems. The capital expenditure is assumed to occur entirely in the first year, and the discount rate r is considered constant over the project lifetime T.

The term $C_{\mathrm{fuel},t}$ corresponds to the fuel cost incurred in year t, calculated as:

$$C_{\mathrm{fuel},t} = P_{\mathrm{fuel},t} \cdot Q_{\mathrm{fuel},t} \tag{6}$$

where $P_{\mathrm{fuel},t}$ is the unit price of fuel and $Q_{\mathrm{fuel},t}$ is the quantity of fuel consumed in year t.

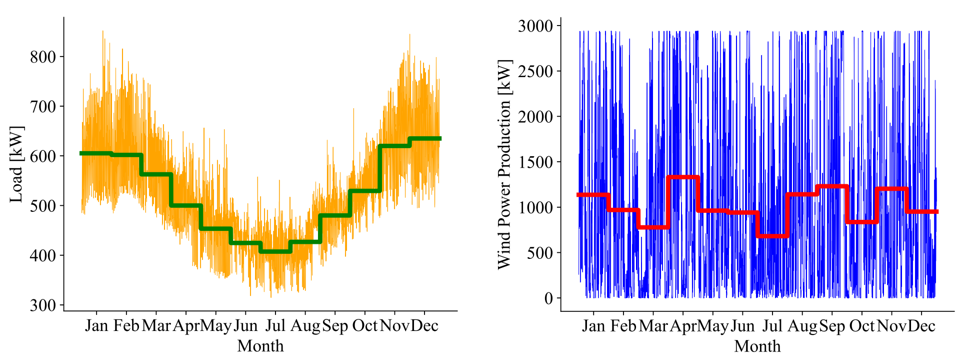
Similarly, $C_{\mathrm{CO_2},t}$ denotes the CO_2 emissions cost in year t, given by:

$$C_{\mathrm{CO_2},t} = E_{\mathrm{CO_2},t} \cdot P_{\mathrm{CO_2},t} \tag{7}$$

The CO_2 emissions associated with diesel consumption are estimated using a fixed emission factor, defined as the amount of CO_2 produced per liter of diesel fuel consumed. The total emissions in year

Table 9
Optimization configuration, including decision variables, objective function weights, and genetic algorithm parameters used in the case study.

Category	Description	Value/Range
Decision variables		
Total renewable capacity	Installed renewable generation capacity	1–7 MW (step: 1 MW)
Wind share	Fraction of wind power within the renewable generation mix	0%–100% (step: 10%)
Battery energy capacity	Installed battery storage capacity	1–7 MWh (step: 1 MWh)
Objective function weights		
LCOE weight	Weight associated with LCOE in the fitness evaluation	–1.0
Diesel displacement weight	Weight associated with diesel displacement in the fitness evaluation	1.0
Genetic algorithm parameters		
Initial population size	Number of individuals in the initial population	10
Number of generations	Total number of evolutionary iterations	10
Parent population size (μ)	Number of individuals selected as parents	5
Offspring population size (λ)	Number of offspring generated per generation	5
Selection method	Multi-objective selection strategy	NSGA-II
Crossover probability ($cxpb$)	Probability of applying crossover	0.5
Crossover method	Type of crossover operator applied	Arithmetic blending
Blend factor (α)	Blending coefficient used in crossover	0.5
Mutation probability ($mutpb$)	Probability of applying mutation	0.5
Mutation method	Type of mutation operator applied	Gaussian-based
Mutation rate	Probability of mutating each decision variable	0.7
Mutation strength	Standard deviation used in Gaussian mutation	0.7



(a) Load (b) Wind

Fig. 3. Load and wind power production profiles: (a) annual variation of the electrical load; (b) annual wind energy production.

Table 10
Capital and operation and maintenance (O&M) cost assumptions for the hybrid microgrid components used in the economic analysis.

Component	Capital cost (CAD/kW)	O&M cost (CAD/kW/year)
Wind system	16 500	250
Solar system	1 700	35
Battery system	800	5
Diesel generator	0	50

t are calculated as:

$$E_{CO_2,t} = Q_{fuel,t} \cdot \gamma_{CO_2} \tag{8}$$

where γ_{CO_2} is the CO_2 emission factor in kg of CO_2 per liter of diesel. In this study, a conservative emission factor of $\gamma_{CO_2} = 2.5$ kg CO_2/L is adopted. This value is slightly lower than the typical standard values reported in the literature, which are approximately 2.68 kg CO_2/L, but it is used here for simplification and to reflect potentially lower emissions due to fuel quality or blending.

In this work, both fuel and CO_2 costs are considered constant over time; however, dynamic modeling of fuel price fluctuations, carbon taxation, or emissions trading schemes can also be integrated into these parameters.

The denominator represents the discounted sum of energy generated over the project's lifetime, denoted by E_t for each year t. This formulation ensures that both the economic and environmental performance of the energy system are captured in a unified cost metric.

4.1.2. Considerations and tables for optimization scenarios S 2.1 and S 2.2

For the optimization process in this case, refer to the decision variables and steps outlined in Table 9.

By analyzing examples of LCOE tables in Fig. 4 at different levels of penetration of wind power - 0% (Fig. 4(a)), 50% (Fig. 4(b)) and

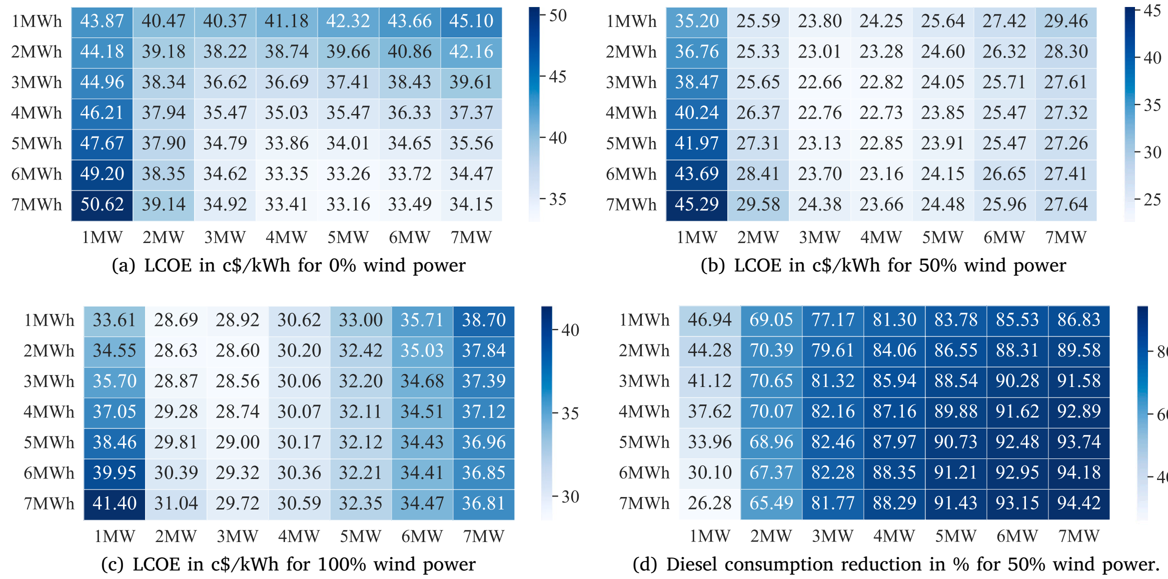


Fig. 4. LCOE and diesel consumption reduction tables for percentages of wind penetration over the total renewable power installed.

Table 11
Optimal solution values obtained for optimization Scenarios S2.1 and S2.2.

Scenario	Objective	Value	Decision variable	Value
S2.1	LCOE	22.6 c$/kWh	Total renewable capacity	3 MW
			Wind share	50%
			Battery energy capacity	3 MWh
S2.2	LCOE	22.73 c$/kWh	Total renewable capacity	4 MW
	Diesel displacement	87.16%	Wind share	50%
			Battery energy capacity	4 MWh

100% (Fig. 4(c)) one can observe how various combinations of wind and solar energy, along with different battery sizes, impact the economic viability of the renewable energy system. Furthermore, Fig. 4(d) illustrates the percentage of reduction in diesel consumption in 50% wind penetration.

The horizontal axis represents the increase in renewable energy, and the vertical axis shows the increase in energy storage. Without wind, LCOE reaches 33.16 c$/kWh as renewable energy and storage increase proportionally. At 50% wind penetration, the lowest LCOE shifts to more moderate levels, reaching 22.66 c$/kWh. At 100% wind, the minimum LCOE is 28.56 c$/kWh, still following a proportional relationship between renewable energy and storage. LCOE is generally lower at or below 50% wind penetration but increases at 100%, driven by higher capital and operating expenses for wind turbines, particularly in isolated MG where upfront costs are high and economies of scale are absent. Solar energy, with its lower costs, helps reduce overall costs. In 50% wind penetration (Fig. 4(d)), higher renewable energy and storage lead to greater diesel displacement, as expected.

The data in these tables can guide decision-making processes, helping to determine the most cost-effective configurations to integrate renewable energy sources into existing energy systems.

For clarity in the presentation of the results, Table 11 reports the optimal solution values obtained for Scenarios S2.1 and S2.2.

Fig. 5 shows the evolution of the minimum, average, and maximum fitness values during a ten-generation run of scenario S 2.2 using the GA. The minimum fitness corresponds to the least fit individual in the population, the average fitness reflects the mean performance across all individuals, and the maximum fitness represents the best-performing solution.

During the first five generations, the minimum and average fitness values increase significantly, indicating that the algorithm effectively identifies and retains better solutions. By Generation 5, the minimum fitness improves to approximately −0.3, matching the average fitness. This convergence demonstrates a reduction in population diversity, as weaker solutions are replaced by fitter ones.

From generation 5 onward, the minimum, average, and maximum fitness values stabilize at approximately −0.3, indicating convergence of the population for the studied search space and hyperparameter configuration. This behavior suggests that the algorithm rapidly identifies a stable set of high-quality solutions for this scenario. Rapid convergence (approximately 30–40 s for the complete optimization run in this case study) highlights the computational efficiency of the selected parameter configuration.

4.2. Results for gensets associated variables

Fig. 6 shows diesel consumption, CO_2 emissions, and fuel costs across all scenarios. The data reveal a general trend of increased fuel

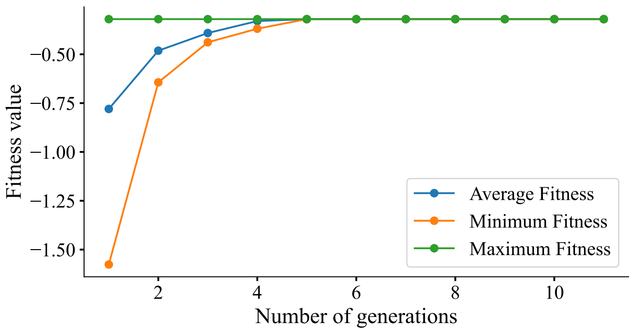


Fig. 5. GA convergence curves for minimum, maximum, and average normalized fitness values over generations. The fitness function is a dimensionless, normalized metric combining LCOE minimization and diesel consumption reduction.

consumption during the winter months and lower consumption in late spring, summer, and early fall, mainly due to increased energy demand in winter. Direct proportionality between variables indicates that fuel costs and emissions increase and decrease in tandem with consumption.

In Scenario S 1.1, where only DG are used, the system exhibits high diesel consumption, with average values of 97.4 kL, 254.1 tons of CO_2, and \$194.7k in fuel costs. However, in Scenario S 2.2, where a single 3 MW wind turbine is integrated into the isolated system, these values decrease to 48.5 kL, 126.7 tons of CO_2, and \$97.37k—representing approximately a 50% reduction compared to S 1.1. Adding a 0.9 MWh battery further reduces these values by approximately 72%, with consumption at 27.5 kL, emissions at 71.7 tons, and costs at \$54.9k. These reductions result in noticeably flatter curves.

The optimal decision variables that minimize the LCOE in Scenario S 2.1 lead to an approximate 82% reduction compared to S 1.1, with values of 17.6 kL, 35.1 tons of CO_2, and \$45.8k. Finally, when the optimization also targets maximizing the reduction in diesel consumption, the reduction reaches about 86%, with averages of 13.7 kL, 27.4 tons of CO_2, and \$35.7k.

Fig. 7 presents the results for the performance of the group, the capacity factor and the operating frequency. Genset operations are defined as the number of times a change in the operating genset occurs, such as when a higher-capacity genset starts because a smaller one cannot cover the load.

Specifically, Fig. 7(a) shows that the most significant difference in performance occurs between S 1.1 (average of 3.9 kWh/L) and S 1.2 (average of 3.64 kWh/L), while the performance variations in S 1.3, S 2.1, and S 2.2 remain closer, with an average of 3.8 kWh/L. This difference can be attributed to the fact that gensets in S 1.1 operate at full capacity when they must meet the entire load alone. In contrast, in S 1.2, where the gensets provide only the remaining load that is not covered by the wind turbine, their performance decreases. In this scenario, the generators must remain operational to provide a backup or a spinning reserve, even at low loads. In contrast, in other scenarios, where a battery system provides a spinning reserve, generators can be turned off when not needed, avoiding inefficient operation, hence the higher overall performance under these conditions.

Fig. 7(b) illustrates the correlation between the factors influencing performance and the capacity factor, with the lowest capacity factor observed in S 1.2, averaging around 43%. In S 1.3, S 2.1, and S 2.2, the average capacity factor of 63% suggests that the gensets operate closer to their optimal performance levels when needed, which is roughly 10% below the average in S 1.1.

Fig. 7(c) indicates that the frequency of genset operations in S 1.1 increases during the transition periods between summer and winter. This is likely due to varying energy demands, which require multiple generators to operate intermittently rather than continuously, as seen during the winter months. This pattern reflects inefficient engine use and frequent fluctuations in energy management practices.

In S 1.2 and S 1.3, there is a noticeable increase in the number of operations during the summer months. In S 1.2, this can be attributed to variations in wind availability, which require frequent generator on/off cycles. In S 1.3, the increase is due to the battery acting as a buffer, allowing the generators to shut off when their power is not needed. Although this may cause generators to not run constantly, it results in frequent changes in operating state. Finally, in optimization scenarios, the decision variables appear to reduce operational changes during spring and fall compared to other scenarios. This reduction in start-up and shutdown operations could also lead to lower maintenance costs.

4.3. Results for the renewable curtailment

Fig. 8 illustrates that curtailment peaks occur in April and September, exceeding 0.7 GWh. These high values indicate periods when wind energy production exceeds the system's consumption or storage capacity. In contrast, months such as March, July, and October show lower curtailment values due to decreased wind production during these periods, as shown in Fig. 3(b).

The reduction of curtailment by an annual average of 0.1 GWh in S 1.3 compared to S 1.2 is attributed to the battery system's ability to store excess wind energy that would otherwise be wasted, improving overall system efficiency. Furthermore, S 2.1 shows an average yearly curtailment of 0.27 GWh, indicating that the larger battery capacity required for optimal LCOE requires more renewable energy to recharge. S 2.2, which maximizes both LCOE and diesel consumption reduction, presents a higher yearly curtailment of 0.42 GWh. Despite increased battery storage capacity, this scenario still does not fully absorb the excess renewable energy generated, especially given the constant load.

4.4. Sample calculation, Scenario 2.2

Given the stochastic nature of genetic algorithms, a deterministic step-by-step derivation of the optimal solution is not meaningful. Instead, the optimizer evaluates multiple configurations of the decision variables, and each candidate is assessed by running the dispatch simulator to compute performance indicators (e.g., diesel consumption, LCOE, and curtailment). Through selection, crossover, and mutation, the population converges toward high-quality solutions according to the defined objectives.

Nevertheless, to illustrate how the tool functions, one representative result from Scenario 2.2 (minimization of LCOE and diesel consumption) is presented. In this case, the optimal solution consisted of 4 MW of renewable energy, 4 MWh of battery storage and a wind percentage of 50%. With this configuration, the simulator reported an 87% reduction in diesel consumption compared to the base scenario without renewables. The corresponding LCOE was 22.73 c\$/kWh. To illustrate these results, Table 12 is presented below.

It is worth noting that the values for total load supplied by diesel and renewables, as well as the corresponding energy generation and consumption variables, represent aggregated results for the entire year of simulation. Under the previously described conditions, and after tuning the genetic algorithm parameters, the optimization process using the simulator takes approximately 40 s on a standard machine equipped with an Intel Core i7 processor and 8 GB of RAM. It is also valuable to mention that, for the simulator it takes about 0.5 s to calculate one iteration for all the variables for a whole year of study, which allow to say that for the same period, in the minute time scale, the time it takes per iteration sits around 30 to 40 s.

4.5. Transversal comparison of all scenarios

Table 13 summarizes the annual results across all scenarios. As expected, increasing renewable integration progressively reduces diesel consumption and associated CO_2 emissions. Relative to the baseline

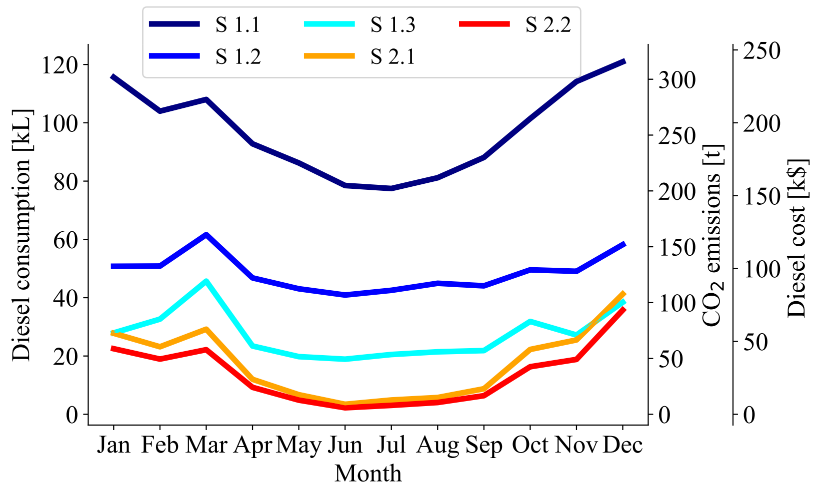
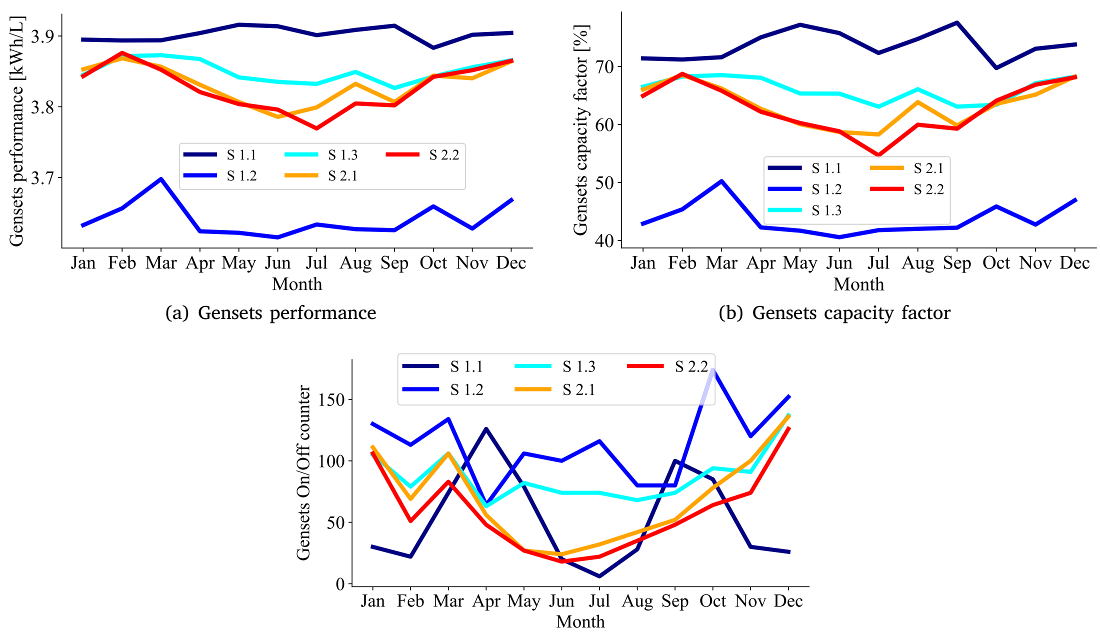


Fig. 6. Diesel consumption, CO_2 emissions, and fuel cost for all scenarios.



(a) Gensets performance

(b) Gensets capacity factor

(c) Gensets operations

Fig. 7. Gensets interest variables for all the scenarios.

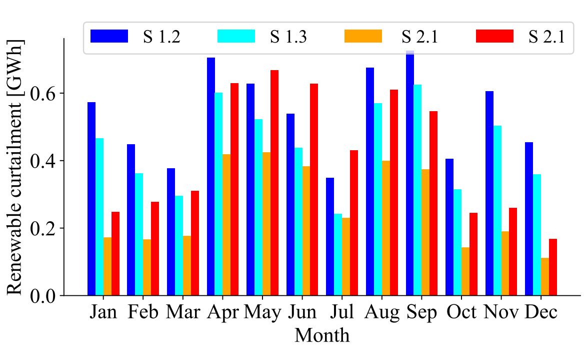


Fig. 8. Energy curtailment for all scenarios with renewable components integration.

case (S 1.1), the optimized configurations (S 2.1 and S 2.2) achieve the largest reductions, reaching 81.32% and 87.16%, respectively, and yielding the lowest LCOE values (approximately 22.7 cents/kWh). These results highlight the benefit of jointly tuning renewable capacity, renewable mix, and storage size rather than relying on a fixed configuration.

A trade-off is observed in genset operating conditions. As renewables displace diesel energy, gensets run fewer hours and may operate more frequently at low load when required to provide backup and reserve, which slightly reduces average efficiency compared to the baseline. Nevertheless, the absolute reduction in fuel use dominates, resulting in substantially lower annual fuel consumption. In addition, scenarios with moderate renewable penetration (e.g., S 1.2) exhibit increased start–stop cycling, whereas optimized scenarios reduce cycling relative to S 1.2, which may contribute to improved operational stability and reduced maintenance burden.

Curtailment reflects the mismatch between renewable availability and demand. The optimized scenario that minimizes LCOE (S 2.1)

Table 12
Simulator Results for Optimized Scenario 2.2.

Metric	Value	Unit
Average load (excluding auxiliaries)	520.53	kW
Average load (including battery auxiliaries)	600.53	kW
Total load (including auxiliaries)	5,260,642	kWh
Total diesel-supplied load (baseline, no renewables)	4,559,842	kWh
Diesel consumption (baseline, no renewables)	1,168,447.19	liters
Genset efficiency (baseline)	3.90	kWh/l
Total diesel-supplied load (with renewables)	590,634.66	kWh
Diesel consumption (with renewables)	149,987.22	liters
Genset efficiency (with renewables)	3.85	kWh/l
Diesel load reduction	3,969,207.34	kWh
Diesel consumption reduction	1,018,459.97	liters
Diesel consumption reduction	87.16	%
Total renewable energy generated	9,459,880	kWh
Net renewable energy delivered (after battery/storage)	4,668,634.69	kWh
Renewable curtailment	4,791,244.59	kWh
Renewable curtailment	50.65	%
Battery output (total discharge)	751,733.22	kWh
Battery cycles (full equivalent)	187.93	cycles
Levelized Cost of Energy (LCOE)	22.73	¢/kWh

Table 13
Annual performance indicators for all simulation and optimization scenarios considered in the case study.

Metric/Scenario	S1.1	S1.2	S1.3	S2.1	S2.2
Total diesel consumption (kL)	1168	582	330	211	164
Total CO_2 emissions (t)	3050	1520	860	550	429
Average diesel generation efficiency (kWh/L)	3.90	3.64	3.85	3.83	3.82
Average genset capacity factor (%)	74	44	66	63	62
Total genset start–stop cycles	626	1369	1047	833	702
Total renewable energy curtailment (GWh)	–	6.48	5.30	3.19	5.02
LCOE (cents/kWh)	54.45	42.07	30.79	22.66	22.73
Diesel consumption reduction (%)	–	47.6	71.7	81.32	87.16

yields the lowest curtailment among renewable cases (3.19 GWh), indicating a better balance between installed capacity, storage sizing, and load absorption. In contrast, higher curtailment in S 2.2 (5.02 GWh) is associated with the additional objective of maximizing diesel displacement, which favors higher renewable capacity even when part of the energy cannot be utilized under the given load profile.

5. Discussion

This study presents a Python-based tool for the techno-economic analysis of isolated MG, enabling the determination of optimal renewable penetration to minimize LCOE and diesel consumption. The results demonstrate its effectiveness in addressing these tasks.

Using a GA-based optimization approach introduces limitations, particularly rapid convergence and loss of population diversity, which may reduce exploration of the search space in some problems. Internal tuning of the GA hyperparameters was carried out during development, and the final configuration used in the case study reflects the outcome of this process. Although the number of generations and population size are relatively small, they proved sufficient for the scope and complexity of the studied case. For larger or more complex systems, users can adjust these parameters to increase exploration.

Unit commitment, particularly for diesel generators, is an important aspect of isolated microgrid operation. The present study adopts planning-level operational constraints, and detailed dynamic limits such as ramp rates, warm-up behavior, and minimum up/down times are not explicitly modeled. Nevertheless, the tool automates multi-generator commitment decisions based on load coverage and explicitly evaluates spinning reserve at each time step; when reserve deficits occur, additional generator capacity is committed to satisfy reserve requirements. This supports realistic assessment of diesel operation while maintaining computational efficiency.

Despite the tool's ability to support scenarios with high renewable penetration, achieving fully renewable operation remains a significant challenge, especially in isolated northern regions such as Nunavik. In practice, diesel generators continue to play a critical role in ensuring reliability due to harsh weather, long supply chains, and limited seasonal access for equipment delivery, which must often be scheduled up to a year in advance. These operational realities, observed in ongoing collaboration with industry partners, reinforce the importance of modeling DGs accurately and realistically. Nevertheless, the tool is designed to minimize DG use by maximizing renewable energy and storage deployment, aligning with long-term sustainability goals while maintaining feasibility under real-world constraints.

While the current study focused on hourly-resolution simulations with simplified operational constraints, future work will address these limitations more explicitly. A complementary study currently in preparation investigates minute-level resolution, detailed generator ramp behavior, and refined downscaling methods for wind and load profiles. This follow-up work aims to extend the tool's applicability (specifically the simulator) to short-term operational planning while maintaining its modular structure and transparency.

Some economic and technical simplifications were adopted for consistency with the modeling approach used by the industrial partner. For instance, battery dispatch does not explicitly include dynamic degradation or detailed depth-of-discharge tracking, although efficiency and DoD limits can be adjusted. Similarly, the LCOE formulation does not explicitly include component replacement cycles. These simplifications were retained to preserve transparency and usability for early-stage design, but future versions of the tool may extend both the technical and economic models.

A parallel branch of the project, currently under development, focuses on advanced battery modeling, including auxiliary consumption and operational variability, and is intended for a future publication.

A rule-based EMS poses challenges, notably excessive generator cycling, which can accelerate wear. Although advanced optimization techniques could mitigate this, our results show that a rule-based approach remains practical for real-world applications. More complex numerical methods often require specialized software that may not be easily integrated into MG operations.

The modularity of the tool and the Python-based design offer key advantages. Compared with commercial tools such as HOMER, which provide predefined optimization and dispatch options, the proposed framework emphasizes modularity and transparency in the EMS logic, enabling targeted modifications and extensions (e.g., alternative dispatch heuristics or refined component models).

Few studies adopt a nested optimization approach, instead favoring either complex operational strategies or HOMER-based optimization. Among the reviewed literature, few works integrate both methodologies. Our two-layered approach with simulator and optimizer enhances flexibility, facilitating both optimization and practical adjustments to generator dispatch and storage strategies.

Overall, the modular structure of the tool extends its applicability beyond the case study presented here, enabling future methodological and application-oriented developments, which are outlined in the Conclusions section.

6. Conclusions

This work presented a Python-based, modular tool for the techno-economic analysis and optimization of renewable energy penetration in isolated microgrids. The framework combines a rule-based dispatch simulator with a genetic algorithm optimizer, allowing evaluation of single- and bi-objective problems focused on economic performance (e.g., LCOE) and diesel consumption reduction. The simulator implements multi-generator dispatch based on efficiency-oriented commitment and explicitly accounts for spinning reserve requirements, while supporting user-defined simulation time steps.

Results from the Nunavik case study show that optimized configurations significantly outperform non-optimized renewable integration scenarios. Compared to fixed configurations, optimization reduced LCOE by more than 50% relative to the diesel-only baseline and achieved diesel consumption reductions exceeding 85%. The genetic algorithm converged rapidly for the studied problem, typically within a few generations, and produced stable solutions with low computational cost, demonstrating the suitability of the proposed framework for planning-level analyses.

The main contribution of this work lies not in proposing a new optimization algorithm, but in integrating transparent dispatch logic, multi-generator management, spinning reserve modeling, and flexible optimization within a single modular framework. While the full implementation cannot be publicly released due to confidentiality constraints, the paper provides explicit formulations, inputs/outputs, and algorithmic descriptions to support methodological transparency and independent reimplementation.

Future work will extend the framework toward more detailed operational modeling. Planned developments include sub-hourly simulations with refined generator dynamics, improved downscaling of wind and load profiles, and enhanced battery modeling that accounts for degradation and operational constraints. On the economic side, future versions will incorporate component replacement cycles and more detailed lifecycle cost modeling. These extensions will further strengthen the tool's applicability for both planning and operational studies of isolated microgrids.

Abbreviations

The following abbreviations are used in this manuscript:

CO_2	Carbon dioxide
CIGRE	International Committee of Large Electrical Networks
EMS	Energy Management Strategy
HOMER	Hybrid Optimization of Multiple Energy Resources
LCOE	Levelized Cost of Energy
NPC	Net Present Cost
CRF	Capital Recovery Factor
MILP	Mixed-Integer Linear Programming
NSGA-II	Non-dominated Sorting Genetic Algorithm II
GA	Genetic Algorithm
CAPEX	Capital Expenditures
OPEX	Operational Expenditures
MG	Microgrid(s)
DER	Distributed Energy Resource(s)
PVS	Photovoltaic Systems
WT	Wind Turbines
LLD	Low Load Diesel
GAMS	General Algebraic Modeling System
CF	Capacity Factor
SOC	State of Charge
DEAP	Distributed Evolutionary Algorithms in Python
GWO	Grey Wolf Optimizer
MILP	Mixed-Integer Linear Programming
LP	Linear programming
FDL	Flexible Deferrable Loads
BESS	Battery Energy Storage System
BESS	Energy Storage System
DG	Diesel Generator
FC	Fuel Cell
HKT	Hydrokinetic Turbine
PTES	Pumped Thermal Energy Storage
AEFA	Algorithm of Artificial Electric Field
C&GCA	Constraint and Column Generation Algorithm
FLC	Fuzzy Logic Controller
PSO	Particle Swarm Optimization
CS	Cuco Search
ABC	Artificial Bee Colony
ARMA	Auto-regressive Moving Average
MPC	Model Predictive Control
MDOE	Mixture Design of Experiments
NBI	Normal Boundary Intersection
DEA	Data envelopment analysis
IMOEAD	Improved Multi-Objective Evolutionary Algorithm based on Decomposition

CRediT authorship contribution statement

Cristian Cadena-Zarate: Writing – review & editing, Writing – original draft, Validation, Software, Formal analysis, Conceptualization. **Ilaria Tucci:** Validation, Software, Investigation, Formal analysis, Conceptualization. **Dario Della Scalla:** Validation, Software, Methodology, Formal analysis, Conceptualization. **Jersson Garcia:** Validation, Software, Methodology, Formal analysis. **Maurine Crouzier:** Validation, Software, Formal analysis. **Phillipe Cambron:** Validation, Supervision, Software, Methodology, Formal analysis. **Michel Carreau:** Validation, Supervision, Methodology, Funding acquisition, Formal analysis, Conceptualization. **Daniel R. Rousse:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization. **Adrian Ilinca:** Writing – review & editing, Validation, Supervision, Project administration, Investigation, Funding acquisition.

Algorithm A.1 Calculate Gensets Online and Capacity Factor

```
Require: parameters, data_frame, column_name, dataframe_generators
Ensure: index_gen_on, capacity_factor, counters, generators_state_indicator
index_gen_on ← array of zeros of length equal to the number of rows in data_frame
capacity_factor ← array of zeros of length equal to the number of rows in data_frame
generator_array ← values of 'generator' column in dataframe_generators
indicator_array ← values of 'indicator' column in dataframe_generators
rated_array ← values of 'rated' column in dataframe_generators
for each row i in data_frame do
  if value > 0 then
    for each generator in dataframe_generators do
      if generator is able to cover the load then
        Set index_gen_on[i] to the corresponding indicator
        Calculate capacity factor and assign to capacity_factor[i]
        Update counters and generators' states
        Break the loop
      end if
    end for
  else if value = 0 then
    Set index_gen_on[i] to 0
  end if
end for
return index_gen_on, capacity_factor, counters, generators_state_indicator
```

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT in order to improve language and readability, with caution. After using this tool/service, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix. Algorithmic details and pseudocode

This appendix provides the detailed pseudocode of the main routines implemented in the simulator for completeness and transparency. The main manuscript focuses on describing the energy management logic and modeling assumptions at a conceptual level, while the step-by-step algorithmic listings are included here to avoid an overly implementation-oriented presentation in the core methodology.

Algorithm A.2 Calculate Net Load

```
Require: dataframe, dataframe_generator, minimum_gensets, load,
  min_power, renewables
Ensure: net_load
location ← find_in_generator_table(minimum_gensets,
  dataframe_generator, 'indicator')
gen_power ← dataframe_generator.loc[location, min_power]
Define function LogicFunction(load, renewables):
  if load < gen_power:
    return load
  elif (load − renewables) ≥ gen_power:
    return load − renewables
  else:
    return gen_power
Apply LogicFunction to each row of dataframe to calculate net load

Store the resulting net load values in net_load
return net_load
```

Algorithm A.3 Calculate Additional Renewable Curtailment

Require: dataframe, dataframe_generator, location, parameters
Ensure: additional_renewable_curtailment

$gen\_min\_power \leftarrow dataframe\_generator.at[location,' min']$
Calculate $condition\_1$: Load with BESS is less than minimum generator power
Calculate $condition\_2$: Difference between normal minimum percentage and capacity factor of net load renewables times online generators is greater than 0
Calculate $first\_condition$: Difference between normal minimum percentage and capacity factor of net load renewables times rated power of online generators
Calculate $second\_condition$: Difference between renewable power minus integration penalty and renewable curtailment
Calculate additional_renewable_curtailment using NumPy
$additional\_renewable\_curtailment \leftarrow$
    np.where($condition\_1, 0,$ np.where($condition\_2,$ np.minimum($first\_condition,$
    $second\_condition), 0))$
return $additional\_renewable\_curtailment$

Algorithm A.4 Calculate Spinning Reserve Variables

Require: dataframe, dataframe_generator, parameters
Ensure: genset_spinning_reserve, spinning_reserve_missing, index_gensets_on_spinning_reserve_missing, capacity_factor_spinning_reserve_missing, total_spinning_reserve, check_spinning_reserve_deficit

Initialize empty lists for genset_spinning_reserve, spinning_reserve_missing, index_gensets_on_spinning_reserve_missing, capacity_factor_spinning_reserve_missing, total_spinning_reserve, check_spinning_reserve_deficit
Extract necessary columns from dataframe and dataframe_generator
for each index in dataframe **do**
    Extract relevant data points from dataframe
    Determine the location of the genset indicator in dataframe_generator
    Calculate genset spinning reserve value
    Append genset spinning reserve value to genset_spinning_reserve list
    Calculate the total spinning reserve value, including the battery spinning reserve
    Append total spinning reserve value to total_spinning_reserve list
    Calculate the spinning reserve missing value
    Append spinning reserve missing value to spinning_reserve_missing list
    if spinning reserve missing value > 0 **then**
        Update genset index on spinning reserve missing
    end if
    Calculate capacity factor for spinning reserve missing
    Append capacity factor to capacity_factor_spinning_reserve_missing list
    Check spinning reserve deficit and append to check_spinning_reserve_deficit list
end for
return genset_spinning_reserve, spinning_reserve_missing, index_gensets_on_spinning_reserve_missing, capacity_factor_spinning_reserve_missing, total_spinning_reserve, check_spinning_reserve_deficit

Algorithm A.5 Calculate Storage SOC

Require: dataframe_generator, dataframe, column_name, parameters, battery_size_mwh
Ensure: energy_storage_charging, energy_storage_discharging, energy_storage_state_of_charge

Calculate energy storage initial SOC in kWh
Initialize empty arrays for energy_storage_charging, energy_storage_discharging, and energy_storage_state_of_charge
for each index in range(len(load)) **do**
    if index = 0 **then**
        Set initial SOC
    else
        Set previous SOC index
    end if
    Find location in the generator table
    Get genset rated power
    if total renewable curtailment to maintain min CF > 0 **then**
        Calculate energy storage charging
    else if total renewable curtailment to maintain min CF $= 0$ **then**
        Calculate energy storage discharging
    end if
    Update energy storage SOC
end for
return energy_storage_charging, energy_storage_discharging, energy_storage_state_of_charge

Algorithm A.6 Calculate Genset Performance

Require: dataframe, parameters, column_name
Ensure: genset_performance

Get capacity factor table and average table from parameters
Initialize empty list for genset_performance
Interpolate genset performance values using capacity factor table and average table
$genset\_performance \leftarrow$
    interpolate($dataframe[column\_name]$.to_numpy(),
        $capacity\_factor\_table, average\_table$)
return genset_performance

Algorithm A.7 Calculate Diesel Consumption with Renewables and BESS

Require: dataframe

Ensure: diesel_consumption_bess_renewables

1: Use vectorized operations to calculate diesel consumption with renewables and BESS:
2: Check if genset performance with BESS and renewables is greater than 0:
3: - If yes, calculate diesel consumption using net load after storage and genset performance.
4: - If not, set diesel consumption to 0.
5: **return** List of diesel consumption values with renewables and BESS.

Data availability

The data that has been used is confidential.

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