Renewable Energy Optimization in Isolated Microgrids: A Python-Based Tool for Cost-Effective Solutions Using Genetic Algorithms

by

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Optimisation des énergies renouvelables dans les microréseaux isolés : un outil basé sur Python pour des solutions économiques utilisant des algorithmes génétiques

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RÉSUMÉ

Ce travail présente un outil programmé en Python pour l'analyse technico-économique de l'intégration des sources d'énergie renouvelable dans les microréseaux électriques isolés. Cet outil combine un simulateur de microréseau et un optimiseur basé sur des algorithmes génétiques. Le simulateur intègre une stratégie de gestion de l'énergie qui priorise l'utilisation des sources renouvelables et le stockage dans les batteries, tout en garantissant un approvisionnement continu de la charge grâce aux générateurs diesel. Cela est rendu possible par une stratégie de répartition qui détermine la combinaison optimale d'un nombre prédéfini de générateurs en fonction des besoins spécifiques du microréseau.

L'optimiseur, qui agit comme une couche supérieure au simulateur, utilise les résultats de ce dernier dans un processus itératif d'optimisation à objectif unique ou multiple. Dans l'étude de cas présentée, l'optimiseur vise à identifier le niveau optimal de pénétration des énergies renouvelables qui minimise le coût nivelé de l'énergie et maximise la réduction de l'utilisation de diesel. Afin d'accélérer la convergence, le processus d'optimisation inclut le développement de tables préliminaires générées à l'aide d'un algorithme de recherche exhaustive, ce qui réduit l'espace de recherche initial.

Les avantages de cet outil résident dans sa conception modulaire, sa capacité à traiter des données d'entrée avec différents pas de temps et sa convergence rapide dans des cas d'étude. Développé en Python, un logiciel libre, il surmonte les limitations des outils commerciaux comme HOMER, qui imposent des restrictions aux utilisateurs. De plus, l'outil est évolutif et adaptable aux besoins spécifiques de chaque utilisateur.

Enfin, l'application pratique de cet outil est validée à travers une étude de cas appliquée à un microréseau d'une communauté à Nunavik, au Québec. Les résultats montrent que le niveau optimal de pénétration des énergies renouvelables identifié par l'outil peut réduire jusqu'à 87 % la consommation de diesel, par rapport aux scénarios sans intégration de renouvelables. Cela souligne la valeur de cet outil dans des contextes industriels et commerciaux nécessitant des solutions pratiques et applicables.

Mots-clés: Microréseaux isolés, algorithme génétique, coût nivelé de l'énergie, réduction du diesel, Python

Renewable Energy Optimization in Isolated Microgrids: A Python-Based Tool for Cost-Effective Solutions Using Genetic Algorithms

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ABSTRACT

This work presents a Python-based tool for the techno-economic analysis of renewable energy integration in isolated microgrids. The tool combines a microgrid simulator and an optimizer based on genetic algorithms. The simulator incorporates an energy management strategy that prioritizes the use of renewable energy sources and battery storage while ensuring a continuous power supply through diesel generators. This is achieved with a dispatch strategy that determines the optimal combination of a predefined number of generators based on the specific needs of the microgrid.

The optimizer, which operates as a top layer to the simulator, uses the simulator's outputs in an iterative optimization process with single or multiple objectives. In the presented case study, the optimizer aims to identify the optimal renewable energy penetration level that minimizes the levelized cost of energy and maximizes diesel displacement. To speed up convergence, the optimization process includes the development of preliminary tables generated using a brute-force algorithm, which reduces the initial search space.

The tool's advantages lie in its modular design, its ability to process input data with different time steps, and its fast convergence in case studies. Developed in Python, an open-access software, it overcomes the limitations of commercial tools like HOMER, which impose restrictions on users. Additionally, the tool is scalable and adaptable to specific user needs.

Finally, the practical application of the tool is validated through a case study applied to a microgrid in a community in Nunavik, Quebec. The results show that the optimal renewable energy penetration identified by the tool can reduce diesel consumption by up to 87% compared to scenarios without renewable integration. This highlights the tool's value in industrial and commercial contexts requiring practical and applicable solutions.

Keywords: Isolated microgrids, genetic algorithm, levelized cost of energy, diesel displacement, Python

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LIST OF ABBREVIATIONS

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
LP	Linear programming
FDL	Flexible deferrable loads
BESS	Battery energy storage system
ESS	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	Cuckoo Search
ABC	Artificial Bee Colony
ARMA	Auto-regressive moving average
MPC	Model predictive control

LIST OF SYMBOLS AND UNITS OF MEASUREMENTS

Units of Measurement

W	Watt
kW	Kilowatt
MW	Megawatt
kWh	Kilowatt-hour
MWh	Megawatt-hour
GWh	Gigawatt-hour
°C	Degrees Celsius
m	Meter
m^2	Square meter
kg	Kilogram
L	Liter
kL	Kiloliter
t	Ton
y	Year

Symbols

α	Power temperature coefficient
ρ	Air density
η	Efficiency

$	Canadian dollar
c$	Cents of a dollar
k$	Thousands of dollars
%	Percentage

INTRODUCTION

Climate change, primarily caused by the burning of fossil fuels, has effects that, at this point, threaten the safety, well-being, and prosperity of human beings. Globally, 2024 was the hottest year on record, and 2025 is on track to be on top three with 2023 (WMO (2024)). Canada, which is warming faster than most regions on Earth, is experiencing the consequences of climate overheating. This has contributed to worsening wildfires and deteriorating the quality of life for Canadians (CCI (2024)). Specifically in Quebec, elevated summer temperatures in 2024 were associated with 470 deaths, 225 hospitalizations, 36000 emergency room visits, and 7200 ambulance transports (Boudreault, Éric Lavigne, Campagna & Chebana (2024)).

Most Canadian households are connected to the electricity grid, primarily powered by hydropower, alongside natural gas, wind, solar, and nuclear energy (Lovekin, Dave & Heerema, Dylan (2019a)). In contrast, approximately 290 remote Canadian communities, with a total population of about 200000, are not connected to the North American grid or natural gas infrastructure. These include Aboriginal and non-Aboriginal settlements, as well as commercial outposts for industries like mining, fishing, and forestry. According to Natural Resources Canada, 70% of these communities rely on inefficient diesel generators for electricity, 13% on hydro, and 17% use other fossil fuels (Natural Resources Canada (2011)).

Collectively, remote communities consume over 90 million litres of diesel annually for electricity. Nunavut, Ontario, and the Northwest Territories are the largest consumers (Lovekin, Dave & Heerema, Dylan (2019a)). Due to poor building efficiency and harsh climates, energy consumption in these communities is significantly higher than the Canadian average (Lovekin, Dave & Heerema, Dylan (2019a)). Transporting diesel to remote areas is challenging, as many communities are accessible only by truck on seasonal roads, by ship, or by plane, with over half being fly-in only (Government of Canada (2018)). It is costly to transport and often subsidized to keep it affordable. It also contributes to air pollution, and spills during transport or storage are a risk.

Diesel offers reliable, non-variable energy, crucial in extreme climates, and can be stored for long periods. However, aging generators pose reliability issues, as a failure could leave communities without power (Government of Canada (2023)). While diesel generators are affordable and scalable, high operational costs, volatile prices, and environmental concerns make this energy system unsustainable, particularly in Nunavut, where residents face some of the highest energy costs in Canada.

Remote communities, being disconnected from the main grid, form isolated microgrids. These systems include diesel generators, distribution infrastructure, control systems, and potentially renewable energy sources like wind, solar, biomass, combined heat and power, or small-scale hydropower.

As renewable energy integrates into these microgrids, the system's complexity increases, but the marginal cost of electricity often decreases. This is because renewable sources displace diesel-generated power, reducing fuel consumption. Using energy from wind, solar, and other renewables results in lower diesel use, leading to fuel cost savings and potentially reduced operational and maintenance costs for diesel generators. In many cases, renewables can supply the majority of a community's energy needs (Lovekin, Dave & Heerema, Dylan (2019a)).

Like any electrical system, microgrids require continuous real-time balancing of supply and demand. While larger grids are resilient and can manage fluctuations, microgrids, typically reliant on a single diesel generator, are more vulnerable to demand surges or unexpected power source failures. Ensuring 24-hour system reliability is crucial, and while consistent energy sources like diesel and hydropower provide steady output, naturally intermittent and stochastic sources like wind and solar complicate grid operations (Lovekin, Dave & Heerema, Dylan (2019b)).

The percentage of energy supplied by renewable sources in a hybrid microgrid is known as the penetration level. Although much research has focused on the impact of high renewable penetration on large-scale grids, hybrid microgrids face different constraints. Large grids can integrate up to 80-100% intermittent renewables due to their diverse energy sources, whereas microgrids without storage face a technical limit of around 20-30% renewable penetration.

Hybrid microgrids, with limited energy sources, must balance diesel output with the availability of intermittent renewable energy. Older diesel generators, which perform inefficiently when operating at variable speeds, can experience shortened lifespans due to frequent ramping up and down, undermining the cost benefits of integrating renewable energy.

Technological advancements offer solutions to these challenges. Variable speed generators (VSGs) operate efficiently at lower speeds, reducing diesel fuel consumption and enabling higher renewable penetration. Additionally, battery storage, when paired with intermittent renewables, can smooth short-term variations in energy production. However, batteries are unable to address longer-term seasonal fluctuations, such as those seen during Arctic winters with minimal sunlight.

Energy demand also plays a critical role in facilitating renewable integration. Matching supply to fluctuating demand, which varies throughout the day, poses a challenge for microgrids. Energy efficiency measures and smart grid technologies that help stabilize demand can make microgrid operations more manageable.

Transitioning remote communities to clean energy involves significant technical challenges, including managing supply and demand fluctuations, enhancing control systems for intermittent energy sources, and maintaining infrastructure in harsh environments. Moreover, this transformation presents economic, regulatory, and political hurdles.

For the above, it is clear efficient methods to manage the different sources in a microgrid are needed. It is a critical issue for a system designer to make sure that the loads are being reliably satisfied by the generators. Here comes the term “Dispatch strategy". This term is known as the part of the control system that deals with the energy flow among the various components of the microgrid. Dispatch strategy is important because it affects the overall cost of the system and helps to design a more economic and efficient system. In a microgrid, economic dispatch is used as a way to ensure the safe and economic operation of the microgrid.

The main objective of economic dispatch related problems is to ensure fulfillment of the load demand at a minimum operating cost by scheduling the output of the committed generation units along with the system and all generation units' equality and inequality constraints satisfied. An efficient dispatch strategy can save an enormous amount of money and consumption of resources with a reduction in the emission of harmful gases (Fatin Ishraque, Shezan, Ali & Rashid (2021)).

There are various energy dispatch strategies in a microgrid, each aiming at different objectives. In this context, unit commitment, which determines which units should supply energy within the grid based on technical constraints, can be integrated into economic dispatch or considered separately. Some strategies seek to determine optimal renewable energy penetration levels or, in other words, the sizing of microgrid components to minimize the system's total cost or the price at which energy should be sold. On the other hand, some strategies focus strictly on technical objectives, such as performance improvement, the exploration of new technologies, maximizing the use of renewable energy, managing uncertainties in renewable sources, among others.

Energy dispatch strategies, which we will refer to as Energy Management Strategies (EMS) from now on, can be classified into three main categories: rule-based, optimization-based, and hybrid approaches. In rule-based strategies, a set of predefined commands determines which units supply the required energy. In contrast, optimization-based strategies define energy dispatch through a mathematical structure that models the system under study, typically using an objective function and constraints. Hybrid approaches combine both methods, incorporating optimization while also applying predefined dispatch rules. While rule-based strategies are more practical but less efficient, optimization-based ones can achieve greater efficiency at the cost of increased implementation complexity.

The implementation of these strategies, in the context of studies and simulations, is generally carried out using either open-source or commercial software. In the former case, programming languages such as Python are widely used due to their flexibility and scalability. Among commercial tools, HOMER is one of the most commonly employed, offering advanced capabilities in optimization, dispatch, and user interface. However, its use can present limitations in terms of flexibility for adapting to specific user needs.

In this regard, the scientific literature shows that while there is a wide range of studies addressing energy management strategies from technical and economic perspectives, often employing advanced optimization methodologies, most of them lack practicality and ease of application in real-world scenarios, including industrial environments.

0.1 Objectives

The overall objective of this work is the development and implementation of a Python-based tool that performs techno-economic optimization of renewable energy integration in isolated microgrids using a genetic algorithm.

To achieve this, the following specific objectives are proposed:

- To analyze and implement a rule-based energy management strategy in Python.

- To develop a modular Python-based tool that integrates the rule-based strategy and a multi-objective optimization module, the latter based on a genetic algorithm.
- To apply the tool to a case study based on a real isolated microgrid in northern Quebec, in order to determine the optimal renewable penetration that minimizes energy costs and diesel consumption.

0.2 Work Methodology

The methodology of this work is based on several key stages:

Initially, the rule-based energy management strategy is studied, analyzing its functionality, the variables involved, as well as its expected inputs and outputs. Subsequently, this strategy is implemented in Python, maintaining a modular approach and incorporating improvements such as the ability to perform calculations with variable time-step input data.

Next, the optimizer based on a genetic algorithm is developed, also in Python and following a modular structure. In this stage, the parameters of the different phases of the algorithm are adjusted to balance convergence time and the search for an optimal solution.

Finally, the tool is applied to a case study of an isolated microgrid located in the Nunavik region of northern Quebec.

0.3 Thesis Structure

The core of this work is contained within a research article titled **"Renewable Energy Optimization in Isolated Microgrids: A Python-Based Tool for Cost-Effective Solutions Using Genetic Algorithms"**, which is presented in Chapter 2 of this document.

The article provides a detailed description of the contributions of this work in relation to the literature review conducted. It also explains the methodology and each of its stages, including the description of input data, the development of the simulator and the energy management strategy, the development of the optimizer, and a detailed explanation of each phase of the genetic algorithm. Finally, the case study and the obtained results are presented, followed by a critical discussion and conclusions.

After the article, the conclusions and recommendations section is presented, followed by the appendices and references.

CHAPTER 1

LITERATURE REVIEW

1.1 Renewable energy penetration into isolated microgrids

The integration of renewable energy into power systems is driven by environmental, economic, and energy security concerns. Although large grids have gradually adopted wind and solar power, isolated microgrids face different challenges (Thomas, Deblecker & Ioakimidis (2016)). These systems, common in remote areas, typically depend on diesel generators, which involve high costs, logistical difficulties, and environmental drawbacks. To address these issues, increasing the penetration of DER in microgrids has become a key focus.

The penetration of renewable energy in isolated microgrids refers to the share of total demand met by renewable sources. It can range from minimal contributions to fully renewable systems. Higher penetration is supported by advances in energy storage, demand management, and intelligent control strategies that improve stability and reliability. Optimizing DER installed capacity is crucial to balance generation fluctuations, maintain grid stability, and reduce dependence on conventional backups (Aoun, Adda, Ilinca, Ghandour & Ibrahim (2024a)).

Increasing DER penetration in isolated microgrids offers benefits in economic, environmental, and energy security. Reducing diesel dependence reduces costs, especially in areas with expensive fuel logistics. Environmentally, integration of DER reduces emissions and improves air quality, helping mitigate climate (Stringer & Joanis (2023)). It also improves energy independence, making remote communities less vulnerable to supply disruptions and fuel price fluctuations.

Integrating DER in isolated microgrids presents technical and operational challenges. The variability of wind and solar power requires efficient storage and control strategies to ensure stability (Moradi, Esfahanian, Abtahi & Zilouchian (2018)). Limited inertia increases the risk of frequency and voltage fluctuations, requiring solid regulation techniques. Additionally, optimizing microgrid performance involves managing load variations, forecasting uncertainties, and coordinating diverse energy sources (VanderMeer, Green, Darbali-Zamora & Thompson

(2023)). Proper DER sizing is key to maintaining reliability and cost-effectiveness while avoiding energy deficits or unnecessary investments (Ma *et al.* (2022)).

Given these challenges, studying DER integration in isolated microgrids is essential. Assessing the technical, economic, and environmental impacts of DER integration helps develop efficient energy management strategies.

This work contributes to the study of resilient, low-carbon systems in remote areas by exploring energy management strategies combined with optimization techniques to evaluate renewable integration in an isolated microgrid. To provide context and clarify the study's objectives, key definitions and concepts are presented in this review.

1.2 Microgrids

A microgrid (MG) can be defined as a flexible and efficient energy system that works at medium or low voltage. It comprises several DG (distributed generators), energy storage systems (ESS) and Energy Management Systems (EMS) in charge of supplying a set of variable loads. Distributed generators can be renewable (such as photovoltaic or wind systems) or conventional (such as diesel generators) (Rodriguez, Arcos–Aviles & Martinez (2023)).

1.2.1 Configurations of Isolated Microgrids

Isolated microgrids, also known as off-grid microgrids, operate independently from the main power grid, relying entirely on local energy generation and storage to meet demand. Their configurations vary depending on available energy sources, load characteristics, and operational strategies. The main configurations include:

- Diesel-Based Microgrids

  Traditionally, isolated microgrids have relied on diesel generators as the primary energy source. These systems provide reliable power but face high fuel costs, logistical challenges for fuel transport, and environmental concerns due to greenhouse gas emissions. Typically used in remote communities, mining operations, and industrial sites.

- Renewable-Based Microgrids with Storage

  Incorporate renewable energy sources such as solar photovoltaics (PV), wind turbines, or small hydropower to reduce fuel dependency. Require battery energy storage systems (BESS) or other storage technologies (e.g., flywheels, supercapacitors) to manage variability in renewable generation. Advanced control strategies are needed to optimize generation, storage, and load management.
- Hybrid Microgrids (Diesel + Renewables + Storage)

  A widely adopted configuration that combines diesel generators with renewable energy and storage. Diesel generators provide backup power when renewable generation is insufficient or storage is depleted. This setup balances reliability, cost-effectiveness, and emissions reduction by optimizing fuel consumption and renewable penetration.
- Hydrogen-Based Microgrids

  Emerging systems that use excess renewable energy to produce hydrogen via electrolysis, which can be stored and later used in fuel cells to generate electricity. Suitable for long-term energy storage and addressing seasonal variations in renewable production. Still in early deployment stages due to high costs and efficiency challenges.
- Microgrids with Demand-Side Management (DSM)

  Incorporate intelligent load management strategies to optimize energy consumption. Use demand response mechanisms, controllable loads, and smart appliances to adjust electricity demand according to generation availability. Enhances system stability and reduces reliance on fossil-fuel-based backup generation.

1.3 Energy Management Strategies for Microgrids

This section describes the typical models for the elements of the components of a microgrid, and presents the main types or categories of EMS for isolated microgrids,

1.3.1 Modeling of the elements for energy management strategies

There are different models to represent the elements of a microgrid depending on the aim of the study they are used for. In the case of the EMS modeling and simulation, one of the most commonly used, and for the most common components of a microgrid, are presented below:

1.3.1.1 Photovoltaic Systems Modeling

The output power of a photovoltaic system can be expressed as follows (Arcos-Aviles *et al.* (2019); Ameen, Pasupuleti & Khatib (2015); Abid *et al.* (2019)):

$$P_{PV} = P_{STC}\frac{G}{G_{STC}}[1 + \alpha(T_C - T_{STC})] \tag{1.1}$$

Where P_{STC} is the PV module output power (W) under Standard Test Conditions (STC), G is the incident irradiance on the plane of panels (W/m2), α is the power temperature coefficient, T_{STC} is the temperature under STC (°C), and T_C is the cell temperature (°C). T_C is defined considering the ambient temperature, T_a (°C) and the Nominal Operating Cell Temperature ($NOCT$) (°C), as follows (Arcos-Aviles *et al.* (2019)):

$$T_C = T_a + \frac{G}{800}(NOCT - 20) \tag{1.2}$$

1.3.1.2 Wind Turbine Systems Modeling

The output power of a wind turbine (WT) is defined as follows (Arcos-Aviles *et al.* (2019); Abid *et al.* (2019); Vahidzadeh & Markfort (2019)):

$$P_{WT} = \frac{1}{2} \cdot \rho \cdot A \cdot C_{P,WT} \cdot V_Z^3 \tag{1.3}$$

Where ρ is the air density (kg/m^3), V_Z^3 is the wind speed at the wind turbine hub-height (m/s), a is the rotor sweep area (m^2), and $C_{(P,WT)}$ is the WT power coefficient.

1.3.1.3 Battery Energy Storage System Modeling

For EMS purposes the behavior of the battery energy storage system (BESS) can be described by mean of the State of Charge (SOC) (Arcos-Aviles *et al.* (2019); Abid *et al.* (2019)). The SOC can be described by the equation shown below:

$$SOC(t) = SOC(t_0) - \frac{100}{E_{BESS}} \int_{t_0}^{t} \eta \cdot P_{BESS}(t) \cdot dt \tag{1.4}$$

Where E_{BESS} is the rated capacity of the BESS in kWh, and P_{BESS} is the power of the battery in kW, η is the battery efficiency ($\frac{1}{\eta_d}$ for discharge, with $P_{BESS} > 0$; η_c for charge, with $P_{BESS} < 0$) (Rodriguez *et al.* (2021)).

1.3.1.4 Diesel Generator Modeling

The diesel generator (DG) model for EMS purposes can be expressed in terms of the fuel consumption (Ameen *et al.* (2015); Abid *et al.* (2019)). The fuel consumption of a DG varies depending on the manufacturer and, in general, varies from 0.32 to 0.53 l/kWh (Ameen *et al.* (2015)). For its part, the fuel consumption can be modeled in terms on the DG output power as shown in the equation below:

$$FC_G = A_G \cdot P_G + B_G \cdot P_{R\_G} \tag{1.5}$$

Where P_G, P_{R_G} are the output power and the rated power of the DG, respectively, and A_G and B_G are the coefficients of the fuel consumption curve. Typical values for these coefficients are $A_G = 0.246$l/kWh and $b_G = 0.08145$ l/kWh (Dufo-López *et al.* (2011)).

1.3.2 Energy Management Strategies Classification

The classification of energy management strategies for isolated microgrids can be addressed from different fronts, for example, talking about the control and decision making processes, the classification can be into centralized, distributed, and hybrid approaches:

- Centralized: In a centralized strategy, decision-making and control functions are managed from a central point within the microgrid. This central entity typically gathers data from various sources across the grid, analyzes it, and makes decisions regarding energy generation, storage, and consumption. It often involves algorithms or optimization techniques to ensure efficient management of resources. Centralized strategies offer a comprehensive view of the entire microgrid but may face challenges related to communication dependencies and potential single points of failure (Zia, Elbouchikhi & Benbouzid (2018); Sharma, Dutt Mathur, Mishra & Bansal (2022)).
- Distributed: Distributed strategies delegate decision-making and control functions across multiple local entities or nodes within the microgrid. Each node might possess some level of autonomy to make decisions based on local information. These nodes can communicate with each other to coordinate actions, but they operate semi-autonomously. Distributed strategies offer more flexibility and resilience as they can adapt to local conditions swiftly, but they might face challenges in achieving global optimization and coordination (Zia *et al.* (2018); Sharma *et al.* (2022)).
- Hybrid: Hybrid strategies combine elements of both centralized and distributed approaches. They aim to leverage the advantages of each strategy while mitigating their respective limitations. This could involve having both a central decision-making authority for overarching coordination while allowing localized decision-making for specific nodes or subsystems within the microgrid. Hybrid strategies seek to balance the need for global optimization and local adaptability.

However, another classification for EMS for isolated microgrids depending on the strategy considered for the whole microgrid is presented more in detail in this section.

1.3.2.1 Rule-based strategies

The main characteristic of this kind of strategies are Threshold-Based control and Priority-Based Dispatch. In the first case, specific thresholds are set for energy generation and consumption to trigger actions like starting or stopping generators or adjusting loads. In the second case, energy sources and loads are prioritized based on predefined hierarchies to ensure critical services receive power first.

For example, (Lopez-Santiago *et al.* (2022)) proposed a rule-based strategy that enables a form of self regulation of the battery charge relative to an also introduced reliability index in the microgrid. The main inputs for the strategy are short-term demand predictions, the power generation from the renewable sources and current measurements in the microgrid. This strategy determines the scheduling of the conventional generators, the storage units and the renewable sources without using optimization while considering the physical and operational limits of each element. The facts of not using optimization and considering short term horizons make the strategy to operate faster and to be less complex in comparison to optimization based approaches. The strategy is tested in a microgrid test bed related to a real microgrid in Colombia.

For its part (Arcos-Aviles *et al.* (2019)) also develop an EMS that, despite its a Fuzzy Logic-based one (strategy used to deal with non linearities in the microgrid model), also define a set of rules that defines the operation some of the components of the microgrid. In this case, the microgrid is formed by a photovoltaic system, a diesel generator, and an energy management system. The rules are specifically set to manage the diesel generator's on/off cycles and the battery's state of charge (SOC) to decrease fossil fuel usage and minimize power losses in the PV and DLG generators. This approach leads to reduced operational expenses for the microgrid. Additionally, the state of health (SOH) is employed as a metric to ensure the effective functioning of the Energy Storage System (ESS), assessing battery degradation over periods of one and ten years. Optimization is also used in this case not for the energy management itself but for find the best parameters for the Fuzzy Logic Strategy.

A direct comparison for rule-based and optimization based strategies is made by (Rodriguez *et al.* (2021)). Regarding to the rule-based part, studied in a test bed microgrid with two diesel generators, battery energy storage systems and renewable sources such as wind an solar, the strategy is based on states. Each state represent an operation condition and it has defined the rules that allow to transfer to other states. For example, the states are define for the operation only with the battery, for just the diesel generator one, for diesel generator two, for both of them, or for when a curtailment in generation or load must be made.

1.3.2.2 Optimization-based strategies

Inside of the optimization based strategies, two of the more outstanding categories are optimal scheduling, where mathematical optimization techniques are used to schedule energy generation, storage, and consumption to minimize costs or maximize efficiency, and model predictive control, with predictive models to anticipate future energy availability and demand, optimizing control actions in real time.

For example, (Restrepo, Cañizares, Simpson-Porco, Su & Taruc (2021)) in order to compare with the rule based strategy, proposed an optimization based technique where, for the same microgrid considered in the first case, they propose an optimization problem in which the objective function aims to minimize the generation costs over a future time horizon, by mean of a linear function calculated from the heat rate of the generation units. The function also considers the costs for start up and shut down the generators and the costs related to the curtailment of generation sources and loads. The main constraints for the problem include, the load balance, the dispatchable generation output limits, battery state of charge limits, minimum run time for generators, load and generation curtailment, minimum spinning reserve, among others. The optimization problem was addressed using the Python's Pyomo package.

For its part, (Olivares, Lara, Cañizares & Kazerani (2015)) introduce a stochastic-predictive energy management system designed for isolated microgrids, presenting its mathematical formulation and control structure. The proposed strategy addresses uncertainties by employing a two-stage decision-making process in conjunction with a receding horizon methodology. The initial stage involves determining decision variables (unit commitment) via a stochastic mixed-integer linear programming formulation, while the subsequent stage refines variables (optimal power flow) using a nonlinear programming approach.

The optimization function in this case seeks to minimize the general operating costs of the microgrid (generation, start up, shut down) ant the restrictions are related to the demand supply balance, spinning reserve, shiftable demand, active and reactive limits, ramps, and power balance equations for the energy management systems.

Moreover, (Violante, Cañizares, Trovato & Forte (2020)) also propose an EMS for an isolated microgrid that incorporates thermal energy resources. This components, in addition to photovoltaic systems, wind turbines, battery energy storage systems and diesel powered generators, enable a microgrid not only to provide energy but also to provide heat to a building. The Energy Management Strategy aims to reduce fuel expenses while incorporating considerations for thermal comfort and building characteristics, by using an optimization challenge structured as a Mixed Integer Linear Programming (MILP) problem. This formulation is easily managed by commonly available commercial solvers, rendering the EMS suitable for real-time applications. In this case, the objective function also considers the operating costs of the generation units and load curtailment costs. The constraints are also related to active and reactive power balance, availability of spinning reserve for each time step, up and down ramps to represent how fast a generator can turn on or off respectively, among others.

In this matter, the optimization based strategies can be also classified depending on the specific type of programming, such as linear on non linear. That classification will be addressed in the continuation of this report.

1.3.2.3 Adaptive strategies

The adaptive strategies mainly are divided into Machine Learning approaches and Fuzzy logic control.

In the first case, machine learning algorithms continuously learn and adapt to changing patterns in energy generation and consumption, improving decision making over time.

The definition of machine learning is broad and covers several techniques such as supervised learning, unsupervised learning, reinforcement learning, neural networks, decision trees among others.

For example, artificial networks has some advantages such as the ability to learn and to process parallel data, its non linear and adaptive structure, its generalization skills (do not depend on system parameters), and fast response. However, it also face some drawbacks such as the fact that it is generally treated as a black box with a complex structure inside which makes challenging to determine its layers. In addition, historical data is needed for the learning and tuning process, which will later influence the optimality of the network (Phan & Lai (2019)).

In the second case, fuzzy logic systems are used to handle uncertainties in renewable energy generation and demand, making decision based on imprecise or incomplete information. Some of the advantages of this method are that the rules for its membership functions are easy to understand, its insensitive to variation of parameters and do not need a good model for the system and training process. On the other hand, the disadvantages are related to the need of trial and error method to determine the membership functions (time consuming and not optimal) and that a greater number or variables increase the complexity to optimize the membership functions (Phan & Lai (2019)).

(Rodriguez *et al.* (2023)) develop a comprehensive energy management system based on Fuzzy Logic for an independent microgrid involving various components like photovoltaic systems, diesel generators, and energy storage systems. The procedure encompasses the entire process of fine-tuning the parameters of a fuzzy logic controller through the utilization of metaheuristic optimization algorithms.

(Dong *et al.* (2023)) analyze an isolated microgrid that includes the energy supply, load, battery, and a central controller. The power supply included wind power and a diesel generator. The load comprised the energy demand of a building and an independent hydrogen production system. Based on the forecasted results/data (analysis also developed in the study), the stochastic optimization scheduling of the EMS is solved using deep reinforcement learning to minimize the economic cost of the microgrid life cycle. That's why the objective function includes the components of equipment investment costs, operation and maintenance cost and resource purchase cost.

The deep reinforcement learning architecture treated in this study considered various system parameters at 15-minute intervals, predicting actions and executing them based on forecasted results. Using a deep Q-network, DRL iteratively determines actions, updating them based on rewards obtained from system responses, aiming to minimize costs effectively.

For its part, (Lan *et al.* (2021)) propose a machine learning based approach for the energy management in a microgrid that used advanced machine learning via Support Vector Regression for accurate electric vehicle charging demand prediction, offering reliability without overfitting, unlike conventional methods like Artificial Neural Networks (ANNs). To optimize SVR parameters for this complex, chaotic data, a new dragonfly-based optimization approach is introduced. This dragonfly algorithm (DA) manages the intricate scheduling of microgrid units, loads, storage, and switches, solving discrete optimization problems effectively by mimicking insect flight patterns, providing a robust solution to challenging problems. Once again, in this document, the objective function aims to minimize the mix of the operation and technical costs, whit associated constraints for the diesel generators (active power limits, ramps, and minimum run times), energy storage systems, adjustable loads, and power balance limits.

1.3.2.4 Hybrid Strategies

Hybrid strategies can be a combination of rule-based and optimization techniques for quick decision making with optimization methods for long term planning and efficiency. It also can refer to integrated hierarchical control when talking about the integration of multiple layers of control systems, such as local controllers coordinating with a central controller, to manage different aspects in the microgrid.

(El-Bidairi, Duc Nguyen, Jayasinghe, Mahmoud & Penesis (2018)) present an example of an hybrid approach between a Fuzzy system and Grey Wolf Optimization meta-heuristic method not only for energy management but also for battery sizing. In general terms, the authors present a multi objective method in which the fuzzy system is used to set the power output of the battery energy storage, while the energy management strategy itself is carried out by the Grey Wolf Optimization, In the end, the aim is to determine the optimal power generation scheduling aiming to enhance the system performance in both, the renewable energy penetration level and economic aspects. The minimization in usage of diesel generators and the emission levels is also considered.

For its part, (Mao, Jin, Hatziargyriou & Chang (2014)) introduce a hybrid EMS for microgrids, presenting the benefits of both centralized and decentralized control of energy flows. This system achieves energy distribution across various control levels to align with diverse coordinated objectives. Within this framework, a three-tier hierarchical and distributed energy control strategy for the microgrid is shown, employing a collaborative approach utilizing the contract net protocol and a multi-factor evaluation mechanism.

1.3.2.5 Demand-Side Management Strategies

In this cases, the energy management strategies for isolated microgrids embraces the concept of demand side management by mean of demand response programs, encouraging the consumers to adjust their energy consumption based on grid conditions or price signals, or through load shifting and peak shaving, where the energy consumption is redistributed across different times to avoid peak loads and optimize energy use.

(Solanki, Bhattacharya & Cañizares (2017)) present a mathematical model for unit commitment in isolated microgrids, that simultaneously minimizes operating costs and pollutant emissions considering demand shifting load models. One of the objectives of the analysis is to examine if the demand response strategy has an impact in the total system emissions and costs. For that purpose, the models of emissions for the generators are proposed, and the objective function and constraints are, once again, related to the minimization of operating costs of the microgrid, but it is worth to mention that there is a new restriction associated to the controllable demand, that can be shifted and at least paid back within the same day, considering the maximum and the minimum limits for the shiftable demand.

In the case of the study of (Yuan, Lu, Zhang & Li (2019)), even if the main purpose is an hybrid prediction based energy management strategy to predict interrupted data for the centralized dispatching process of the microgrid, the demand side response is also included in the study. The whole optimization problem including the demand side management is designed and then solved using particle swarm optimization. In this case, the microgrid is formed for a wind turbine, a photovoltaic system, a micro turbine, an energy storage unit a fuel cell and three different types of loads: interruptible load, which can be removed directly from the system; flexible load, that has adjustable usage time; and fixed load, that is a critical load that must be met as required. The interruptible and flexible loads have its respective constraints in the optimization problem, added to an objective function and other constraints similar to the ones discussed in the previous reviewed documents.

1.3.2.6 Resilience and reliability Strategies

This strategies aims to coordinate the system and its redundant components and backup power sources to ensure continuous operating during failure. Fault detection in real time to initiate recovery procedures also falls in this category.

(Silva, López, Arias, Rider & da Silva (2021)) developed a stochastic mixed-integer nonlinear programming model to optimize the operation of unbalanced three-phase alternating current microgrids. This model aims to efficiently schedule energy storage systems, diesel generators, electric vehicle chargers, and includes provisions for direct load control and photovoltaic management. The formulation also considers unexpected grid outages by integrating contingency constraints in the optimization problem. The ability of the microgrid to operate isolated from the main grid when there is a problem is what makes it resilient. Moreover, to address uncertainties related to demands, photovoltaic generation, and reference voltage, a scenario-based approach was employed. In addition, a series of linearization methods were utilized to convert the initial mixed-integer nonlinear programming model into a mixed-integer linear programming model.

For its part, (Jia, Pannala, Kandaperumal & Srivastava (2022)) propose an EMS for and hydro-diesel-battery islanded microgrid. The dispatch strategy is a resilience based because it use signals of past events to be able to identify when a new high impact low probability event will hit and make the energy storage systems to be fully prepared before the event strikes. In the strategy, the authors achieve that the microgrid is able to operate in two modes: economical one in normal conditions and a resiliency one to anticipate the occurrence of an event. The resilience in this case is quantified by mean of a set of metrics.

1.3.2.7 Community Engagement and Behavioral Strategies

These kind of strategies can be educational campaigns where local communities are informed and encouraged to adopt energy-efficient behaviors and practices. Incentive-Based Programs also falls inside of this category, where rewards or incentives for energy conservation or utilizing renewable energy sources are offered to the users.

The work developed in a doctoral thesis (Oviedo Cepeda (2021)) a outstanding an original study is develop to include demand side management strategies not only in the dispatch but in the whole planning of isolated microgrids. The thesis assumes that the users of the microgrid to be planned are in isolated/rural areas where they have no access to devices that can be controlled or switched by signals. This assumption makes it necessary for the study to base demand side management on the users' behavior, and this behavior, aimed at modifying consumption patterns, must be guided by price-based signals. These price-based signals are included in the study as tariff schemes. However, there was no procedure in the literature capable of proposing tariffs that use price signals to modify users' consumption patterns. The thesis integrated a technical analysis of the energy sources and demand behavior with financial analysis to overcome this challenge.

The hypothesis of the mentioned thesis is that to influence the patterns of consumption of electrical energy of the customers of an isolated microgrid, the levelized cost of energy will decrease compared to a base case where no demand side management is applied. The study also hypothesizes that demand side management will lead to better performance of other variables in the project, such as payments for the energy, diesel consumption (improved operation of diesel generators), total project cost, among others. In the end, the results of the study allow to conclude that the proposed hypothesis was correct.

1.4 Software and programming languages for microgrid studies

The study and optimization of microgrids require specialized software tools and programming languages capable of modeling, simulating, and optimizing power systems. Several widely used tools offer different functionalities, ranging from techno-economic assessments to advanced optimization techniques.

- HOMER (Hybrid Optimization of Multiple Energy Resources): It is a widely used software for techno-economic modeling of microgrids. It allows users to simulate and optimize hybrid energy systems by analyzing different configurations to determine the most cost-effective solution (Fatin Ishraque *et al.* (2021)). HOMER is particularly useful for feasibility studies, as it considers load variations, renewable generation, storage, and economic parameters.
- MATLAB/Simulink: with its Simulink toolbox, is a powerful numerical computing environment frequently used in microgrid studies. It provides extensive capabilities for modeling, control system design, and dynamic simulations of electrical systems (Semshchikov, Negnevitsky, Hamilton & Wang (2020a)). Simulink enables time-domain simulations of microgrids, allowing for detailed analysis of transient behavior, stability, and control strategies.
- Python: It is a versatile programming language extensively used for data analysis, simulation, and optimization in microgrid studies. With libraries such as NumPy, Pandas, SciPy, and PuLP (Lambert & Hassani (2023)), Python is well-suited for modeling energy systems.

Additionally, optimization frameworks like Pyomo and machine learning tools facilitate advanced control and predictive analysis in microgrid management .

- GAMS (General Algebraic Modeling System): It is a high-level modeling system for mathematical optimization. It is commonly employed in energy system studies for formulating and solving linear, nonlinear, and mixed-integer programming problems. GAMS is particularly useful for economic dispatch, unit commitment, and energy management strategies in microgrids (Nasr, Rabiee & Kamwa (2020b)).
- Gurobi: It is a state-of-the-art solver for linear, quadratic, and mixed-integer optimization problems. It is widely used in microgrid optimization for problems requiring high computational efficiency, such as unit commitment, economic dispatch, and power flow optimization (Tostado-Véliz, Rezaee Jordehi, Fernández-Lobato & Jurado (2023)). Gurobi is often integrated with programming languages like Python and GAMS for solving complex optimization models.
- Other Tools Other software tools used in microgrid studies include PSS/E (Power System Simulator for Engineering) for power flow and stability analysis, OpenDSS for distribution system modeling, and DIgSILENT PowerFactory (Cadena-Zarate & Osma-Pinto (2024)) for comprehensive power system simulations. Additionally, EnergyPLAN and RETScreen are used for energy planning and renewable integration assessments.

The previous descriptions indicate that the selection of software or programming language depends on the specific objectives of the microgrid study. HOMER is ideal for economic feasibility analysis, MATLAB/Simulink is suited for dynamic simulations, Python offers flexibility in custom modeling and machine learning applications, while GAMS and Gurobi provide powerful optimization capabilities. Furthermore, combining these tools maximizes their potential in research analysis.

1.5 Optimization techniques in microgrids

Microgrid operation and planning require advanced optimization techniques to ensure economic efficiency, reliability, and sustainability. This section presents an overview of commonly used optimization techniques in microgrid studies, their main characteristics and general solution procedures.

1.5.1 Economic Dispatch and Unit Commitment

Economic dispatch (ED) and unit commitment (UC) are two fundamental optimization problems in power system operation.

Economic Dispatch focuses on determining the optimal power output of available generating units to meet a given load at the lowest operational cost while satisfying technical constraints such as generation limits and ramp rates (Semshchikov, Negnevitsky, Hamilton & Wang (2020b)). ED assumes that the units are already committed and seeks to distribute the load among them optimally. The problem is often formulated as a nonlinear or linear programming model.

Unit Commitment, on the other hand, extends economic dispatch by also deciding which generators should be turned on or off over a given time horizon. It incorporates additional constraints such as startup and shutdown costs, minimum up/down times, and reserve requirements. UC is typically modeled as a mixed-integer linear programming (MILP) problem (Nasr, Nikkhah, Gharehpetian, Nasr-Azadani & Hosseinian (2020a)), making it computationally more complex than ED.

1.5.2 Genetic Algorithms (GA)

GA are search heuristics inspired by the principles of natural selection. They are particularly suitable for optimization problems that are non-linear, non-convex, or multi-modal, such as microgrid optimization (Zhou, Yan & Saha (2020)). The general steps in a GA are:

1. Initialization: Generate an initial population of possible solutions. Each individual in the population represents a candidate solution, often encoded as a chromosome.

2. Evaluation: Evaluate the fitness of each candidate solution using a predefined fitness function. The fitness function typically reflects the objective of the optimization (e.g., cost, energy efficiency, or emissions).

3. Selection: Select the best solutions (parents) based on their fitness. Techniques like roulette wheel selection, tournament selection, or rank-based selection can be used.

4. Crossover (Recombination): Combine two parent solutions to create offspring. This process mimics the concept of reproduction and results in new candidate solutions, as represented in Eq. (1.6).

$$\text{Offspring} = \text{Crossover}(\text{Parent}_1, \text{Parent}_2) \tag{1.6}$$

5. Mutation: Introduce small random changes (mutations) to some offspring to maintain diversity in the population and avoid premature convergence, as shown in Eq. (1.7).

$$\text{Mutation}(x) = x + \delta \tag{1.7}$$

where δ is a small random value.

6. Termination: The algorithm stops when a convergence criterion is met, such as reaching a maximum number of generations or when the fitness of the population stabilizes.

GA is suitable for problems like unit commitment, economic dispatch, and renewable energy integration, where the search space is large and complex.

1.5.3 Grey Wolf Optimizer (GWO)

The Grey Wolf Optimizer (GWO) is a nature-inspired optimization algorithm based on the leadership hierarchy and hunting behavior of grey wolves. It mimics the pack structure of wolves, consisting of alpha, beta, delta, and omega wolves. These wolves guide the search for prey, which is analogous to finding the optimal solution in an optimization problem (Mirjalili, Mirjalili & Lewis (2014)).

1. Encircling Prey: Wolves update their positions based on the best solutions found, as represented in Eq.(1.8). The alpha wolf leads, and other wolves follow.

$$\text{Position}_i = \text{Position}_{\text{best}} - A \cdot |C \cdot \text{Position}_{\text{best}} - \text{Position}_i| \tag{1.8}$$

where A and C are coefficient vectors that control the exploration and exploitation balance.

2. Hunting: Wolves refine solutions based on the influence of the alpha, beta, and delta wolves. This helps in guiding the search to promising areas of the solution space.

3. Attacking Prey: As the search process converges, the wolves reduce the exploration and focus on refining the best solutions found so far.

GWO is particularly useful for optimizing problems with nonlinearities, such as in energy management and power flow optimization in microgrids.

1.5.4 Mixed-Integer Linear Programming (MILP)

Mixed-Integer Linear Programming (MILP) is a powerful optimization approach used for solving problems with both continuous and integer decision variables. MILP is often applied to problems such as unit commitment, optimal power flow, and energy management in microgrids (Ehsan & Yang (2018)).

The general structure of an MILP problem is presented in Eq (1.9):

$$\text{Minimize} \quad \mathbf{c}^T \mathbf{x} \tag{1.9}$$

Subject to equations (1.10) and (1.11):

$$\mathbf{A}\mathbf{x} \leq \mathbf{b} \tag{1.10}$$

$$\mathbf{x} \in \mathbb{Z}, \mathbb{R} \tag{1.11}$$

where $\mathbf{x}$ represents the decision variables (including both integer and continuous variables), $\mathbf{c}$ is the vector of objective coefficients, $\mathbf{A}$ is the constraint matrix, and $\mathbf{b}$ is the constraint vector.

The MILP process consists of three main steps. First, the objective function is formulated, which typically involves minimizing operational costs, emissions, or losses. Next, constraints are incorporated to ensure feasibility, including power balance, generation limits, unit on/off states, and storage limits. Finally, the problem is solved using optimization solvers such as CPLEX or Gurobi to obtain the optimal solution (Lambert & Hassani (2023)). MILP guarantees globally optimal solutions but may be computationally expensive, especially for large-scale systems.

1.5.5 Fuzzy Logic Optimization

Fuzzy Logic Optimization is used when there is uncertainty or imprecision in decision-making. It allows partial truths rather than just binary true/false decisions, which is beneficial in microgrid control where data is often imprecise or incomplete (Vivas *et al.* (2020)).

The basic steps involved in fuzzy logic are as follows (Yüksel, Börklü, Sezer & Canyurt (2023)). First, fuzzification is performed, where crisp inputs (such as temperature or power demand) are converted into fuzzy sets using membership functions. This allows the input values to have degrees of membership within a set, rather than being fixed values. The second step, rule evaluation, uses fuzzy if-then rules to determine the system's behavior based on the fuzzy inputs. For example, a rule might state that if the load is high, the generator output should also be high. Finally, defuzzification takes place, where the fuzzy outputs are converted into precise actions or decisions. This is often done using methods like centroid or mean of maxima.

1.5.6 Artificial Bee Colony (ABC) Optimization

The Artificial Bee Colony (ABC) algorithm is a swarm intelligence optimization technique inspired by the foraging behavior of honey bees. The algorithm consists of three types of bees: employed bees, onlooker bees, and scout bees (Dashtdar *et al.* (2022)).

Employed bees search for food sources, representing candidate solutions, and share their findings with other bees. Onlooker bees, in turn, evaluate the food sources shared by the employed bees and select the best ones for further exploration. Scout bees, on the other hand, randomly explore new areas of the search space to avoid premature convergence. The algorithm is driven by the fitness of food sources, with the aim of maximizing or minimizing a given fitness function, such as cost, power losses, or emissions.

1.5.7 Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a relatively new approach within the field of evolutionary computational metaheuristics, inspired by the collective movement of bird flocks or schools of fish. This method operates stochastically, where each member of the population is represented by a particle. The position of each particle corresponds to a potential solution to the problem, while the particle's velocity indicates how far it will move in the next step. The fitness of each particle is calculated using an objective function based on its current position. With each iteration, the particle's velocity and position are updated to improve the solution and move towards the global best one (Anoune, Bouya, Astito & Abdellah (2018)).

The PSO method effectively combines local search and global search strategies. However, the standard PSO algorithm struggles with multi-objective optimization problems because there is no single global optimum in such cases (Boqiang & Chuanwen (2009)).

1.5.8 Linear Programming (LP)

The Linear Programming (LP) method is employed to validate mathematical models that involve linear relationships between multiple variables, aiming to find optimal candidate solutions, such as maximizing profit or minimizing cost. It optimizes an objective function assigned linearly while considering defined linear equality and inequality constraints. LP becomes an integer linear programming (ILP) problem when all decision variables are integers. However, when some variables are continuous, it is referred to as MILP. The key components of an LP problem include decision variables, constraints, data, and objective functions (Panda *et al.* (2022)). The general formulation of the optimization problem can be written by mean of Eq. (1.12)

$$\text{Minimize} \quad \mathbf{f}^T\mathbf{x} \tag{1.12}$$

Subject to equations (1.13) and (1.14):

$$\mathbf{A} \cdot \mathbf{x} \leq \mathbf{b} \tag{1.13}$$

$$\mathbf{x} \geq 0 \tag{1.14}$$

Where x is the vector of decision variables (e.g., generation levels), f is the vector of cost coefficients, A is the matrix of constraint coefficients, b is the vector of constraint value

LP has been widely studied for its applicability in solving straightforward and linear optimization problems, thanks to its efficient and simple computational approach compared to other methods. However, when system complexity increases, alternative optimization techniques need to be employed.

1.6 Dispatch strategies for generators

In this case, dispatch strategies for generators can be considered as a set of rules or regulations is used for the control of generators and storage operation whenever there is not enough renewable resource to satisfy the load. The dispatch strategy tries to control the system in a way that the load demand is supplied properly. Among them, load following (LC), cycle charging (CC), generator order (GO), combined dispatch (CD), and HOMER predictive dispatch can be identified (Fatin Ishraque *et al.* (2021)).

Load following is a dynamic dispatch strategy that adjusts power generation in real-time to match electricity demand. In microgrids, this ensures that generators operate efficiently to meet the load while minimizing excess generation. This strategy is particularly beneficial for systems with variable renewable energy sources, as it helps balance the fluctuations between supply and demand. To further enhance operational efficiency, cycle charging comes into play. By running a generator at its peak efficiency to charge a battery while simultaneously supplying the load, cycle charging maximizes fuel use. Once the battery reaches a set charge, the generator shuts down, allowing stored energy to meet the demand, optimizing both generation and storage (Shezan *et al.* (2022a)).

To ensure this process is as cost-effective as possible, the concept of generator order is employed. This strategy prioritizes the most efficient and cost-effective generators, ensuring they are dispatched first. Less efficient or more expensive generators are only activated when necessary, which helps in reducing operational costs and optimizing fuel consumption. These strategies can be integrated in a more complex approach known as combined dispatch. Combined dispatch blends multiple methods, such as load following and cycle charging, to optimize generator operations and storage utilization. This hybrid approach ensures a balance between cost, efficiency, and reliability (Shezan *et al.* (2022b)).

Finally, the HOMER predictive strategy offers a more advanced control method that anticipates future load and renewable energy availability. Unlike traditional rule-based strategies, this predictive approach uses forecasting techniques to make proactive decisions, reducing the reliance on fuel-based generators. By considering future energy needs, the predictive strategy enhances the integration of renewable sources and improves overall system performance and cost-effectiveness. This seamless integration of strategies helps microgrids function more efficiently and sustainably (Shezan *et al.* (2022b)).

1.7 Future trends and innovations

The integration of renewable energy in isolated microgrids is becoming increasingly important for remote and off-grid areas. As technology evolves, several trends will shape energy management and optimization, leading to more sustainable and cost-effective solutions.

One major trend is the integration of advanced energy storage technologies. Innovations like solid-state batteries, flywheels, and hydrogen storage offer longer durations, faster charge cycles, and lower environmental impacts than traditional batteries. Alongside this, energy management systems (EMS) will become more sophisticated. These systems use real-time data and machine learning to optimize energy generation, storage, and distribution, incorporating predictive analytics to anticipate fluctuations in demand and renewable generation (Uddin *et al.* (2023)).

Demand-side management (DSM) will also be key, using smart technologies like controllable loads and demand response programs to balance energy supply and demand. This reduces reliance on fossil fuels and ensures system stability. Advanced grid-forming inverters and virtual power plants (VPPs) will help coordinate renewable resources and storage. Additionally, blockchain technology could enable decentralized energy trading, optimizing energy allocation and creating new economic opportunities (Mariam, Basu & Conlon (2016)).

In summary, the future of renewable energy in isolated microgrids relies on innovations in energy storage, EMS, DSM, and decentralized technologies, which will improve efficiency, sustainability, and reliability while reducing environmental impact.

1.8 Summary and conclusions

This review has covered key concepts that are either fundamental to or directly related to the article presented in this work. The approach has been descriptive, aiming to provide the reader with background information and definitions they may not be familiar with. In this regard, an overview of renewable energy penetration in microgrids was presented, highlighting its relevance as a research topic. The concept of microgrids and their configurations was also described and contextualized.

Following this, the discussion shifted to the importance of energy management strategies and their critical role in integrating renewable energy into microgrids. A detailed classification of these strategies was provided, along with an overview of optimization approaches, their key characteristics, and the commonly used software tools in related studies. Finally, a brief summary of future trends in this field was included.

Meanwhile, a more in-depth analysis of existing literature, focusing on its relation to the research objectives, the problem at hand, the applied methodology, and this study's contributions compared to previous findings, is extensively developed in the article that forms the core of this thesis. Therefore, readers are referred to that article for a deeper understanding and further context on the significance of this work.

CHAPTER 2

ARTICLE 1

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 depend on diesel generators (DG), which are both costly and harmful to the environment due to carbon emissions. Microgrids (MG) offer a sustainable alternative by integrating renewable energy sources for electricity generation and storage. Energy management strategies (EMS) in MG optimize energy flow to meet economic, technical, environmental, or user-specific objectives. However, despite extensive research, practical tools for techno-economic analyses—such as optimal sizing, cost assessment, and emissions reduction—are limited, especially when not using commercial softwares like HOMER, which restricts flexibility.

This paper addresses these gaps by presenting a Python-based tool for the determination of renewable energy penetration in hybrid systems through single or bi-objective optimization. The tool includes a dispatch simulator and a genetic algorithm-based optimizer. Applied to a hybrid system case study located in Nunavik, Quebec, the tool evaluates five scenarios: no renewable integration, wind turbine integration, wind turbine with storage, and two scenarios optimizing for Levelized Cost of Energy (LCOE) and diesel consumption reduction. The results demonstrate that optimizing the LCOE and diesel reduction with 4MW wind energy penetration can reduce diesel consumption by up to 87% compared to scenarios without renewable integration.

Higlights

- Developed a modular Python code for fast techno-economic optimization in microgrids.
- Implemented an automated dispatch strategy for diesel generators using efficiency criteria.
- Enabled reading input data with varying time steps and operating accordingly.
- Executed bi-objective optimization using a genetic algorithm.
- Analyze multiple diesel generators and other sources simultaneously.

Key words

Isolated microgrids, genetic algorithm, Levelized cost of energy, diesel displacement, Python

2.1 Introduction

The global energy transition is crucial due to its significant implications for environmental sustainability, economic prosperity, and social equity. As the urgency of climate change grows, shifting from fossil fuels to renewable energy sources, along with adopting sustainable practices and promoting energy efficiency, is essential to reduce greenhouse gas emissions and mitigate global warming's effects.

In Canada, a large part of the energy supply comes from renewable sources, particularly hydroelectric power, which accounts for 60% of the total energy demand (Government of Canada

(2024)). However, in remote areas lacking an electrical infrastructure, diesel generation has been widely used because of its ease of installation, reliability, and flexibility in power distribution. Despite these benefits, there is increasing interest in reducing reliance on diesel generation due to its environmental impact and expected increases in operation and tax costs, leading to a greater focus on promoting the integration of renewable energy technologies in electrical microgrids (MG) (Stringer & Joanis (2023)).

The International Committee of Large Electrical Networks (CIGRE) defines MG as electrical distribution systems containing distributed energy resources (DER) and loads (such as generators, storage devices, and controllable loads) that can operate in a controlled manner, either connected to the main network or in isolation (Alvarado-Barrios, Álvaro Rodríguez del Nozal, Boza Valerino, García Vera & Martínez-Ramos (2020); Aoun *et al.* (2024c)). MGs can autonomously manage the distribution, utilization, and supply of energy according to real-time conditions, resulting in more efficient energy use and reduced carbon emissions (Li, Pei & Shen (2023)).

Maintaining a balance between generation and demand is critical within MGs, particularly due to the intermittent nature of renewable sources such as photovoltaic systems (PVS) and wind turbines (WT), which depend on variables such as sunlight and wind availability (Aoun *et al.* (2024a)). This balance becomes especially vital for isolated operations, where resources for demand management are limited (Ullah *et al.* (2022); Restrepo *et al.* (2021)).

Energy management strategy (EMS) algorithms are vital for maintaining the generation-load balance and achieving other MG objectives. They can be optimized at various levels, addressing both operational aspects and dynamic changes in climate and environmental conditions (Solano, Jimenez & Ilinca (2020)).

EMS can be categorized into centralized, distributed, or hybrid systems. Centralized EMS make decisions at a central point (Sharma *et al.* (2022)), while distributed systems delegate decision-making to local nodes (Zia *et al.* (2018)). Hybrid systems combine both approaches, offering flexibility and resilience. EMS strategies are further classified into rule-based, optimization-based, hybrid, adaptive, demand-side management, resilience-focused, and community-engagement approaches.

Rule-based strategies are based on predefined thresholds to trigger actions and prioritize essential services (Lopez-Santiago *et al.* (2022)), and are chosen in multiple studies due to their simplicity and practicality. For example, Arcos et al. (Arcos-Aviles *et al.* (2019)) manage diesel generators (DG) cycles to reduce fuel consumption, and Rodriguez et al. (Rodriguez *et al.* (2021)) ensure smooth transitions between generator operations and renewable curtailment. Luca et al. (Moretti, Meraldi, Niccolai, Manzolini & Leva (2021)) go one step further and propose a strategy in which the parameters that define the control rules are optimally tuned using evolutionary algorithms.

Optimization-based strategies use mathematical techniques that often require describing the system in terms of its technical constraints and identifying a temporal window over which the scheduling decisions constitute the problem variables, to minimize costs or maximize efficiency, including predictive control (Restrepo *et al.* (2021); Olivares *et al.* (2015); Violante *et al.* (2020)). These approaches often involve tools such as Pyomo (Restrepo *et al.* (2021)) or mixed-integer linear programming (Olivares *et al.* (2015); Violante *et al.* (2020); Aoun, Adda, Ilinca, Ghandour & Ibrahim (2024b)). The last is widely used because it can handle a large number of integer variables and provide the globally optimal solution (Moretti *et al.* (2021)). The authors in (Moradi *et al.* (2018)) propose an optimization model to minimize the operational, maintenance and pollution costs of MG, while also including a probabilistic technique to consider the stochastic nature of renewable sources in their analysis.

Hybrid strategies blend rule-based and optimization techniques (El-Bidairi *et al.* (2018)). Zhao et al. (Zhao *et al.* (2021)) propose a rule-based strategy to the power allocation in the MG and at the same time propose an improved multi-objective gray wolf optimization in order to solve a three-objective problem.

Adaptive strategies, such as those based on machine learning and fuzzy logic, adjust to changing patterns and handle uncertainties (Phan & Lai (2019)). Machine learning requires extensive data (Dong *et al.* (2023)), while fuzzy logic can be time consuming (Rodriguez *et al.* (2021)).

Demand-side management strategies adjust energy consumption based on grid conditions (Yuan *et al.* (2019)). Resilience-focused strategies ensure continuous operation during system failures (Silva *et al.* (2021)). Community-oriented strategies encourage energy-efficient behaviors through education and incentives (Oviedo Cepeda (2021)).

Beyond their classification, EMS play a critical role in determining the penetration level or size of renewable energy resources in isolated areas based on specific objectives (Yang, Feng & Li (2019); Wang, Hsu, Zheng, Chen & Li (2020)), as well as managing economic dispatch and unit commitment in isolated MGs, separately or in combination.

Numerous studies have explored renewable energy integration in isolated MGs with various objectives. For example, Thomas et al. (Thomas *et al.* (2016)) highlight the economic feasibility of replacing fossil fuels with renewable hybrids. Ma et al. (Ma *et al.* (2022)) examine the optimal sizing and feasibility of MGs, comparing different dispatch strategies and control techniques. Hamilton et al. (Hamilton, Negnevitsky, Wang & Lyden (2019)) investigate wind plus storage integration, low-load diesel, and demand side management. Michael et al. (Semshchikov *et al.* (2020b)) emphasize control strategies and low-load diesel (LLD) to achieve 60-80% renewable penetration while minimizing costs. Kiptoo (Kiptoo *et al.* (2020)) evaluates the costs associated with the varying levels of penetration of renewable energy, ranging from 0% to 100%. Even when specific penetration levels aren't explicitly stated, the overarching goal is often to maximize renewable energy participation. For example, Zhou et al. (Zhou *et al.* (2020)) report over 100% photovoltaic (PV) penetration with 84-85% utilization, while Nasr et al. (Nasr *et al.* (2020b)) describe an 8MW wind penetration in a 27MW MG. Using EMS, Cleantechnol et al. (Tran, Davies & Sepasi (2021)) report a 40.6% PV contribution to the total annual electricity production. Belboul et al. (Belboul *et al.* (2024)) propose an improved Salp Swarm Algorithm for optimization that had not been applied before to MG studies and that has significant capabilities regarding convergence and local minima avoidance. It is tested in several MG configurations and considers technical and environmental concepts while determining the size of the MG elements.

In studying generator behavior, Zhou et al. (Zhou *et al.* (2020)) conducted a significant study aimed at finding optimized control strategies and capacities to integrate high levels of renewable energy into diesel-powered remote networks. Their analysis included ideally optimized dispatch and rule-based dispatch strategies, using minute-resolution time series data for load and photovoltaic generation to provide a detailed methodology. Furthermore, Khirennas et al. (Khirennas, Kaabeche, Talha & Bakelli (2021)) determine the optimal storage-less photovoltaic system to modernize a system based on multiple DG. That procedure is performed with respect to the LCOE and for that the authors developed a period-ahead optimal operating-scheduling algorithm. Lambert and Hassani (Lambert & Hassani (2023)) present a novel mixed-integer linear programming (MILP) model for the real-time deterministic optimization of prime power DG, incorporating startup and shutdown constraints, minimum runtime requirements, generation limits, prime power rating conditions, load sharing constraints, as well as operational and penalty costs

For its part, economic dispatch aims to meet energy demand at minimal cost by scheduling the output of predefined generation units, focusing on energy or power flows while adhering to system and unit constraints. This approach primarily emphasizes cost minimization and demand fulfillment, often without directly addressing MG controls or voltage and frequency stability, which are typically maintained by balancing generation and demand. However, some studies have incorporated strategies to quantify voltage and frequency stability within the economic dispatch framework (Ishraque *et al.* (2021)).

Rezaee et al. (Jordehi, Sadegh Javadi & Catalão (2020)) optimize dispatch solutions by considering demand and generation capabilities, incorporating load demand curtailment to reduce operational costs. Hou et al. (Hou *et al.* (2022)) explore economic dispatch using artificial intelligence for day-ahead planning, accounting for uncertainties in generation and loads. Similarly, Xu et al. (Xu, Meng & Wang (2020)) address uncertainties while managing the load to shift peak demand to off-peak hours, optimizing economic factors such as fuel, maintenance, and pollution costs. Studies on economic dispatch often employ various evaluation indices. These include cost-related metrics such as net present cost (NPC), Levelized Cost of Energy (LCOE) and capital recovery factor (CRF) (Fatin Ishraque *et al.* (2021)); reliability-related metrics such as expected load loss, probability of load loss, expected energy not served, curtailed energy, and curtailed generation (Zhou *et al.* (2020)); technical metrics like CO_2 emissions (Ishraque *et al.* (2021)); and user satisfaction-related indicators (Xu *et al.* (2020)).

With respect to unit commitment, it determines which generation units should be turned on or off at different time intervals to meet the load demand while considering constraints such as generator minimum up/down times, startup/shutdown costs, and system reliability. Several authors have addressed it by testing various dispatch strategies while simultaneously determining the optimal size of renewable sources for isolated hybrid systems. For example, Ishraque et al. (Fatin Ishraque *et al.* (2021)) examine five different dispatch strategies: load following, cycle charging, generator order, combined dispatch, and HOMER predictive dispatch. Using indicators such as NPC, LCOE, and CO_2 emissions, they determine the optimal component sizes through simulation. Kutaiba et al.(El-Bidairi *et al.* (2018)) pursue those same goals by mean of energy management, but focusing specifically in the Energy Storage System (ESS) sizing while combining fuzzy logic with Grey Wolf Optimizer (GWO). In another study, Ishraque et al. (Ishraque *et al.* (2021)) evaluate the impact of these dispatch strategies on generators and storage systems when renewable energy is not sufficient to meet the load, conducting an optimization process for sizing and cost reduction. Salvatore et al. (Vergine, Álvarez Arroyo, D'Amico, Escaño & Alvarado-Barrios (2022)) employ a two-step optimization program for unit commitment, where the first step determines the operational status of the energy sources and the second step sets the actual power output based on forecasts and demand.

In the approaches previously mentioned, as a way to properly manage the energy in the sources, spinning reserve is used to ensure the stability and efficiency of the system. One document details the design and implementation of a control strategy for autonomous hybrid plants, where the spinning reserve is innovatively managed by incorporating battery energy storage systems (BESS) (Martín-Arroyo, Cebollero, García-Gracia & Llamazares (2021)). This approach minimizes the use of nonrenewable generators and maximizes renewable energy production. Another document explores methods to reduce or replace the requirement of spinning reserves in diesel MG by integrating wind energy, highlighting that the use of battery energy storage systems (BESS) yields the highest fuel savings and that controllable loads can regulate wind power (VanderMeer *et al.* (2023)). The third document proposes a cooperative control strategy for reserve management in isolated MG, demonstrating how the regulation burden can be shared among all energy sources and storage systems to maintain adequate reserve margins (Cagnano, Caldarulo Bugliari & De Tuglie (2018)).

Table 2.1 presents an organized comparison of relevant features of the MG studies, including elements forming the MG, optimization approaches, rule based aproaches, the most used software, the spinning reserve handling and other and energy management particularities.

Table 2.1 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
Semshchikov *et al.* (2020b)	2020	Australia	Off-grid	DG (1), PVS, WT, BESS, LLD, FDL	Economic dispatch	Total cost (DG+BESS+FDL)	Priority dispatch renewable	MATLAB	No
Zhou *et al.* (2020)	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
Kharrich *et al.* (2021)	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
Nasr *et al.* (2020b)	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
Tran *et al.* (2021)	2021	Vietnam	Off-grid	DG (1), PVS, BESS	Homer economic optimization for components sizing	NPC, LCOE	Not mentioned	HOMER	No
Tostado-Véliz *et al.* (2023)	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
Fatin Ishraque *et al.* (2021)	2021	Bangladesh (Mymensingh,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
Ellabban & Alassi (2021)	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
Lambert & Hassani (2023)	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
Chebabhi, Tegani, Benhamadouche & Kraa (2023)	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
Ali, Abdulgalil, Habiballah & Khalid (2023)	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
Rodriguez *et al.* (2023)	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
Dashtdar *et al.* (2022)	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
Vergine *et al.* (2022)	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
Jordehi *et al.* (2020)	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
Hou *et al.* (2022)	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
Ishraque *et al.* (2021)	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
Xu *et al.* (2020)	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
Thomas *et al.* (2016)	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
Ma *et al.* (2022)	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
Hamilton *et al.* (2019)	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
Kiptoo *et al.* (2020)	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

As seen in the previous table, the literature review reveals that most works are simulation-based, with Matlab (Kiptoo *et al.* (2020); Semshchikov *et al.* (2020b); Zhou *et al.* (2020); Tostado-Véliz *et al.* (2023)) and HOMERPro (Tran *et al.* (2021); Ellabban & Alassi (2021); Chebabhi *et al.* (2023); Thomas *et al.* (2016)) being the most widely used software, often employed separately or in combination (Kharrich *et al.* (2021); Ishraque *et al.* (2021); Rodriguez *et al.* (2023)). Other studies use GAMS (General Algebraic Modeling System) (Nasr *et al.* (2020b); Ali *et al.* (2023)), while some use Python (Oviedo Cepeda (2021); Hou *et al.* (2022); Xu *et al.* (2020)). Optimization problem formulations typically rely on methodologies such as MILP (Kiptoo *et al.* (2020)), genetic algorithms (GA) (Zhou *et al.* (2020); Dashtdar *et al.* (2022)), HOMER models (Tran *et al.* (2021); Ellabban & Alassi (2021); Chebabhi *et al.* (2023)), particle swarm optimization (Jordehi *et al.* (2020); Xu *et al.* (2020)), ant colony optimization (Gutiérrez-Oliva, Colmenar-Santos & Rosales-Asensio (2022)), and fuzzy logic (Rodriguez *et al.* (2023)), among others (Gutiérrez-Oliva *et al.* (2022); Kharrich *et al.* (2021)).

In conclusion, the literature highlights that EMS is a critical research focus, essential for the safe and efficient operation of isolated hybrid MGs, both operationally and economically. Various advanced strategies are applied not only to coordinate energy flows between sources and loads but also to size renewable energy sources within the MG, determining their penetration levels. These optimization techniques often depend on accurate forecasting of demand and generation data, which may not always be feasible in industrial operations or real-world applications. In contrast, rule-based strategies offer practical solutions with fixed and easy-to-implement control parameters, providing flexibility for different operating scenarios. However, a notable gap exists in the literature: no study presents an explicit, practical, and quick procedure for optimal sizing or penetration of sources according to technical and economic objectives. In addition, no study prioritizes the operation of multiple DG, which remain crucial in MG operations despite efforts to minimize their use. In addition, although some studies consider spinning reserve management for these generators, it is sometimes achieved by over-sizing DG or storage systems. Furthermore, most analyses are based on commercial software, such as HOMER, which can limit dispatch strategies. When HOMER is not used, objective functions typically cater to specific case-based problems. Many studies use hourly resolution for predefined generation and load profiles, while real-world operations require a minute-scale analysis, as demonstrated in the study by Zhout et al. (Zhou *et al.* (2020)). However, the authors in (Zhou *et al.* (2020)) do not present a strategy adaptable to dispatch multiple DG to meet load requirements.

To address these limitations, this article introduces a modular real Python-based tool for evaluating the penetration of renewable energy in isolated MGs. The core of the tool includes a simulator and an optimizer. The simulator incorporates a rule-based EMS that prioritizes the use of renewable energy sources while ensuring the safe operation of the MG by guaranteeing the availability of spinning reserve, whether from diesel generation, storage systems or available renewable sources. The optimizer is GA-based and uses the simulator to calculate objective functions while adjusting the decision variables. It can perform bi-objective optimization and introduces a method for incorporating multiple DG into the analysis. Additionally, a sensitivity analysis is conducted to narrow the search space for the GA's initial values, enhancing its performance. The tool is applied to the hybrid system of a small village located in Nunavik, a northern territory located in the province of Quebec, Canada. Five scenarios are assessed: no renewable integration, wind turbine integration, wind turbine combined with storage, and two scenarios optimizing for LCOE and reduction of diesel consumption.

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

Contributions of this work

- Development of a modular Python code for practical and fast techno-economic optimization of renewable energy source penetration in isolated MG. The tool includes
  - Implementation of an automated dispatch strategy for DG based on efficiency criteria.
  - Deployment of an EMS that prioritizes renewable usage while ensuring energy balance through spinning reserve handling, whether from diesel, renewable, or storage systems.
  - Capability to read input data with varying time steps and operate accordingly.

- Provision of detailed information on multiple MG parameters, such as spinning reserve, curtailed energy, fuel consumption, CO_2 emissions, among others.
- Execution of bi-objective optimization.
- Sensitivity analysis to refine the GA's search space.
- Fast execution tool applicable and scalable to similar contexts.
- Simultaneous consideration of multiple DG and other sources in the analyzes.

The remainder of this paper is organized as follows. Section 2.2 outlines the general methodology, covering input data and parameters, the gensets dispatch strategy, as well as descriptions of the simulator and the principles of its embedded EMS, optimizer, and the modular approach implemented. Section 2.4 presents the results, starting with a description of the case study, followed by an explanation of the proposed scenarios and the formulation of the LCOE along with related considerations. The section also includes optimization tables and a discussion of the simulation results. The final section provides the conclusions of the study.

2.2 Methodology and numerical formulations

The proposed tool consists of several key stages or modules: input files and parameters, DG dispatch strategy, simulator, and optimizer. Although the DG stage could technically be integrated into the simulator stage, it is described separately here for clarity.

The tool is designed to read time-stamped input data related to load and renewable energy production. Additionally, a component is included to set simulation parameters. Once the input data and parameters are configured, the simulator performs energy flow calculations. The results of these calculations, such as fuel consumption or LCOE for different levels of renewable energy penetration, can then be analyzed and optimized.

The optimizer module employs a GA to refine parameters based on the simulator's output. This process involves evaluating the simulator's results, followed by crossover, mutation, and selection operations. Based on these operations, new inputs are generated for the simulator, enabling an iterative optimization process that continues until optimal values are found.

Given the potentially large search space for initial input values during optimization, an extension model is implemented to create data tables that narrow down this space, speeding up the convergence of the optimization process. These tables are generated using a brute-force method, which involves multiple iterations to identify trends toward the maximum and minimum values of the variables being optimized in response to changes in certain input variables.

Figure 2.1 illustrates the overall procedure in four global stages leading to the development of the tool.

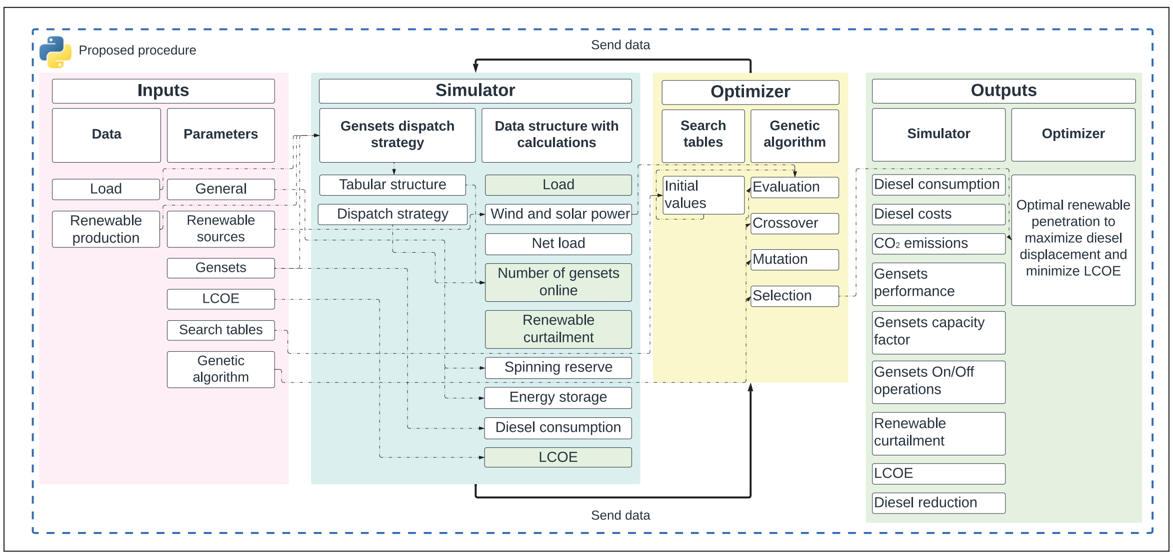


Figure 2.1 General diagram of the proposed procedure

A detailed description of each stage of the procedure is provided in the following sections.

2.2.1 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.

2.2.1.1 Input data

The input data consists of time-stamped vectors, which allow for calculations with variable time steps, accommodating data at hourly or minute intervals. The procedure's code dynamically adjusts to the vector lengths and processes the data accordingly. These input vectors include the electric load and renewable production (wind and solar) in the isolated MG, all of which should be provided as text files for the algorithm to process.

2.2.1.2 Parameters

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

These parameters are categorized as described in Table 2.2. This table presents categories of parameters in the first column along with their corresponding description in the second column. The table eases the understanding of the upcoming explanations.

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.

Table 2.2 Input parameters categorization

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.
Genetic algorithm (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.

2.2.2 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 Figure 2.2.

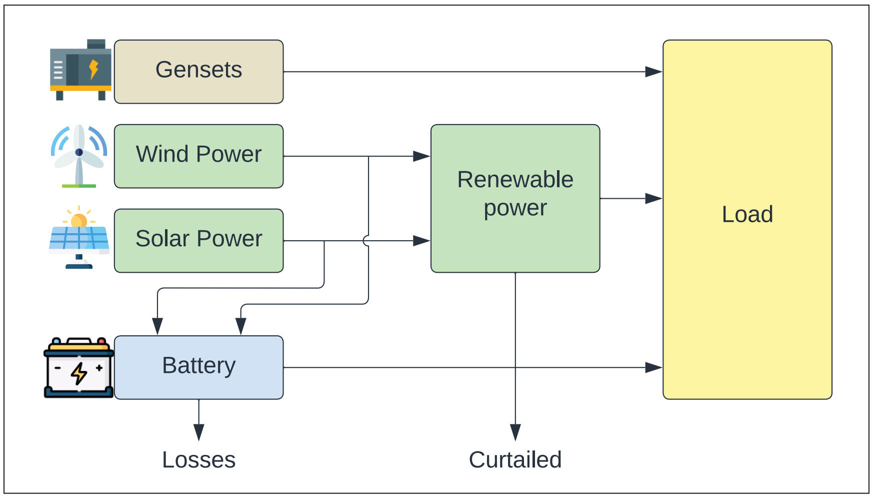


Figure 2.2 General diagram of the considered hybrid system

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

To improve clarity and manage the length of the document, these calculations will be organized and explained within six primary categories: gensets dispatch strategy, wind and solar power, spinning reserve, capacity factor, energy storage, and performance and diesel consumption.

2.2.2.1 Gensets dispatch strategy

The genset dispatch strategy involves two main components. The first component details the organization of the generators information within 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

   This procedure accommodates a variable number of gensets, which may have identical or different nominal capacities, and identifies combinations that prevent redundancy while ensuring that specific loads are serviced by the appropriate genset(s). To achieve this, an algorithm analyzes a vector derived from the input parameters, where each vector element, ordered in ascending sequence, represents the nominal power of a genset.

A unique identifier (“key") is then automatically generated for each genset and paired with its respective rated power. These pairs are used to generate all possible combinations of gensets on the basis of their nominal power, covering various operational scenarios. The algorithm ensures that no duplicate combinations are created, even when the generators have identical capacities.

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 2.3.

Table 2.3 Gensets Information

Indicator	**Generator**	**Rated**	**Min**	**Max**
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

Please note that the values in the “Rated" column correspond to the sum of the nominal capacities of the generators. The values of “Min" and “Max" represent the product of these sums by the maximum and minimum operating percentages specified in the input parameters, which in this example are 30% and 90%, respectively. Furthermore, it is important to note that a combination like g1 linked to g3 could have been possible. However, in such a scenario, the rated powers of the generators would be identical to the combination of g1 and g2. Hence, repeated combinations are not taken into account.

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. The decision on which group from Table 2.3 should be used is therefore determined by this efficiency-based approach.

   It's important to note that the procedure's variable time step, particularly when operating on a minute scale, necessitates considering the minimum run time for generators. 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 depends on the load value, fitting within the “Min" and “Max" ranges for genset(s).
   - The strategy adjusts the time step based on the length of the input data vector. For hourly time steps, the generators can be turned on/off as needed. For minute-scale steps, gensets can be turned off if active for at least one hour.
   - Genset(s) can be in three states: On, Off, and Running. A generator in the “Running" state operates in parallel without providing load, serving as a spinning reserve. A generator can be turned off if in the “On" or “Running" states for at least one hour.
   - The strategy calculates the capacity factor for each genset(s) per time step, alongside an index to identify which generator or group operates at that time step.

   The pseudocode describing the developed genset dispatch strategy is shown in Algorithm 2.1.

Algorithm 2.1 Calculate Gensets Online and Capacity Factor

```
Input: parameters, data_frame, column_name, dataframe_generators
Output: 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;
            end if
        end for
    else
        Set index_gen_on[i] to 0;
    end if
end for
return index_gen_on, capacity_factor, counters, generators_state_indicator;
```

In Algorithm 2.1, 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 2.1 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. (2.1), where $l(t)$ represents the load value and $r(t)$ denotes the rated power of a genset or the sum of rated powers when multiple gensets operate.

$$CF(t) = \frac{l(t)}{r(t)} \tag{2.1}$$

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.

2.2.2.2 Data structure with calculations

The data structure with calculations forms the core of the methodology, incorporating the rule-based EMS. This EMS prioritizes the operational efficiency of DG. Renewable energy sources are used not only to supply the load or recharge storage systems but also to keep the generators within their optimal operating range, set between 30% and 90% of their capacity.

Figure 2.1 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 Figure 2.1, 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 below.

Table 2.4 Input and Parameters Description

Parameter	**Description**
Load	Input load profile.
Wind and solar power	Renewable power input profiles.
Total renewable power	Total energy produced from renewable sources.
Renewable contribution	Portion of renewable energy that directly supplies the load.
Renewable energy curtailment	Renewable energy not used due to system constraints.
Net load	The load that is supplied by DG.
Generators online	Number of generators required to meet net load in a given time step.
Spinning reserve	Power readily available from DG, renewable, or storage systems to offset load deficits caused by fluctuations in renewable generation.

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 (nl) and the renewable curtailment ($rcur$) are calculated using Equations (2.2) and (2.3), respectively:

$$nl = l - rcon \tag{2.2}$$

$$rcur = rt - rcon \tag{2.3}$$

Where l is the load, rt is the total renewable energy, and $rcon$ is the renewable contribution, that is, the portion of the renewable that is supplying the load.

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.

1. Calculation of the net load

   The net load at each time step is determined based on the following conditions:

   - If the load is less than the minimum starting power of the minimum number of online generators (30% of their nominal capacity), the net load equals the total load profile. Note: The minimum number of online generators may not correspond to the smallest generator; thus, a new set of generators can be selected to cover 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 above is described in Algorithm 2.2:

Algorithm 2.2 Calculate Net Load

```
Input: dataframe, dataframe_generator, minimum_gensets, load, min_power,
       renewables
Output: 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);
begin
    if load < gen_power then
        return load;
    else
        if (load − renewables) ≥ gen_power then
            return load − renewables;
        else
            return gen_power;
        end if
    end if
end
Apply LogicFunction to each row of dataframe to calculate net load;
Store the resulting net load values in net_load;
return net_load;
```

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

Equation (2.3) 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:

$$addcur = 30\% - CF \times r \tag{2.4}$$

Where $addcur$ is the additional curtailment, CF is the capacity factor and r denotes the rated power of a genset or the sum of rated powers when multiple gensets operate.

The process is described in Algorithm 2.3:

Algorithm 2.3 Calculate Additional Renewable Curtailment

Input: dataframe, dataframe_generator, location, parameters
Output: 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;

$$\text{additional\_renewable\_curtailment} \leftarrow \text{np.where}(condition\_1, 0, \text{np.where}(condition\_2, \text{np.minimum}(first\_condition, second\_condition), 0))$$

return $additional\_renewable\_curtailment$;

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.

This stage's main characteristics are presented in Algorithm 2.4.

Algorithm 2.4 Calculate Spinning Reserve Variables

```
Input: dataframe, dataframe_generator, parameters
Output: 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, and check_spinning_reserve_deficit;
Extract necessary columns from dataframe and dataframe_generator;
for each index i 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 to genset_spinning_reserve list;
    Calculate total spinning reserve including battery reserve;
    Append total to total_spinning_reserve list;
    Calculate spinning reserve missing value;
    Append 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 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;
```

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 state of charge (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 SOC of the battery at each time step is calculated as the SOC value in the previous time step, plus the charging power in the current time step, minus the discharge power in the same time step.

This process is detailed in Algorithm 2.5.

Algorithm 2.5 Calculate Storage SOC

```
Input: dataframe_generator, dataframe, column_name, parameters,
       battery_size_mwh
Output: energy_storage_charging, energy_storage_discharging,
        energy_storage_state_of_charge

Calculate energy storage initial state of charge 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 state of charge;
    end if
    else
        Set previous state of charge 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;
    end if
    else if total renewable curtailment to maintain min CF = 0 then
        Calculate energy storage discharging;
    end if
    Update energy storage state of charge;
end for
return energy_storage_charging, energy_storage_discharging,
  energy_storage_state_of_charge;
```

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. The detailed procedure is described in Algorithms 2.6 and 2.7.

Algorithm 2.6 Calculate Genset Performance

Input: dataframe, parameters, column_name
Output: 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 2.7 Calculate Diesel Consumption with Renewables and BESS

Input: dataframe
Output: diesel_consumption_bess_renewables

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

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.

2.2.3 Description of the optimizer

The optimization method used in this study does not rely on a predefined objective function. Instead, it uses a simulator 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 (Torkan, Ilinca & Ghorbanzadeh (2022)).

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 2.4.1.2.

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 towards 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.

2.2.3.2 Genetic Algorithm

The GA begins by initializing a population of candidate solutions. Each is evaluated on the basis of a fitness function. Selection methods, such as roulette wheel or tournament selection, favor the fittest individuals for reproduction. 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 (Dashtdar *et al.* (2022)).

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 solution is determined by identifying combinations of these attributes that best achieve the objectives.

For implementing the GA, we use the DEAP (Distributed Evolutionary Algorithms in Python) library, which is specifically designed for evolutionary algorithms. Within this library, a toolbox defines and manages genetic operations and components essential for executing the algorithm.

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 with the command pop, logbook = algorithms.eaMuPlusLambda(). 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.

2.2.4 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 2.5. 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.

Table 2.5 Outputs' description for this study case

Results	Variable	Units
Simulator	Diesel consumption: Fuel consumption of the genset at each time step	L / kL
	Diesel costs: Cost of fuel consumed by the genset at each time step	$ (CAD) / k$
	CO_2 emissions: Carbon dioxide emissions from genset operation	t
	Gensets performance: Efficiency of energy production relative to fuel usage	kWh/L
	Gensets capacity factor: Ratio of actual power output to maximum possible output	%
	Gensets On/Off operations: Startups and shutdowns of gensets	Dimensionless
	Renewable curtailment: Reduction of energy output from renewable sources	GWh
	LCOE: Levelized cost of energy	cents/kWh
	Diesel reduction: Reduction in fuel consumption after optimization	%
Optimizer	Optimal renewable penetration to maximize diesel displacement and LCOE	MW (renewables) / MWh (storage) / % (wind)

2.2.5 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 2.6 for the reader who may be interested in implementing the proposed method.

Table 2.6   Python Implementation Structure

Folder or Main File	**Modules or Files**	**Description**
Main	-	Reading input parameters. Reading input data (load, renewable). Computes sensitivity analysis tables OR Executes optimization with GA.
Input	input_load.txt	Text file containing MG load power consumption data.
	input_solar_power.txt	Text file containing data on solar photovoltaic panels' power production.
	input_wind_power.txt	Text file containing data on wind turbine power production.
	import_functions.py	Python module responsible for importing input data into the application.
	parameter.json	JSON file containing input parameters required for calculations.
Hybrid Power	gensets_data.py	Python module that structures genset information including identification indexes, combinations, and rated minimum and maximum powers for each combination.
	calculation_function.py	Python module containing functions for performing calculations and operations, such as determining the number of operating gensets and their capacity factors.
	simulator.py	Python module that computes energy management and performs calculations to obtain the LCOE using functions from "calculation_function.py".
	tables_optimizer.py	Python module dedicated to performing sensitivity analysis to narrow down the search space of decision variables.
	optimizer.py	Python module that performs optimization using a GA. This module retrieves information from the simulator's output variables (maximized/minimized variables) and sets values for decision variables.

2.3 Validation of the proposed method

The introduction of this article highlights that most simulations that analyze EMS performance are conducted with an hourly time step. Although a one-hour time step can meet the needs of many applications, EMS typically requires a minute-level analysis to ensure proper control of energy supply and demand in a MG, especially when analyzing variables that can change rapidly in less than an hour.

In this case study, data for the specific location in Nunavut are only available at an hourly time step, so the analysis was carried out accordingly. However, the hourly-scale simulation tools previously used by the authors, validated in numerous real-world projects, were employed to verify the newly developed Python code. To further assess the consistency of the code, the hourly data were transformed into minute-level data, allowing for preliminary validation at a finer time resolution before conducting simulations at the hourly scale. The results (not included here) confirm that the formulation and implementation of the proposed code are sound.

In addition, further validation was performed using minute-scale input data for wind profiles and a randomly modified load, primarily to test the computational efficiency of the algorithm. Although these results are also not included, the code was demonstrated to function properly.

Once this validation was completed, the code was used to produce the results presented in the next section.

2.4 Results

This section presents the results of applying the proposed procedure using the data associated with a hybrid system for a selected remote location in Quebec.

2.4.1 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 2.3. The comprehensive information on the system is presented in Table 2.7.

Table 2.7 The hybrid system parameters and element description

	Parameter	**Description**
Gensets	Minimum operating percentage	30%
	Maximum operating percentage	90%
	Rated power	g1 = 560 kW, g2 = 855 kW
	Diesel price	2$/l
Battery	Initial SOC	50%
	Battery size	0.9 MW
	Battery auxiliary load	20 kW/MWh
	Battery spinning reserve	0.9 MW
Wind Turbine	Number of turbines	1
	Turbine size	3.02 MW
General	CO_2 production	2.5 kg/l
	CO_2 cost	0.05$/kg
	Discount rate	4%
	Life time	25 years

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 2.8.

The input parameters for the optimization in Scenarios 2.1 and 2.2 are presented in Table 2.9.

Furthermore, Table 2.10 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

Table 2.8 Description of scenarios for both renewable integration and optimization

Identifier	Scenario	Description
S 1.1	No renewable integration	Only gensets operating
S 1.2	Wind turbine (3 MW)	Wind turbine operates with backup gensets
S 1.3	Wind Turbine (3MW) Battery system (0.9 MWh)	Wind turbine operates with a battery system and backup gensets
S 2.1	Minimization of LCOE	Variation of three decision variables: wind power installed, total renewable power installed, and battery installed
S 2.2	Minimization of LCOE Maximization of diesel consumption reduction	Variation of three decision variables: wind power installed, total renewable power installed, and battery installed

Table 2.9 Input values for the decision variables and the GA parameters

Component	Description	Value
Decision variables	Renewable power installed	1-7 MW (Step: 1 MW)
	Wind percentage	0% - 100% (Step: 10%)
	Battery size	1 - 7 MWh (Step: 1 MWh)
GA	LCOE weight	0.5
	Diesel consumption weight	0.5
	Initial population	10
	Number of generations	5
	Number of individuals surviving in parent selection	5
	Number of offspring to generate	10
	Mutation probability	0.5
	Crossover probability	0.5

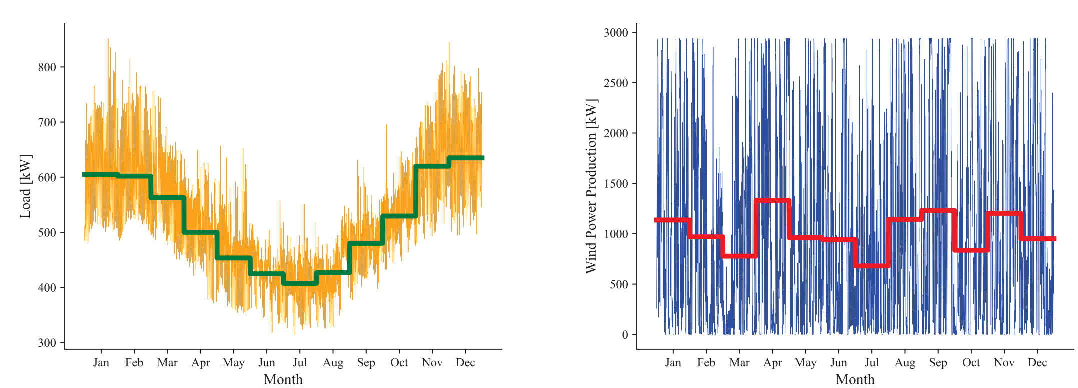
2.7 and 2.10, as well as the discount rate of 4% and the project life cycle of 25 years, are provided by Hatch. Furthermore, the equivalent CO_2 emissions per liter of fuel, the cost of CO_2, and the fuel price are set at 2.5 kg/l, 0.05 \$/kg, and 2 \$/l, respectively.

Figure 2.3 presents the yearly variation of the total load (Figure 2.3a) and the production of wind power (Figure 2.3b) 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.

Table 2.10 The hybrid system global elements Capital and O&M Costs. Data provided by Hatch (unpublished)

Component	Capital Cost ($/kW)	O&M Cost ($/kW/y)
Wind system	16500	250
Solar system	1700	35
Battery system	800	5
Genset	0	50

Figure 2.3a 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, Figure 2.3b shows that net normalized wind production remains relatively steady throughout the year, averaging approximately 1,000 kW, which corresponds to a turbine capacity factor of approximately 33%. April stands out as the month with the highest production, reaching around 1,250 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.



a) Load b) Wind

Figure 2.3 Profiles for the load and the wind power production: a) yearly variation of the load; b) yearly production of wind energy

2.4.1.1 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:

$$LCOE = \frac{CAPEX + \sum_{y=1}^{lf} \frac{OPEX+fc+CO_2c}{(1+dr)^y}}{\frac{E}{(1+dr)^y}} \tag{2.5}$$

Where $CAPEX$ and $OPEX$ represent capital expenditures and the annual operating and maintenance costs associated with renewable sources, DG, and storage, respectively. y denotes the year, lf is the life of the project in years, fc is the fuel cost, CO_2c is the cost of carbon dioxide emissions, dr is the discount rate expressed as a percentage, and E is the energy produced. Here, $CAPEX$ is spent for one year, and the discount rate is considered constant over the life of the project. Furthermore, in this work, the CO_2 cost has been assumed constant, but additional factors such as carbon taxes and price evolution over time could be incorporated into the parameter.

2.4.1.2 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 2.9.

By analyzing examples of LCOE tables in Figure 2.4 at different levels of penetration of wind power - 0% (Figure 2.4a), 50% (Figure 2.4b) and 100% (Figure 2.4c) 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, Figure 2.4d 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 (Figure 2.4d), 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.

	1MW	2MW	3MW	4MW	5MW	6MW	7MW
1MWh	43.87	40.47	40.37	41.18	42.32	43.66	45.10
2MWh	44.18	39.18	38.22	38.74	39.66	40.86	42.16
3MWh	44.96	38.34	36.62	36.69	37.41	38.43	39.61
4MWh	46.21	37.94	35.47	35.03	35.47	36.33	37.37
5MWh	47.67	37.90	34.79	33.86	34.01	34.65	35.56
6MWh	49.20	38.35	34.62	33.35	33.26	33.72	34.47
7MWh	50.62	39.14	34.92	33.41	33.16	33.49	34.15

a) LCOE in c$/kWh for 0% wind power

	1MW	2MW	3MW	4MW	5MW	6MW	7MW
1MWh	35.20	25.59	23.80	24.25	25.64	27.42	29.46
2MWh	36.76	25.33	23.01	23.28	24.60	26.32	28.30
3MWh	38.47	25.65	22.66	22.82	24.05	25.71	27.61
4MWh	40.24	26.37	22.76	22.73	23.85	25.47	27.32
5MWh	41.97	27.31	23.13	22.85	23.91	25.47	27.26
6MWh	43.69	28.41	23.70	23.16	24.15	26.65	27.41
7MWh	45.29	29.58	24.38	23.66	24.48	25.96	27.64

b) LCOE in c$/kWh for 50% wind power

	1MW	2MW	3MW	4MW	5MW	6MW	7MW
1MWh	33.61	28.69	28.92	30.62	33.00	35.71	38.70
2MWh	34.55	28.63	28.60	30.20	32.42	35.03	37.84
3MWh	35.70	28.87	28.56	30.06	32.20	34.68	37.39
4MWh	37.05	29.28	28.74	30.07	32.11	34.51	37.12
5MWh	38.46	29.81	29.00	30.17	32.12	34.43	36.96
6MWh	39.95	30.39	29.32	30.36	32.21	34.41	36.85
7MWh	41.40	31.04	29.72	30.59	32.35	34.47	36.81

c) LCOE in c$/kWh for 100% wind power

	1MW	2MW	3MW	4MW	5MW	6MW	7MW
1MWh	46.94	69.05	77.17	81.30	83.78	85.53	86.83
2MWh	44.28	70.39	79.61	84.06	86.55	88.31	89.58
3MWh	41.12	70.65	81.32	85.94	88.54	90.28	91.58
4MWh	37.62	70.07	82.16	87.16	89.88	91.62	92.89
5MWh	33.96	68.96	82.46	87.97	90.73	92.48	93.74
6MWh	30.10	67.37	82.28	88.35	91.21	92.95	94.18
7MWh	26.28	65.49	81.77	88.29	91.43	93.15	94.42

d) Diesel consumption reduction in % for 50% wind power.

Figure 2.4 LCOE and diesel consumption reduction tables for percentages of wind penetration over the total renewable power installed

For clarity in the presentation of the subsequent result, Table 2.11 presents the optimal values found by the algorithm in S 2.1 and S 2.2.

Table 2.11 Results of optimization in S 2.1 and S 2.2

<table>
<tr><th>Scenario</th><th>Objectives</th><th>Values</th><th>Decision variables</th><th>Values</th></tr>
<tr><td rowspan="3">S 2.1</td><td rowspan="3">LCOE</td><td rowspan="3">22.6 c$/kWh</td><td>Renewable energy</td><td>3 MW</td></tr>
<tr><td>Wind percentage</td><td>50 %</td></tr>
<tr><td>Battery</td><td>3 MWh</td></tr>
<tr><td rowspan="3">S 2.2</td><td>LCOE</td><td>22.73 c$/kWh</td><td>Renewable energy</td><td>4 MW</td></tr>
<tr><td rowspan="2">Diesel consumption reduction</td><td rowspan="2">87.16 %</td><td>Wind percentage</td><td>50 %</td></tr>
<tr><td>Battery</td><td>4 MWh</td></tr>
</table>

Figure 2.5 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, all fitness values, including the maximum, stabilize at approximately -0.3. This uniformity indicates that the population has converged and that all individuals have the same optimal fitness value. The result suggests that the GA successfully identified the global optimum for the problem in five generations. Rapid convergence (32 second average) highlights the efficiency of the algorithm's parameter tuning for this specific scenario.

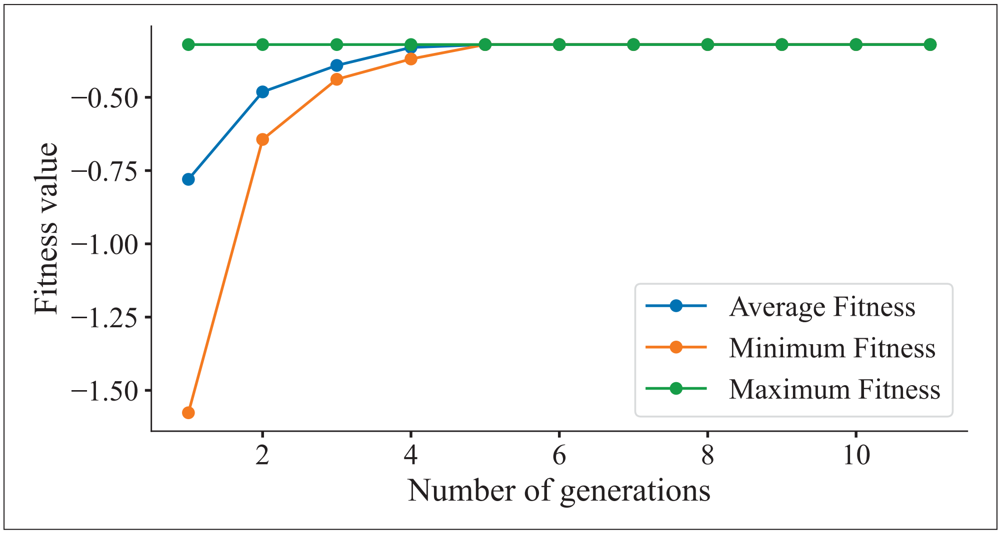


Figure 2.5 GA convergence curves for minimum, maximum and average fitness values over generation

2.4.2 Results for gensets associated variables

Figure 2.6 shows diesel consumption, CO_2 emissions, and fuel costs across all scenarios. The data reveal a general trend of increased fuel 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.

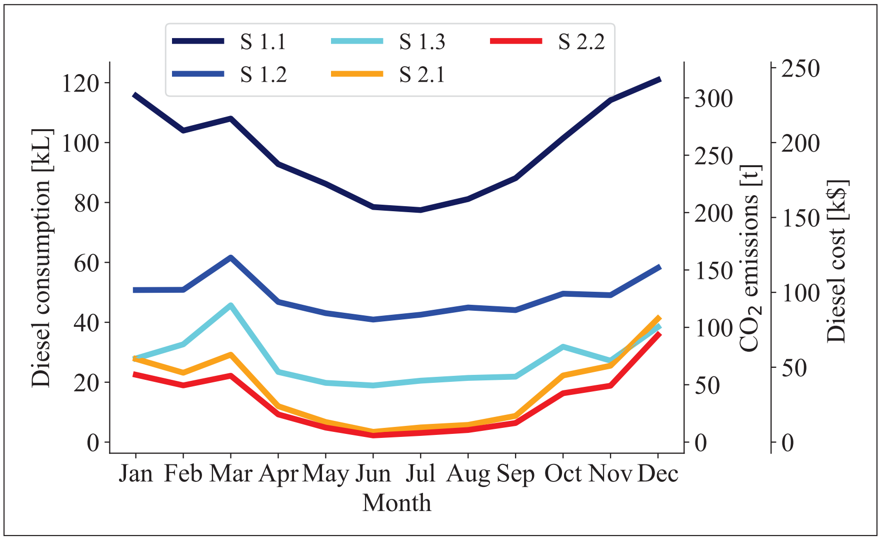


Figure 2.6 Diesel consumption, CO_2 emissions, and fuel cost for all scenarios

Figure 2.7 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, Figure 2.7a 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.

Figure 2.7b 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.

Figure 2.7c 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.

2.4.3 Results for the renewable curtailment

Figure 2.8 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 Figure 2.3b.

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

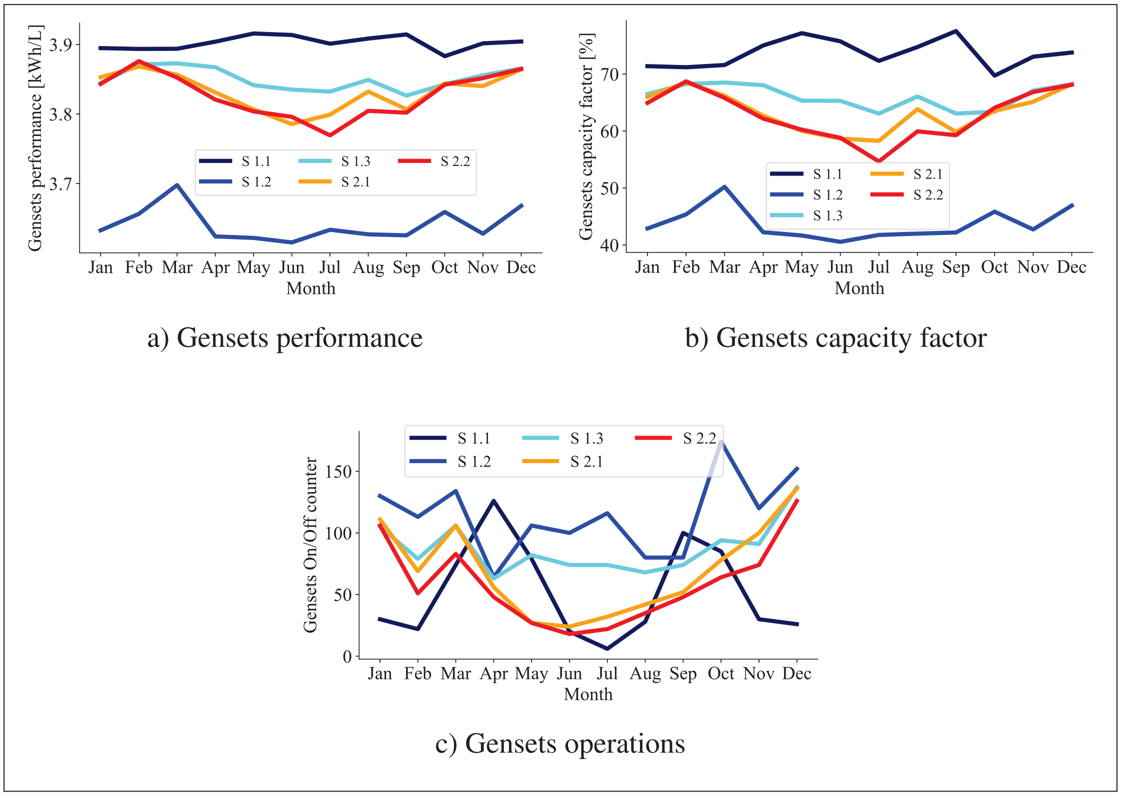


Figure 2.7 Gensets interest variables for all the scenarios

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.

2.4.4 Transversal comparison of all scenarios

Table 2.12 presents a comparative analysis of the annualized results for all scenarios evaluated. The two scenarios derived from the optimization process (S 2.1 and S 2.2) exhibit the best performance in almost all metrics, highlighting the effectiveness of the optimization strategy in reducing diesel dependence and lowering the overall cost of energy.

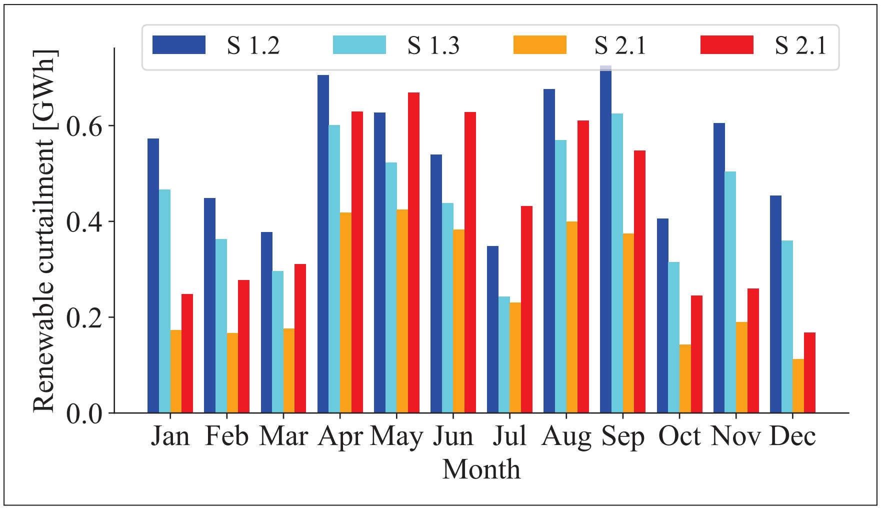


Figure 2.8 Energy curtailment for all scenarios with renewable components integration

A key observation is the significant reduction in total diesel consumption, which decreases progressively across the scenarios. The optimized scenarios achieve reductions of 81.32% and 87.16%, respectively, compared to the baseline scenario (S 1.1). This reduction directly translates into a substantial decrease in CO_2 emissions, strengthening the environmental benefits of greater penetration of renewable energy.

Despite improved economic and environmental performance, there is a slight decrease in genset efficiency in scenarios with greater renewable integration. This is due to reduced operating hours, which can lead to lower average load factors and potentially higher fuel consumption per unit of energy produced. However, the overall reduction in fuel use compensates for these minor efficiency losses.

The average genset capacity factor follows a decreasing trend as the penetration of renewables increases. In optimized scenarios, the gensets operate at a capacity factor of around 62 to 63%, compared to 74% in the baseline scenario. Although this suggests less intensive use of diesel generators, it also indicates a more balanced operation with reduced wear and tear, potentially extending the useful life.

The number of genset operational cycles increases significantly in scenarios with moderate renewable integration (e.g., S 1.2), suggesting more frequent start-stop events. However, as optimization improves the dispatch strategies, the number of cycles stabilizes in S 2.1 and decreases in S 2.2, ensuring more reliable and efficient operation.

Renewable energy curtailment reflects the extent to which excess renewable generation is not utilized. The levels of curtailment vary between scenarios, and S 2.1 achieving the lowest curtailment (3.19 GWh), indicating a better balance between generation and demand. In contrast, S 1.2 exhibits the highest curtailment, suggesting that its renewable integration is not optimally managed.

Finally, LCOE decreases significantly in optimized scenarios, reaching approximately 22.7 cents/kWh, which is less than half the cost of the baseline scenario (54.45 cents / kWh). This reduction underscores the financial benefits of an optimized hybrid energy system, making renewable integration not only technically feasible but also economically advantageous.

In general, the comparative analysis shows that the optimization approach effectively reduces diesel dependency, reduces energy costs, and improves system sustainability. However, careful consideration must be given to generator operation strategies to mitigate efficiency losses and excessive cycling, ensuring a stable and reliable power supply.

Table 2.12 Transversal comparison of the results for all the scenarios

Metric |Scenario	S 1.1	S 1.2	S 1.3	S 2.1	S 2.2
Total diesel consumption [kl]	1168	582	330	211	164
Total CO_2 emissions [t]	3050	1520	860	550	429
Average energy consumption efficiency [kWh/l]	3.9	3.64	3.85	3.83	3.82
Average gensets capacity factor [%]	74	44	66	63	62
Total gensets operational cycles	626	1369	1047	833	702
Total renewable energy curtailment [GWh]	-	6.48	5.3	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

2.5 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 can lead to local minima or overlooked solutions. To mitigate this, careful tuning of the GA parameters has been implemented to balance convergence speed and solution diversity.

Unit commitment, particularly for DG, presents another consideration. While generator ramp constraints, such as warm-up and load allocation, are not included in this case study, they become relevant at shorter time steps, which our tool can handle. The tool effectively automates unit commitment for multiple generators and enforces minimum runtime constraints for sub-hourly steps. In addition, it ensures an adequate spinning reserve under all operating conditions, prioritizing network stability even if additional generators must be started.

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. Unlike HOMER, which provides robust optimization and unit commitment strategies, but remains a commercial software with limited scalability, our tool supports customized applications, including potential future developments in frequency and voltage stability analysis, as well as improved DG modeling.

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.

Ultimately, the modularity of the tool extends its applicability beyond the case study that has been presented in this work, enabling future improvements and opportunities that are discussed in the Conclusions section.

2.6 Conclusions

This work presents a Python-based tool designed not only as a computational resource but also as an effective means for rapid techno-economic analysis of renewable energy penetration and sizing in isolated MG. The tool optimizes one or two objectives using a GA, a heuristic technique that, when combined with a modular design, offers flexibility and scalability. These objectives can be economic, for example, reducing the LCOE, or technical, such as minimizing fuel consumption. The tool also implements a dispatch strategy for multiple DG (selected by the user) that follows an efficiency principle, activating the smallest combination of generators required to meet load demand. In addition, it can handle input data with a user-definable variable time step.

Results from various scenarios demonstrate that applying optimization can nearly double reductions in LCOE and fuel consumption compared to non-optimized renewable integration scenarios. The GA shows a rapid convergence, typically within five generations, aided by the use of tables that narrow the search space for decision variables. The Python code executes efficiently, allowing results to be analyzed in minutes when using time-step data on an hourly scale.

For future work, particularly concerning software, the literature suggests incorporating stochastic analysis for input data related to renewable sources and loads to reduce uncertainty. Exploring artificial intelligence techniques to predict load behavior and renewable generation, as well as investigating the performance of the dispatch strategy with alternative energy storage methods, would also be beneficial. Specifically, in the DG dispatch strategy, studying the startup (speed control, load uptake, warm-up period, and load-sharing process) and shutdown procedures could offer valuable insight. Recognizing that these transitions do not occur instantaneously between time steps, as assumed in this study, could help extend the lifespan of the equipment and further reduce fuel consumption and associated emissions.

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	Cuckoo Search
ABC	Artificial Bee Colony
ARMA	Auto-regressive Moving Average
MPC	Model Predictive Control

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CRediT authorship contribution statement

Conceptualization: Michel Carreau, Daniel Rousse, Adrian Ilinca; Methodology: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia; Software: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia, Phillipe Cambron; Validation: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia, Maurine Crouzier, Phillipe Cambron; Formal Analysis: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia, Phillipe Cambron; Investigation: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia; Resources: Michel Carreau, Daniel Rousse, Adrian Ilinca; Data Curation: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia, Maurine Crouzier, Phillipe Cambron; Writing—Original Draft Preparation: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia; Writing—Review and Editing: Daniel Rousse, Adrian Ilinca, Phillipe Cambron; Visualization: Cristian Cadena, Dario Della, Ilaria Tucci, Jersson Garcia; Supervision:

Daniel Rousse, Adrian Ilinca; Project Administration: Daniel Rousse, Adrian Ilinca, Michel Carreau; Funding Acquisition: Daniel Rousse, Adrian Ilinca.

All authors have read and agreed to the published version of the manuscript.

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Declaration of competing interest

The authors declare no conflict of interest.

Data availability

The data and the full version of the Python code used in this study are considered private and are not publicly available. This restriction is due to a private collaboration agreement between the École de Technologie Supérieure and the Hatch company. Access to the data and code may be requested from the corresponding author, subject to the terms of this agreement.

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.

CONCLUSION AND RECOMMENDATIONS

This thesis has presented a Python-based tool for the techno-economic analysis of isolated microgrids, focusing on optimizing renewable energy penetration to minimize the LCOE and diesel consumption. The tool employs a GA for optimization and integrates a rule-based EMS to determine generator dispatch. The results demonstrate that optimizing renewable integration significantly enhances economic and technical performance compared to non-optimized scenarios, with the GA achieving rapid convergence within a few generations.

One of the key strengths of the tool lies in its modularity and adaptability, allowing users to define time-step granularity and dispatch strategies based on specific system requirements. Unlike commercial software such as HOMER, which offers predefined optimization strategies, this tool provides greater flexibility for researchers and practitioners in industry to tailor their analyses to particular microgrid configurations. The ability to automate generator dispatch while maintaining a minimum runtime and ensuring spinning reserve further enhances its applicability to real-world scenarios.

Despite its advantages, the study highlights certain limitations. The GA-based optimization approach, while effective, may converge prematurely to local optima depending on parameter tuning. Additionally, the rule-based EMS, while practical, may lead to excessive generator cycling, which could accelerate wear and reduce overall system efficiency. Furthermore, the simplified treatment of generator startup and shutdown dynamics does not account for transient effects that could impact fuel consumption and emissions.

Based on these findings, several recommendations can be made for future work. First, incorporating stochastic analysis for renewable generation and load forecasting could improve the robustness of optimization results by accounting for uncertainties in resource availability. Additionally, integrating machine learning techniques to predict load demand and renewable output could enhance the adaptability of the EMS, allowing for more proactive decision-making.

Further research could also focus on refining the generator dispatch model by incorporating dynamic constraints, such as ramp rates, startup delays, and load-sharing mechanisms, as well as exploring generators powered by alternative fuels. This would provide a more accurate representation of generator operation and potentially reduce wear and tear on diesel generators. Exploring alternative storage technologies, such as hydrogen or flywheels, and assessing their impact on microgrid performance could also be valuable. Finally, expanding the tool's capabilities to include frequency and voltage stability analysis would further strengthen its applicability to real-world microgrid operations.

Overall, the developed tool provides a solid foundation for renewable energy integration studies in isolated microgrids. By addressing the identified limitations and exploring the proposed improvements, future research can enhance its capabilities and contribute to more efficient, reliable, and sustainable microgrid solutions.

LIST OF REFERENCES

Abid, S., Alghamdi, T. A., Haseeb, A., Wadud, Z., Ahmed, A. & Javaid, N. (2019). An Economical Energy Management Strategy for Viable Microgrid Modes. *Electronics*, 8(12), 1-20. doi: 10.3390/electronics8121442.

Ali, M., Abdulgalil, M. A., Habiballah, I. & Khalid, M. (2023). Optimal Scheduling of Isolated Microgrids With Hybrid Renewables and Energy Storage Systems Considering Demand Response. *IEEE Access*, 11, 80266-80273. doi: 10.1109/ACCESS.2023.3296540.

Alvarado-Barrios, L., Álvaro Rodríguez del Nozal, Boza Valerino, J., García Vera, I. & Martínez-Ramos, J. L. (2020). Stochastic unit commitment in microgrids: Influence of the load forecasting error and the availability of energy storage. *Renewable Energy*, 146, 2060-2069. doi: https://doi.org/10.1016/j.renene.2019.08.032.

Ameen, A. M., Pasupuleti, J. & Khatib, T. (2015). Simplified performance models of photovoltaic/diesel generator/battery system considering typical control strategies. *Energy Conversion and Management*, 99, 313-325. doi: https://doi.org/10.1016/j.enconman.2015.04.024.

Anoune, K., Bouya, M., Astito, A. & Abdellah, A. B. (2018). Sizing methods and optimization techniques for PV-wind based hybrid renewable energy system: A review. *Renewable and Sustainable Energy Reviews*, 93, 652-673. doi: https://doi.org/10.1016/j.rser.2018.05.032.

Aoun, A., Adda, M., Ilinca, A., Ghandour, M. & Ibrahim, H. (2024a). Centralized vs. Decentralized Electric Grid Resilience Analysis Using Leontief's Input-Output Model. *Energies*, 17, 1-21. doi: 10.3390/en17061321.

Aoun, A., Adda, M., Ilinca, A., Ghandour, M. & Ibrahim, H. (2024b). Optimizing Virtual Power Plant Management: A Novel MILP Algorithm to Minimize Levelized Cost of Energy, Technical Losses, and Greenhouse Gas Emissions. *Energies*, 17, 1-23. doi: 10.3390/en17164075.

Aoun, A., Adda, M., Ilinca, A., Ghandour, M., Ibrahim, H. & Salloum, S. (2024c). Efficient Modeling of Distributed Energy Resources' Impact on Electric Grid Technical Losses: A Dynamic Regression Approach. *Energies*, 17, 1-28. doi: 10.3390/en17092053.

Arcos-Aviles, D., Guinjoan, F., Pascual, J., Marroyo, L., Sanchis, P., Gordillo, R., Ayala, P. & Marietta, M. P. (2019). A Review of Fuzzy-Based Residential Grid-Connected Microgrid Energy Management Strategies for Grid Power Profile Smoothing. In Motoasca, E., Agarwal, A. K. & Breesch, H. (Eds.), *Energy Sustainability in Built and Urban Environments* (pp. 165–199). Singapore: Springer Singapore. doi: 10.1007/978-981-13-3284-5_8.

Belboul, Z., Toual, B., Bensalem, A., Ghenai, C., Khan, B. & Kamel, S. (2024). Techno-economic optimization for isolated hybrid PV/wind/battery/diesel generator microgrid using improved salp swarm algorithm. *Scientific Reports*, 14(1), 2920. doi: 10.1038/s41598-024-52232-y.

Boqiang, R. & Chuanwen, J. (2009). A review on the economic dispatch and risk management considering wind power in the power market. *Renewable and Sustainable Energy Reviews*, 13(8), 2169-2174. doi: https://doi.org/10.1016/j.rser.2009.01.013.

Boudreault, J., Éric Lavigne, Campagna, C. & Chebana, F. (2024). Estimating the heat-related mortality and morbidity burden in the province of Quebec, Canada. *Environmental Research*, 257, 119347. doi: https://doi.org/10.1016/j.envres.2024.119347.

Cadena-Zarate, C. & Osma-Pinto, G. (2024). Study of the variation of operation of a low voltage electric network due to the integration of distributed energy resources—Steady state condition. *International Journal of Electrical Power & Energy Systems*, 155, 109649. doi: https://doi.org/10.1016/j.ijepes.2023.109649.

Cagnano, A., Caldarulo Bugliari, A. & De Tuglie, E. (2018). A cooperative control for the reserve management of isolated microgrids. *Applied Energy*, 218, 256-265. doi: https://doi.org/10.1016/j.apenergy.2018.02.142.

CCI. (2024). FACT SHEET: Climate change and heat waves. Retrieved on 2024-10-01 from: https://climateinstitute.ca/news/fact-sheet-heat-waves/.

Chebabhi, A., Tegani, I., Benhamadouche, A. D. & Kraa, O. (2023). Optimal design and sizing of renewable energies in microgrids based on financial considerations a case study of Biskra, Algeria. *Energy Conversion and Management*, 291, 117270. doi: https://doi.org/10.1016/j.enconman.2023.117270.

Dashtdar, M., Flah, A., Hosseinimoghadam, S. M. S., Kotb, H., Jasińska, E., Gono, R., Leonowicz, Z. & Jasiński, M. (2022). Optimal Operation of Microgrids with Demand-Side Management Based on a Combination of Genetic Algorithm and Artificial Bee Colony. *Sustainability*, 14(11), 1-26. doi: 10.3390/su14116759.

Dong, W., Sun, H., Mei, C., Li, Z., Zhang, J. & Yang, H. (2023). Forecast-driven stochastic optimization scheduling of an energy management system for an isolated hydrogen microgrid. *Energy Conversion and Management*, 277, 116640. doi: https://doi.org/10.1016/j.enconman.2022.116640.

Dufo-López, R., Bernal-Agustín, J. L., Yusta-Loyo, J. M., Domínguez-Navarro, J. A., Ramírez-Rosado, I. J., Lujano, J. & Aso, I. (2011). Multi-objective optimization minimizing cost and life cycle emissions of stand-alone PV–wind–diesel systems with batteries storage. *Applied Energy*, 88(11), 4033-4041. doi: https://doi.org/10.1016/j.apenergy.2011.04.019.

Ehsan, A. & Yang, Q. (2018). Optimal integration and planning of renewable distributed generation in the power distribution networks: A review of analytical techniques. *Applied Energy*, 210, 44-59. doi: https://doi.org/10.1016/j.apenergy.2017.10.106.

El-Bidairi, K. S., Duc Nguyen, H., Jayasinghe, S., Mahmoud, T. S. & Penesis, I. (2018). A hybrid energy management and battery size optimization for standalone microgrids: A case study for Flinders Island, Australia. *Energy Conversion and Management*, 175, 192-212. doi: https://doi.org/10.1016/j.enconman.2018.08.076.

Ellabban, O. & Alassi, A. (2021). Optimal hybrid microgrid sizing framework for the mining industry with three case studies from Australia. *IET Renewable Power Generation*, 15(2), 409-423. doi: https://doi.org/10.1049/rpg2.12038.

Fatin Ishraque, M., Shezan, S. A., Ali, M. & Rashid, M. (2021). Optimization of load dispatch strategies for an islanded microgrid connected with renewable energy sources. *Applied Energy*, 292, 116879. doi: https://doi.org/10.1016/j.apenergy.2021.116879.

Government of Canada, C. E. R. [Last Modified: 2023-11-28]. (2018). CER – Market Snapshot: Overcoming the challenges of powering Canada's off-grid communities. Retrieved on 2024-10-02 from: https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/market-snapshots/2018/market-snapshot-overcoming-challenges-powering-canadas-off-grid-communities.html.

Government of Canada, C. E. R. [Last Modified: 2023-11-24]. (2023). CER – Market Snapshot: Clean Energy Projects in Remote Indigenous and Northern Communities. Retrieved on 2024-10-02 from: https://www.cer-rec.gc.ca/en/data-analysis/energy-markets/market-snapshots/2023/market-snapshot-clean-energy-projects-remote-indigenous-northern-communities.html.

Government of Canada, S. C. [Last Modified: 2024-03-14]. (2024). Hydroelectricity generation dries up amid low precipitation and record high temperatures: Electricity year in review 2023. Retrieved on 2024-05-06 from: https://www.statcan.gc.ca/o1/en/plus/5776-hydroelectricity-generation-dries-amid-low-precipitation-and-record-high-temperatures.

Gutiérrez-Oliva, D., Colmenar-Santos, A. & Rosales-Asensio, E. (2022). A Review of the State of the Art of Industrial Microgrids Based on Renewable Energy. *Electronics*, 11(7). doi: 10.3390/electronics11071002.

Hamilton, J., Negnevitsky, M., Wang, X. & Lyden, S. (2019). High penetration renewable generation within Australian isolated and remote power systems. *Energy*, 168, 684-692. doi: https://doi.org/10.1016/j.energy.2018.11.118.

Hou, H., Wang, Q., Xiao, Z., Xue, M., Wu, Y., Deng, X. & Xie, C. (2022). Data-driven economic dispatch for islanded micro-grid considering uncertainty and demand response. *International Journal of Electrical Power and Energy Systems*, 136, 107623. doi: https://doi.org/10.1016/j.ijepes.2021.107623.

Ishraque, M. F., Shezan, S. A., Rashid, M. M., Bhadra, A. B., Hossain, M. A., Chakrabortty, R. K., Ryan, M. J., Fahim, S. R., Sarker, S. K. & Das, S. K. (2021). Techno-Economic and Power System Optimization of a Renewable Rich Islanded Microgrid Considering Different Dispatch Strategies. *IEEE Access*, 9, 77325-77340. doi: 10.1109/ACCESS.2021.3082538.

Jia, L., Pannala, S., Kandaperumal, G. & Srivastava, A. (2022). Coordinating Energy Resources in an Islanded Microgrid for Economic and Resilient Operation. *IEEE Transactions on Industry Applications*, 58(3), 3054-3063. doi: 10.1109/TIA.2022.3154337.

Jordehi, A. R., Sadegh Javadi, M. & Catalão, J. P. S. (2020). Dynamic Economic Load Dispatch in Isolated Microgrids with Particle Swarm Optimisation considering Demand Response. *2020 55th International Universities Power Engineering Conference (UPEC)*, pp. 1-5. doi: 10.1109/UPEC49904.2020.9209769.

Kharrich, M., Kamel, S., Alghamdi, A. S., Eid, A., Mosaad, M. I., Akherraz, M. & Abdel-Akher, M. (2021). Optimal Design of an Isolated Hybrid Microgrid for Enhanced Deployment of Renewable Energy Sources in Saudi Arabia. *Sustainability*, 13(9), 1-26. doi: 10.3390/su13094708.

Khirennas, A., Kaabeche, A., Talha, A. & Bakelli, Y. (2021). A new optimal sizing methodology of storage-less PV system for retrofitting existing diesel-based power generation system within mini-grids. *Energy Conversion and Management*, 250, 114854. doi: https://doi.org/10.1016/j.enconman.2021.114854.

Kiptoo, M. K., Lotfy, M. E., Adewuyi, O. B., Conteh, A., Howlader, A. M. & Senjyu, T. (2020). Integrated approach for optimal techno-economic planning for high renewable energy-based isolated microgrid considering cost of energy storage and demand response strategies. *Energy Conversion and Management*, 215, 112917. doi: https://doi.org/10.1016/j.enconman.2020.112917.

Lambert, M. & Hassani, R. (2023). Diesel genset optimization in remote microgrids. *Applied Energy*, 340, 121036. doi: https://doi.org/10.1016/j.apenergy.2023.121036.

Lan, T., Jermsittiparsert, K., T. Alrashood, S., Rezaei, M., Al-Ghussain, L. & A. Mohamed, M. (2021). An Advanced Machine Learning Based Energy Management of Renewable Microgrids Considering Hybrid Electric Vehicles' Charging Demand. *Energies*, 14(3), 1-25. doi: 10.3390/en14030569.

Li, L., Pei, J. & Shen, Q. (2023). A Review of Research on Dynamic and Static Economic Dispatching of Hybrid Wind–Thermal Power Microgrids. *Energies*, 16(10), 1-23. doi: 10.3390/en16103985.

Lopez-Santiago, D. M., Caicedo Bravo, E., Jiménez-Estévez, G., Valencia, F., Mendoza-Araya, P. & Marín, L. G. (2022). A novel rule-based computational strategy for a fast and reliable energy management in isolated microgrids. *International Journal of Energy Research*, 46(4), 4362-4379. doi: https://doi.org/10.1002/er.7433.

Lovekin, Dave & Heerema, Dylan. (2019a). Diesel, renewables, and Canada's remote communities. Retrieved on 2024-10-02 from: https://www.pembina.org/blog/remote-microgrids-intro.

Lovekin, Dave & Heerema, Dylan. (2019b). Remote communities meet renewable energy challenges. Retrieved on 2024-10-03 from: https://www.pembina.org/blog/remote-energy-challenges.

Ma, Q., Huang, X., Wang, F., Xu, C., Babaei, R. & Ahmadian, H. (2022). Optimal sizing and feasibility analysis of grid-isolated renewable hybrid microgrids: Effects of energy management controllers. *Energy*, 240, 122503. doi: https://doi.org/10.1016/j.energy.2021.122503.

Mao, M., Jin, P., Hatziargyriou, N. D. & Chang, L. (2014). Multiagent-Based Hybrid Energy Management System for Microgrids. *IEEE Transactions on Sustainable Energy*, 5(3), 938-946. doi: 10.1109/TSTE.2014.2313882.

Mariam, L., Basu, M. & Conlon, M. F. (2016). Microgrid: Architecture, policy and future trends. *Renewable and Sustainable Energy Reviews*, 64, 477-489. doi: https://doi.org/10.1016/j.rser.2016.06.037.

Martín-Arroyo, S., Cebollero, J. A., García-Gracia, M. & Llamazares, Á. (2021). Stand-Alone Hybrid Power Plant Based on SiC Solar PV and Wind Inverters with Smart Spinning Reserve Management. *Electronics*, 10(7), 1-27. doi: 10.3390/electronics10070796.

Mirjalili, S., Mirjalili, S. M. & Lewis, A. (2014). Grey Wolf Optimizer. *Advances in Engineering Software*, 69, 46-61. doi: https://doi.org/10.1016/j.advengsoft.2013.12.007.

Moradi, H., Esfahanian, M., Abtahi, A. & Zilouchian, A. (2018). Optimization and energy management of a standalone hybrid microgrid in the presence of battery storage system. *Energy*, 147, 226-238. doi: https://doi.org/10.1016/j.energy.2018.01.016.

Moretti, L., Meraldi, L., Niccolai, A., Manzolini, G. & Leva, S. (2021). An Innovative Tunable Rule-Based Strategy for the Predictive Management of Hybrid Microgrids. *Electronics*, 10(10), 1-16. Retrieved from: https://www.mdpi.com/2079-9292/10/10/1162.

Nasr, M.-A., Nikkhah, S., Gharehpetian, G. B., Nasr-Azadani, E. & Hosseinian, S. H. (2020a). A multi-objective voltage stability constrained energy management system for isolated microgrids. *International Journal of Electrical Power & Energy Systems*, 117, 105646. doi: https://doi.org/10.1016/j.ijepes.2019.105646.

Nasr, M.-A., Rabiee, A. & Kamwa, I. (2020b). MPC and robustness optimisation-based EMS for microgrids with high penetration of intermittent renewable energy. *IET Generation, Transmission & Distribution*, 14(22), 5239-5248. doi: https://doi.org/10.1049/iet-gtd.2020.0460.

Natural Resources Canada. (2011). Status of Remote/Off-Grid Communities in Canada 2011. Retrieved on 2024-10-02 from: https://natural-resources.canada.ca/sites/nrcan/files/canmetenergy/files/pubs/2013-118_en.pdf.

Olivares, D. E., Lara, J. D., Cañizares, C. A. & Kazerani, M. (2015). Stochastic-Predictive Energy Management System for Isolated Microgrids. *IEEE Transactions on Smart Grid*, 6(6), 2681-2693. doi: 10.1109/TSG.2015.2469631.

Oviedo Cepeda, J. C. (2021). *A Methodology to Compare the Effects of Demand-Side Management Strategies in the Planning of Islanded/Isolated Microgrids*. (Ph.D. in Engineering, Electrical Engineering Area, Universidad Industrial de Santander, Bucaramanga, Colombia). Retrieved from: tangara.uis.edu.co/biblioweb/pags/cat/popup/pa_detalle_matbib.jsp?parametros=190264||1|7.

Panda, S., Mohanty, S., Rout, P. K., Sahu, B. K., Bajaj, M., Zawbaa, H. M. & Kamel, S. (2022). Residential Demand Side Management model, optimization and future perspective: A review. *Energy Reports*, 8, 3727-3766. doi: https://doi.org/10.1016/j.egyr.2022.02.300.

Phan, B. C. & Lai, Y.-C. (2019). Control Strategy of a Hybrid Renewable Energy System Based on Reinforcement Learning Approach for an Isolated Microgrid. *Applied Sciences*, 9(19), 1-24. doi: 10.3390/app9194001.

Restrepo, M., Cañizares, C. A., Simpson-Porco, J. W., Su, P. & Taruc, J. (2021). Optimization- and Rule-based Energy Management Systems at the Canadian Renewable Energy Laboratory microgrid facility. *Applied Energy*, 290, 116760. doi: https://doi.org/10.1016/j.apenergy.2021.116760.

Rodriguez, M., Arcos-Aviles, D., Llanos, J., Salazar, A., Guinjoan, F., Motoasca, E. & Martinez, W. (2021). Fuzzy-based energy management system for isolated microgrids using generation and demand forecast. *2021 23rd European Conference on Power Electronics and Applications (EPE'21 ECCE Europe)*, pp. 1-10. doi: 10.23919/EPE21ECCEEurope50061.2021.9570529.

Rodriguez, M., Arcos–Aviles, D. & Martinez, W. (2023). Fuzzy logic-based energy management for isolated microgrid using meta-heuristic optimization algorithms. *Applied Energy*, 335, 120771. doi: https://doi.org/10.1016/j.apenergy.2023.120771.

Semshchikov, E., Negnevitsky, M., Hamilton, J. & Wang, X. (2020a). Cost-Efficient Strategy for High Renewable Energy Penetration in Isolated Power Systems. *IEEE Transactions on Power Systems*, 35(5), 3719-3728. doi: 10.1109/TPWRS.2020.2975236.

Semshchikov, E., Negnevitsky, M., Hamilton, J. & Wang, X. (2020b). Cost-Efficient Strategy for High Renewable Energy Penetration in Isolated Power Systems. *IEEE Transactions on Power Systems*, 35(5), 3719-3728. doi: 10.1109/TPWRS.2020.2975236.

Sharma, P., Dutt Mathur, H., Mishra, P. & Bansal, R. C. (2022). A critical and comparative review of energy management strategies for microgrids. *Applied Energy*, 327, 120028. doi: https://doi.org/10.1016/j.apenergy.2022.120028.

Shezan, S. A., Ishraque, M. F., Muyeen, S. M., Abu-Siada, A., Saidur, R., Ali, M. & Rashid, M. (2022a). Selection of the best dispatch strategy considering techno-economic and system stability analysis with optimal sizing. *Energy Strategy Reviews*, 43, 100923. doi: https://doi.org/10.1016/j.esr.2022.100923.

Shezan, S., Ishraque, M. F., Muyeen, S., Arifuzzaman, S., Paul, L. C., Das, S. K. & Sarker, S. K. (2022b). Effective dispatch strategies assortment according to the effect of the operation for an islanded hybrid microgrid. *Energy Conversion and Management: X*, 14, 100192. doi: https://doi.org/10.1016/j.ecmx.2022.100192.

Silva, J. A. A., López, J. C., Arias, N. B., Rider, M. J. & da Silva, L. C. (2021). An optimal stochastic energy management system for resilient microgrids. *Applied Energy*, 300, 117435. doi: https://doi.org/10.1016/j.apenergy.2021.117435.

Solanki, B. V., Bhattacharya, K. & Cañizares, C. A. (2017). A Sustainable Energy Management System for Isolated Microgrids. *IEEE Transactions on Sustainable Energy*, 8(4), 1507-1517. doi: 10.1109/TSTE.2017.2692754.

Solano, J., Jimenez, D. & Ilinca, A. (2020). A Modular Simulation Testbed for Energy Management in AC/DC Microgrids. *Energies*, 13, 1-23. doi: 10.3390/en13164049.

Stringer, T. & Joanis, M. (2023). Decarbonizing Canada's remote microgrids. *Energy*, 264, 126287. doi: https://doi.org/10.1016/j.energy.2022.126287.

Thomas, D., Deblecker, O. & Ioakimidis, C. S. (2016). Optimal design and techno-economic analysis of an autonomous small isolated microgrid aiming at high RES penetration. *Energy*, 116, 364-379. doi: https://doi.org/10.1016/j.energy.2016.09.119.

Torkan, R., Ilinca, A. & Ghorbanzadeh, M. (2022). A genetic algorithm optimization approach for smart energy management of microgrids. *Renewable Energy*, 197, 852–863. doi: 10.1016/j.renene.2022.07.055.

Tostado-Véliz, M., Rezaee Jordehi, A., Fernández-Lobato, L. & Jurado, F. (2023). Robust energy management in isolated microgrids with hydrogen storage and demand response. *Applied Energy*, 345, 121319. doi: https://doi.org/10.1016/j.apenergy.2023.121319.

Tran, Q. T., Davies, K. & Sepasi, S. (2021). Isolation Microgrid Design for Remote Areas with the Integration of Renewable Energy: A Case Study of Con Dao Island in Vietnam. *Clean Technologies*, 3(4), 804–820. doi: 10.3390/cleantechnol3040047.

Uddin, M., Mo, H., Dong, D., Elsawah, S., Zhu, J. & Guerrero, J. M. (2023). Microgrids: A review, outstanding issues and future trends. *Energy Strategy Reviews*, 49, 101127. doi: https://doi.org/10.1016/j.esr.2023.101127.

Ullah, Z., Wang, S., Wu, G., Xiao, M., Lai, J. & Elkadeem, M. R. (2022). Advanced energy management strategy for microgrid using real-time monitoring interface. *Journal of Energy Storage*, 52, 104814. doi: https://doi.org/10.1016/j.est.2022.104814.

Vahidzadeh, M. & Markfort, C. D. (2019). Modified Power Curves for Prediction of Power Output of Wind Farms. *Energies*, 12(9), 1-19. doi: 10.3390/en12091805.

VanderMeer, J. B., Green, N., Darbali-Zamora, R. & Thompson, W. (2023). MicroGrid Renewable Integration Dispatch and Sizing (MiGRIDS) Analysis of Spinning and Regulating Reserve Options for Wind in an Alaskan Diesel Microgrid. *IEEE Access*, 11, 121637-121645. doi: 10.1109/ACCESS.2023.3327693.

Vergine, S., Álvarez Arroyo, C., D'Amico, G., Escaño, J. M. & Alvarado-Barrios, L. (2022). Optimal management of a hybrid and isolated microgrid in a random setting. *Energy Reports*, 8, 9402-9419. doi: https://doi.org/10.1016/j.egyr.2022.07.044.

Violante, W., Cañizares, C. A., Trovato, M. A. & Forte, G. (2020). An Energy Management System for Isolated Microgrids With Thermal Energy Resources. *IEEE Transactions on Smart Grid*, 11(4), 2880-2891.

Vivas, F. J., Segura, F., Andújar, J. M., Palacio, A., Saenz, J. L., Isorna, F. & López, E. (2020). Multi-Objective Fuzzy Logic-Based Energy Management System for Microgrids with Battery and Hydrogen Energy Storage System. *Electronics*, 9(7). doi: 10.3390/electronics9071074.

Wang, R., Hsu, S.-C., Zheng, S., Chen, J.-H. & Li, X. I. (2020). Renewable energy microgrids: Economic evaluation and decision making for government policies to contribute to affordable and clean energy. *Applied Energy*, 274, 115287. doi: https://doi.org/10.1016/j.apenergy.2020.115287.

WMO. (2024). 2025 outlook: in top three warmest years on record. Retrieved from: https://wmo.int/media/news-from-members/2025-outlook-top-three-warmest-years-record.

Xu, H., Meng, Z. & Wang, Y. (2020). Economic dispatching of microgrid considering renewable energy uncertainty and demand side response. *Energy Reports*, 6, 196-204. doi: https://doi.org/10.1016/j.egyr.2020.11.261. 2020 The 7th International Conference on Power and Energy Systems Engineering.

Yang, F., Feng, X. & Li, Z. (2019). Advanced Microgrid Energy Management System for Future Sustainable and Resilient Power Grid. *IEEE Transactions on Industry Applications*, 55(6), 7251-7260. doi: 10.1109/TIA.2019.2912133.

Yuan, D., Lu, Z., Zhang, J. & Li, X. (2019). A hybrid prediction-based microgrid energy management strategy considering demand-side response and data interruption. *International Journal of Electrical Power & Energy Systems*, 113, 139-153. doi: https://doi.org/10.1016/j.ijepes.2019.05.045.

Yüksel, N., Börklü, H. R., Sezer, H. K. & Canyurt, O. E. (2023). Review of artificial intelligence applications in engineering design perspective. *Engineering Applications of Artificial Intelligence*, 118, 105697. doi: https://doi.org/10.1016/j.engappai.2022.105697.

Zhao, G., Cao, T., Wang, Y., Zhou, H., Zhang, C. & Wan, C. (2021). Optimal Sizing of Isolated Microgrid Containing Photovoltaic/Photothermal/Wind/Diesel/Battery. *International Journal of Photoenergy*, 2021(1), 5566597. doi: https://doi.org/10.1155/2021/5566597.

Zhou, A., Yan, R. & Saha, T. K. (2020). Capacity and Control Strategy Design of Isolated Micro-Grid With High Renewable Penetration. *IEEE Transactions on Sustainable Energy*, 11(3), 1173-1184. doi: 10.1109/TSTE.2019.2920274.

Zia, M. F., Elbouchikhi, E. & Benbouzid, M. (2018). Microgrids energy management systems: A critical review on methods, solutions, and prospects. *Applied Energy*, 222, 1033-1055. doi: https://doi.org/10.1016/j.apenergy.2018.04.103.