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Mean-Guided Elite Selection Genetic Algorithm for Multi-Objective Optimization of Operational Costs and Voltage Control in Grid-Connected Microgrids

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ABSTRACT

This paper presents a bi-objective optimisation approach for grid-connected microgrids, aiming to minimise operational costs and voltage deviation at the connection nodes of distributed energy resources and loads. Existing research typically addresses these objectives separately, and the simultaneous consideration of economic performance and voltage deviation in grid-connected community microgrids with multiple generation resources remains in an early stage of development. To advance the research in this area, a novel mean-guided elite selection genetic algorithm (MGES-GA) is proposed to enhance the balance between convergence and diversity in multi-objective optimisation. The proposed algorithm enhances the selection process by re-evaluating low-performing individuals through gene mixing with elite solutions, thereby preserving diversity and avoiding premature convergence. Comparative analysis of the MGES-GA with the enhanced genetic algorithm, differential evolution with heuristic, and improved differential evolutionary optimisation algorithms demonstrates its superior performance in optimising the economic dispatch of a grid-connected microgrid. In a bi-objective comparison with state-of-the-art algorithms, tested on a modified IEEE European low-voltage test feeder and IEEE 33-bus network, MGES-GA demonstrates its effectiveness in balancing conflicting objectives by producing lower voltage deviations at comparable or lower costs.

1 | Introduction

Urban development is rapidly evolving, placing increased pressure on traditional power infrastructures, which often struggle to meet modern energy demands. Frequent power outages and rising electricity costs underscore the need for more flexible, cost-effective, and environmentally sustainable energy systems [1]. Community microgrids have emerged as a promising solution, offering small-scale, decentralised power systems that can generate and manage local renewable energy sources (RES) while minimising transmission losses and associated costs.

When connected to the main grid, community microgrids must ensure stable operation by balancing power supply and demand, maintaining voltage levels within acceptable limits, and addressing economic considerations, such as energy pricing. By considering the dynamic electricity pricing, the problem becomes even more complex. Therefore, the microgrid's Energy Management System (EMS) plays a vital role in meeting these goals by identifying optimal solutions within technical and economic constraints.

The literature abounds with optimisation techniques for power flow optimisation in microgrids, and researchers are continuously striving to improve existing ones by considering different scenarios or complementing the objective functions with additional parameters that define the microgrids' operation. However, in modern microgrids, the optimal power flow (OPF) can be conducted by managing the load, known as demand-side management (DSM). The EMS controls the generation, storage, and load, and it can adjust the controllable loads in real time to optimise system performance alongside generation and storage resources. This is achieved by controlling, shifting, or curtailing electricity consumption to match the generation availability [2].

Most research investigates how to implement different strategies to optimise microgrid operational costs, power losses, and voltage deviations by managing the power demand. In [3], the authors conducted a comparative analysis of two different incentive-based demand response (DR) policies for load curtailment. The first policy employs a price elasticity matrix to incentivise customers to reduce consumption during peak hours, while the second policy focuses on compensating customers for load shedding during peak periods. The research conducted in [4] recommends a combined intellect method that considers carbon tax as a constraint for lowering the pollutant emissions and lowering the total costs of employing loads in a microgrid.

Another addition to the complexity of the modern microgrids are the electric vehicles (EVs), which serve as flexible loads or distributed energy storage systems. In order to maintain stability and meet economic objectives, EMS controls the EVs by providing a charging and discharging schedule. Additionally, the EMS determines when the EVs should shift their load, ensuring that both economic and technical objectives are met. The research conducted in [2] and [5] introduces a hybrid DSM approach that combines load shifting and load curtailment strategies to optimise the operation of a microgrid integrated with plug-in hybrid electric vehicles (PHEVs). In [6], a double-layer optimisation framework to minimise the total operating costs of a low-voltage grid-connected microgrid system is presented. The study considers the integration of EVs of varying sizes and their impact on microgrid operation. The research conducted in [7] introduces a hybrid demand-side policy that combines load shifting and curtailment strategies with a smart charging approach for PHEVs.

In [8], an innovative EMS that integrated both supply-side management and DSM is introduced. The DSM optimises load scheduling based on the electricity pricing, while the supply-side management determines the power generation from the photovoltaic (PV) system, energy storage system, and the utility grid. Using the particle swarm optimisation (PSO), the electricity costs and the peak-to-average ratio are decreased.

The research conducted in references [9–13] shows that PSO and genetic algorithm (GA), along with its variations and hybrids with other optimisation techniques, are the most commonly used optimisation techniques for solving the OPF problem. Studies indicate that GA often yields higher quality solutions, exhibits low variability across iterations, and quickly converges to optimal results [14]. For instance, in comparative studies such as [15], GA outperforms PSO in solution quality, although PSO typically converges faster. Additionally, GA offers greater flexibility in selecting and tuning hyperparameters, making it well suited for complex optimisation problems, as confirmed in multiple studies, including [16].

The literature review indicates that the primary objective of OPF research, regardless of the optimisation technique employed, is the minimisation of operational costs, the minimisation of gas emissions, or voltage/frequency variations. The analysis conducted in [9] shows that GA, or its hybrids with other optimisation algorithms, is still among the most commonly used for energy management and optimisation of diverse objectives regarding microgrids, indicating that using GA for the optimisation of microgrids is not a novelty. However, this demonstrates the flexibility and adaptability of GA to different optimisation problems.

In [17], an improved GA (GA + PSO) is presented, which uses elite thinking and catastrophe thinking to optimise the selection operation. Elitism preserves the most advantageous traits from one generation to the next, while the catastrophe approach aims to eliminate the top-performing individuals if they remain unchanged after multiple iterations. The combination of these two approaches ensures avoiding local optima. The proposed algorithm optimises operational costs and scheduling between microgrids in multi-microgrids. Reference [18] proposes the dragonfly algorithm for minimising the operational costs of grid-connected microgrids by integrating the demand response program (DRP) into the EMS. The algorithm is tested on an enhanced IEEE 34-node test system.

The research conducted in [19] proposes an improved adaptive GA (AGA) for optimisation of grid-connected microgrids with RES and a standalone diesel generator (DG) system. The algorithm dynamically adapts mutation and crossover rates to avoid premature convergence, ensuring better exploration and exploitation of the solution space. The EMS aims to minimise operational costs, reduce emissions, and enhance reliability by scheduling resources effectively. In [20], an efficient heuristic-enhanced differential evolution (DE) approach is proposed for operational costs optimisation considering the energy storage degradation costs in community microgrids. The study balances economic operation, renewable integration, and grid interaction. Simulations are carried out under different operating conditions, and results show that the proposed method enhances cost savings, renewable penetration, and energy efficiency compared to conventional strategies. In [21], a detailed comparative study and multi-objective optimisation of AC and DC power system structures using a multi-objective particle swarm optimisation (MOPSO) algorithm are presented. The study aims to minimise total network cost while maximising system availability by determining the optimal capacity and configuration of system components. By analysing both AC and DC architectures under different operational scenarios, the authors highlight the trade-offs between cost, reliability, and efficiency. In [22], an improved multi-objective improved differential evolutionary (IMODE) optimisation algorithm is applied for multi-objective optimisation with various equality and inequality limitations for lowering operational costs and environmental pollution effects of microgrids. The algorithm is tested on multiple different situations regarding the power limitations of trading with the grid and RESs engagement.

The research conducted in [23] proposes an improved biogeography-based optimisation algorithm to optimally size and operate a battery energy storage system (BESS) within a microgrid with wind energy penetration. The objective is to minimise the total cost (capital and operational) while respecting battery health constraints (depth of discharge and lifespan) and ensuring supply–demand balance over hourly intervals. Through simulation of three scenarios which consider no BESS, a fixed-size BESS, and an optimally sized BESS, the authors show that a 150 kWh battery yields the best trade-off, significantly reducing operating costs compared to a fixed 100 kWh battery.

In [24], a novel framework for minimising voltage deviation and operational costs in active distribution systems based on multi-agent deep reinforcement learning is proposed. The research proposes a multi-agent twin delayed deterministic policy gradient (MATD3) for solving the complex optimisation problem that addresses key issues such as renewable intermittency, economic operation, and system reliability. The authors propose an optimisation-based control strategy that schedules power flow among different resources while considering grid interactions. Reference [25] introduces a simultaneous economic dispatch (ED) and OPF optimisation framework. The study optimises the allocation of the generation units to minimise the operational costs while ensuring system stability and power balance, using the mixed-integer non-linear programming (MINLP). In [26], a multi-objective framework for day-ahead scheduling is presented. The study uses a quantum-inspired particle swarm optimisation (QIPSO) approach to simultaneously minimise costs and emissions. In [27], a two-stage framework for managing modern distribution networks is presented. In the first stage, the operational costs are optimised for consumers that participate in the distribution network operator (DNO), while the second stage involves a multi-objective optimisation for minimisation of power losses, voltage deviation, operational costs, and gas emissions using a combination of technique for order of preference by similarity to ideal solution (TOPSIS) and elephant herding optimisation (EHO) techniques. In [28], the imperialist competitive algorithm and GA are used for optimisation of voltage deviations in microgrids through the DR strategy. The study suggests managing load based on electricity prices and voltage deviation at the nodes. However, the study does not investigate the power balance and operational costs in the microgrid. The study conducted in [29] used combined GA and model-predictive control (MPC) to minimise the cost of energy and power imported from the grid. In [30], an EMS for an islanded microgrid, equipped with PV panels, fuel cells (FCs), microturbine (MT), and gas engine (GE), is presented. The study uses mixed-integer linear programming (MILP) for simultaneous optimisation of operational costs and voltage deviations. The cost functions include operational costs of DER units for generation of active and reactive power and costs of RES power generation and load-shading expenses. In [31], a MILP approach is used to reduce the operating costs, considering energy losses, environmental impacts, and DR in microgrids. The study incorporates multiple generation sources, including PVs, wind turbines (WTs), FC, MT, DGs, and BESS. The study analyses microgrids working in both grid-connected and islanded mode. The multi-objective optimisation focuses on ED, determining the optimal operating capacity of power generators and storage systems. The study considers voltage levels as one of the constraints. In [32], the joint minimisation of operational cost and voltage deviation in grid-tied unbalanced microgrids, incorporating distributed generation (PV, DG, and WT), battery systems, and EVs, is analysed. Their contribution lies in applying a ladder spherical evolution (LSE) search algorithm to this multi-objective problem while modelling the system with a full 3-phase unbalanced power flow framework, thereby capturing more realistic network constraints. The approach explicitly deals with uncertainties in generation and load, and the authors report that their method achieves substantially lower costs compared to alternative metaheuristic approaches. The research conducted in [33] proposes a novel multi-objective optimisation framework for EV-integrated distribution grids, addressing challenges such as energy losses, procurement costs, load shedding, and voltage deviations. The model proposed employs the hiking optimisation algorithm (HOA), which utilises an adaptive search mechanism based on Tobler's hiking function to enhance exploration and avoid local optima. Simulations on an IEEE 33-bus distribution grid demonstrate that integrating EVs leads to a reduction in operational costs, a decrease in energy losses, a reduction in load shedding, and an improvement in voltage deviations compared to scenarios without EVs. The paper [34] aims to optimise the voltage fluctuations and power losses caused by integrating RES into the power grid. On the demand side, the integrated coordination of DR following time-of-use electricity prices, on-load tap changers, and switched capacitor banks in a flexible interconnected distribution network maximises the consumers' satisfaction, while load variance is minimised. Using a fuzzy-transitive-closure method (FTCM) to segment periods and a multi-objective NSGA-II optimiser, the authors aim to minimise both operating costs and voltage deviation. In this way, the paper aims to construct a demand–supply coordinated optimal scheme for interconnected distribution networks.

A summary of related studies is presented in Table 1, highlighting the optimisation techniques employed, the objectives considered, and the types of distributed energy resources (DERs) and test systems used. From the presented, it can be concluded that the OPF problem in microgrids is analysed from many different aspects, applying different optimisation techniques, including simultaneous optimisation of operational costs and emissions, optimisation of operational costs including DRP and optimisation of operational costs and voltage deviations. The majority of the work is applied on low-voltage toy microgrids or the IEEE 33-bus system, without consideration of European low-voltage feeders that better reflect community microgrid configurations. Additionally, the research that proposes a multi-objective optimisation of operation costs and voltage deviations is limited to a small number of DERs incorporated.

To address this gap in the literature, the present study introduces an MGES-GA approach that jointly optimises costs and voltage deviations, incorporates a wide range of DERs (PV, WT, FC, MT, BESS, and power grid trade), and applies the methodology on a modified IEEE European LV feeder, as well as the IEEE 33-bus network.

The MGES-GA enhances traditional GA by selecting top-performing individuals for breeding while also re-evaluating the lower performing individuals to preserve population diversity and mitigate premature convergence. The proposed algorithm is built upon the enhanced genetic algorithm (EGA) that was presented in [35], by refining the selection mechanism to improve diversity and convergence of the optimisation process.

The proposed optimisation method is applied to a representative microgrid incorporating PVs, WTs, BESS, an FC, and an MT.

TABLE 1 | Literature review.

Ref.	Optimisation method	Objective(s)		System/ case study	RES considered	Main contributions
		Cost optimisation	Voltage optimisation			
[17]	Improved GA and PSO	✓	✗	Grid-connected multi-microgrid	PV, WT, BESS	Introduces elite and catastrophe thinking for selection optimisation
[19]	Improved AGA	✓	✗	Grid-connected microgrid	PV, WT, BESS, DG	Minimisation of microgrid operational costs through energy allocation and utilisation. There is a voltage controller on the DC and AC bus bar
[20]	DE-H	✓	✗	Grid-tied hybrid system	PV, WT, BESS, FC, MT	Proposes multi-objective optimisation considering the impact of the battery degradation on the operation costs
[21]	MOPSO	✓	✗	Residential microgrid	PV, WT, BESS	Optimisation considers the operation costs of the RES and their availability
[22]	IMODE	✓	✗	Typical low-voltage grid-connected microgrid	PV, WT, BESS, FC, MT	Simultaneous optimisation of costs and emissions is performed, considering various equality and inequality limitations
[24]	MATD3	✓	✓	IEEE 33-bus and 69-bus distribution networks	PV, WT, BESS, DG	Proposes a framework for optimising power management of BESS and DGs to reduce dependency on the external grid and ensure voltage stability
[25]	MINLP	✓	✓	Single-bus islanded and three-bus grid-tied microgrids	PV, WT, BESS, CHP, DG, Natural gas unit	Proposes a framework for joint ED and OPF, analysing active and reactive power through busses and maintaining voltage stability
[26]	QIPSO	✓	✗	Grid-connected microgrid	PV, WT, BESS, FC, MT	Proposes a novel PSO-based algorithm for balanced cost and emission reduction
[27]	TOPSIS and EHO	✓	✓	IEEE 33-bus network	PV, WT, DG	Implements DRP for maximising DNO profit and customers' power curtailment, and multi-objective optimisation to reduce energy losses, voltage deviation, total operational cost, gas emissions, and maximise the voltage stability index
[29]	GA and MPC	✓	✗	Hybrid microgrid	PV, WT, BESS, FC	Cost optimisation and reducing the carbon footprint, considering battery degradation and reduced resilience on the main grid

(Continues)

Ref.	Optimisation method	Objective(s) Cost optimisation	Objective(s) Voltage optimisation	System/ case study	RES considered	Main contributions
[30]	MILP	✓	✓	Islanded microgrid	PV, WT, MT, FC, GE	Multi-objective optimisation of voltage deviations, operational costs, and pollution. The method aims to minimise the absolute magnitude of the expected voltage fluctuations compared to the steady-state values before power fluctuations occur
[31]	MILP	✓	✗	Islanded and grid-connected microgrids	PV, WT, BESS, FC, MT, DG	The multi-objective optimisation focuses on minimising the operating costs and optimising the storage capacity
[32]	LSE	✓	✓	Grid-tied unbalanced microgrids	PV, WT, BESS, DG, EV	Considers two objective functions for the minimisation of the operating costs and the minimisation of voltage deviations of small-scale grid-connected unbalanced microgrids
[33]	HOA	✓	✓	IEEE 33-bus network	PV, WT, BESS, DG, EV	Multi-objective optimisation that combines to minimise the overall operational cost, which includes energy losses, electricity purchase, load shedding, distributed generation, energy storage, and electric vehicle operation, all over 24 h
[34]	FTCM and NSGA-II	✓	✓	IEEE 33-bus network	PV, WT, capacitor banks	Coordinated demand–supply optimal operation considering DR on the consumers' side and operational costs and voltage deviation minimisation on the supply side
[35]	EGA	✓	✓	Grid-connected microgrid, IEEE European low-voltage network	PV, WT, BESS	Simultaneous optimisation of operational costs and voltage deviations, considering a small-scale grid-connected microgrid with prosumers
Present work	MGES-GA	✓	✓	IEEE European low-voltage network, IEEE 33-bus network	PV, WT, BESS, FC, MT	Proposes a novel selection method for GA. Multi-objective optimisation considering operational costs and voltage deviations

The EMS oversees energy transactions with the grid, determining whether to store or sell excess energy and whether to draw from the grid or the BESS during shortages, all while maintaining voltage stability at key nodes, including the point of common coupling (PCC).

Comparative results with EGA and DE with heuristic (DE-H) demonstrate the superiority of MGES-GA. It achieves cost reductions of 4.16% and 3.19% relative to DE-H and EGA, respectively, while also producing more stable voltage profiles. This confirms MGES-GA's effectiveness in addressing the dual objectives of operational cost minimisation and voltage control in complex grid-connected community microgrid systems.

The main contributions of this research can be summarised as follows:

1. A new variant of the GA is proposed, incorporating a re-evaluation selection mechanism that enhances population diversity by allowing low-performing individuals to mix genes with elite solutions. This addresses premature convergence and improves exploration of the solution space.
2. The algorithm is applied to the simultaneous optimisation of operational costs and voltage deviations in grid-connected microgrids, integrating both economic and technical objectives that are often studied independently.
3. The method is verified by a comparison with state-of-the-art optimisation algorithms (EGA, NSGA-II, DE-H, and IDE) for a single-objective optimisation and with (EGA, NSGA-II, and MATD3) for a bi-objective optimisation.
4. The algorithm is implemented on a modified IEEE European low-voltage feeder representing a community microgrid with multiple distributed generation and storage resources, extending beyond the standard IEEE radial feeders commonly used in the literature.
5. The algorithm is also tested on a modified IEEE 33-bus system benchmark to analyse its performance on a larger system.

2 | The Problem Definition

Today's microgrids consist of many different generators on RES (PVs, WTs, hydro, biomass, etc.), consumers and prosumers, as well as storage systems (batteries, hydro-pumped storage, and hydrogen storage) and backup generators (DGs, FCs). This means that the microgrids could be either quite simple or very complex systems that require proper management to operate in balance with themselves and with the power grid to which they are connected. Complex systems have multiple variables that need to be considered in the optimisation process. Chief among these is the need to simultaneously minimise operational costs and maintain voltage stability across the system. These two objectives often conflict, making their joint optimisation a complex, multi-objective problem. Additionally, the intermittent nature of RES and dynamic pricing schemes further complicate energy management. Therefore, an EMS is a crucial part of the microgrid's stable and balanced operation, enabling optimal usage, storage, and trade with the power grid while meeting all relevant constraints [36].

This paper analyses the OPF problem of a grid-connected microgrid that consists of PVs and WTs, an FC, an MT, and a BESS. The microgrid trades power with the power grid under defined conditions and electricity prices. To solve this problem, a mean-guided elite selection genetic algorithm (MGES-GA) is proposed. The proposed algorithm considers individuals with fitness scores higher than the population's average fitness value to go directly into the next phase. This explains the mean-guided part of the algorithm's name. Those with values below the average are re-evaluated via recombination with the elite individual. The offspring with the highest value that also surpass the average threshold proceed to the next generation; otherwise, they are discarded. Therefore, the name "elite selection" appears as part of the algorithm's name. This double-stage selection improves the diversity of the population by preserving the high-quality solutions and improving the quality of the individuals with poor fitness values.

3 | Problem Solution and Proposed Algorithm

3.1 | Definition of Objective Functions

The algorithm integrates two functions: (f_1), the cost function that minimises the costs of the microgrid's operation, and (f_2), the voltage drop function that minimises the voltage drop in the PCC, presented with Equations (1) and (2).

$$f_1 = \min\left\{\sum_{i=1}^{T}\left(\left(C_i\left(P\right) + C_i\left(Q\right)\right)\Delta t\right)\right\} \tag{1}$$

$$\begin{gathered} f_2 = \min\left\{\left(\frac{P_i}{V_\mathrm{r}}\cdot r + \frac{Q_j}{V_r}\cdot x\right)\cdot l - \Delta V\right\}, \\ \forall t \in [1, \mathrm{T}],\ \forall i\ [\mathrm{PV,\ WT,\ bat,\ FC,\ MT, grid, load}], \\ j \in [\mathrm{WT, grid}] \end{gathered} \tag{2}$$

The optimisation employs the weighted-sum method to define the correlation between the two objective functions, as shown in Equation (3).

$$g = \min\left(f_1, f_2\right) = w f_1 + (1 - w) f_2,\ \forall w \in [0, 1] \tag{3}$$

The cost function considers the microgrid's revenue from selling power to the power grid when there is excess power and the revenue from power production from the PVs, WTs, FC, MT, and the battery discharging, while the costs for the microgrid's operation include charging the battery and buying power from the power grid, as shown in Equation (4). Equations (5)–(8) present how each of these costs is calculated.

$$C_t\left(P\right) = \sum_{i=1}^{N_\mathrm{RES}} C_{\mathrm{RES},i,t} + C_{\mathrm{grid},t} + \sum_{i=1}^{N_\mathrm{DG}} C_{\mathrm{DG},i,\ t} + C_{\mathrm{bat},t},\ \forall t \in [1, \mathrm{T}] \tag{4}$$

$$\sum_{i=1}^{N_\mathrm{RES}} C_{\mathrm{RES},t} = P_{\mathrm{pv,t}}\cdot c_\mathrm{pv} + P_{\mathrm{wind,t}}\cdot c_\mathrm{wind},\ \forall t \in [1, \mathrm{T}] \tag{5}$$

$$C_{\mathrm{grid},t} = \begin{cases} P_{\mathrm{grid},t}\cdot c_\mathrm{buy}, & P_{\mathrm{grid},t} > 0 \\ P_{\mathrm{grid},t}\cdot c_\mathrm{sell}, & P_{\mathrm{grid},t} < 0 \\ 0, & P_{\mathrm{grid},t} = 0 \end{cases},\quad \forall t \in [1, \mathrm{T}] \tag{6}$$

$$\sum_{i=1}^{N_{\mathrm{DG}}} C_{\mathrm{DG},t} = \left(\frac{P_{\mathrm{FC}}}{\eta_{\mathrm{FC}}} c_{\mathrm{run,FC}} + P_{\mathrm{FC}} c_{\mathrm{maint,FC}}\right) + \left(\frac{P_{\mathrm{MT}}}{\eta_{\mathrm{MT}}} c_{\mathrm{run,MT}} + P_{\mathrm{MT}} c_{\mathrm{maint,MT}}\right),\ \forall t \in [1, \mathrm{T}] \quad (7)$$

$$C_{\mathrm{bat},t} = \begin{cases} P_{\mathrm{bat},t} \cdot c_{\mathrm{bat}}, & P_{\mathrm{bat},t} > 0 \\ P_{\mathrm{bat},t} \cdot c_{\mathrm{bat}}, & P_{\mathrm{bat},t} < 0,\ \forall t \in [1, \mathrm{T}] \\ 0, & P_{\mathrm{bat},t} = 0 \end{cases} \quad (8)$$

The battery can be charged only if there is excess power in the system and the SOC is below the maximum value; otherwise, it discharges. The SOC in each hour is calculated with Equation (9), whether the battery is being charged or discharged [37, 38].

$$\mathrm{SOC}(t+1) = \begin{cases} \mathrm{SOC}(t) + P_{\mathrm{bat},i}\eta_{\mathrm{ch}}, & P_{\mathrm{bat}} < 0 \\ \mathrm{SOC}(t) - \dfrac{P_{\mathrm{bat},i}}{\eta_{\mathrm{dis}}}, & P_{\mathrm{bat}} > 0 \\ \mathrm{SOC}(t) & P_{\mathrm{bat}} = 0 \end{cases} \quad (9)$$

The power balance in the microgrid depends on the power generation from the RES (PVs and WTs), BESS charge and discharge, power from the FC and MT, as well as the trading with the power grid, as described in Equation (10).

$$\sum_{t=1}^{T} (P_{\mathrm{pv},t} + P_{\mathrm{wind},t} + P_{\mathrm{bat},t} + P_{\mathrm{FC},t} + P_{\mathrm{MT},t} + P_{\mathrm{grid},t}) = \sum_{t=1}^{T} P_{\mathrm{load},t} \quad (10)$$

In this paper, it is assumed that the FC and MT can provide power at all times under defined costs. The voltage variation limits to the consumers are defined with Equation (11), and the voltage limits to the installed generators (PVs, WT, BESS, FC, and MT) are defined with Equation (12).

$$V_{\mathrm{load,min}} \le V_{\mathrm{load},i} \le V_{\mathrm{load,max}},\ \forall\, i \in [0, \mathrm{T}] \quad (11)$$

$$V_{\mathrm{DER,min}} \le V_{\mathrm{DER,\ n},i} \le V_{\mathrm{DER,max}},\ \forall\, i \in [0, \mathrm{T}] \ \wedge\ \forall\, n \in [\mathrm{PV,\ WT, bat,\ FC, MT}] \quad (12)$$

where $V_{\mathrm{load},i}$ denotes the voltage of the consumers that is located further from the PCC of the transformer station for each hour, and $V_{\mathrm{DERs},i}$ denotes the voltage in the nodes where each of the generators (PVs and WT), BESS, FC, and MT is connected. The voltage drop calculation is presented with (13).

$$V(t, i+1) = V(t, i) + \frac{\sum P_{\mathrm{i}}(t)\, rl + \sum Q_j(t)\, xl}{V_{\mathrm{r}}},\ \forall t \in [1, \mathrm{T}],\ \forall i\ [\mathrm{PV,\ WT,\ bat,\ FC,\ MT, grid, load}],\ j \in [\mathrm{WT, grid}] \quad (13)$$

3.2 | Genetic Algorithm Modification

This section describes the core structure of the MGES-GA. In Figure 1, the flowchart of the proposed algorithm is presented, and in Figure 2, a flowchart of the MGES-GA is shown.

3.2.1 | Initialisation

In the beginning, the algorithm retrieves data for the power consumption (load), power production from the PVs and WTs, and the battery's SOC. Additionally, the technical constraints are defined. Then, for each of the changing parameters, which include the power drawn from the FC, the MT, the BESS, and the interactions with the power grid, a hundred randomly generated values that are in the defined range are assigned. This phase is called the initialisation state.

3.2.2 | Fitness Evaluation

In the next step, each of the changing parameters is tested for the randomly assigned value on the optimisation functions with respect to the constraints. The results of how well each of the values of the changing parameters performed represent the fitness evaluation scores, which are scaled by rank scaling. The output of the optimisation are values for how much of the generated power by each of the distributed generators will be used to supply the consumers, how much power will be stored or taken from the battery, how much power will be generated from the FC and/or MT, and how much power will be traded with the grid.

3.2.3 | Selection

In the selection process, the individuals are being selected to serve as parents and generate the next generation, based on their fitness values, following defined selection criteria. In standard GA, individuals are often selected based on their fitness score following fitness-proportionate selection. That means that the fittest individuals have a higher chance to be selected, while the individuals with a lower fitness score may not be considered adequate to proceed to the breeding process.

In the proposed approach, the individuals with a fitness score higher than the population's average fitness value are promoted directly to the next phase. The remaining individuals, with values below the average, undergo a secondary evaluation. Specifically, each individual is paired with the elite individual, the one with the highest fitness score, to perform a single-point crossover. Then, among the two offspring created, the one with the higher value is selected and compared with the average value. If the offspring meets or exceeds the average fitness value, it proceeds to the next generation; otherwise, it is discarded. This strategy ensures that only high-rated individuals and individuals with sufficient improvement potential are kept, while promoting both convergence efficiency and population diversity.

3.2.4 | Crossover

After the selection process, the individuals that proceeded forward are subject to a crossover. In this paper, a scattered crossover is performed. This type of crossover suggests creating an offspring while taking the genes with value 1 from the first parent and the genes with value 0 from the second parent. The set of offspring s is called the children generation, and it is the generation

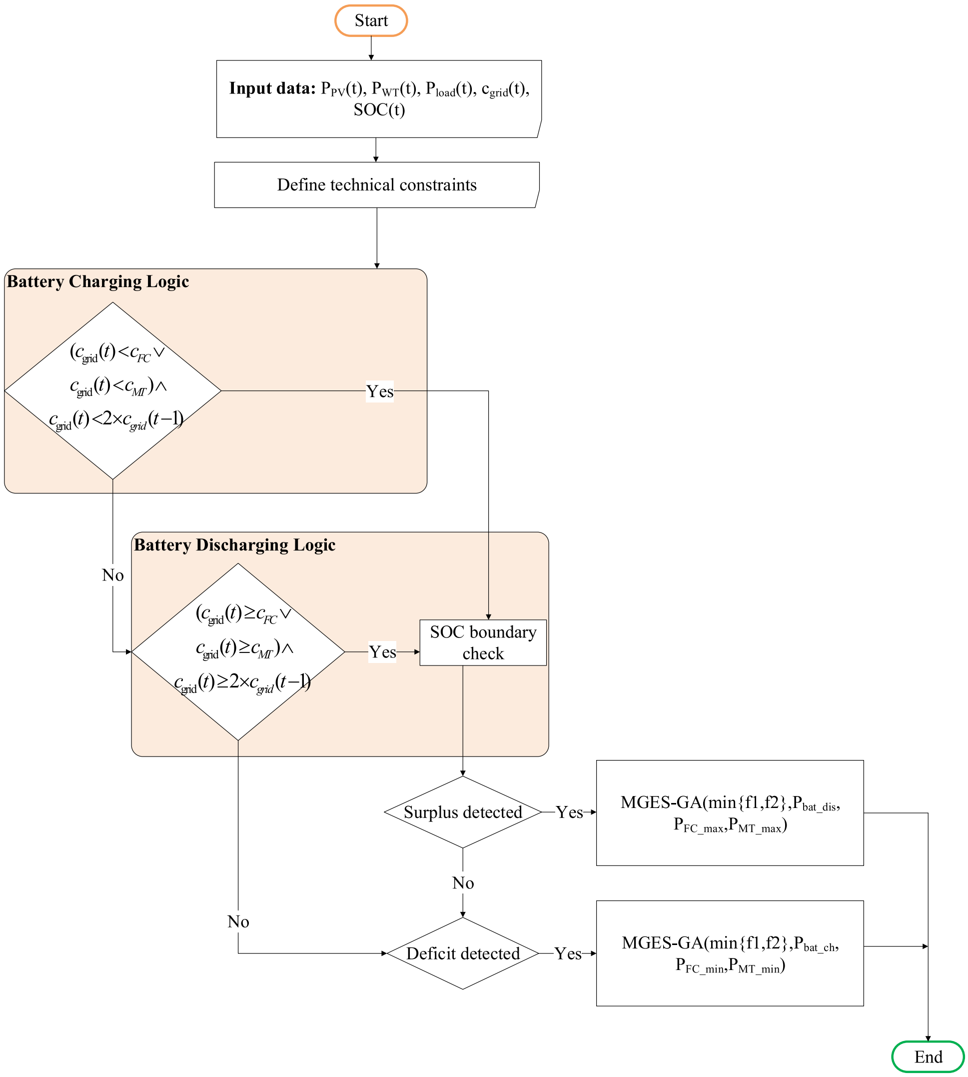

FIGURE 1 | Flowchart of the proposed algorithm.

that proceeds to the final phase where the optimal solution is conducted.

3.2.5 | Mutation

The children generation also consists of mutations. The mutations are created by some of the parents. In this paper, the mutation rate is 0.05. The value is selected for the utmost performance of the algorithm.

3.2.6 | Stopping Criteria

The algorithm stops performing when it reaches the maximum number of iterations or if the solution does not converge further.

4 | Simulation

The proposed optimisation methodology with an MGES-GA is tested on a grid-connected microgrid with PVs, WTs, FCs, MTs, and residential consumers. Additionally, a BESS, with a rated capacity of 222 kWh, supports the microgrid. The minimum and maximum capacities of the BESS are 40 and 200 kWh, respectively. At the beginning of the analysed period, the battery is set to the minimum value. The microgrid trades with the power grid under defined electricity prices, and the power exchange is limited to 50 kW of power sold and 100 kW of power bought from the grid. For testing purposes, it is assumed that the purchase and sale of electricity prices are the same.

The simulation analyses two benchmark systems to demonstrate the trend of MGES-GA performance. The simulation of the proposed system is analysed on an IEEE European low-voltage feeder in Section 4.1 and on the IEEE 33-bus network in Section 4.2.

4.1 | European Low-Voltage Test Feeder Simulation

The microgrid test data is taken from [20], and the grid topology is the modified IEEE European low-voltage test feeder, based on the one presented in [39]. The analysis considers a period of 24 h.

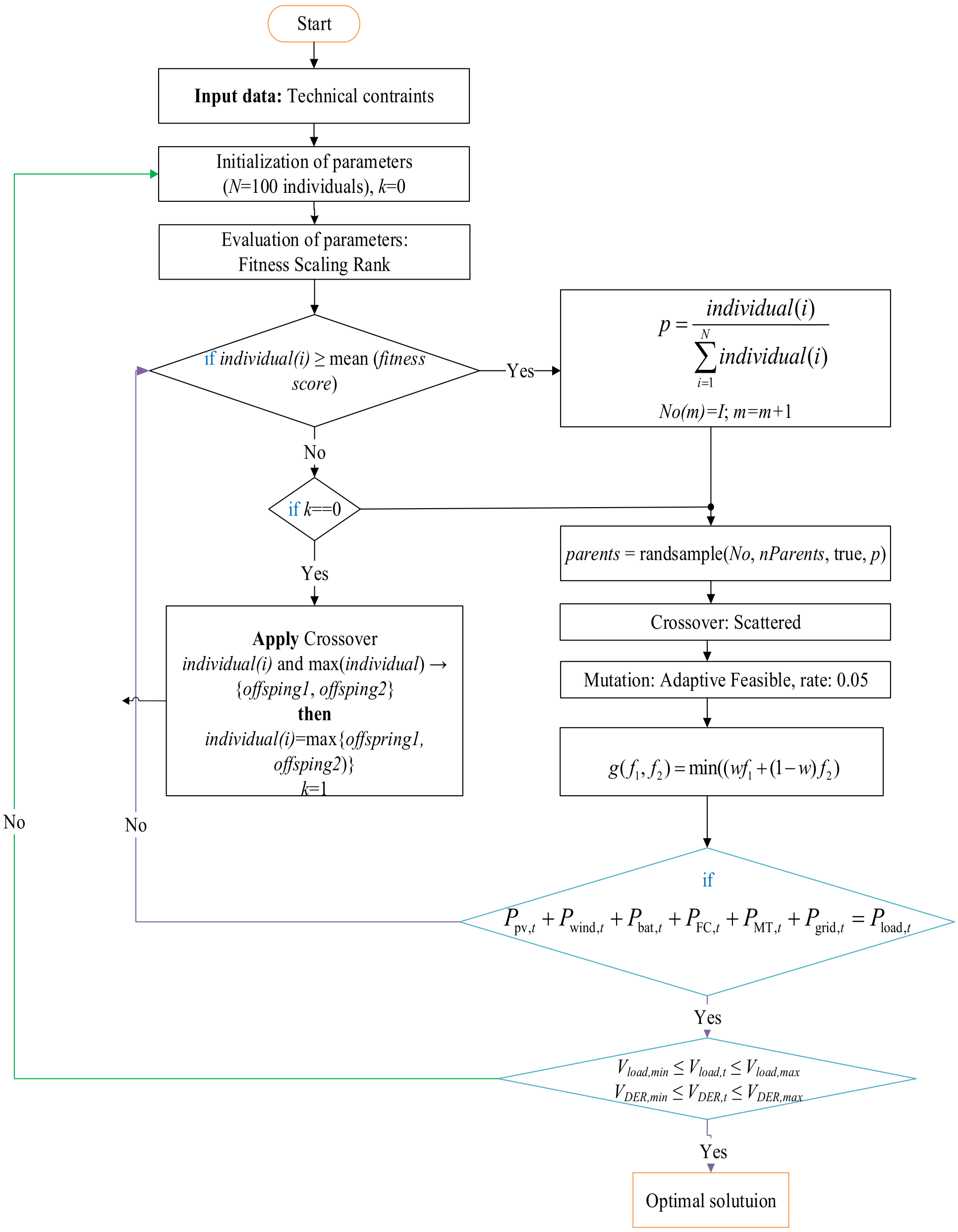

FIGURE 2 | Flowchart of the proposed modification of the genetic algorithm.

The microgrid test system, with nodes numbered according to the low-voltage test network, is presented in Figure 3.

The simultaneous charging and discharging of the BEES, as well as simultaneous buying and selling power to the grid, is not feasible. The EMS that controls the microgrid's operation, besides the initial input data, also receives real-time information about the system's performance and the electricity prices. The system's input data are presented in Figure 4, and the equipment's technical constraints and maintenance costs are presented in Table 2.

4.2 | IEEE 33-Bus Network Simulation

To evaluate the generalisability of the proposed MGES-GA, additional tests were performed on the modified IEEE 33-bus network, which includes a larger number of nodes and distributed generation units compared with the European LV test feeder.

The grid topology is based on the modified IEEE 33-node network presented in [24], which represents a symmetrical system with BESS, DERs, and DGs connected to multiple nodes. Additionally, the proposed algorithm was tested on the same topology, but instead of the DGs, FC and MT were placed as presented in Figure 5. The active power constraints and BESS capacity are given in Table 3. The analysis spans 24 h.

The input data for the power generated from the PVs and the WTs, as well as the load curve and electricity prices, are taken from [24] and presented in Figure 6. The electricity prices for purchasing electricity from the grid vary by the following scheme: 2.6369 THB/kWh from 22:00 to 9:00, and 5.7982 THB/kWh from

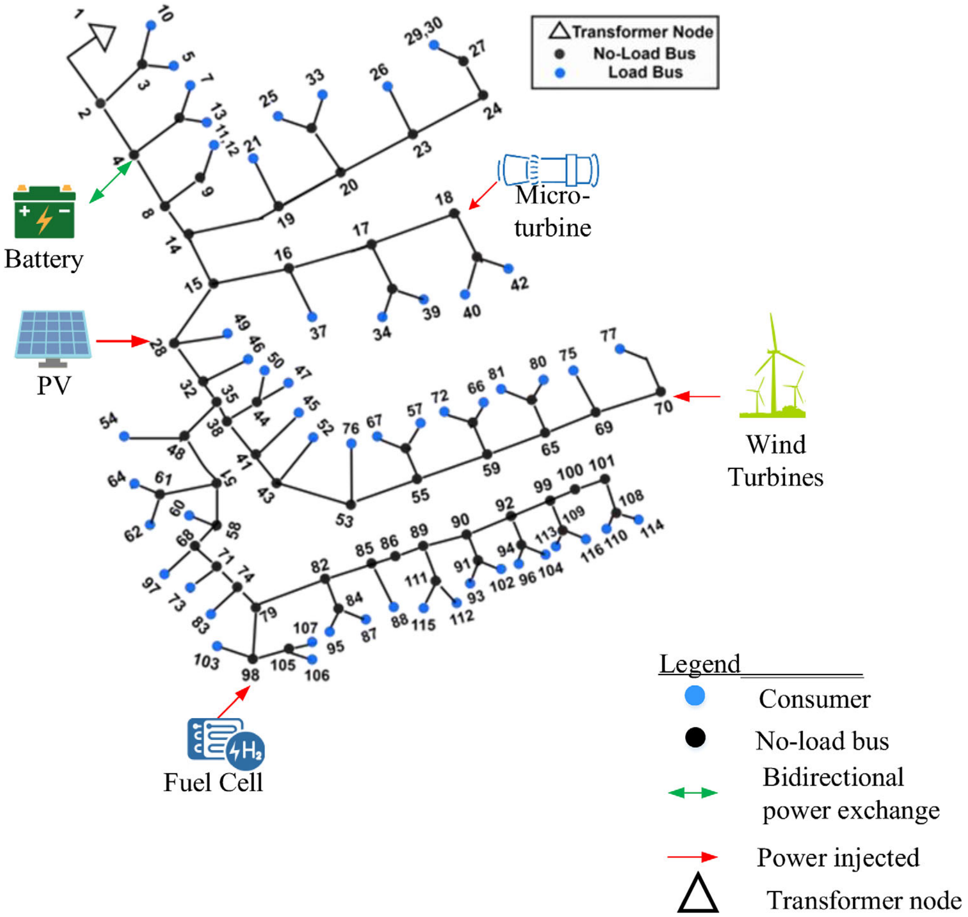

FIGURE 3 | Modified IEEE European low-voltage test feeder.

TABLE 2 | Technical constraints of the installed equipment.

Parameter	Min (kW)	Max (kW)	Operational cost (€ct/kWh) according to [20]	Maintenance cost (€ct/kWh) according to [20]	Cost ($/kWh) according to [22]
PV	0	25	—	0.08	2.584
WT	0	15	—	0.11	1.073
BESS	−30	30	—	0.02	0.38
FC	3	30	0.2	0.04	0.294
MT	6	30	0.4	0.12	0.457

TABLE 3 | DERs' active power and capacity at various nodes in the modified IEEE 33-bus system.

Type of DER		Total number of units	Node connection	Active power limits (kW)	Capacity (kWh)
BESS		6	(5,10,14,19,24,31)	[−1000,1000]	25,000
PV		4	(11,22,23,29)	[0,2609.07]	/
WT system		2	(6,32)	[0,235.61]	/
I variant	DG	2	(16,26)	[0,1000]	/
II variant	FC	1	(16)	[0,1000]	/
	MT	1	(26)	[0,1000]	/

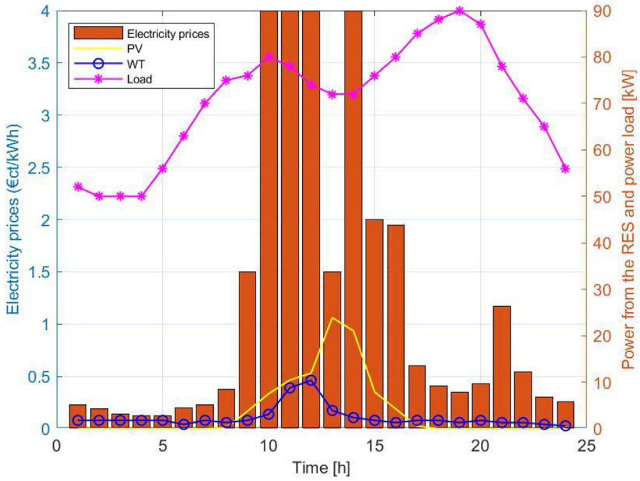

FIGURE 4 | System input data [20, 22].

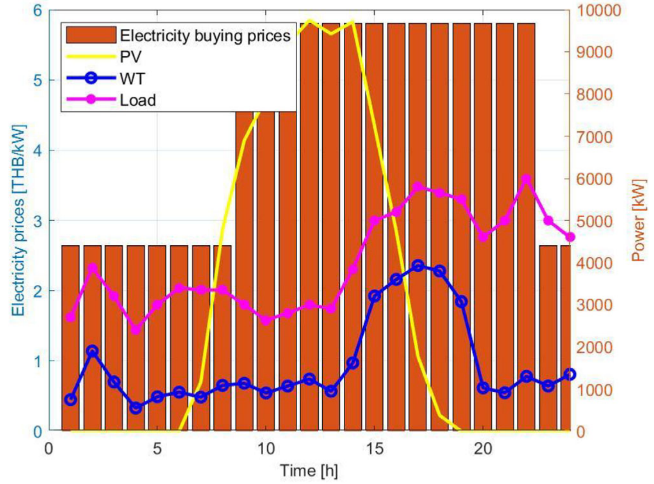

FIGURE 6 | Input data for PV and WT power generation, load, and electricity price variation.

9:00 to 22:00. The electricity selling price is fixed throughout the day, and it is 17.15 THB/kWh.

5 | Results and Discussion

5.1 | Results

5.1.1 | Single-Objective Function

The results obtained from the simulation of the MGES-GA are presented in Figure 7. The negative values for the battery indicate charging, and the negative values for the grid power indicate power being sold to the utility grid.

It can be concluded that when the price of electricity is lower than the costs for using power from the FC and MT, the microgrid buys power from the grid to satisfy the consumption and to charge the battery. In times of expensive electricity prices, and when buying power from the utility grid is the costliest solution, the microgrid sells the excess power to the grid and discharges the battery. However, when a sudden drop of price occurs, the microgrid buys power to satisfy the consumption and charge the battery for further usage and uses the least costly resources available (FC and/or MT).

Generally, electricity prices are lowest in the evenings, when the power consumption is also at the lowest point, and the proposed algorithm takes that into consideration. Therefore, by the end of the day, it tends to drain the battery to a minimum and start the next day (01:00 h) with an empty battery.

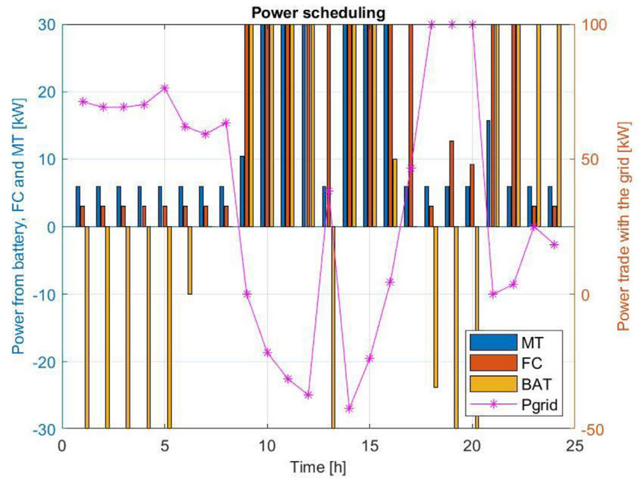

FIGURE 7 | Optimal economic dispatch of the microgrid, using MGES-GA.

In Table 4, the power traded with the grid and the total operational costs are presented. The results are compared with an enhanced version of GA that deals with the same microgrid optimisation problem, presented in [35], and a state-of-the-art differential evolutionary algorithm (DE-H), presented in [20],

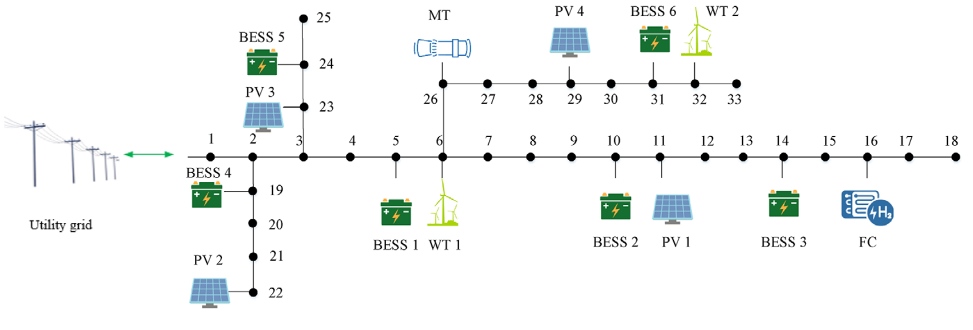

FIGURE 5 | Modified IEEE 33-node test system.

TABLE 4 | Comparison of the obtained results using MGES-GA, EGA [35], and DE-H [20].

Optimisation method	Fitness value (€ct)	Energy production cost (€ct)
MGES-GA	518.26	1096.08
EGA	545.05	1118.85
DE-H	550.6	1160.6

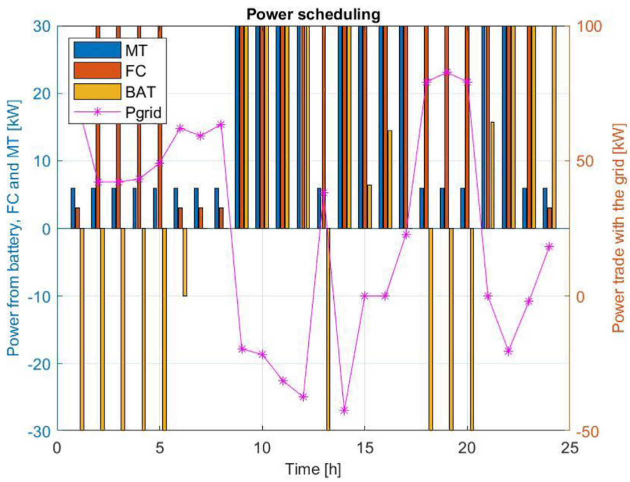

FIGURE 8 | Power scheduling using MGES-GA without limitations of upstream exchange.

that analyses energy production costs on a similar microgrid system. For a fair comparison with the DE-H algorithm, a single-objective function was considered, not taking into consideration the voltage variations.

Additionally, the study conducted in [22] evaluates a comparable microgrid system under two operational scenarios: one without limitations on upstream power exchange (from +100 kW to −50 kW) and another restricting grid power exchange to ±30 kW. The results from implementing the proposed MGES-GA on the system analysed in [22] are presented in Table 5, alongside those obtained with the IDE method for operational cost optimisation.

In Figures 8 and 9, the power scheduling when the upstream power exchange is not limited and when the upstream exchange is limited is presented, respectively.

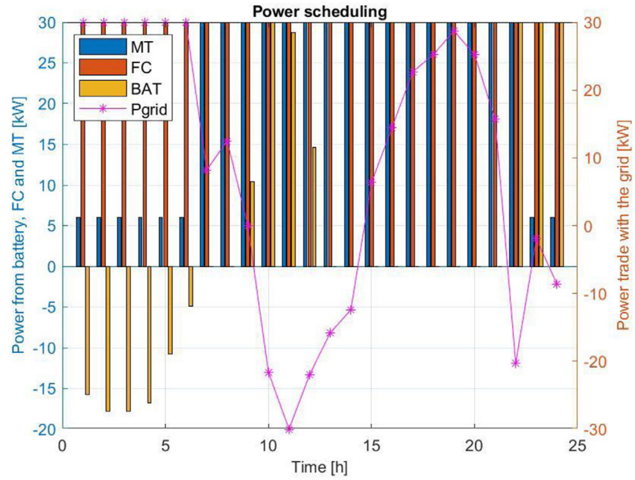

FIGURE 9 | Power scheduling using MGES-GA with limitations of upstream exchange.

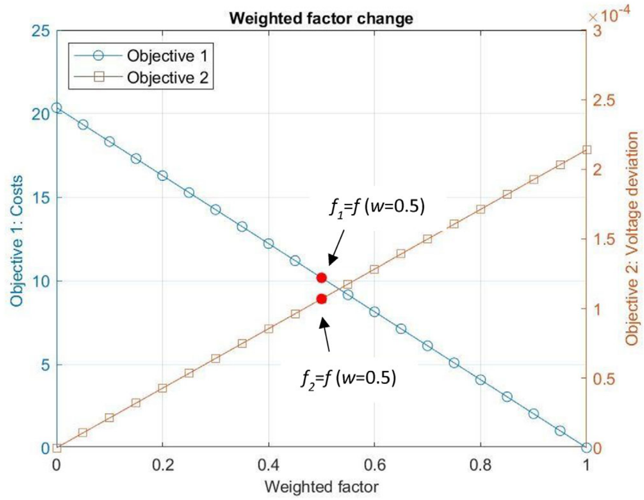

FIGURE 10 | Variations of the objective functions' values with respect to the weight factor w.

5.1.2 | Multi-Objective Optimisation

5.1.2.1 | IEEE European Low-Voltage Feeder. The multi-objective optimisation considers both the operational costs and voltage variations in the microgrid. Figure 10 illustrates the variation of the two objective functions, in correlation to the weighting factor w, used in the weighted-sum formulation. As the weight assigned to the cost objective increases, the resulting

TABLE 5 | Comparison of MGES-GA and IDE performance in operation cost optimisation.

Optimisation method	Without limitations of upstream exchange		With limitations of upstream exchange	
	Fitness value ($)	Standard deviation ($)	Fitness value ($)	Standard deviation ($)
MGES-GA	335.229	40.51	544.11	26.01
IDE	618.91	45.22	661.37	10.81

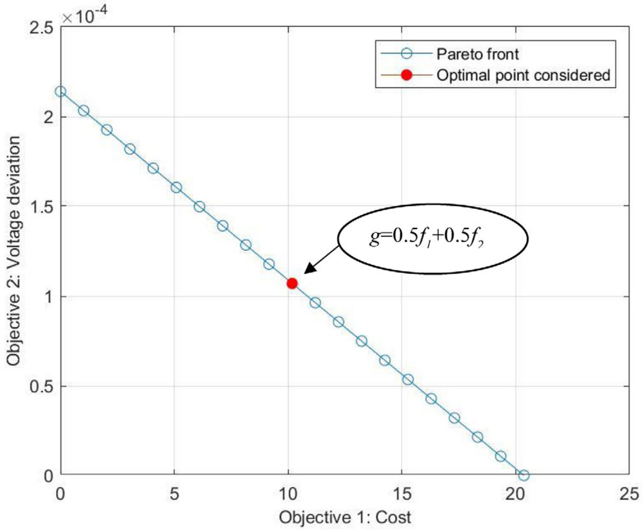

FIGURE 11 | Pareto front illustrating the trade-off between operational cost and voltage deviation obtained using the MGES-GA.

operational cost decreases accordingly, while the voltage deviation increases, demonstrating the expected trade-off between the two objectives. The point corresponding to $w = 0.5$ is highlighted, representing the balanced case in which both objectives contribute equally. This weight configuration is selected for further analysis, since it provides a representative compromise solution between economic efficiency and voltage quality.

The Pareto front when using MGES-GA is presented in Figure 11. The MGES-GA was executed for each weight value, which was varied from 0 to 1 in steps of 0.05. The resulting Pareto front presents the mean operational costs and mean voltage deviation from the 24-h analysis for each weight factor. The Pareto front appears linear due to the proportional relationship between operational cost and voltage deviation across the entire operating range.

Additionally, the proposed algorithm is compared with NSGA-II, as one of the most commonly used optimisation algorithms for microgrid optimisation. Figure 12 shows the Pareto front obtained when using MGES-GA, EGA, and NSGA-II independently. The three algorithms demonstrate the expected trade-off relationship, as lower operational costs are generally associated with higher voltage deviations. However, notable differences exist in the shape, spread, and smoothness of the Pareto fronts, reflecting each algorithm's convergence and diversity capabilities.

The results show that when using MGES-GA, there is lower voltage deviation (0.00022 or less); hence, there is better voltage stability compared to EGA, when the highest voltage deviation is 0.001, and NSGA-II, when the highest voltage deviation is 0.028.

Regarding the costs, the highest operation costs are obtained when using EGA, and the lowest when MGES-GA is applied. However, since the voltage deviation is significantly higher when using EGA, it can be concluded that MGES-GA outperforms EGA and NSGA-II.

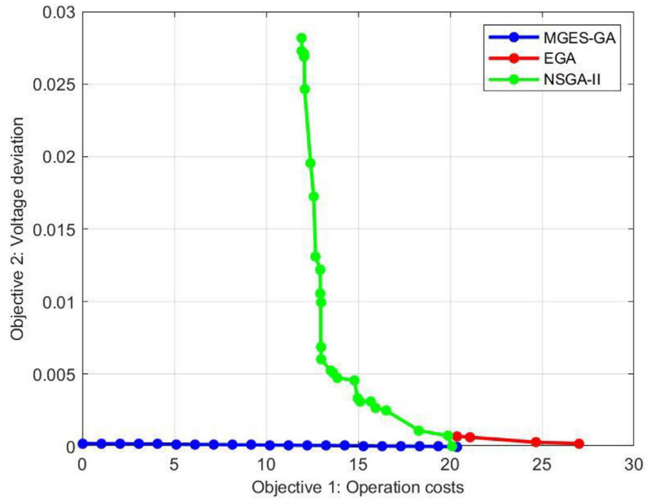

FIGURE 12 | Pareto front comparison between MGES-GA, EGA, and NSGA-II.

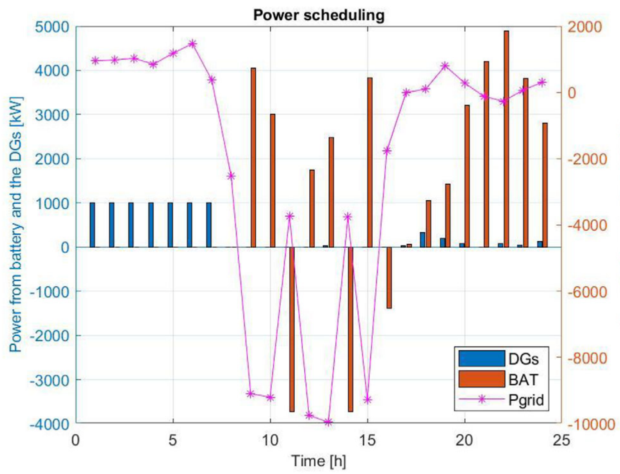

FIGURE 13 | Optimal DERs scheduling in an IEEE 33-bus system (with two DGs).

5.1.2.2 | IEEE 33-Bus System. The proposed algorithm was also tested on a more complex microgrid system on a benchmark IEEE 33-bus system, as the one presented in Figure 5. The performance of the MGES-GA is compared with the performance of MATD3 presented in [24], because its formulation addresses the same multi-objective microgrid scheduling problem on the modified IEEE 33-bus test system and uses similar objective functions and constraints (operational costs and voltage deviations). Therefore, MATD3 is directly comparable. The results from the simulation are presented in Tables 6 and 7, and the comparison shows that MGES-GA excels MATD3 in total system profit and average voltage deviation.

The results of power scheduling are presented in Figures 13 and 14, with DGs and with FC and MT units, respectively. It can be noted that during the high-tariff periods, the microgrid sells the excess power to the grid and does not engage the DGs and FC and MT units much during that period. Instead, the power stored in the battery is used to satisfy the power demand.

TABLE 6 | Comparison of the operation costs and system profit under two different optimisation methods.

Model	MATD3	MGES-GA (DGs)	MGES-GA (FC+MT)
Operational costs BESS (THB)	−32,038.99	−15,102	−16,411
Operational costs DGs (THB)	−25,968.71	−5197.9	/
Operational costs FC and MT (THB)	/	/	−5295.8
System profit (THB)	782,781.56	992,150.28	1,012,398.81
Total operation costs (THB)	−56,837.85	−20,270	−21,676
Total system profit (THB)	725,943.71	971,879.92	990,722.39

TABLE 7 | Comparison of the voltage deviations under different optimisation methods.

Method	Average voltage deviation (p.u.)	Standard deviation (p.u.)
MATD3	0.0042	0.0065
MGES-GA (DGs)	0.21×10^{-4}	0.2×10^{-5}
MGES-GA (FC+MT)	0.05×10^{-4}	0.023×10^{-5}

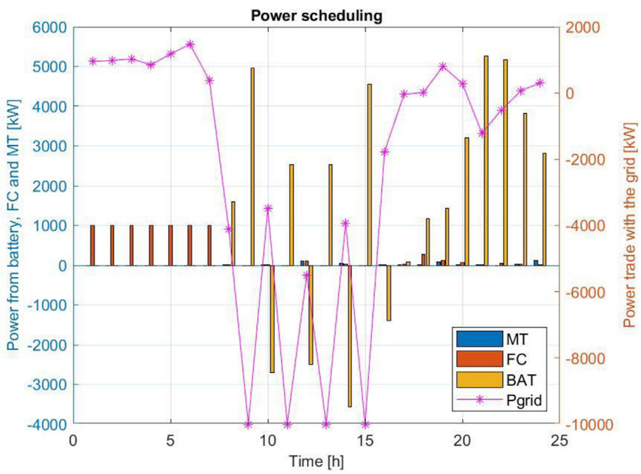

FIGURE 14 | Optimal DERs scheduling in an IEEE 33-bus system (with FC and MT units).

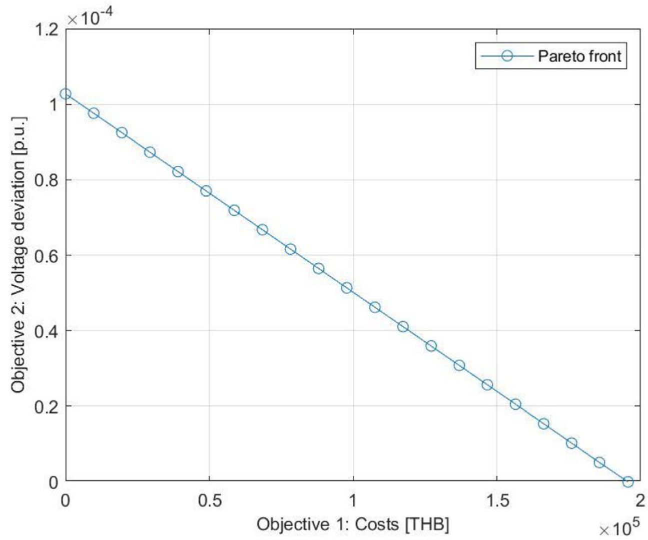

FIGURE 15 | Pareto front of MGES-GA tested on a modified IEEE 33-bus system.

Figure 15 represents the average Pareto front of the 24-h period when MGES-GA is applied to the modified IEEE 33-bus network. The resulting Pareto front shows a clear and continuous trade-off between the two objectives, demonstrating that MGES-GA preserves its convergence characteristics and ability to identify non-dominated solutions in a higher dimensional search space. The algorithm maintained stable performance with moderate increases in computational time, confirming its suitability for larger scale microgrid optimisation problems.

5.2 | Discussion of the Results

The results presented in Table 4 show that MGES-GA achieves improvement in the final solution, resulting in 5.87% and 4.9% lower fitness values compared to DE-H and EGA, respectively. This means that more power is sold to the utility grid and the consumption is mostly managed by the DERs connected to the microgrid. Additionally, MGES-GA reduces the energy production cost compared to the IDE algorithm, indicating that the proposed algorithm maintains competitive performance with the state-of-the-art algorithms in single-objective optimisation. However, since the primary goal of MGES-GA is to optimise both operational costs and voltage deviation, an additional comparison in bi-objective optimisation is performed. Results presented in Figure 12 show that MGES-GA ensures a more stable voltage for end-consumers and shows better performance than EGA and NSGA-II in this comparison by producing lower voltage deviations at comparable costs. This means that fewer voltage magnitude deviations are detected throughout the microgrid's nodes while maintaining the operation costs as low as possible.

The proposed algorithm was also tested on a modified IEEE 33-bus network, incorporating different types of DERs and a storage system. In comparison to the MATD3 algorithm, MGES-GA provides lower costs and voltage deviations, as shown in Tables 6 and 7. Additionally, the analysis of incorporating an FC and an MT, compared with the two-DG case scenario, shows an increase in total profit but, at the same time, an increase in costs and voltage deviation.

The overall results highlight the improvements MGES-GA provides, show its effectiveness as a multi-objective optimisation algorithm, and confirm its generalisability to larger, more complex microgrid systems.

6 | Conclusion

This paper presented a novel MGES-GA for the joint optimisation of operating costs and the voltage drop variations of the grid-connected microgrids. The primary objective is to maximise the internal use of RES, store excess generation efficiently, and minimise operational costs, while maintaining voltage within acceptable limits. Surplus energy is sold to the grid when storage is full, whereas energy deficits are resolved through cost-effective decisions between storage discharge and grid purchases. The key improvement in the proposed algorithm lies in its modification of the selection process. The improvement enables both the more competitive and less competitive individuals to reproduce the next generation, enhancing diversity and convergence while providing a better solution to the problem.

Simulation results on a modified IEEE European low-voltage test feeder show that MGES-GA performs better than both conventional and state-of-the-art algorithms in single-objective cost minimisation, achieving lower fitness values and reduced energy production costs while preserving the grid trading pattern. In the bi-objective case, in the comparative analysis of Pareto fronts, it can be concluded that MGES-GA delivers superior voltage regulation with lower operational costs compared to EGA and NSGA-II.

The proposed MGES-GA was further evaluated on a modified IEEE 33-bus distribution network and compared with the MATD3 algorithm reported for a similar case study. The results demonstrate that MGES-GA achieves improved results compared to MATD3 in both economic and technical performance by obtaining lower operational costs while maintaining smaller voltage deviations.

The comparative results between the base and extended test systems highlight the superior convergence and Pareto front diversity achieved by MGES-GA. These outcomes demonstrate its effectiveness in balancing conflicting objectives and its capacity to generalise well to larger, more heterogeneous microgrids.

Future work will extend the test system and evaluate the performance of the MGES-GA on larger networks, including EV integration and prosumers.

Nomenclature

g	objective function
f_1	operational costs function to be minimised
f_2	voltage drop function to be minimised
T	analysed period of time
Δt	time interval for data sampling
C	total costs of the microgrid
P_{PV}	power generated from the photovoltaic generator
P_{WT}	power generated from the wind generator
P_{bat}	power charged/discharged from the battery
P_{grid}	power bought/sold from/to the grid
P_{FC}	power discharged from the fuel cell
P_{MT}	power discharged from the microturbine
P_{load}	load of the consumers
Q	reactive power
η_{ch}	efficiency of charging the battery
η_{dis}	efficiency of discharging the battery
c_{pv}	costs for power generation from the photovoltaic generator
c_{wind}	costs for power generation from the wind generator
c_{grid}	costs for buying/selling the power to the grid
c_{bat}	costs for charging/discharging the battery
$c_{\mathrm{run,FC}}$	operational costs of the fuel cell
$c_{\mathrm{run,MT}}$	operational costs of microturbine
$c_{\mathrm{maint,FC}}$	maintenance costs of the fuel cell
$c_{\mathrm{maint,MT}}$	maintenance costs for microturbine
V_{r}	rated voltage
ΔV	permitted voltage drop
R	longitudinal active resistance, Ohms/meter
X	longitudinal reactance, Ohms/meter
L	distance between nodes
η_{FC}	efficiency of fuel cell
η_{MT}	efficiency of microturbine

Author Contributions

Natasha Dimishkovska Krsteski: conceptualization, software, formal analysis, investigation, methodology, writing – original draft, writing – review and editing. **Atanas Iliev:** supervision, validation, project administration, writing – review and editing.

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The authors have nothing to report.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data that support the findings of this study are openly available in IEEE DataPort at https://doi.org/10.21227/0d2n-j565 [39]. All results generated from these data are included in the manuscript.

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