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Bellman–Genetic Hybrid Algorithm Optimization in Rural Area Microgrids

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Abstract: Incorporating renewable Distributed Energy Resources (DER) into the main grid is crucial for achieving a sustainable transition from fossil fuels. However, this generation system is complicated by the fluctuating behavior of renewable resources and the variable load demand, making it less reliable without a suitable energy storage system (ESS). This study proposes an Optimal Power Flow Management (OPFM) strategy for a grid-connected hybrid Micro Grid (MG) comprising a wind turbine (WT), a photovoltaic (PV) field, a storage battery, and a Micro Gas turbine (MGT). This proposed strategy includes (i) minimizing the MG's daily energy cost, (ii) decreasing CO_2 emissions by considering the variable load, weather forecast, and main grid fees to optimize the battery charging/discharging strategy, and (iii) optimizing the decision-making process for power purchase/sell from/to the main grid. The suggested OPFM approach is implemented using a Genetic Algorithm and compared with the Bellman Algorithm and a restricted management system via several simulations under the Matlab environment. Furthermore, the hybridization of the Bellman Algorithm and the Genetic Algorithm is proposed to enhance the OPFMC strategy's efficiency by leveraging both algorithms' strengths. The simulation results demonstrate the effectiveness of the proposed strategy in lowering energy costs and CO_2 emissions and enhancing reliability. Additionally, the comparison of the hybridized GA algorithm reveals a cost 16% higher than the Bellman Algorithm; however, the use of the hybridized GA algorithm leads to a reduction in GHG emissions by 31.4%. These findings underscore the trade-off between cost and environmental impact in the context of algorithmic optimization for microgrid energy management.

Keywords: optimal power flow management (OPFM); hybrid micro-grid; renewable energy; Bellman Algorithm; Genetic Algorithm (GA); energy management system (EMS); distributed energy sources (DES)

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1. Introduction

1.1. Motivation

Inefficient energy management practices contribute to the increase in carbon emissions and grid strain during peak consumption periods, and raise energy expenses. This compels a shift towards sustainable energy integration, featuring intelligent microgrids and OPFM energy management systems. Our study embarks on a journey to tackle these complex challenges by presenting a bespoke Optimal Power Flow Management Control (OPFM) strategy tailored to rural smart grids.

At the core of our research lies a profound comprehension and optimization of the intricate dynamics between renewable energy sources, energy storage systems, the primary grid, and the auxiliary source (GT). The formulated strategy is designed to achieve diverse objectives, encompassing cost-efficient energy consumption, reduction in carbon emissions, consideration of battery degradation costs, and effective power interchange with the main grid.

This investigation introduces an OPFM strategy employing a Genetic Algorithm, a type of evolutionary algorithm. This approach is benchmarked against two alternate management strategies: the first employs a rule-based management system grounded in common sense, while the second is based on the Bellman Algorithm, a dynamic programming methodology. Moreover, we propose a hybridization of the Genetic Algorithm and the Bellman Algorithm, leveraging the strengths of both to enhance the overall results.

1.2. Literature Review

The urgent global climate change campaign, combined with the unpredictability of fossil fuel prices provides a compelling impetus for us to actively reduce our power usage and carbon dioxide emissions, in an effort to combat the negative effects of global warming on our planet.

Accepting the challenge of mitigating climate change needs a coordinated effort to minimize our energy usage and carbon dioxide emissions to promote a sustainable future and ensure the well-being of future generations. By combining renewable energy resources into our existing electrical networks, companies not only ease the transition away from fossil fuels but also provide a practical method for mitigating CO_2 emissions, setting the groundwork for cleaner and more friendly responsible energy employment.

The fight against climate change and the ambivalence of fossil fuels price variation encourages the decrease in our energy usage and our greenhouse gas (GHG) emissions to limit planet global warming. Injecting renewable energy sources in electrical grids can relay fossil energies effectively and mitigate the impact of CO_2 emissions. Thus, the structure of the grid has been adapted [1,2].

Distributed Energy Resources (DER) play a critical role in improving grid efficiency and security in a Smart Micro Grid. Unlike typical centralized power systems, which generate and distribute electricity from a single point, a Smart Micro Grid incorporates numerous DERs spread across the grid. One of the primary benefits of DERs is their capacity to generate power in response to a changing load profile. The pattern of power consumption throughout the day, which might vary depending on elements like time of day, weather conditions, and unique consumer demands is referred to as the load profile. Solar panels, WTs, and small-scale generators are examples of DERs that can alter their power generation to reflect the changing load profile. Therefore, to enhance grid efficiency and security in Smart Micro Grid, DER generates their power corresponding to the varying load profile [3,4].

Several methodologies are adopted to identify the most efficient energy distribution in Smart Micro Grids (SMGs) by taking into account numerous objectives and utilizing optimization algorithms. However, a common thread unites these approaches: preserving the balance between electricity provided by DERs and power needed by loads [5,6]. This guarantees that energy production would match the needed consumption, reduce energy waste, and increase production efficiency.

Another strategy seeks to reduce the cost of SMG electricity [7,8]. The overall cost of energy can be decreased by optimizing the allocation and utilization of DERs, which benefits both grid operators and customers. This entails smart energy management systems that use real-time data and predictive algorithms to improve power source dispatch and balance supply and demand. Furthermore, grid stability is a major goal in SMGs [9,10]. For instance, advanced control strategies and algorithms are used to regulate power flow, maintain voltage and frequency stability, and prevent potential interruptions.

To accomplish these objectives, several algorithms are utilized to address the optimization challenge. Different mixes and combinations of electrical generators are connected in these SMGs. Hereafter is a review of some associated articles. For example, the authors of [8] present a Q-learning method based on energy control for OPFM in SMG, taking into account the sporadic nature of the electric vehicles' power and grid-connected WTs. In [11], to solve the Dynamic optimal active power dispatch (DOAPD), a fully distributed algorithm is suggested in a hybrid grid. To obtain the best power exchange with the grid, in a grid-connected, average consensus and the projected gradient method are used (with a power fixed price), two ESS units, two distributed generators, and four loads. The study by [12] proposes a stochastic optimal operating framework to lower the functional cost for a grid-connected SMG. "Hong's 2 m point estimate method" and a planted probabilistic optimization algorithm are employed to reach the best generation schedule, storage system dispatch approach, and the optimal motivating price for an incentive-dependent load response program. G. et al., 2021, in [13], present a hybrid solution for power flow management. By combining the consolidation of turbulent flow of water-based optimization (TFWO) with battle royale optimization (BRO), referred to as TFW-BRO, this paper targets the optimization of power fluctuations and cost and the control of power flow. To lower the likelihood of power blackouts with the Power cost while considering CO_2 emanations, the authors of [14] propose a Multi-Objective Particle Swarm Optimization (MOPSO) approach within an SMG composed of ESS, a hydrogen tank, and sustainable energy sources. In [15], an alternating direction method of multipliers (ADMM) based on a distributed model predictive control (DMPC) algorithm employs a distributed approach, reducing the operational cost and making power load fluctuations flat. It studies the online scheduling of both load flexibility and optimal power flow management. In the study by authors [16], a Multi-stage Energy Management System is proposed. This system encompasses two main components: (i) a forecasting system that predicts load demand and renewable power generation for the next day using an Artificial Neural Network and (ii) an optimal power dispatching mechanism in a grid-connected Smart Microgrid (SMG), equipped with a PV system and an Energy Storage System (ESS).

In the present paper, we address several key aspects that are not considered in the existing literature. Firstly, we tackle the issue of CO_2 emissions, which are not effectively curtailed in the studies referenced in [8,11,12,15,16]. Additionally, we take into account the variability of grid power fees based on energy market costs throughout the day, a factor that is often overlooked [11,14]. Furthermore, we emphasize the importance of integrating ESS within the microgrid, a crucial element for peak shifting and minimizing power costs, as opposed to the studies mentioned in [8,15]. Lastly, we recognize the significance of considering ESS fees [17], an aspect that has been overlooked by the authors of [12–15]. As a matter of fact, by addressing these important factors, our research provides a more comprehensive and realistic analysis of power management in rural smart grids. It compares a power management strategy study over 24 h of three different optimization techniques: Genetic Algorithms, the Bellman Algorithm, and a Constrained Management Technique. These algorithms were used to optimize the GHG footprint and the electricity costs in an SMG respecting technical constraints. This energy management approach hinges on multiple factors, including weather predictions, load patterns, the battery's state of charge (SOC), electricity pricing, and the energy cost associated with each power source. The study was contextualized in a rural fishing village in southern Morocco, where the challenges of optimizing smart grids are particularly acute. We then tested a hybrid algorithm that combines Bellman's solution with the Genetic Algorithm to obtain an optimal solution.

The investigated MG is grid-connected. It comprises the following (cf. Figure 1):

- A 100 kWp photovoltaic array harnessing sustainable energy;
- A 60 kWp wind turbine installation harnessing sustainable energy;
- A 125 kW electrochemical storage system serving for storage purposes;
- A 30 kW gas turbine serving as an additional source;
- A 220 V/50 Hz electrical grid operating in a single-phase configuration.

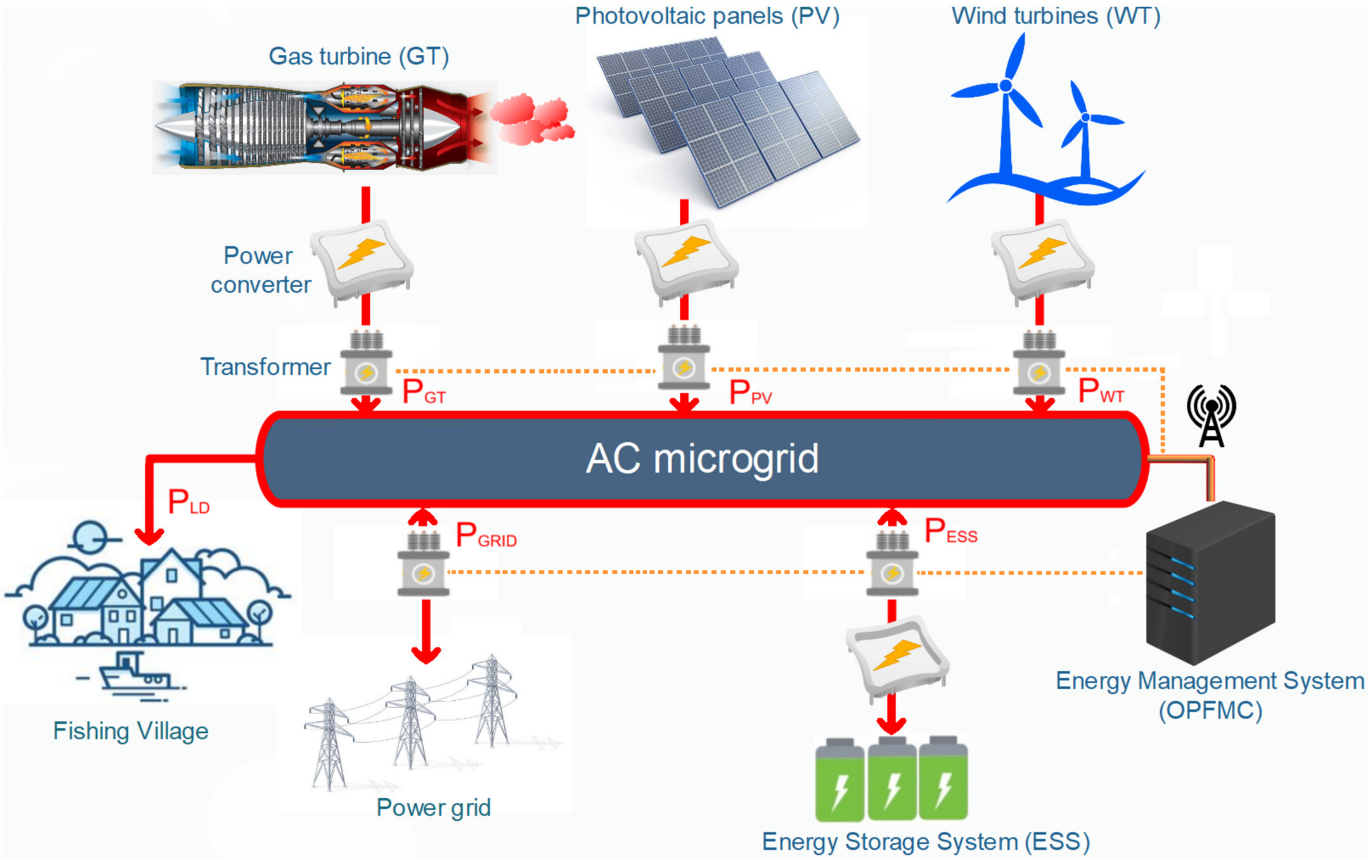


Figure 1. Architecture of the considered microgrid.

This article is structured as follows: First, we provide a general background of the issue. In the second section, details on the microgrid (MG) architecture, including the electric model, functional costs, and technical constraints associated with each power source are provided. In Section 3, we describe the proposed management optimization models, which include the restricted management, GA, and Bellman algorithm. The final section is dedicated to presenting the simulation results and discussing the improvements obtained after the hybridization was adopted in the Lamhiriz fishing village. The results are then compared and discussed within each method.

2. Microgrid Overview

2.1. Overview of Distributed Energy Resources

In this chapter, a comprehensive overview of the MG's energy sources is provided. These sources define the intricate energy dynamics that power the microgrid: photovoltaic (PV) cells, wind turbines, micro gas turbines, and energy storage systems.

- Photovoltaic Characterization:

PV cells generate electrical energy from solar irradiation. The hourly power extracted from these cells at the maximum power point is defined with [18]

$$P_{PV\_GEN} = N_{PV} \times P_S \times \frac{G_i}{G_S} \times (1 + \alpha(T_j - T_{jS})) \quad (1)$$

where PPV_GEN is the hourly extracted power from PV modules; N_{PV} is the PV modules number; P_S is the photovoltaic peak power in *Wc*; G_i is the global irradiance in W/m^2; G_s is the Standard Test Conditions irradiance in W/m^2; α is the (PV) temperature coefficient of power in %°C; and T_j and T_{jS} are the PV and STC PV cells temperature, respectively.

For PV arrays, it is important to note that factors such as oxidation, corrosion, and thermal stresses have not been taken into consideration.

- Wind Turbine Characterization:

Wind turbines extract electricity from wind speed. The WT's output power, denoted as P_{WT_GEN}, can be calculated as described [19]:

$$P_{WT_{GEN}} = \begin{cases} 0.0 & V < V_{cut_{in}} \\ 137.17V^3 & V_{cut_{in}} \leq V \leq V_R \\ 137.17V_R^3 & V_R \leq V \leq V_{cut_{out}} \\ 0.0 & V > V_{cut_{out}} \end{cases} \quad (2)$$

In this context, V represents the wind speed, V_R stands for the rated speed, $V_{cut\text{-}in}$ refers to the *WT cut-in* speed, and $V_{cut\text{-}out}$ indicates the *WTcut-out* speed.

- Gas Turbine Characterization:

A micro gas turbine (MGT) serves as an additional source. Compared to diesel generators, WT has better efficiency, reduced CO_2 emanations, and rapid reaction time. The WT combustion emits CO, CO_2, and NOx [19,20]. The cost and CO_2 emanations of the GA are acknowledged for MGT.

- Energy Storage System Characterization:

An energy storage system (ESS) has a crucial function in modern energy systems, enabling the efficient management and utilization of renewable energy sources, grid stability, and load balancing.
The ESS State of Charge is evaluated as [21]:

$$SOC(k) = 1 + \frac{Q_{ch}(k) - Q_{dis}(k)}{C_{nom}} \quad (3)$$

where C_{ref} is the storage energy nominal capacity.
Q_{ch} and Q_{dis} are the quantity of charge that is stored and released from the battery during a specific charging and discharging cycle, respectively.

- Grid Characterization:

Renewables have intermittent behavior, the utility grid feeds the load if DER is not sufficient, and if there is a power surplus produced by renewables, the grid purchases it.
Renewable energy sources exhibit intermittent characteristics, whereby the utility grid supplies the load when the distributed energy resources (DERs) are insufficient. Conversely, when renewables generate a surplus of power, the excess energy is purchased by the grid.

2.2. Optimization Problem

To fulfill the objective of our study, we pursue these goals, which include the following:

- Ensure the SMG power balance without any suspension;
- Minimize electricity costs;
- Reduce GHG emissions;
- Maximize the use of renewables;
- Fulfill all technical constraints.

Objective Function (Cost Function)

The objective cost function encompasses the summation of expenses from all power generators along with the associated cost of CO_2 emissions.

$$Obj = \min \sum_{t=t_0}^{24} \left(\underbrace{C_{ESS}(t)}_{Battery\ cost} + \underbrace{C_{Grid}(t)}_{Main\ grid\ cost} + \underbrace{Cost(\mathrm{P_{MGT}}(t)) + \delta C_{MGT_{ON/OFF}}(t)}_{Gas\ Turbine\ Cost} + C_{CO_{2eq}}(t) \right) \quad (4)$$

In Equation (4), the upper bound of summation (24) corresponds to the 24 h in a day. This value signifies the integration of the optimization process over the entire daily time period.

- Gas Turbine Energy Cost:

The MGT power price is associated with a combusted natural gas total cost, the start and stop turbine operational cost, and the GHG emanations corresponding cost.

The combusted gas price during τt is [22]

$$\mathrm{Cost}(\mathrm{P_{MGT\_GEN}}) = \mathrm{M_{gas}} \times \mathrm{Cg} \times \tau\mathrm{t} \tag{5}$$

with

$$\mathrm{M_{gas}} = \frac{\mathrm{E_{elec}}}{\mathrm{d_g} \times \eta_\mathrm{G}} \tag{6}$$

M_{gas} represents the mass of combusted gas, C_g is the price of one kilogram of natural gas, d_g is the energy density of consumed gas (d_g = 13.5 Kwh/kg), and η_G refers to the turbine efficiency.

$$C_{CO_{2eq}}(k) = M_{CO2_{eq}}(k) \times Cost_{penal\_CO2} \tag{7}$$

The assessment of GHG emanations is limited to the most environmentally harmful gases: NOx, CO, and CO_2 [20]. To measure equivalent CO_2 emanation's charge $\left(C_{CO_{2eq}}\right)$, we acknowledge equivalent Carbon Dioxide mass [22,23] and 30 euros per ton as the ecological penalty price [24].

- Grid Energy Cost:

The industrial electricity pricing information is available in the references [25,26]. The pricing for electricity purchased from the grid varies based on the consumption period:

$$\mathrm{G_{cost\_buy}} = \begin{cases} 0.18€\ /\mathrm{kWh}\ ,\ 8\mathrm{h} \le k \le 22\mathrm{h} \\ 0.13€\ /\mathrm{kWh}\ ,\ 23\mathrm{h} \le k \le 7\mathrm{h} \end{cases} \tag{8}$$

The pricing for the electricity supplied to the grid will be as follows:

$$\mathrm{G_{cost\_sell}} = 0.1176€\ /\mathrm{kWh} \tag{9}$$

If the purchased energy outstrips the stipulated power with the grid operator after 24 h, the Subscribed Power Exceeding Charge (SPEC) is priced as follows [27]:

$$SPEC = \frac{1.5 \times fixed\_increase}{365} \times (P_A - P_S) \tag{10}$$

P_S represents the stipulated power and P_A denotes the utmost power bought within a day. As a result, the exchanged main grid power price is determined as follows:

$$C_{Grid} = \mathrm{G_{cost\_buy}} + SPEC - \mathrm{G_{cost\_sell}} \tag{11}$$

- Battery bank cost:

An electrochemical storage system in the form of a lead–acid battery bank is utilized. Every hour, battery aging is linked to a deterioration charge, and is expressed as [26,28,29].

$$\mathrm{C_{ESS}(k)} = \frac{\mathrm{Bic} \times \Delta\mathrm{SOH(k)}}{1 - \mathrm{SOH_{min}}} \tag{12}$$

with

$$\mathrm{SOH(k)} = \mathrm{SOH(k-1)} \times \left(1 - \frac{\mathrm{N^{eq_{100}}_{cycles}(k)}}{\mathrm{N^{100\%}_{cycles\_max}}}\right) \tag{13}$$

- Renewables energy cost:

Wind turbines and solar panels extract power at no cost to fully harness their energy potential.

- Equality and Inequality Constraints:

At every moment, the equilibrium between energy production and consumption must be fulfilled (14).

$$P_{PV\_GEN} + P_{WT\_GEN} + P_{Grid} + P_{GT\_GEN} - P_{ESS} = P_{LD} \tag{14}$$

If generated, a provision of ten percent of DER power is stated by electrical grid rules. Thus, the exchanged power must respect

$$P_i \leq 0.9 \times P_{i\_GEN} \tag{15}$$

i: PV, WT, and ESS.

The MGT should operate at more than 50% of its maximum power to increase efficiency and weaken GHG emanations [20,30].

$$0.5 \times \mathrm{P_{MGT}} \leq \mathrm{P_{MGT\_GEN}} \leq 0.9 \times \mathrm{P_{MGT}} \tag{16}$$

The maximum $\mathrm{SOC_{max}}$ and the minimum $\mathrm{SOC_{min}}$ allowed for the State of Charge are defined as (17) and (18) [28–31].

$$\mathrm{SOC_{min}} \leq \mathrm{SOC} \leq \mathrm{SOC_{max}} \tag{17}$$

$$\Delta\mathrm{SOC(k)} \leq \Delta\mathrm{SOC_{max}} \tag{18}$$

The State of Health (SOH) is limited to $\mathrm{SOH_{min}}$ to increase battery lifetime and storage autonomy [28].

$$SOH(k) \geq SOH_{min} \tag{19}$$

2.3. Optimization Problem Solving

In this section, we will examine the Genetic Algorithm selected for OPFM Problem Solving. Also, we will see two distinct management strategies, namely the Rule-Based Management System (RBMS) and the Bellman Algorithm to rigorously evaluate the results obtained from the Genetic Algorithm.

2.3.1. Genetic Algorithm Application

A Genetic algorithm (GA) is a metaheuristic evolutionary algorithm. It is a popular optimization approach. J. H. Holland detailed GA in the 1970s [32].

GAs are widely employed for addressing complex global optimization problems and have demonstrated favorable outcomes in terms of computational efficiency [33–35]. Figure 2 presents different GA steps. Those steps are as follows:

Step 1: The GA begins with a first population; it consists of all the probable solutions of the studied constrained optimization. The population size helps maintain diversity to prevent premature convergence, striking a balance between a large population, which may slow down the Genetic Algorithm (GA), and a smaller one, which might compromise a suitable mating pool. The individuals must respect upper and lower boundaries.

$$LB \leq x \leq UB \rightarrow bounding\ of\ variables \tag{20}$$

Step 2: During the Selection phase, candidates (the best-fit offspring) from the current population are chosen for the production of offspring of the new generation. The chosen candidates are subsequently grouped in pairs to optimize reproduction. These pairs then transfer their genetic information to the subsequent generation.

For good diversity in the next generation, crossover or mutation strategies help create the other population of chromosomes.

Step 3: Crossover generates children by combining two parents. The fraction of crossover children is also an optimization parameter.

Step 4: The mutation strategy helps the production of remaining children in a population; those individuals are created only by one parent.

Step 5: The fitness function assesses the performance of each chromosome, indicating how effectively it aligns with the cost function: the criteria the algorithm is striving to optimize (Equation (4)). The fitness function is calculated for all chromosomes (individuals), and the subsequent generation is formed based on the fitness function scores. The population chromosomes must respect the technical and economic requirements. It consists of the following: (1) maintaining power balance: (Equation (14)) and (2) Equality and Inequality Constraints: (Equations (15)–(19)).

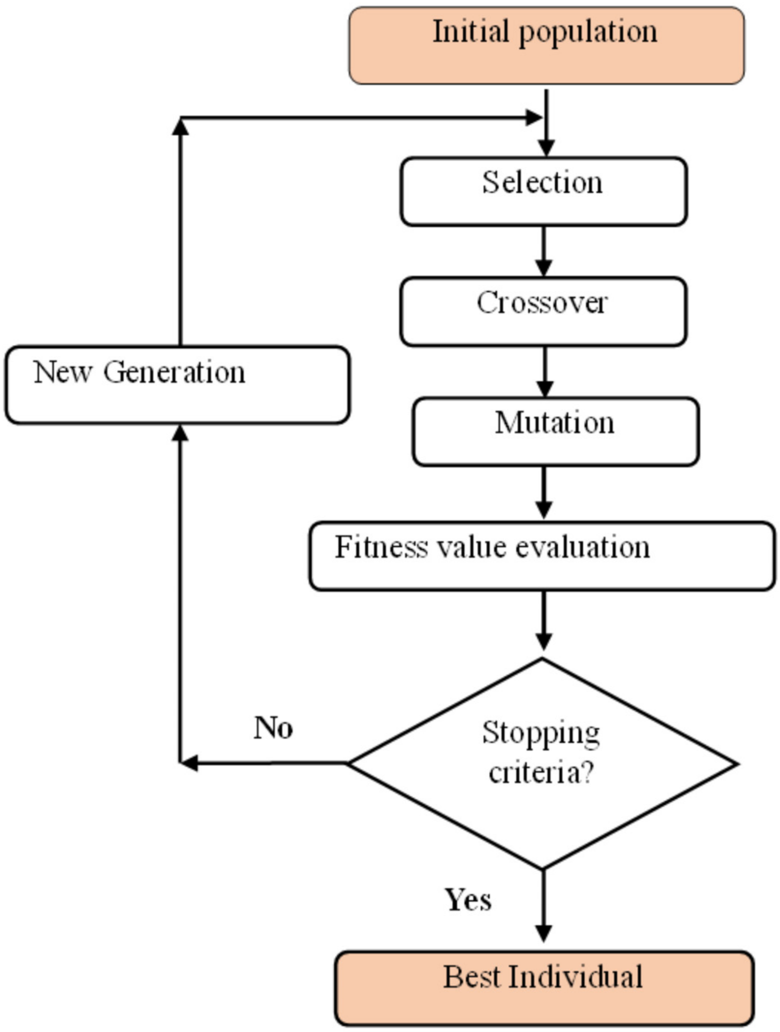


Figure 2. Genetic Algorithm flowchart.

This process cycle is started over until a termination criterion is found. The termination criteria could be a fixed best fitness individual that satisfies the function tolerance condition over a stall generation number or a calculation time threshold.

The used values for the parameters of GA optimization are listed in Table 1.

Table 1. GA chosen parameters.

GA Options	Selected Option
Selection strategy	Stochastic uniform
Mutation strategy	Adaptive feasible
Crossover strategy	Scattered
Non-linear constraints strategy	Augmented Lagrangian
Scaling function	Rank
Selection strategy	Stochastic uniform
Mutation strategy	Adaptive feasible
Population size	1000
Crossover fraction	70%
Stall generations	50
Function tolerance	10^{-6}
Elite count	50
Selection strategy	Stochastic uniform
Mutation strategy	Adaptive feasible

2.3.2. Validation Approaches for Genetic Algorithm

Rule-Based Management Strategy

The Rule-Based Management Strategy (RBMS) is a simple but effective approach for optimizing smart grids in rural areas. It is established on a set of predefined guidelines and priorities that are used to manage the flow of electricity in the system. As shown in Figure 3 [36,37], the strategy starts by prioritizing the utilization of renewable sources, like solar and wind power, to meet the electricity demand. If there is not enough renewable power available, the battery bank is used to provide additional power. If there is excess renewable power, it is stored in the battery bank or sold back to the grid. If DERs and the ESS do not provide enough power to satisfy the load, then the residual power is taken out via the main grid and/or from a gas turbine generator (MGT), depending on which is more cost-effective [28,38]. The RBMS is easy to implement and requires minimal computational resources, making it a practical solution for small-scale smart grid systems in rural areas.

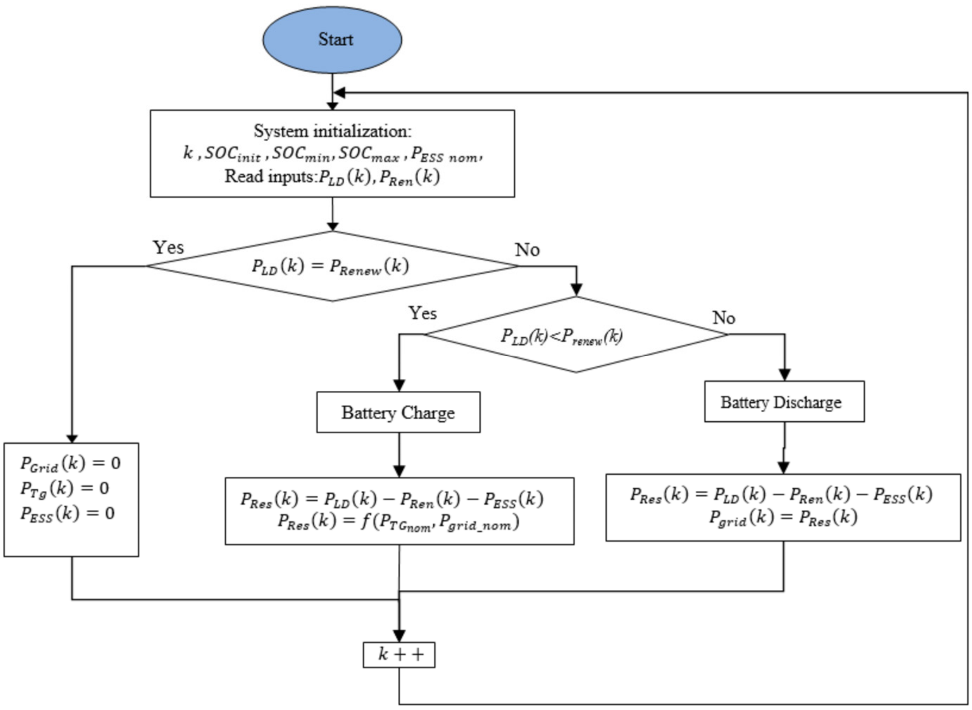


Figure 3. Rule-Based Management flowchart.

Bellman Algorithm Application

The Bellman Algorithm [39,40], also known as the dynamic programming algorithm, is a well-known optimization technique that is used to solve a wide range of complex optimization problems in various fields, including energy management. The algorithm is founded on the optimality principle, which means that an optimal solution to a problem can be obtained by decomposing it into smaller sub-tasks and determining the best solution for each distinct task. The Bellman Algorithm is particularly useful for addressing complex problems involving multiple decision variables and constraints, which contributes to its popularity in optimizing energy management in SMG. This algorithm is applied to determine the optimal power dispatch schedule for a microgrid by iteratively solving a series of subproblems. By doing so, it can provide a solution that balances energy supply and demand while minimizing costs and ensuring system stability.

The flowchart of the Bellman algorithm in Figure 4 was adapted from [18], depicting the steps of the algorithm. The MG management in this optimization problem solving is a progressive Bellman optimization. We start by the following steps:

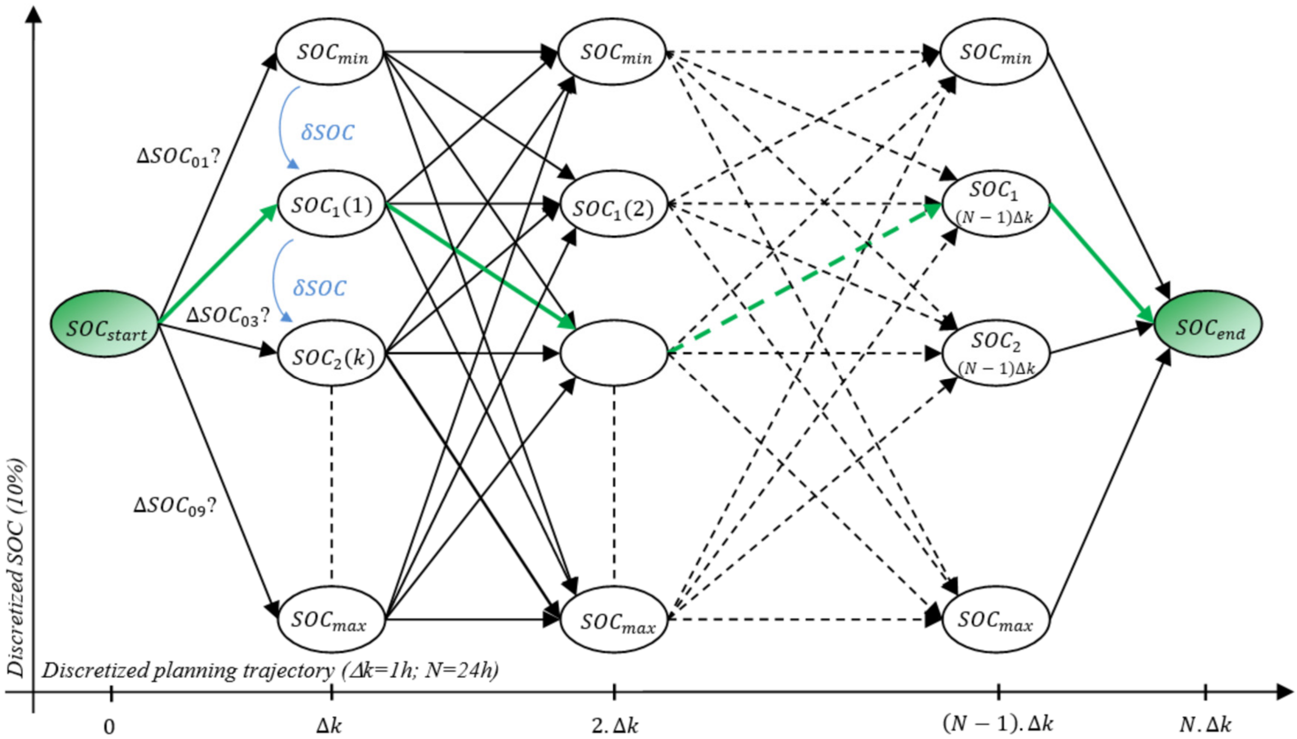


Figure 4. Bellman SOC optimization graph.

- Active power dispatching: P_{ESS} discretization (SOC is first discretized by a 10% step);
- Active power dispatching: P_{pv} discretization;
- Any leftover power is allocated to the grid and the MGT, according to the objective function [18]. This allocation is determined via the use of linear programming [41] techniques.

The organizational chart of Figure 5 provides a simple description of the proposed management procedure. Indeed, the ESS's power and the PV system are discretized within nested loops with a small step size. Thus, any combination of these powers with the active power demanded by the loads defines a residual power (rf Figure 5). During the resolution, each level of this power will be allocated between the main grid and the gas turbine using statistical repairing [18]. This constitutes a sub-optimization problem.

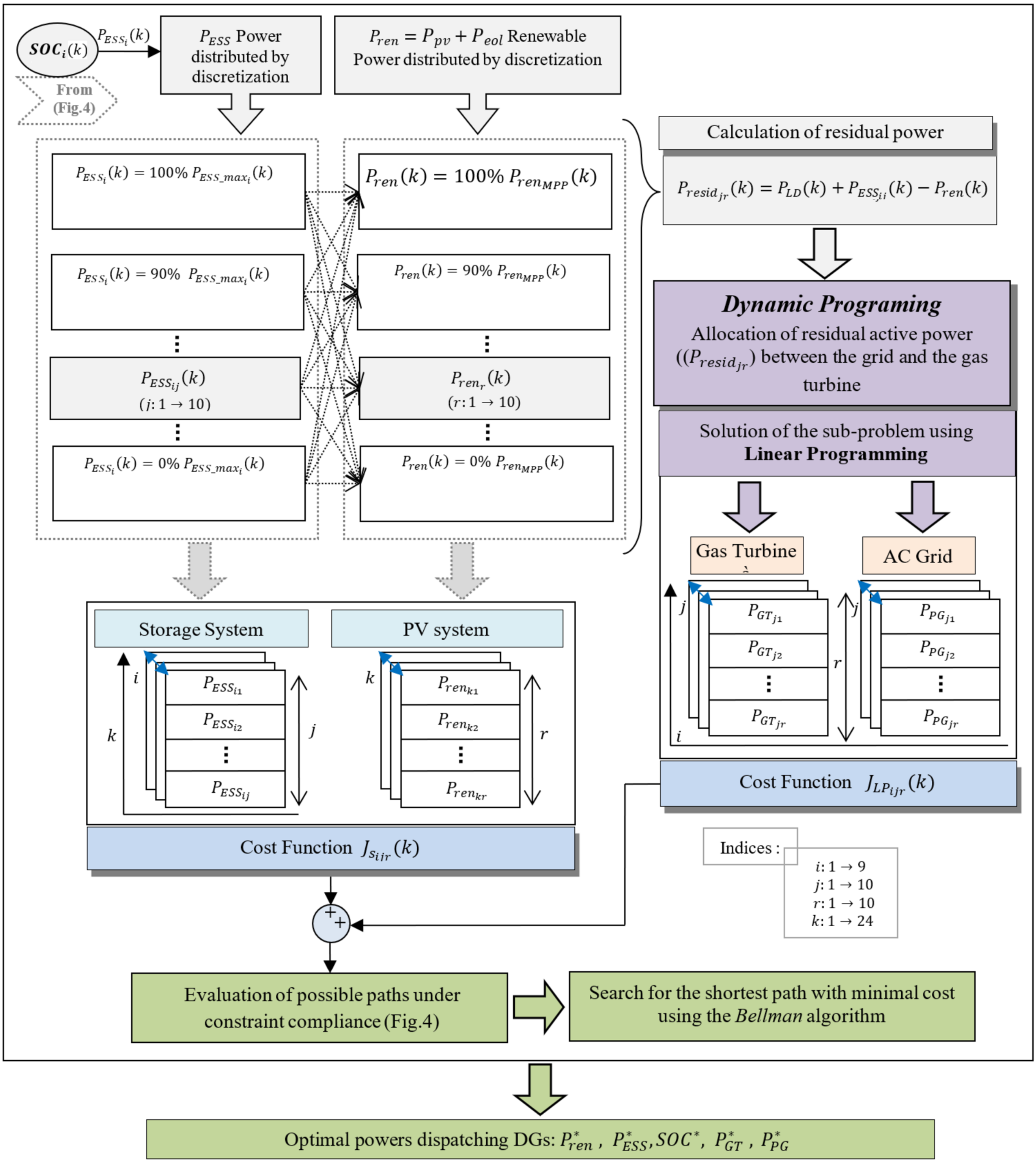


Figure 5. Bellman overall optimization flowchart [41].

Furthermore, the dynamic programming [40] loops will exhaustively test different power strategies that meet the residual power, load balancing, and constraints associated with each source (Equation (14)). At this point, the Bellman algorithm is triggered by calculating the total transition costs (battery wear costs) between each state, located at two successive steps (see Bellman algorithm). Thus, the total cost of each possible solution is the sum of the two objective functions (Equation (12)) and (Equations (5), (7), and (8)). The objective is to find, starting from the initial state, the optimal SOC trajectory that enables reaching the final state with minimal cost.

3. Simulation and Results

3.1. Simulation Context—Lamhiriz Village

Lamhiriz is a small fishing village nestled in the southernmost region of Morocco with a population of 4625 [42] inhabitants spread over an area of 178 hectares. The village is renowned for its unique natural landscapes and its potential for ecotourism. Despite its popularity among tourists, Lamhiriz faces challenges related to its basic infrastructure and access to reliable electricity. Therefore, Lamhiriz has been selected as an exemplary case study for implementing DER and microgrids to meet the community energy needs effectively. This article explores the feasibility of using various optimization algorithms to manage a microgrid system in Lamhiriz, considering technical and financial limitations.

The daily load profile of Lamhiriz Village [42] in Figure 6 exhibits significant fluctuations throughout the day. There is a relatively consistent energy consumption during the early hours, followed by an increase from the sixth hour until the ninth hour. The load then stabilizes at a lower level for several hours, with two consumption peaks at the twelfth and thirteenth hour. A significant increase in consumption is observed in the late afternoon, reaching its peak at the nineteenth hour. Afterward, the load gradually decreases until the twenty-fourth hour. This analysis of the load profile provides insights into the energy consumption patterns of Lamhiriz Village, which is crucial to implement efficient energy management approaches and optimize the village's microgrid system.

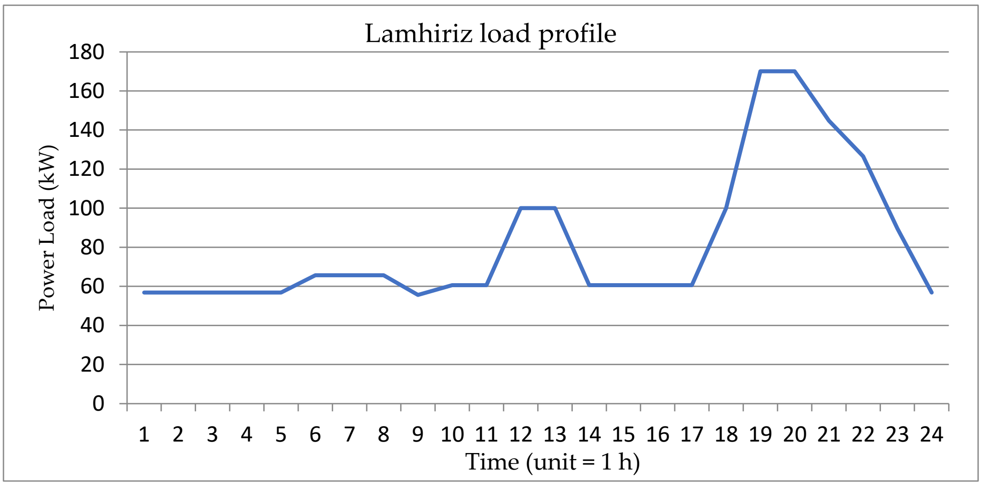
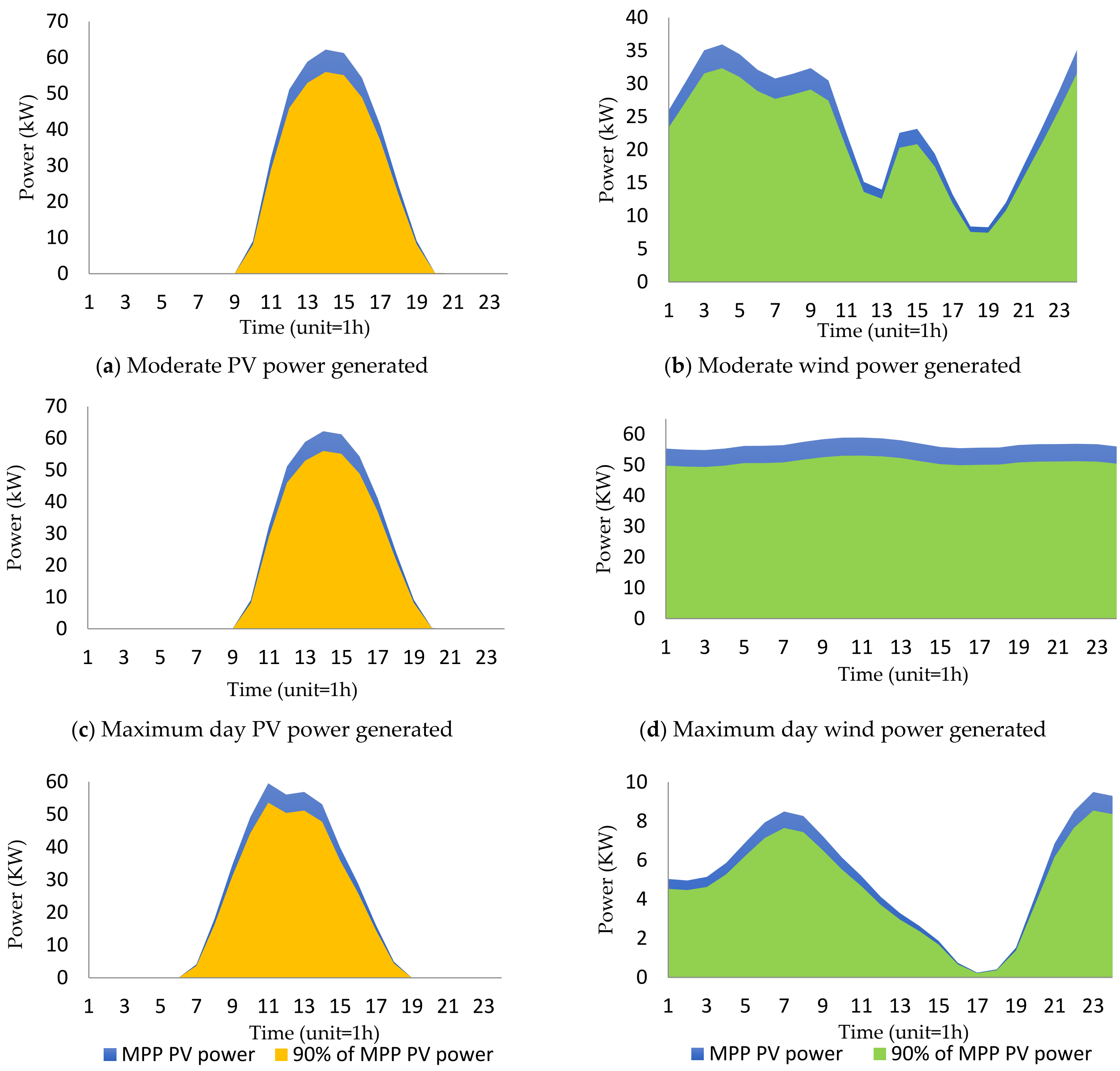


Figure 6. Daily power load profile.

The daily power load profile in Figure 6 includes the load of desalination, public lighting, and household demand, all aggregated on an active day at 20 °C.

To conduct this study, power generation data for solar panels and wind turbines was acquired from the website Renewables.ninja [43]. The following three days were selected from the year 2019 (rf. Figure 7):

- 29 December: this particular date was selected because it represents a day with moderate renewables production.
- 29 November: represents the day with the maximum renewables production in the year 2019.
- 25 August: represents the day with the minimum renewables production.



(**a**) Moderate PV power generated (**b**) Moderate wind power generated

(**c**) Maximum day PV power generated (**d**) Maximum day wind power generated

(**e**) Minimum day PV power generated (**f**) Minimum day wind power generated

Figure 7. Specific days for solar and wind power in Lamhiriz Village.

A Photovoltaic field with a capacity of 100 kWp generates solar energy, and two 30 kWp wind turbines are considered as the sources of generated renewable energy.

3.2. Simulation for a Random Load Profile

Within this section, we showcase the simulation outcomes of various optimization techniques applied to a randomly generated load profile. Our main goal is to assess the effectiveness of the Genetic Algorithm and compare it to both strategies: rule-based management and the Bellman algorithm. The comparison is carried out in terms of energy cost and GHG emissions. Furthermore, we propose a novel approach that combines the Bellman and Genetic algorithms to improve optimization outcomes. We also evaluate the simulation time necessary for each technique. These findings provide vital insight into the success of each strategy for optimizing the power system for a certain load profile. This knowledge can aid in making educated decisions when picking appropriate optimization strategies in practical circumstances.

During the analysis, the days under consideration are divided into 24 one-hour intervals [44,45].

The provided values represent a random daily load profile used for simulation purposes in a random environment. These values indicate the load power (in kilowatts) at different hours of the day.

In Figure 8, the load power varies throughout the day, with peaks occurring at certain hours, such as 4, 6, 10, and 15. These peaks indicate higher energy demands during those specific hours. On the other hand, there are periods of relatively lower load power, such as during hours 2, 7, 18, and 22. This highlights that these values are used for testing algorithms and may not reflect actual load profiles in real-world scenarios.

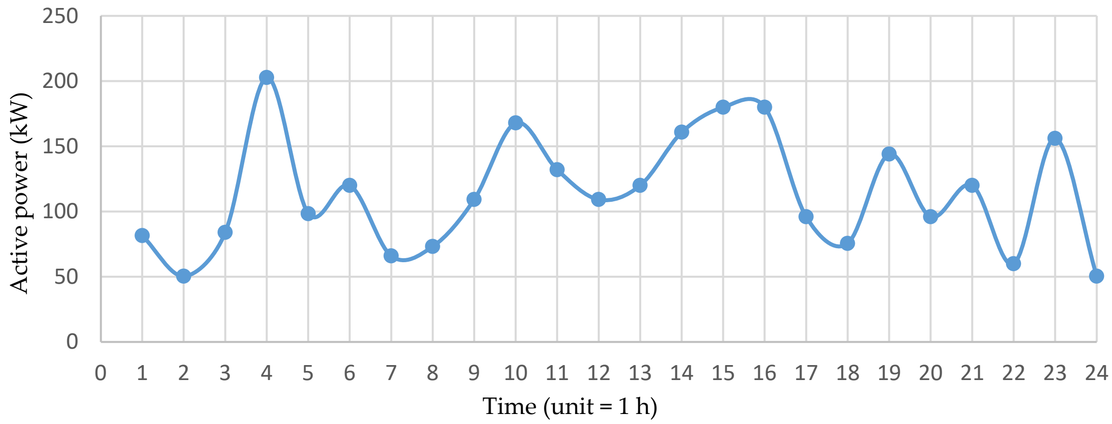


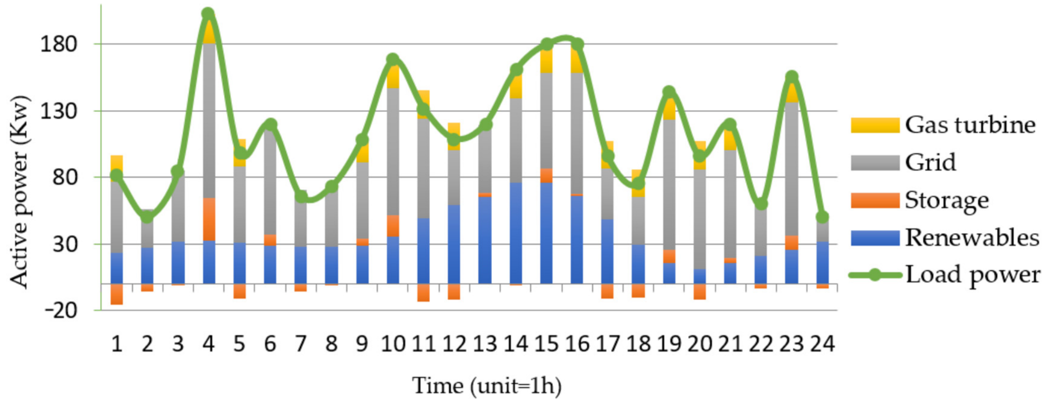
Figure 8. Random load power.

The primary objective of this study is to achieve a dual optimization goal: minimizing both the overall cost and the CO_2 emissions in the microgrid. To attain this, the optimization process will be subject to various constraints. First and foremost, the power balance Equation (14) will be strictly adhered to, ensuring that the power generated and consumed in the microgrid is balanced at all times. Additionally, the optimization will respect the technical constraints mentioned in Section 2.2, which encompass limitations related to the capacity and operation of individual power sources and storage systems. By integrating these constraints into the optimization algorithms, we aim to identify the power dispatching strategy that not only reduces costs but also promotes environmental sustainability by minimizing CO_2 emissions. To tackle this optimization problem, we have employed three Energy Management System (EMS) algorithms, including Rule-Based Management, Genetic Algorithm, and the Bellman Algorithm.

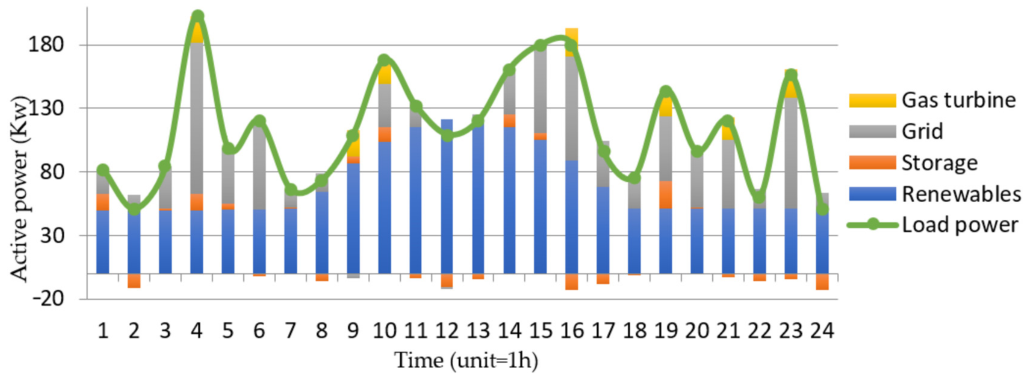
3.2.1. Genetic Algorithm Optimization Results

Below is the graph depicting the results of the system optimization using GA. The displayed values represent the optimal power allocation among the different energy resources to meet the demand load. Analyzing the results will provide us with a better understanding of the algorithm's effectiveness in optimizing the system and its overall influence on the energy system's performance.

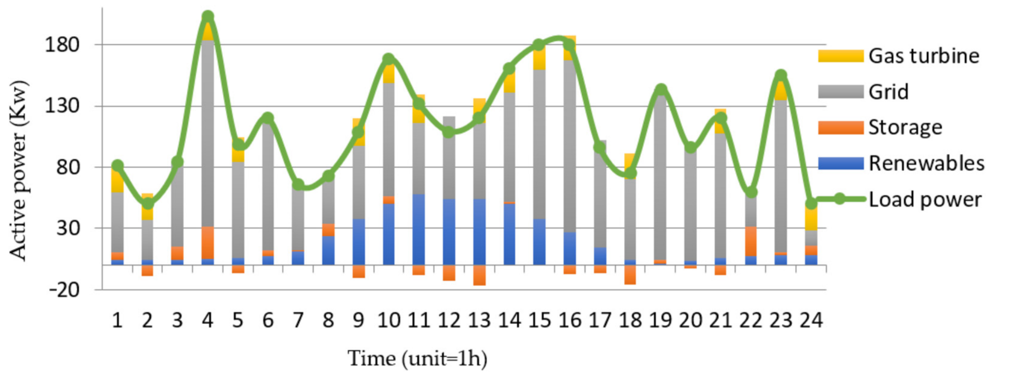
The results in Figure 9 represent the optimal power dispatching by the genetic algorithm for each hour of the day in kilowatts (kW). The optimization is conducted for the three studied days. The gas turbine is utilized as an alternative power source if renewable generation and storage are insufficient to fulfill the load demand. The algorithm optimizes the gas turbine usage to minimize its operation while ensuring the load demand is fulfilled. Negative values indicate the discharge of stored energy during periods of high demand, while positive values represent energy being stored for later use when renewable generation is abundant. We observe that the ESS plays a role in maintaining the balance between energy supply and demand, although its contribution is moderate. Overall, the results demonstrate the effectiveness of the genetic algorithm in optimizing the power dispatching in the system, maximizing the utilization of renewable energy sources, minimizing the use of non-renewable sources, and reducing the overall energy costs.



(**a**) GA optimal power dispatch for a moderate renewable generation day.



(**b**) GA optimal power dispatch for a maximum renewable generation day.



(**c**) GA optimal power dispatch for a minimum renewable generation day.

Figure 9. Power optimal dispatching by Genetic Algorithm during three different days.

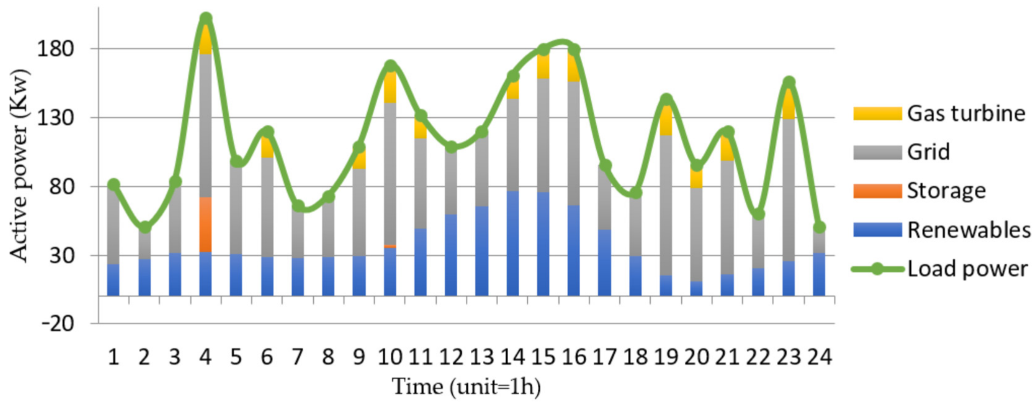
3.2.2. Validation of Genetic Algorithm Results via RBMS and Bellman Algorithm Comparisons

Rule-Based Management

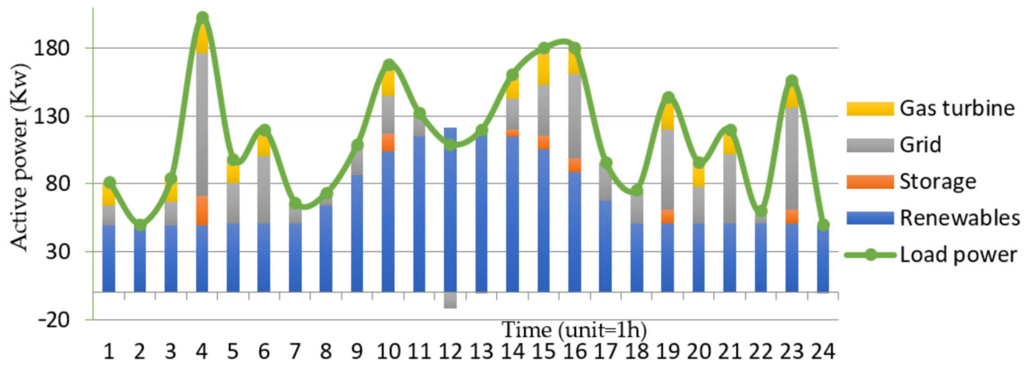
This part shows the results obtained by applying the Rule-Based management technique to a random load profile.

Rule-Based Management is a technique used in energy management that relies on predefined rules and conditions to make decisions. It simplifies decision-making processes by following a set of predetermined guidelines. However, it may lack adaptability and struggle with complex and dynamic environments. It is a straightforward approach but may not be as effective in handling trade-offs or exploring a wide range of solutions compared to more advanced optimization methods.

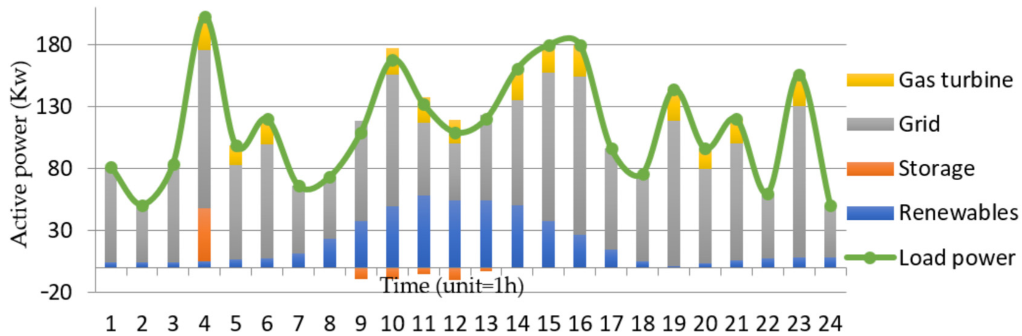
Figure 10 depicts the contributions of renewable sources, storage, the grid, and the gas turbine in fulfilling the power demand, during the studied days. The findings emphasize the varying roles of each source in the overall power supply. We observe that the ESS has a moderate contribution in maintaining the power balance.



(**a**) RBMS optimal power dispatch for a moderate renewable generation day.



(**b**) RBMS optimal power dispatch for a maximum renewable generation day.

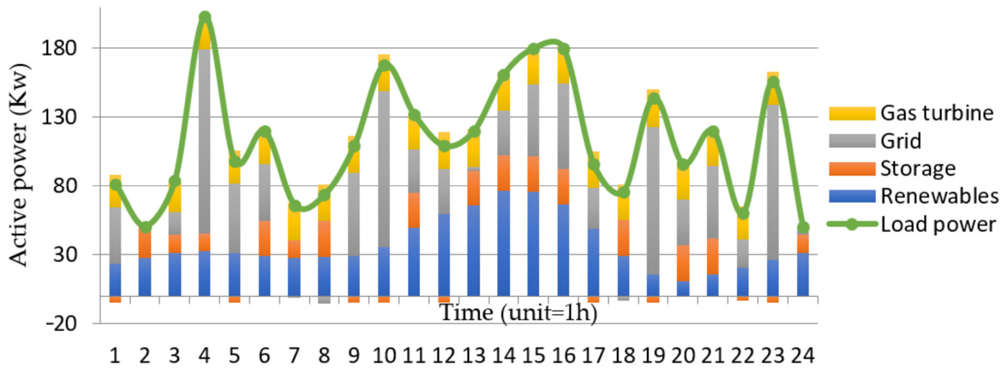


(**c**) RBMS optimal power dispatch for a minimum renewable generation day.

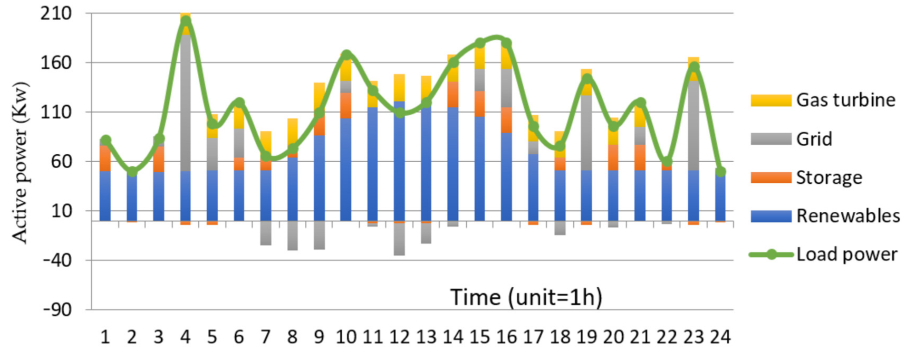
Figure 10. Power optimal dispatching using rule-based management.

Bellman Optimization Results

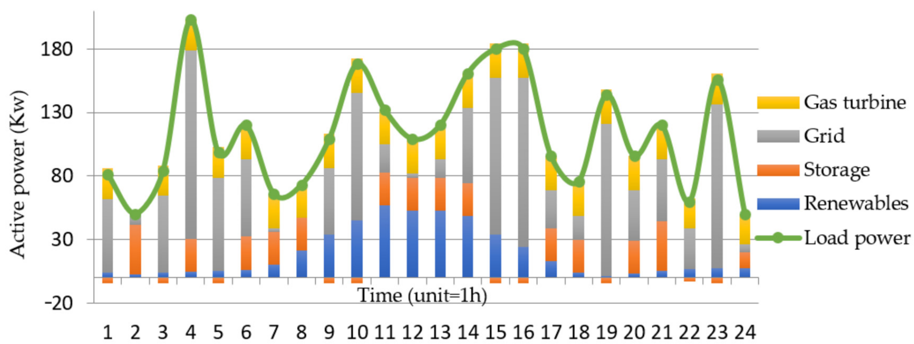
Based on Figure 11, the participation of each power source in the power balance can be summarized as follows: Renewable sources contribute varying amounts of power throughout the day. The ESS is utilized to store excess energy generated by renewables or during periods of low demand. In Bellman Optimization, the ESS actively contributes to maintaining the balance between energy supply and demand. The grid serves as an external power source and contributes to the power balance when additional energy is needed. The values represent the amount of power purchased from or supplied to the grid. The gas turbine acts as a backup power source when other DERs are insufficient to meet the load demand. The combination of these sources allows for balancing the power supply and demand, optimizing the utilization of renewable energy, and minimizing reliance on conventional power sources.



(**a**) Bellman's optimal power dispatch for a moderate renewable generation day.



(**b**) Bellman's optimal power dispatch for a maximum renewable generation day.



(**c**) Bellman's optimal power dispatch for a minimum renewable generation day.

Figure 11. Power optimal dispatching by Bellman Optimization.

Comparison of Energy Cost, GHG Emissions, and Computation Time

In this section, a comparison over the three studied days is conducted to explore the outcomes related to energy cost, greenhouse gas (GHG) emissions reduction, and computation time.

In Figure 12, for the three specific days, the cost associated with the Bellman algorithm is lower than that of both GA and RBMS. Among the three optimization strategies, RBMS incurs the highest cost. RBMS is 17% more expensive than the other management strategies. Bellman is less costly and economizes up to 24% compared to GA management.

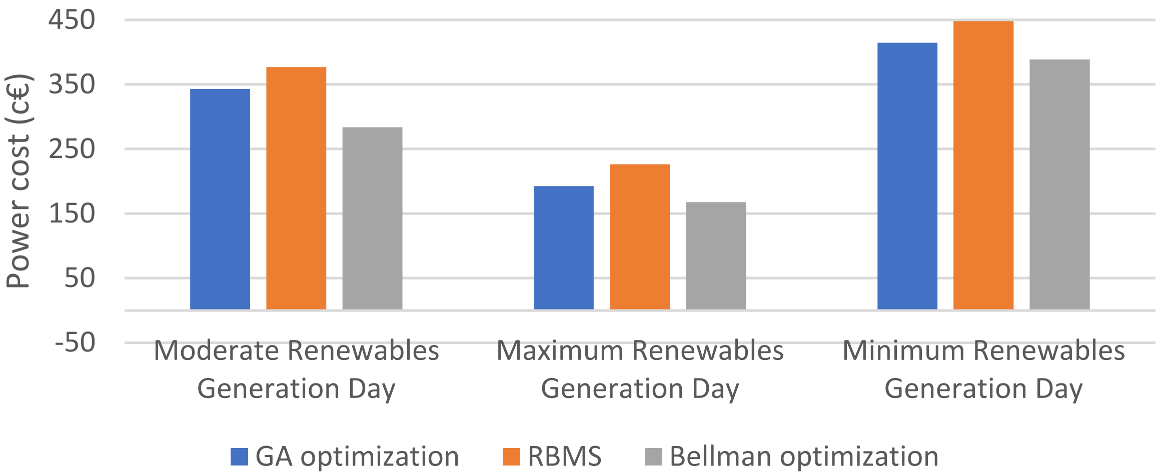
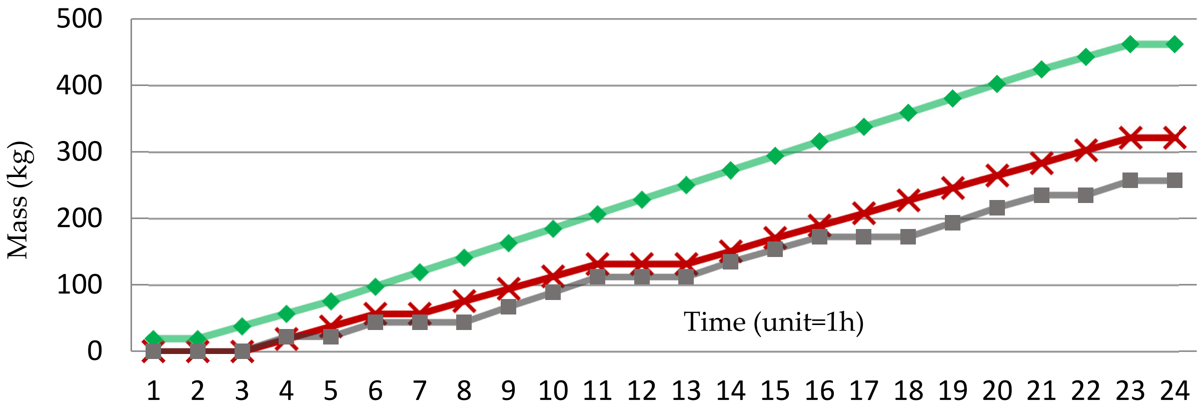


Figure 12. Comparison of total cost emissions between the three OPFM strategies.

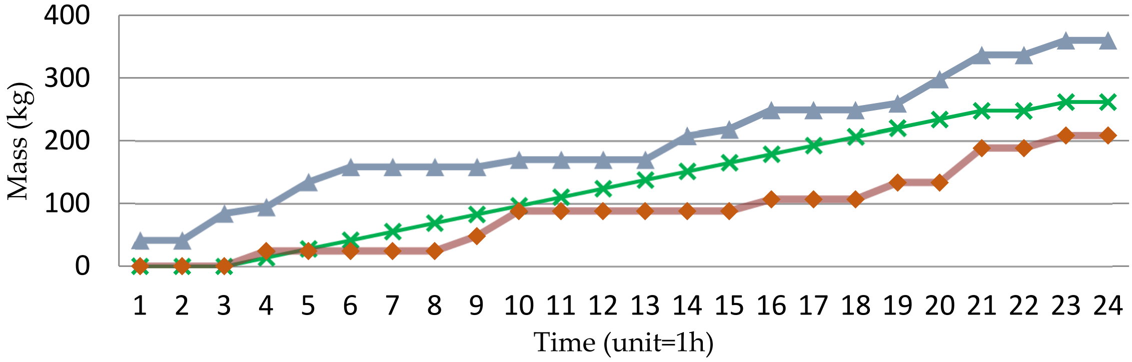
Upon analyzing the results presented in Figure 13, it becomes evident that RBMS exhibits variability in its performance when compared to the GA and Bellman Algorithm across the three studied days. Notably, RBMS outperforms GA in terms of CO_2 emissions on the day with moderate renewable energy generation, with a 19% reduction in emissions. However, on the day with the minimum renewables generated power, RBMS lags behind both GA optimization, leading to a 17% increase in CO_2 emissions. It is also worth noting that when comparing the Bellman Algorithm to GA optimization, the results reveal a significant disparity in GHG gas emissions. In particular, the Bellman Algorithm can result in emissions up to 45% higher than those achieved with GA optimization. This finding highlights the potential environmental benefits of employing GA in microgrid energy management, particularly in scenarios where minimizing GHG emissions is a crucial objective.

The optimization problem is addressed using the MATLAB environment, and the computations are carried out on a laptop equipped with an i7-8750H processor of 16 GB RAM and running at 2.20 GHz.

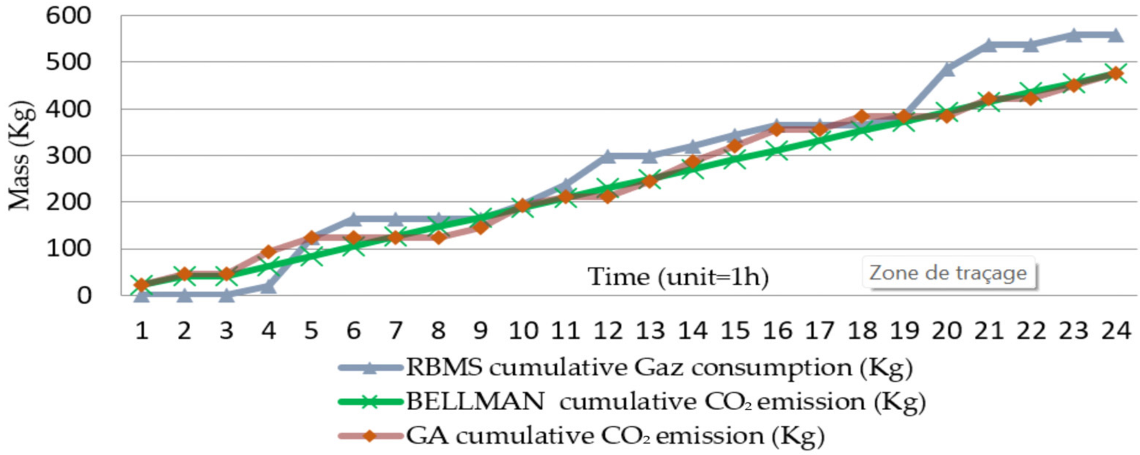
Table 2 provides insights into the simulation times for each of the management strategies, the computation times for the three different management strategies vary considerably. The Rule-Based Management strategy is the fastest, taking only 2 s to complete. In contrast, the Bellman Management strategy is the most time-consuming, requiring approximately 1950 s (or 32.5 min). The Genetic Algorithm (GA) management falls in between, taking around 600 s for 200 generations. This variation in simulation times reflects the different computational complexities and optimization approaches employed by these strategies. While Rule-Based Management offers quick results, it may sacrifice optimization performance compared to the more time-intensive Bellman Algorithm and GA management. Therefore, the choice of strategy should consider a trade-off between computational efficiency and optimization quality based on specific application requirements.



(**a**) Cumulated CO_2 emissions for a moderate renewable generation day.



(**b**) Cumulated CO_2 emissions for a maximum renewable generation day.



(**c**) Cumulated CO_2 emissions for a minimum renewable generation day.

Figure 13. Comparison of CO_2 emissions between the three OPFM strategies.

Table 2. Comparison summary of time simulation.

	Simulation Time (s)
Rule-Based Management	2
GA management	600 for 200 generations
Bellman Management	1950

3.3. Hybridization of Bellman and GA Optimization

3.3.1. Methodology for Hybridization

The hybridization of Bellman and GA optimization is a technique that combines the strengths of both Bellman and Genetic Algorithm (GA) optimization methods.

The initial step of population generation is a fundamental component in any genetic algorithm application, as it produces a range of potential solutions or individuals that are randomly generated or initialized experimentally and serve as input for the GA. While this phase is only carried out once, it significantly contributes to the GA's performance improvement; other steps in the GA process are replicated iteratively.

We used the solution generated by the Bellman optimization, which consists of power values for the grid, micro-gas turbines, and ESSs for each hour of the day:

$$\left[P_{Grid_1}, P_{MTG_1}, P_{ESS_1}, P_{Grid_2}, P_{MTG_2}, P_{ESS_2}, \ldots\ldots,\ P_{Grid_{24}}, P_{MTG_{24}}, P_{ESS_{24}}\right] \tag{21}$$

We created 100 individuals by applying the Bellman solution while ensuring compliance with the power balance criteria and grid power constraints. The power values for each hour are adjusted by adding $\rho_i, \sigma_i,$ andβ_i, where ρ_i, σ_i and β_i represent the adjustments for the grid, micro-gas turbines, and ESS powers, respectively.

$$\begin{gathered}\Big[P_{Grid_1}+\rho_1,\ P_{MTG_1}+\sigma_1, P_{ESS_1}+\beta_1, P_{Grid_2}+\rho_2,\ P_{MTG_2}+\sigma_2, P_{ESS_2}+\beta_2\ , \\ \ldots, P_{Grid_{24}}+\rho_{24},\ P_{MTG_{24}}+\sigma_{24}, P_{ESS_{24}}+\beta_{24}\Big]\end{gathered} \tag{22}$$

With $\rho_i + \sigma_i + \beta_i = 0\ |\rho_i, \sigma_i, \beta_i| \leq 50kW\ i = 1...24$.

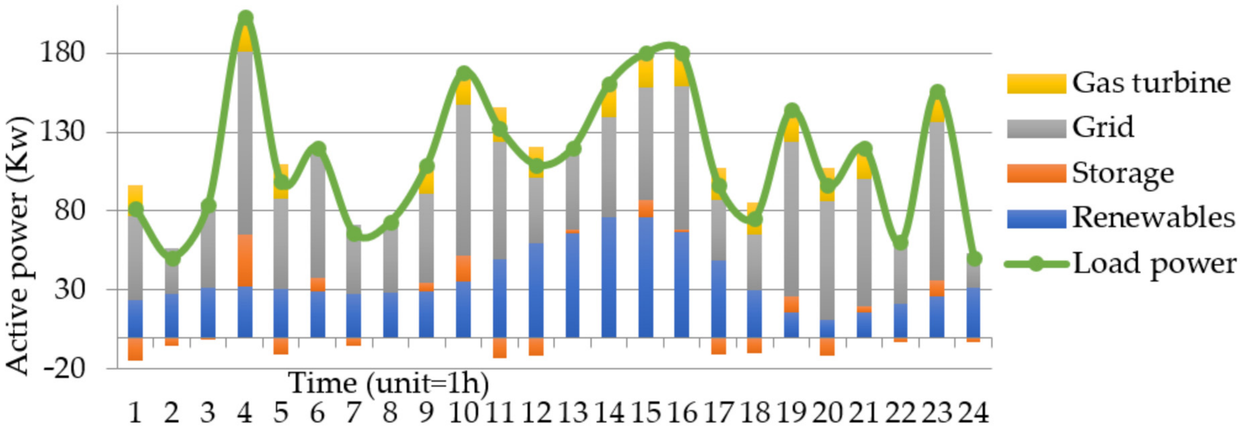
In this approach, the optimal energy dispatch generated from the Bellman optimization is employed to generate the initial population, while GA optimization is used to find the fast optimal scheduling strategy. By combining these two methods, the hybrid optimization technique can achieve better results in terms of cost, GHG emissions, and simulation time compared to using either the Bellman or GA optimization alone. This chapter presents the results of applying the hybridization technique to a random load profile and the comparison of the results with those obtained using Bellman and GA optimizations separately [46].

3.3.2. Results of Bellman and GA Hybridization

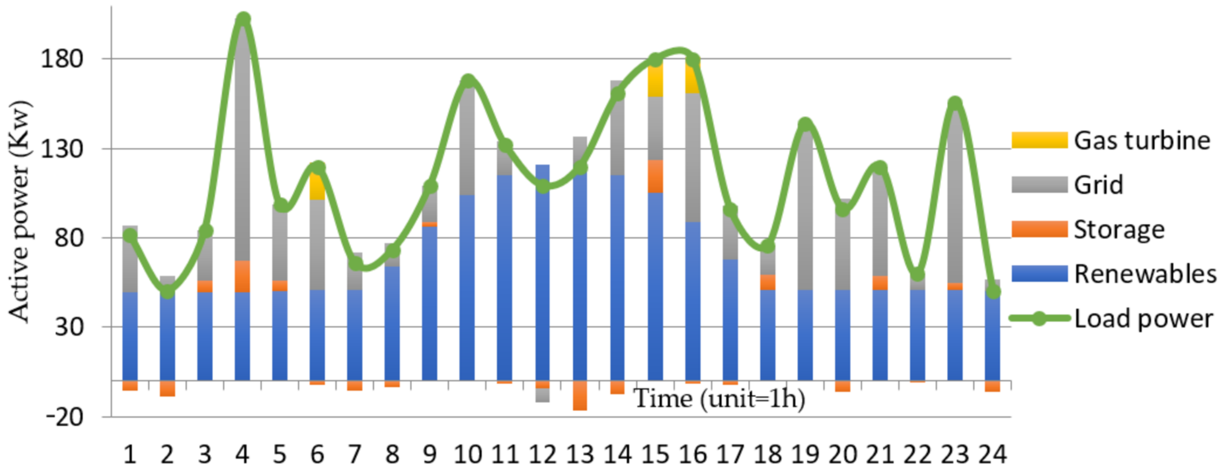
Figure 14 showcases the results of applying a refined Genetic Algorithm (GA) optimization technique to achieve optimal power dispatching. The simulation is conducted for the three studied days. Overall, these results demonstrate the optimized power dispatching strategy achieved via improved GA optimization, considering the participation of different energy sources to meet the load demand efficiently.

Figure 15 offers a comprehensive visual comparison of CO_2 emissions between the Genetic Algorithm (GA) and the proposed improved GA management strategies over the three studied days.

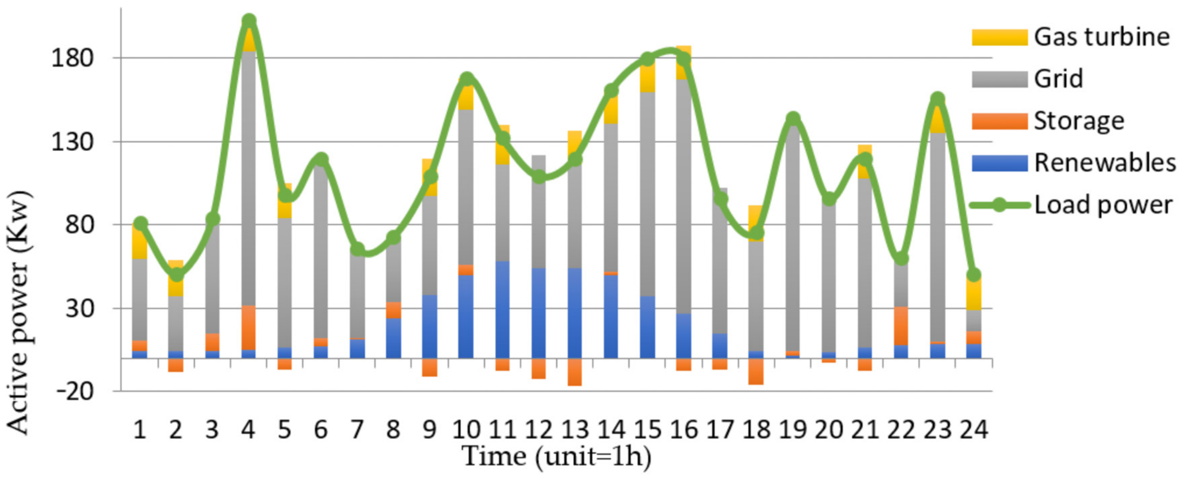
The results depicted in Table 3 are noteworthy, showcasing a consistent improvement in overall cost efficiency. The proposed improved GA management led to a remarkable cost reduction of at least 4% across various scenarios. This substantial cost saving highlights the efficacy of our strategy in optimizing energy resource allocation. Furthermore, the positive environmental impact of these improvements is strikingly evident. GHG equivalent emissions have been significantly curtailed, with reductions of up to 59%. This reduction underscores the potential for our improved GA management to significantly lower the carbon footprint of energy operations. Moreover, Table 4 reveals that the implementation of our improved GA management strategy has not only enhanced cost-efficiency and reduced GHG emissions but has also expedited the optimization process. The simulation time has been notably reduced, taking approximately 25% less time. This efficiency gain is primarily attributed to the provision of an initial population, expediting the convergence of the algorithm. In summary, the results strongly support the effectiveness of our proposed improved GA management strategy, demonstrating its potential to achieve cost savings, reduce GHG emissions, and enhance computational efficiency.



(**a**) Improved GA optimal power dispatch for a moderate renewable generation day.

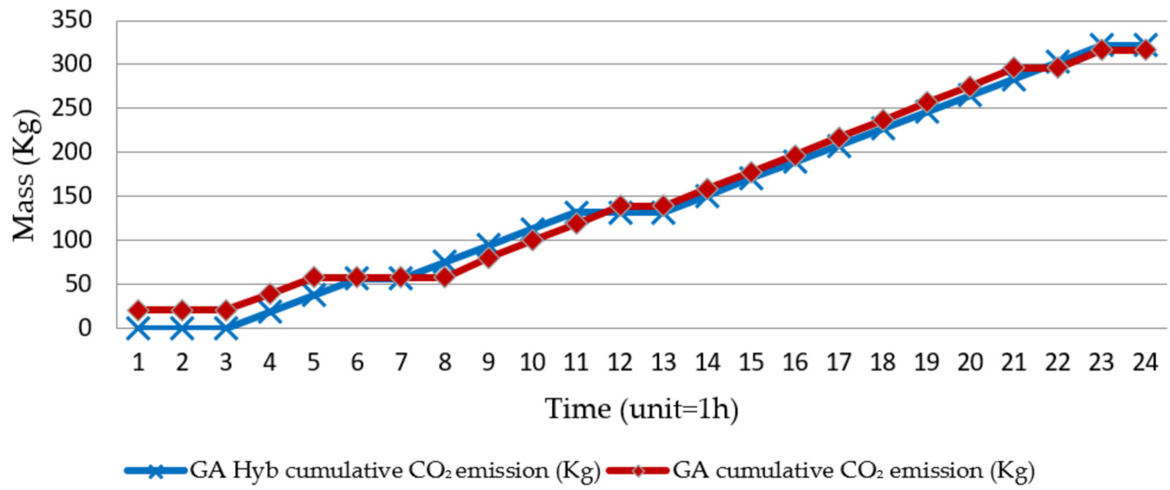


(**b**) Improved GA Optimal Power Dispatch for a Maximum Renewable Generation Day

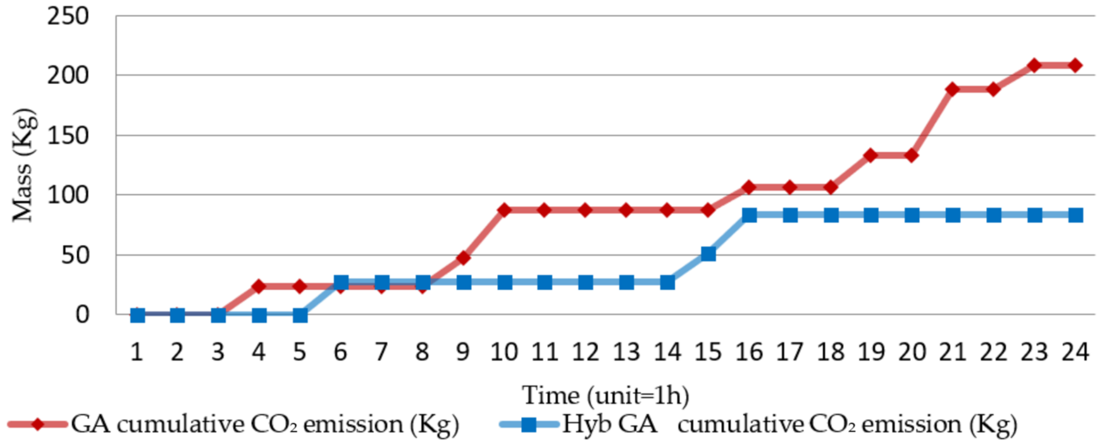


(**c**) Improved GA optimal power dispatch for a minimum renewable generation day.

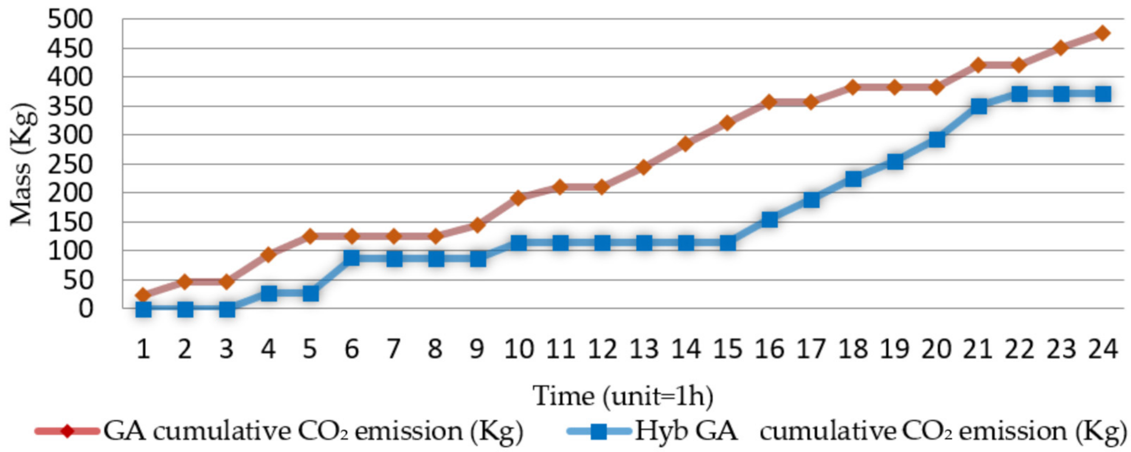
Figure 14. Power optimal dispatching by improved GA optimization.



(**a**) Cumulated CO_2 emissions for a moderate renewable generation day.



(**b**) Cumulated CO_2 emissions for a maximum renewable generation day.



(**c**) Cumulated CO_2 emissions for a minimum renewable generation day.

Figure 15. Comparison of CO_2 emissions between GA and the proposed improved GA management strategies.

Table 3. Comparison summary of time simulation, energy cost, and GHG emissions.

	Optimization Strategy	Power Cost (c€)	GHG Equivalent Emission (kg)
Moderate Renewables Generation Day	GA	342.9242	316.8
	Hybrid GA	331.9803	316.80
Maximum Renewables Generation Day	GA management	192.4991	208.4713377
	Hybrid GA	186.5361	84.0004243
Minimum Renewables Generation Day	GA management	414.3854	475.91
	Hybrid GA	403.7089	372.3391267

Table 4. Time simulation comparison.

	Simulation Time (s)
GA management	600 for 200 generations
Improved GA Management	450 for 200 generations

3.3.3. Hybridization of Bellman and GA Optimization: Simulation for Lamhiriz Profile

The previous sections of this study presented the individual outcomes of the GA and the Hybrid GA management approaches applied to a random load profile. Building upon these findings, this section focuses on the results obtained from the hybridization of the Bellman and GA optimization techniques specifically tailored to the Lamhiriz case. By combining the strengths of both algorithms, the hybrid approach aims to enhance the overall performance in terms of energy cost, GHG emissions, and simulation time. These observations offer significant insights into the effectiveness and potential advantages of combining these optimization approaches in the context of the Lamhiriz microgrid system.

Figure 16 presents the optimal power dispatching achieved via Bellman optimization during a moderate renewable generation day. This dispatching strategy plays a crucial role as it serves as the foundation for generating the initial population for the subsequent genetic algorithm optimization process. By leveraging the insights gained from the Bellman optimization, the genetic algorithm can further refine and enhance the power dispatching strategy to achieve even more efficient and optimal results.

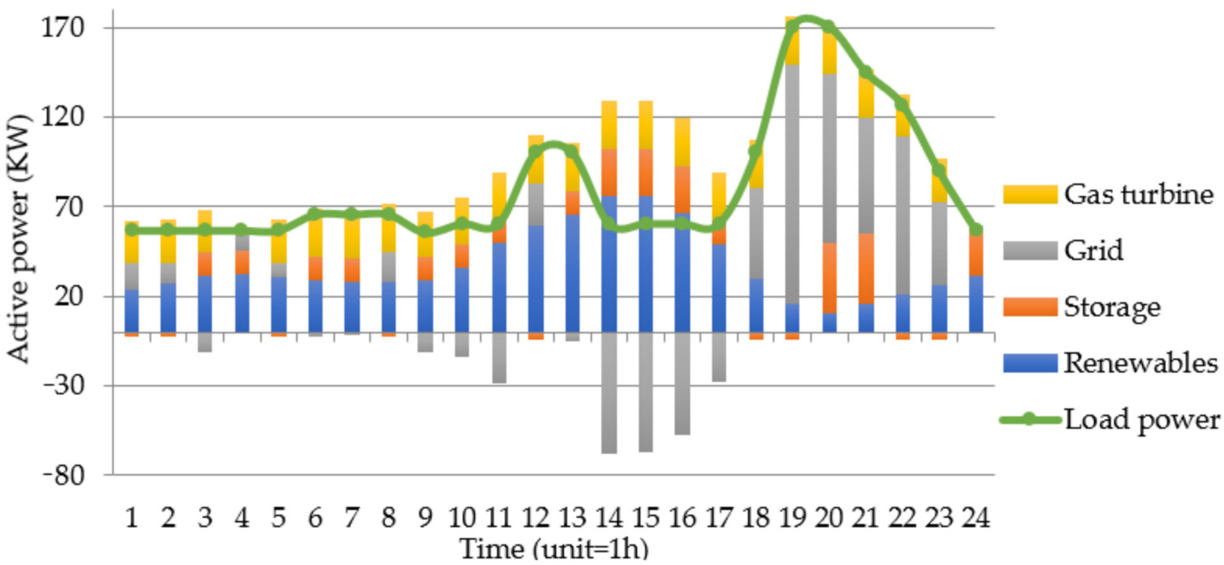


Figure 16. Power optimal dispatching by Bellman optimization.

The optimal power dispatching by the improved Genetic Algorithm in Lamhiriz Village's power distribution is presented in Figure 17. It reveals the varying contribution of different sources in meeting the load power demand. Notably, renewable energy sources show fluctuating values, while the storage system illustrates moderate variability. The power grid exhibits positive values to sell the necessary energy to cover the village's load. The gas turbine remains relatively inactive throughout the hours. Therefore, we can observe how different sources work together to maintain the power balance.

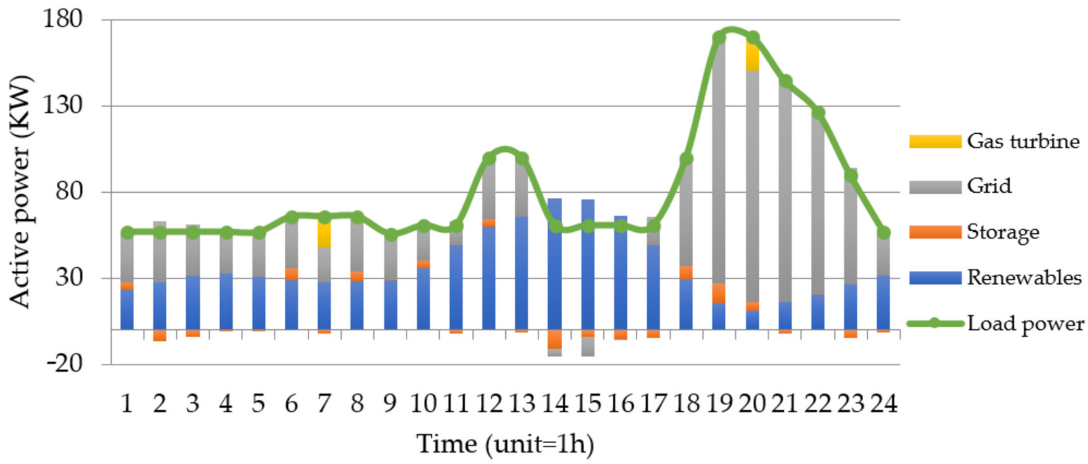


Figure 17. Power optimal dispatching by the improved Genetic Algorithm in Lamhiriz Village.

The results presented in Table 5 highlight the power cost in c€, GHG equivalent emissions in kg, and simulation time in seconds for the different management strategies, specifically the improved GA management for the studied day with moderate renewable generation power.

Table 5. Improved GA Management: time simulation, energy cost, and GHG emissions.

	Power Cost (c€)	GHG Equivalent Emission (kg)	Simulation Time (s)
Improved GA Management	192.7954	40.26	500 for 200 generations

4. Conclusions

The outcomes derived from the integration of Bellman and genetic algorithm (GA) optimization techniques for the Lamhiriz case demonstrate great promise. This hybridized approach, termed 'Improved GA Management', exhibits notable enhancements across various performance metrics. The proposed Improved GA Management resulted in a significant cost reduction of at least 4% across various scenarios, highlighting the effectiveness of our strategy in optimizing energy resource allocation.

Moreover, the positive environmental impact of these improvements is evident as GHG equivalent emissions have been significantly reduced. This reduction underscores the potential of our Improved GA Management to lower the carbon footprint of energy operations, contributing to a more sustainable energy solution.

Additionally, the computational time required for the Improved GA Management approach is noteworthy, taking only 500 s for 200 generations, which is approximately 25% less time compared to individual GA and Bellman algorithms.

Furthermore, the Hybrid Genetic Algorithm proves to be the most effective Energy Management System (EMS) for the gas turbine, achieving a significantly reduced power usage of up to 59%. This highlights the potential of the Hybrid Genetic Algorithm in enhancing microgrid system performance and promoting sustainable energy solutions via optimal power resource allocation and improved efficiency.

Author Contributions: F.Z.Z. performed the simulations for Genetic Algorithm and Rule-Based Management and wrote this paper as the first author. M.E.-t. performed the simulations for Bellman Optimization and RBMS as the second author. H.E.C. performed the simulations for Bellman Optimization and RBMS as the third author. H.O. guided the design and analysis as the fourth author. B.E. helped in funding the paper as a fifth author. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflict of interest.

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