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Research Article

Optimum Energy Management of Distribution Networks with Integrated Decentralized PV-BES Systems

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Abstract

This paper introduces an optimized method for reducing operational costs by integrating a microgrid consisting of photovoltaic (PV) panels and battery energy storage systems (BESS), thereby decreasing dependence on the main grid. Traditionally, electricity demands have been met primarily by the main grid. However, with the increased use of renewable energy sources and BESS in microgrids, it's now possible to lower generation costs, improve environmental sustainability, and enhance energy efficiency. In this study, the optimization problem is tackled using the SPEA2 algorithm, focusing on three main objectives: (i) minimizing technical issues like power losses and voltage fluctuations in the grid, (ii) maximizing financial returns for distribution network operators, and (iii) reducing grid imports. The paper provides a comprehensive set of numerical results, leveraging detailed data on energy demand, local solar irradiance, and energy storage systems to validate the proposed method. The obtained results, based on two case studies, confirm that the optimal energy combination between power units and the main grid at each time can reduce power losses, voltage deviation and improve financial returns. The results highlight also the added value of BESS integration in minimizing grid imports, especially during peak hours. It can be said that the results underscore the remarkable efficiency and effectiveness of the proposed approach, demonstrating its capability to address the targeted challenges while achieving optimal performance metrics.

Keywords

PV System, Battery Energy Storage System, Optimization, Microgrid, Energy Management

1. Introduction

In recent years, the surge in fossil fuel prices and growing concerns about climate change have driven society to re-evaluate its energy strategies. This shift has led to an increased emphasis on environmental impact assessments and a strong push towards the adoption of clean and efficient energy sources within power systems. The urgency of mitigating environmental damage has propelled the development of renewable energy technologies, such as wind and solar power, as viable alternatives to traditional fossil fuels. This transition not only addresses the environmental challenges but also aims to create a sustainable energy future for generations to come [1]. A microgrid, typically operating at low or medium voltage, functions as a localized energy system with a clearly defined electrical boundary. This boundary allows it to manage the distribution of power within a specific area, often encompassing a mix of residential, commercial, and industrial

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consumers. What makes a microgrid particularly innovative is its ability to integrate a variety of Distributed Energy Resources (DERs), such as solar panels, wind turbines, and energy storage systems, alongside traditional loads. By doing so, a microgrid not only enhances energy reliability and efficiency but also supports the transition towards a more sustainable and resilient power infrastructure. This flexibility enables microgrids to function independently from the main grid during power outages or in remote areas, making them a crucial element in the changing energy landscape [2]. Microgrids offer a powerful solution for generating electricity that is both resilient and eco-friendly, while also being cost-efficient. By harnessing local renewable energy sources and leveraging advanced control systems, microgrids can function autonomously or in tandem with the main grid, providing consistent power even in the face of disruptions. This blend of sustainability and reliability makes microgrids an appealing choice for communities and businesses looking to reduce their carbon footprint and strengthen energy security [3, 4]. Microgrids are flexible systems capable of operating either in connection with the main grid or independently in islanded mode. When linked to the main grid, they optimize energy usage by balancing supply and demand, often incorporating renewable energy sources. In islanded mode, they become self-reliant, delivering reliable power during grid outages or in remote locations. This dual capability boosts energy security and provides greater flexibility in managing local energy needs [5]. Residential microgrids connected to the main grid allow for bi-directional electricity flow, enabling homeowners to both consume and supply power as required. Hybrid microgrids, which integrate multiple renewable energy sources (RES), traditional power generation, and energy storage systems, go a step further. They help mitigate the variability of renewable energy, enhancing system efficiency and strengthening overall resilience. This combination ensures a stable and reliable energy supply, even in the face of changing weather conditions or disruptions to the main grid [6]. A residential microgrid enables the efficient utilization of renewable energy sources (RES) by managing power generation, consumption, and energy storage within a localized system. This study focuses on a microgrid that incorporates Battery Energy Storage Systems (BESS) and Photovoltaic (PV) panels, offering a sustainable energy solution. With global policies increasingly aimed at reducing greenhouse gas emissions and addressing climate change, the shift from fossil fuels to RES is gaining momentum, positioning microgrids as a key component of the future energy landscape [7]. Notably, CO_2 emissions make up over 70% of total greenhouse gas emissions, positioning them as the main contributor to climate change. This underscores the pressing need to transition to cleaner energy sources, such as those employed in microgrids, which can substantially lower our carbon footprint and promote a more sustainable future [8]. The growing integration of Renewable Energy Sources (RES) marks a pivotal step toward a significantly decarbonized power system. In the United States, this shift is clear, with RES penetration rising from 9% in 2004 to 13% in 2014. This increase highlights the continued efforts to decrease dependence on fossil fuels and progress toward a cleaner, more sustainable energy future [9]. However, the variability in RES generation and the switching between grid-tied and off-grid modes in residential microgrids can pose stability challenges. To overcome these issues and ensure a consistent power supply, Battery Energy Storage Systems (BESS) are employed to balance fluctuations between energy generation and consumption. BESS helps maintain the stability and reliability of the microgrid, even when renewable energy production fluctuates or during transitions between operating modes [10]. Addressing the technical and economic constraints of microgrids is crucial for maintaining a balanced relationship between available resources and load demands. Achieving this balance requires optimal planning and design, with components of hybrid microgrids accurately sized to meet specific load requirements. Careful sizing is vital for ensuring both efficiency and reliability, as demonstrated in numerous studies. Properly tailored microgrid components not only improve performance but also optimize costs, making the system both economically feasible and technically resilient [11, 12]. Many researchers have focused on the design, planning, and optimization of hybrid microgrids, employing various optimization techniques. For instance, [13] examines how to optimize the design, selection, and operation of different Distributed Energy Resources (DERs) in commercial buildings. These studies focus on improving the efficiency and reliability of microgrids by strategically selecting and managing resources to meet specific energy needs, showcasing the potential for customized solutions across various environments. Research efforts such as [14] and [15] aim to minimize the total costs and emissions of microgrids by determining the optimal configuration of Distributed Energy Resources (DERs), taking into account constraints within local distribution networks, like voltage profiles and energy losses. However, these studies primarily focus on optimizing voltage profiles and do not fully address the reliability of microgrids. In contrast, [16] and [17] investigate the optimal allocation of energy storage within distribution systems. [16] seeks to reduce system costs by enhancing voltage profiles, lowering line loading, and minimizing both active and reactive power losses. Meanwhile, [17] focuses on reducing costs associated with energy storage installation, energy losses, maintenance, interruptions, and system upgrades. The techno-economic advantages of Battery Energy Storage Systems (BESS) and Photovoltaic (PV) systems under feed-in tariff (FiT) incentives and time-varying electricity rates are analyzed in [18]. Additionally, [19] addresses energy storage sizing and operational strategies, considering economic incentives for storage owners. Various studies also emphasize efforts to reduce CO_2 emissions in microgrid operations. For instance, [20] optimizes the size and dispatch of Distributed Energy Resources (DERs) to lower CO_2 emissions, factoring in heat and cold storage. Similarly, [21] presents an economic scheduling model for electricity and natural gas systems aimed at reducing CO_2 emissions, while [22] explores cost minimization and emission reduction through DER optimization, taking into account utility rates, transportation constraints, and generator states. For industrial parks, [23] proposes an optimal low-carbon economic dispatch model that incorporates real-time multi-energy price incentives, calculating monthly carbon emissions based on real-time monitoring and historical data. In [24], a Mixed Integer Quadratic Programming (MIQP) algorithm is introduced to optimize BESS capacity in grid-tied commercial microgrids with dispatchable generators and renewable energy sources (RES). Additionally, [25] utilizes a hybrid multi-objective sensitivity analysis algorithm to optimize the sizes of PV and storage systems. In [26], the performance of the Grasshopper Optimization Algorithm (GOA) is compared to other optimization algorithms for DER size optimization in isolated microgrids. Lastly, [27] employs meta-heuristic algorithms such as the Imperialistic Competitive Algorithm (ICA), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO) to optimize the size and location of DERs in distribution networks, while [28] focuses on implementing the PSO algorithm for DER optimization with consideration for various load types. Various strategies are used to optimize the allocation of Distributed Energy Resources (DERs), including simulation software tools like HOMER, DER-CAM, and NEPLAN [29-31], deterministic methodologies that involve numerical and iterative techniques [32, 33], and heuristic or metaheuristic optimization algorithms such as CS, GOA, and PSO [26, 34, 35]. While simulation tools provide valuable insights into DER sizing, they are limited by the modeling assumptions of their components and are mainly used for feasibility studies. As a result, simulation software is often utilized as a comparative tool to evaluate the sensitivity of sizing outcomes across different studies. Deterministic sizing methods generally outperform simulation software tools when it comes to DER sizing. However, the complex nature of microgrid design and planning can cause these deterministic approaches to get stuck in local optima, leading to longer times to find an optimal solution [26].

In the literature, several metaheuristic algorithms have been developed and are extensively used to tackle microgrid-related problems. These methods are flexible and skilled at avoiding local optima, often providing better solutions than deterministic approaches [36]. A thorough comparison of optimization methods presented in [37] indicates that Particle Swarm Optimization (PSO) is among the most effective algorithms for microgrid planning. PSO excels at minimizing interruption costs, maximizing reliability, and exhibiting more stable convergence characteristics compared to other stochastic methods [38].

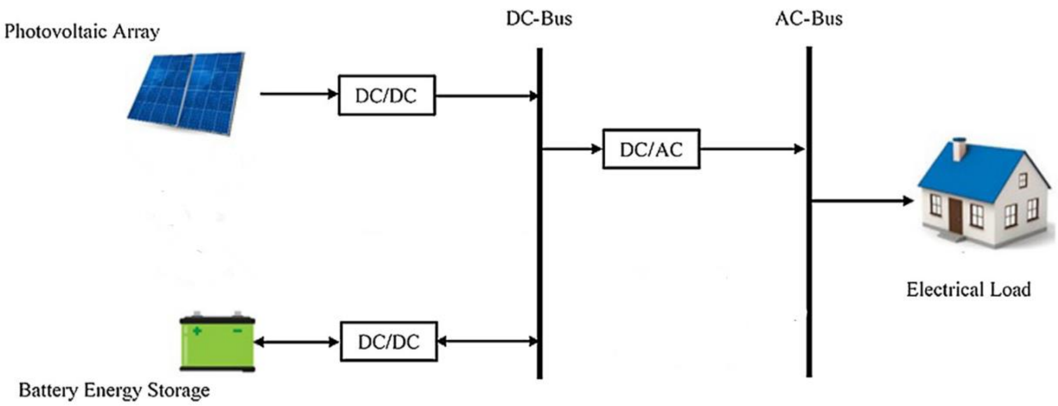

Figure 1. *Schematic structure of the microgrid system.*

2. Literature Review

Extensive research has been conducted on grid-connected solar photovoltaic (PV) systems with battery integration to analyze and quantify the optimal advantages of deploying such systems at the customer level. Studies in the literature have examined various aspects of system-level optimization, including sizing, simulation and optimization of PV-battery systems focusing on self-consumption, Feed-in Tariff (FiT) incentives, wholesale electricity tariffs, and demand forecasting [39, 41-46]. While batteries have traditionally been utilized in standalone PV systems [47], there is a growing interest in integrating batteries into grid-connected PV systems, particularly under FiT and time-of-use tariffs [48]. Despite the initially high installation costs, domestic solar PV systems have witnessed significant adoption rates, largely propelled by energy policies such as FiT schemes in Europe and other regions [1, 40, 49]. Moreover, large-scale installations in the form of solar farms are becoming increasingly prevalent due to favorable energy policies [50]. As per sources [23, 51, 52], integrating battery technology into energy systems characterized by high levels of fluctuating distributed energy resources offers a solution to mitigate against frequent interruptions resulting from specific electricity demand patterns or grid-connected distributed energy systems. A key concern in this domain is the rationale behind the necessity for battery storage within electricity networks. The escalating peak electricity demands in power systems, coupled with the proliferation of distributed energy resources, lead to a disparity between generation and demand, resulting in underutilization of generation, transmission, and distribution infrastructure [52]. Leveraging battery storage alongside PV systems enables utility operators to optimize existing network capacity utilization and defer costly network investments. Consequently, the ability of residential electricity consumers to dynamically respond to fluctuating electricity prices becomes increasingly valuable for seamlessly integrating high levels of distributed energy resources, such as PV, into future electricity networks. In a study outlined in [44], the impact of active demand-side management and battery storage systems on self-consumption levels was investigated. The analysis highlighted the significance of the relationship between electricity energy flows and battery storage capacity as a critical decision variable in optimizing system performance. The optimization model described in [53] is tailored for scenarios involving aggregated demand profiles, allowing aggregators to participate in the day-ahead market. In various other contexts, the minimization of costly demand charges (kVA charges) has been a primary motivation for the deployment of PV-battery systems, as highlighted in references [18, 53, 55]. Exploring the disparity between flat retail electricity prices and FiT export tariffs for PV, [40] investigated the potential value of deploying battery storage to maximize FiT revenue streams. This involved optimizing battery storage deployment to capitalize on periods of peak electricity prices for discharging and periods of lowest prices for charging. In [57], a Mixed-Integer Linear Programming (MILP) model was developed to manage and size residential heat pumps, aiming to maximize self-consumption of PV generation. The PV generation profile was generated based on irradiation data. Furthermore, [58] presented a case study that utilized economic optimization of battery storage size to assist customers in selecting the most suitable battery storage technology for their specific requirements.

3. Mathematical Modeling

3.1. PV System

As a function of solar irradiance, temperature, efficiency coefficient of solar panel and many other parameters, the output produced photovoltaic power $P_{PV,i}^{t}$ at time t and injected at bus i is described in equation (1).

$$P_{PV,i}^{t} = P_{PVr} \times \frac{G^{t}}{1000} \times \left(1 + K_T(T_C - 25)\right) \tag{1}$$

G^{t} is defined as the global solar irradiance at time t, P_{PVr} is the nominal power of the PV, T_C is the temperature of the PV cell and K_T is the PV temperature coefficient.

3.2. BESS System

The behavior of the battery energy storage system is reflected by its state of charge SoC, expressed in % as a function of time as follows:

$$SoC_i^t = SoC_i^{t-1} + \eta_{ch} \frac{P_{ch,i}^{t}}{P_{BESS}} - \frac{1}{\eta_{dis}} \times \frac{P_{dis,i}^{t}}{P_{BESS}} \tag{2}$$

$$SoC_i^t = SoC_i^{t-1} - SD \times \Delta t \tag{3}$$

P_{BESS} represents the nominal power of the storage system. η_{ch}, η_{dis}, $P_{ch,i}^{t}$ and $P_{dis,i}^{t}$ are respectively the charging and discharging efficiencies and powers of BESS at time t and bus i. SD is the self-discharge of the BESS and Δt is the time step.

The BESS power $P_{BESS,i}^{t}$ at each instant t and each bus I is then expressed as follows:

$$P_{BESS,i}^{t} = P_{BESS,i}^{t-1} + \eta_{ch} P_{ch,i}^{t} - \frac{1}{\eta_{dis}} P_{dis,i}^{t} \tag{4}$$

3.3. Load and Utility Grid

Industrial, residential, and commercial loads are considered in order to simulate the variation of the load. The load power P_{load}^{t} at time t is equal to the IEEE 33 bus typical load power at each bus multiplied by the sum of the coefficients of proportions of the 3 types of loads.

The exchange of energy with the main grid depends on the state of the PV sources and BESSs as well as the loads; energy is purchased from the grid in the case of a deficit and sold in the case of excess. The network is therefore modeled by an infinite source.

4. Optimization Problem Formulation

In this section, the proposed optimization model for distribution networks with integrated decentralized PV-BES systems is described. It is a multi-objective non-linear optimization problem that aims to minimize hourly power losses and average voltage deviation and maximize Distribution Network Operator (DNO) revenues, as expressed in equations (5-7).

4.1. Objective Function

The objective function developed in this work includes three main functions, expressed below:

Minimize hourly power losses P^{t}_{L}:

$$OF_1 = \min(P_L^t) = \min\left(\sum_{i=1}^{N} \sum_{k=1}^{N} R_{i,k} {I^{t}}_{i,k}^{2}\right) \tag{5}$$

Minimize average voltage deviation $V^t_{D,\,average}$:

$$OF_2 = min(V^t_{D,average}) = min(\frac{1}{N}\sum_{i=1}^{N}|V_i^t - 1|) \quad (6)$$

Maximize DNO's revenue R^t_{DNO}:

$$OF_3 = max(R^t_{DNO}) = \max(\sum_t\big((P^t_{load} \times C^t_{load}) - (P^t_{PV} \times C_{PV})$$

$$-(P^t_{dis} \times C_{dis}) + (P^t_{ch} \times C_{ch}) - (P^t_{grid,import} \times C^t_{import}) + (P^t_{grid,export} \times C^t_{export})\big) \times \Delta t) \quad (7)$$

$I^t_{i,k}$ is the current that transits between nodes i and k at time t and $R_{i,k}$ is the branch resistance. V_i^t represents the nodal voltage at time t and N is the number of the network nodes.

P^t_{PV}, P^t_{ch} and P^t_{dis} are respectively the total PV, charging and discharging BESS powers at time t, defined by:

$$\begin{cases} P^t_{PV} = \sum_{i=1}^{N} P^t_{PV,i} \\ P^t_{ch} = \sum_{i=1}^{N} P^t_{ch,i} \\ P^t_{dis} = \sum_{i=1}^{N} P^t_{dis,i} \end{cases} \quad (8)$$

$P^t_{grid,import}$ and $P^t_{grid,export}$ are respectively the imported and exported energy from and to the utility grid at time t and C^t_{import} and C^t_{export} are their corresponding costs. C^t_{load} is the cost of the energy sold to costumers, C_{PV} and C_{dis} are the costs of energy purchased from PV and BESS respectively (to support the loads) and C_{ch} is the cost of energy sold to the BESS (to charge it).

The DNO revenue includes purchased electricity from PV, BESS (when discharging) and the main grid and sold electricity to BESS (to be charged), customers and the main grid (when there is an excess of energy).

4.2. Constraints

Based on many technical parameters of PV systems, BESS and utility grid, many restrictions are established in order to simulate the real operation of the system.

$$0.95\, p.u. \leq V_i^t \leq 1.05\, p.u. \quad (9)$$

$$P^t_{grid,import} + P^t_{PV} + \sum_{i=1}^{N} P^t_{BESS,i} = P^t_{load} + P^t_L + P^t_{grid,export} \quad (10)$$

$$10\% \leq SoC^t \leq 90\% \quad (11)$$

$$SoC\,(1) = SoC\,(24) \quad (12)$$

5. The Proposed Energy Management Strategy

The energy management strategy presented in this paper is designed to optimize power losses and voltage deviation while maximizing revenue for the Distribution Network Operator (DNO). To achieve this, the study employs the Strength Pareto Evolutionary Algorithm 2 (SPEA2), an advanced method within the category of Evolutionary Algorithms (EAs), which are inspired by the concept of "survival of the fittest." Evolutionary Algorithms, including genetic algorithms (GAs), evolutionary strategies (ESs), and evolutionary programming (EP), draw on biological principles from Darwin and Mendel, simulating natural selection and adaptation processes.

These evolutionary-based methods have attracted attention across diverse fields such as computer science, engineering, and finance, where optimization is critical. By leveraging Darwinian principles, these algorithms explore vast "fitness landscapes," efficiently navigating through potential solutions to identify the best candidates. The increased computational power available today makes EAs particularly efficient in finding optimal solutions for complex problems, often achieving results faster and more flexibly than traditional optimization techniques.

SPEA2 specifically is well-suited for handling multiple objectives, providing a robust approach for managing trade-offs between competing goals, such as minimizing power losses and maximizing revenue. This flexibility has made Darwinian-based optimization techniques highly attractive to researchers. Figure 2 illustrates a basic flowchart that captures the core structure of Evolutionary Algorithms, highlighting the iterative selection, mutation, and crossover processes that drive the search for optimal solutions. This evolutionary framework offers a powerful, adaptable approach for solving both single and multi-objective optimization problems, as further explored in this study.

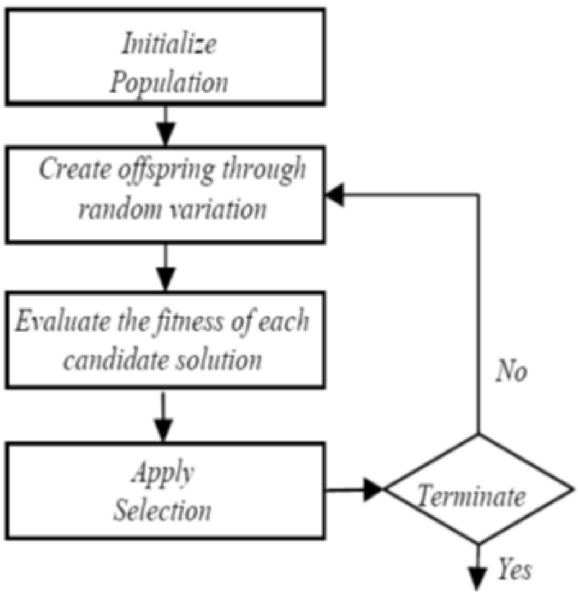

Figure 2. *Flowchart of a typical Evolutionary Algorithm.*

6. Simulation

System Data

The proposed energy management strategy is implemented on a modified IEEE 33-bus distribution network, as depicted in Figure 3. This network incorporates four decentralized photovoltaic (PV) systems and two Battery Energy Storage Systems (BESSs), strategically placed to optimize performance. The locations and sizes of these units were determined based on findings from a prior study, detailed in Table 1, which identified configurations that maximize efficiency while balancing energy supply and demand.

For simplicity and to streamline power flow calculations, it is assumed that both PV and BESS units operate at a unity power factor, supplying purely active power. This assumption ensures that reactive power effects are minimal, allowing a clearer focus on optimizing active power flows within the network and assessing the direct impact of these distributed energy resources. This setup provides a practical and scalable framework to test the proposed strategy's effectiveness in managing real-time power distribution across a decentralized energy grid.

Table 1. *PVs and BESSs data.*

Bus	Unit	Power (kW)
24	PV1	1535
3	PV2	1588
12	PV3	1445
	BESS1	2546
30	PV4	1390
5	BESS2	4538

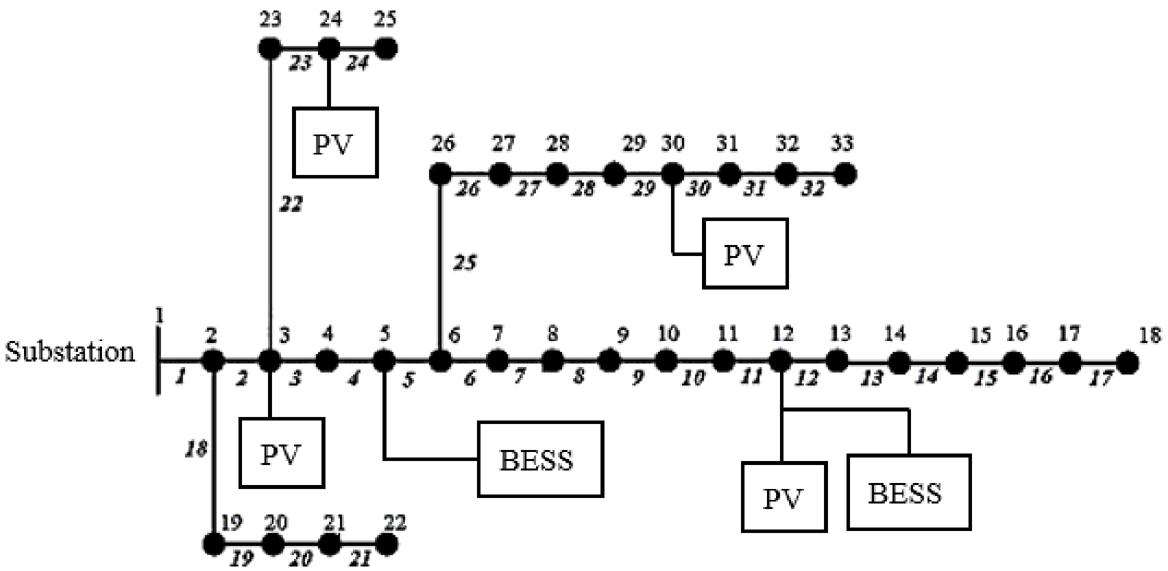

Figure 3. *The modified IEEE 33 bus test network.*

For the simulations in this study, solar irradiance data specific to Casablanca, Morocco, was utilized to reflect realistic conditions for the region. Casablanca, known for its diverse climate and variable irradiance levels across seasons, provided an ideal basis for analyzing the performance of a microgrid under different weather scenarios. The simulations were conducted in MATLAB on a computer equipped with an Intel Core i7 processor and 8 GB of RAM, with each simulation covering a full 24-hour period and a time step of 1 hour. This setup allowed for detailed tracking of load demands and renewable energy (RE) output on a summer and a winter day, as illustrated in Figures 6 and 9.

Since 2017, electricity prices in Morocco have shown moderate fluctuations, ranging between 97.54 USD/MWh in 2022 and 108.48 USD/MWh in 2021. These price variations influence both the economic viability and optimization strategies for microgrid energy management. Table 2 provides a breakdown of energy costs across different customer categories, illustrating the cost structure within the Moroccan energy market. All technical, economic, and simulation parameters used in this study are comprehensively listed in the following tables, offering a clear overview of the inputs driving the analysis and results.

Table 2. Energy costs for each type of costumers.

Type of load	Industrial	Commercial	Residential
Energy cost	0.1 USD/kWh	0.1038 USD/kWh	0.0886 USD/kWh

Table 3. Selling and purchasing tariffs.

	PV	BESS charging from PV	BESS Discharging
Energy cost (USD/kWh)	0.047	0.048	0.065

Table 4. Technical and simulation parameters used in the study.

The used parameters	The proposed value
Technical parameters	
Self-discharge for Li-ion (%/day)	0.1
Charging efficiency (%)	95
Discharging efficiency (%)	95
Simulation parameters	
Maximum iterations	80
Number of populations	50
pmutation	0.1
pcrossover	0.9

The purchased and sold energy prices from and to the grid are represented in Figure 4.

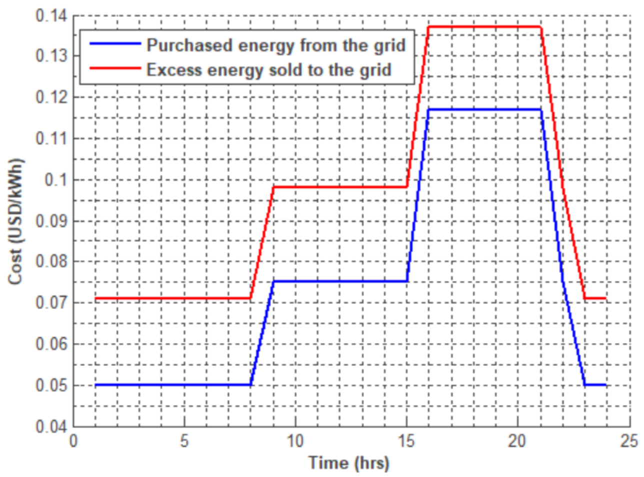

Figure 4. Purchased and sold energy prices from and to the grid.

7. Simulation Results

In order to investigate the effectiveness of the model, the simulation is done for a typical day in summer and winter with three different scenarios:

1) Reference: no PV and BESS are integrated to the network (only the main grid supports the loads).
2) PV without BESS: only 4 PVs are integrated to the network.
3) PV with BESS: both PVs and BESSs are integrated to the network.

7.1. Case Study 1: Summer Day

In this case study, a typical summer day is selected to evaluate the results of the proposed algorithm for the PV systems with and without BESS, as shown in Figure 5 and Figure 6.

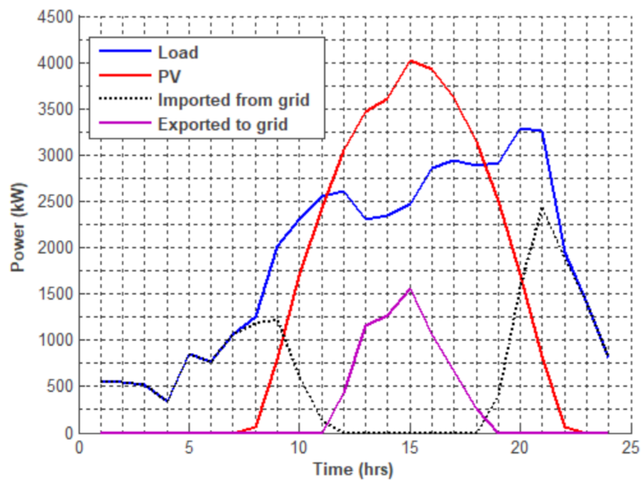

Figure 5. Optimal power profiles for energy management without BESS – case 1.

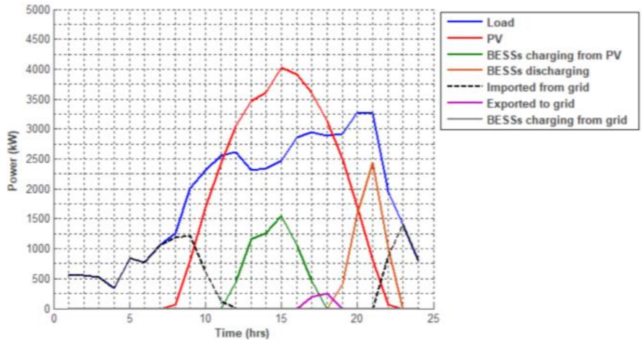

Figure 6. *Optimal power profiles for energy management with BESS – case 1.*

On a typical summer day without grid-integrated BESS, the main grid supplies the load during early morning and evening hours (from 6:00 p.m.) when solar irradiance is absent. PV systems begin contributing around 11:00 a.m., and from 12:00 p.m. to 6:00 p.m., they fully meet electricity demand, with any excess energy sold back to the grid.

When BESSs are integrated into the network, the main grid continues to supply power in the early morning to meet demand. As irradiance increases, PV generation covers the demand, charges the BESS, and exports surplus energy to the main grid (4:00 p.m. to 7:00 p.m.). The amount of stored energy in the BESS is illustrated in Figure 7. In this scenario, PV generation is higher, and main grid imports are lower. Additionally, BESS charges from PV production between 12:00 p.m. and 6:00 p.m., then discharges during peak grid hours (7:00 p.m. to 10:00 p.m.).

Optimal values for power losses, voltage deviation, and revenue maximization across the three scenarios are presented in Table 5.

Table 5. *Optimal objective functions – case 1.*

t	Reference			PV without BESS			PV with BESS		
	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)
1	3,99	0,00728	39,1013	3,99	0,00728	39,1013	3,99	0,00728	39,1013
2	3,99	0,00728	39,1013	3,99	0,00728	39,1013	3,99	0,00728	39,1013
3	3,81	0,00708	37,9124	3,81	0,00708	37,9124	3,81	0,00708	37,9124
4	1,639	0,0046	24,9166	1,639	0,0046	24,9166	1,639	0,0046	24,9166
5	10,118	0,0113	60,679	10,118	0,0113	60,679	10,118	0,0113	60,679
6	8,26	0,0103	55,2561	8,262	0,0103	55,2561	8,262	0,0103	55,2561
7	15,278	0,014	74,8637	15,278	0,014	74,8637	15,278	0,014	74,8637
8	21,57	0,0167	89,0484	20,118	0,0161	89,2501	20,118	0,0161	89,25
9	54,85	0,027	91,1307	31,329	0,0197	113,4491	31,329	0,0197	113,449
10	72,738	0,0311	104,5083	27,369	0,0157	152,0663	27,369	0,0157	152,066
11	90,61	0,0346	115,667	31,486	0,0127	183,6416	31,486	0,0127	183,641
12	95,558	0,0354	118,5635	35,984	0,0081	214,0848	35,143	0,0124	192,083
13	74,206	0,031	104,3484	40,77	0,00056	227,8526	33,377	0,0118	170,135
14	75,86	0,0315	105,7298	42,76	0,000207	235,6455	34,242	0,01208	172,611
15	83,95	0,0332	111,3891	51,76	0,00208	259,8491	39,499	0,01306	182,0408
16	114,41	0,0388	8,421	50,75	0,00382	303,8578	45,109	0,0141	210,025
17	121,56	0,0399	8,5308	47,86	0,0074	275,1484	45,0537	0,012	232,87
18	117,839	0,0392	9,1717	43,609	0,0108	234,1464	43,609	0,0108	234,14
19	122,103	0,0399	10,3609	45,92	0,0170	185,6493	44,858	0,01298	206,801
20	157,37	0,0453	11,5759	78,227	0,029	131,1317	62,572	0,0134	213,003
21	155,719	0,0451	12,1156	110,39	0,0373	69,3029	71,819	0,0125	196,164

t	Reference			PV without BESS			PV with BESS		
	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)	PL (kW)	$VD_{average}$ (p.u.)	Profit (USD)
22	53,86	0,0265	90,1766	51,48	0,0259	92,0598	28,7169	0,0156	102,196
23	27,409	0,0188	99,7803	27,409	0,0188	99,7803	27,409	0,0188	99,7803
24	8,79	0,0107	57,52	8,7919	0,01076	57,52	8,7919	0,01076	57,52
	Average		Sum	Average		Sum	Average		Sum
	62,3139	0,0253	1479,86	33,0481	0,01244	3256,26	28,23	0,0123	3139,62

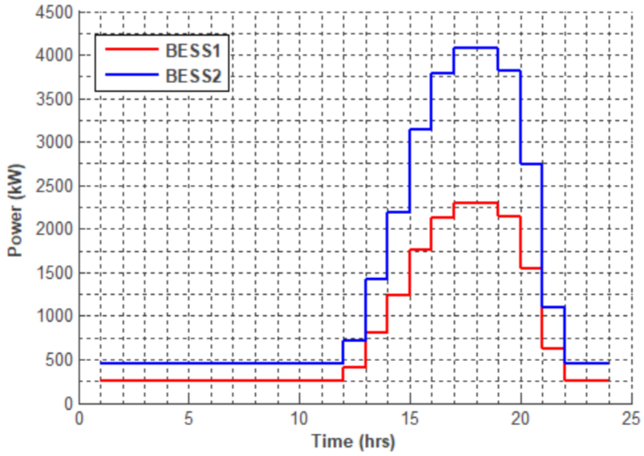

Figure 7. BESSs stored power – case 1.

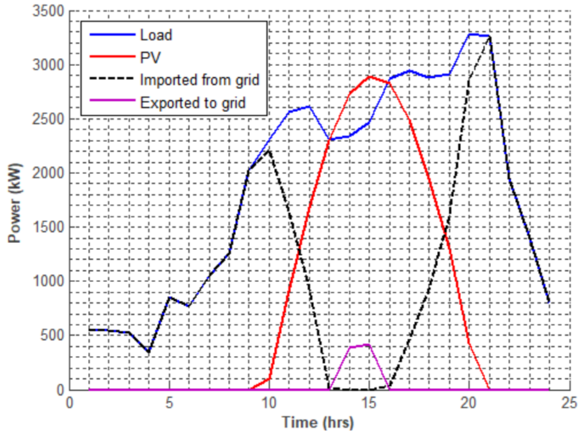

Figure 8. Optimal power profiles for energy management without BESS – case 2.

7.2. Case Study 2: Winter Day

Winter days are characterized by low solar irradiance, explaining the results shown in Figures 8 and 9 and Table 6. Without integrating BESSs into the network, the system yields results similar to those observed on summer days, albeit with greater reliance on the main grid and a reduction in the amount of energy sold back to it.

When BESSs are considered, they charge from the grid at low cost during early morning hours and discharge during peak hours, when electricity prices are higher. From 10:00 a.m. to 9:00 p.m., PV systems primarily supply the demand, with any excess energy sold back to the main grid. Additionally, the main grid supports demand at various times throughout the day, alongside PVs and BESSs, as on-site generation alone was insufficient to fully meet consumption needs.

Table 6. Optimal objective functions – case 1.

t	Reference			PV without BESS			PV with BESS		
	P_L (kW)	$VD_{average}$ (p.u.)	Profit (USD)	P_L (kW)	$VD_{average}$ (p.u.)	Profit (USD)	P_L (kW)	$VD_{average}$ (p.u.)	Profit (USD)
1	3,99	0,00728	39,1013	3,99	0,00728	39,1013	3,99	0,00728	39,1013
2	3,99	0,00728	39,1013	3,99	0,00728	39,1013	22,63	0,0161	39,1013
3	3,81	0,00708	37,9124	3,81	0,00708	37,9124	22,21	0,0159	37,9124

	Reference			PV without BESS			PV with BESS		
t	**P_L (kW)**	**$VD_{average}$ (p.u.)**	**Profit (USD)**	**P_L (kW)**	**$VD_{average}$ (p.u.)**	**Profit (USD)**	**P_L (kW)**	**$VD_{average}$ (p.u.)**	**Profit (USD)**
4	1,639	0,00462	24,9166	1,639	0,00462	24,9166	16,84	0,0134	24,9166
5	10,118	0,0113	60,679	10,118	0,01134	60,679	33,44	0,0203	60,679
6	8,26	0,01032	55,2561	8,26	0,01032	55,2561	30,47	0,01929	55,2561
7	15,278	0,01404	74,8637	15,278	0,01404	74,8637	42,214	0,02309	74,8637
8	21,57	0,01676	89,0484	21,57	0,01676	89,0484	40,78	0,023	89,0484
9	54,85	0,02701	91,1307	54,85	0,02701	91,1307	54,85	0,027	91,1307
10	72,738	0,0311	104,5083	68,54	0,0302	107,258	68,54	0,03	107,258
11	90,61	0,0346	115,667	54,979	0,0262	141,038698	54,979	0,026	141,038
12	95,558	0,0354	118,5635	40,66	0,02	165,72479	40,66	0,02	165,72
13	74,206	0,031	104,3484	27,66	0,01049	168,646175	27,66	0,01049	168,64
14	75,86	0,0315	105,7298	29,287	0,0071	191,115689	29,28	0,00717	191,115
15	83,95	0,0332	111,3891	31,35	0,00747	201,986325	31,35	0,00747	201,986
16	114,41	0,0388	8,421	39,75	0,0132042	206,074163	39,75	0,0132	206,074
17	121,56	0,03992	8,5308	44,2	0,0171	182,562506	44,2	0,01719	182,562
18	117,839	0,03923	9,1717	49,248	0,02128	145,775787	49,248	0,02128	145,77
19	122,103	0,0399	10,3609	66,81	0,027	101,501357	50,908	0,01163	185,16
20	157,37	0,04532	11,5759	131,75	0,0412	41,3623201	78,98	0,01212	189,92
21	155,719	0,0451	12,1156	155,719	0,0451	12,1156	105,48	0,0347	62,367
22	53,86	0,0265	90,1766	53,86	0,0265	90,1766	53,86	0,0265	90,1766
23	27,409	0,0188	99,7803	27,409	0,0188	99,7803	27,409	0,0188	99,7803
24	8,791	0,0107	57,52	8,79	0,0107	57,52	8,79	0,0107	57,52
	Average		Sum	Average		Sum	Average		Sum
	62,31	0,025	1479,86	39,73	0,0179	2424,64	40,7	0,018	2707,09

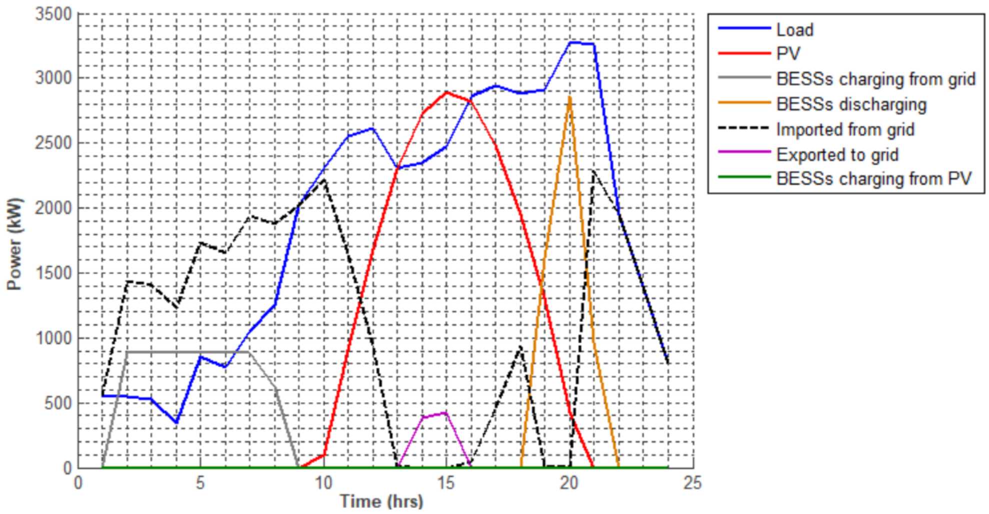

Figure 9. Optimal power profiles for energy management with BESS – case 2.

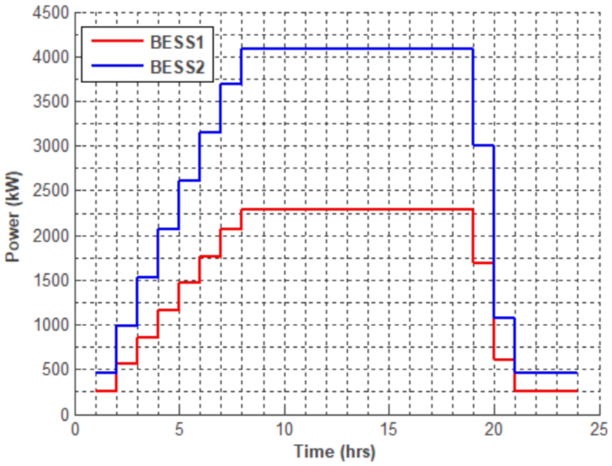

Figure 10. *BESSs stored power – case 2.*

From the results of tables and figures above, it is noted that the storage systems are highly involved during peak hours after being recharged during the day, which optimizes all objective functions during this period. It can be said that the integration of storage systems into the network is cost-effective (compared to the system without storage).

8. Conclusion

This paper introduces an optimal planning and energy management approach for a microgrid (MG) system that takes into account diverse configurations of distributed energy resources (DERs). The strategy is designed to tackle three main objectives: minimizing power losses, reducing voltage deviations, and maximizing revenue for the Distribution Network Operator (DNO). Achieving this delicate balance requires sophisticated optimization, and to this end, the Strength Pareto Evolutionary Algorithm 2 (SPEA2) is applied as a robust multi-objective meta-heuristic. This algorithm effectively navigates complex, competing objectives to identify solutions that best fulfill the overall energy management goals. In this paper, SPEA2 demonstrates once again its efficiency and gives promising results in terms of optimization. For each time step, the model proposes the optimal energy mix that reduces losses in the system and increases the benefit of network operators. A key focus of the study is the role of Battery Energy Storage Systems (BESS) within the MG. By integrating BESS, the strategy enhances the microgrid's flexibility and efficiency. The effects of BESS on essential MG parameters, such as stability, efficiency, and financial return, were rigorously evaluated across both summer and winter case studies. The results underscore the added value of BESS integration: it not only increases revenue for the DNO by improving energy trading opportunities but also significantly reduces power losses and mitigates voltage deviation. This demonstrates the critical role that optimized DER configurations, combined with advanced energy storage solutions, play in modern microgrid management.

Abbreviations

DNO	Distribution Network Operator
SPEA2	Strength Pareto Evolutionary Algorithm 2
BESS	Battery Energy Storage Systems
DERs	Distributed Energy Resources
MG	Microgrid
PV	Photovoltaic

Conflicts of Interest

The authors declare no conflicts of interest.

References

[1] X. Li, Z. Li, Micro-grid resource allocation based on multi-objective optimization in cloud platform, Proceedings of 2017 8th IEEE International Conference on Software Engineering and Service Science (ICSESS), (2017), pp. 509–512, https://doi.org/10.1109/ICSESS.2017.8342966

[2] G. Liu, T. B. Ollis, B. Xiao, X. Zhang, K. Tomsovic, Distributed energy management for community microgrids considering phase balancing and peak shaving, IET Gener. Transm. Distrib. 13 (9) (2019) 1612–1620, https://doi.org/10.1049/iet-gtd.2018.5881

[3] E. Loukakis, E. Karapidakis, Feasibility study of microgrid village with renewable energy sources, Proceedings of 2017 52nd International Universities Power Engineering Conference (UPEC), (2017), pp. 1–6, https://doi.org/10.1109/UPEC.2017.8231889

[4] N. T. Mbungu, R. M. Naidoo, R. C. Bansal, V. Vahidinasab, Overview of the optimal smart energy coordination for microgrid applications, IEEE Access 7 (2019) 163063–163084, https://doi.org/10.1109/ACCESS.2019.2951459

[5] M. Laour, F. Akel, D. Bendib, M. Chikh, Residential microgrid load management and optimal control in grid connected and islanded mode, Proceedings of 2018 6th International Renewable and Sustainable Energy Conference (IRSEC), (2018), pp. 1–4, https://doi.org/10.1109/IRSEC.2018.8702847

[6] A. Saif, V. R. Pandi, H. Zeineldin, S. Kennedy, Optimal allocation of distributed energy resources through simulation-based optimization, Electr. Power Syst. Res. 104 (2013) 1–8, https://doi.org/10.1016/j.epsr.2013.05.019

[7] H. Saboori, R. Hemmati, considering carbon capture and storage in electricity generation expansion planning, IEEE Trans. Sustain. Energy 7 (4) (2016) 1371–1378.

[8] G. Office, The Texas Renewable Energy Industry, 2014.

[9] P. Lazzeroni, S. Olivero, F. Stirano, M. Repetto, Impact of pv penetration in a distribution grid: a middle-east study case, Proceedings of 2015 IEEE 1st International Forum on Research and Technologies for Society and Industry Leveraging a Better Tomorrow (RTSI), (2015), pp. 353–358, https://doi.org/10.1109/RTSI.2015.7325123

[10] C. Huang, Y. Huang, K. Huang, Capacity optimization of a stand-alone microgrid system using charged system search algorithm, Proceedings of 2018 IEEE International Conference on Industrial Electronics for Sustainable Energy Systems (IESES), (2018), pp. 345–350, https://doi.org/10.1109/IESES.2018.8349900

[11] P. B. Borase, S. M. Akolkar, Energy management system for microgrid with power quality improvement, Proceedings of 2017 International conference on Microelectronic Devices, Circuits and Systems (ICMDCS), (2017), pp. 1–6, https://doi.org/10.1109/ICMDCS.2017.8211710

[12] P. Arul, V. K. Ramachandaramurthy, Mitigating techniques for the operational challenges of a standalone hybrid system integrating renewable energy sources, Sustain. Energy Technol. Assess. 22 (2017) 18–24, https://doi.org/10.1016/j.seta.2017.05.004

[13] S. Acha, A. Mariaud, N. Shah, C. N. Markides, Optimal design and operation of distributed low-carbon energy technologies in commercial buildings, Energy 142 (2018) 578–591, https://doi.org/10.1016/j.energy.2017.10.066

[14] E. Ntakou, R. Masiello, F. Farzan, S. Bahramirad, A. Paaso, M. Nayeem, M. Maigha, D. Kushner, Full ac analysis of value of der to the grid and optimal der scheduling, Electr. J. 32 (4) (2019) 45–49, https://doi.org/10.1016/j.tej.2019.03.007 Special Issue on Strategies for a sustainable, reliable and resilient grid.

[15] V. R. Pandi, H. H. Zeineldin, W. Xiao, Determining optimal location and size of distributed generation resources considering harmonic and protection coordination limits, IEEE Trans. Power Syst. 28 (2) (2013) 1245–1254, https://doi.org/10.1109/tpwrs.2012.2209687

[16] C. K. Das, O. Bass, T. S. Mahmoud, G. Kothapalli, M. A. Masoum, N. Mousavi, An optimal allocation and sizing strategy of distributed energy storage systems to improve performance of distribution networks, J. Energy Storage 26 (2019) 100847, https://doi.org/10.1016/j.est.2019.100847

[17] A. S. A. Awad, T. H. M. EL-Fouly, M. M. A. Salama, Optimal ess allocation for benefit maximization in distribution networks, IEEE Trans. Smart Grid 8 (4) (2017) 1668–1678, https://doi.org/10.1109/TSG.2015.2499264

[18] A. S. Hassan, L. Cipcigan, N. Jenkins, Optimal battery storage operation for pv systems with tariff incentives, Appl. Energy 203 (2017) 422–441, https://doi.org/10.1016/j.apenergy.2017.06.043

[19] X. Liu, Z. Yan, J. Wu, Optimal coordinated operation of a multi-energy community considering interactions between energy storage and conversion devices, Appl. Energy 248 (2019) 256–273, https://doi.org/10.1016/j.apenergy.2019.04.106

[20] Y. Yang, S. Zhang, Y. Xiao, Optimal design of distributed energy resource systems coupled with energy distribution networks, Energy 85 (2015) 433–448, https://doi.org/10.1016/j.energy.2015.03.101

[21] L. He, Z. Lu, J. Zhang, L. Geng, H. Zhao, X. Li, Low-carbon economic dispatch for electricity and natural gas systems considering carbon capture systems and power to gas, Appl. Energy 224 (2018) 357–370, https://doi.org/10.1016/j.apenergy.2018.04.119

[22] R. J. Flores, J. Brouwer, Optimal design of a distributed energy resource system that economically reduces carbon emissions, Appl. Energy 232 (2018) 119–138, https://doi.org/10.1016/j.apenergy.2018.09.029

[23] H. Gu, Y. Li, J. Yu, C. Wu, T. Song, J. Xu, Bi-level optimal low-carbon economic dispatch for an industrial park with consideration of multi-energy price incentives, Appl. Energy 262 (2020) 114276, https://doi.org/10.1016/j.apenergy.2019.114276

[24] R. Garmabdari, M. Moghimi, F. Yang, E. Gray, J. Lu, Battery energy storage capacity optimisation for grid-connected microgrids with distributed generators, Proceedings of 2017 Australasian Universities Power Engineering Conference (AUPEC), (2017), pp. 1–6, https://doi.org/10.1109/AUPEC.2017.8282480

[25] I. Kim, Optimal capacity of storage systems and photovoltaic systems able to control reactive power using the sensitivity analysis method, Energy 150 (2018) 642–652, https://doi.org/10.1016/j.energy.2017.12.132

[26] A. L. Bukar, C. W. Tan, K. Y. Lau, Optimal sizing of an autonomous photovoltaic/ wind/battery/diesel generator microgrid using grasshopper optimization algorithm, Sol. Energy 188 (2019) 685–696, https://doi.org/10.1016/j.solener.2019.06.050

[27] H. HassanzadehFard, A. Jalilian, A novel objective function for optimal dg allocation in distribution systems using meta-heuristic algorithms, Int. J. Green Energy 13 (15) (2016) 1615–1625, https://doi.org/10.1080/15435075.2016.1212355

[28] H. Hassanzadehfard, A. Jalilian, Optimal sizing and siting of renewable energy resources in distribution systems considering time varying electrical/heating/ cooling loads using pso algorithm, Int. J. Green Energy 15 (2) (2018) 113–128, https://doi.org/10.1080/15435075.2018.1423981

[29] B. Kroposki, P. K. Sen, K. Malmedal, Optimum sizing and placement of distributed and renewable energy sources in electric power distribution systems, IEEE Trans. Ind. Appl. 49 (6) (2013) 2741–2752, https://doi.org/10.1109/TIA.2013.2262661

[30] A. S. Hassan, L. Cipcigan, N. Jenkins, Impact of optimised distributed energy resources on local grid constraints, Energy 142 (2018) 878–895, https://doi.org/10.1016/j.energy.2017.10.074

[31] L. I. Dulău, M. Abrudean, D. Bică, Optimal location of a distributed generator for power losses improvement, Procedia Technol. 22 (2016) 734–739, 9th International Conference Interdisciplinarity in Engineering, INTER-ENG 2015, 8–9 October 2015, Tirgu Mures, Romania. https://doi.org/10.1016/j.protcy.2016.01.032

[32] A. A. Hamad, M. E. Nassar, E. F. El-Saadany, M. M. A. Salama, Optimal configuration of isolated hybrid ac/dc microgrids, IEEE Trans. Smart Grid 10 (3) (2019) 2789–2798, https://doi.org/10.1109/TSG.2018.2810310

[33] Y. M. Alsmadi, A. M. Abdel-hamed, A. E. Ellissy, A. S. El-Wakeel, A. Y. Abdelaziz, V. Utkin, A. A. Uppal, Optimal configuration and energy management scheme of an isolated micro-grid using cuckoo search optimization algorithm, J. Frankl. Inst. 356 (8) (2019) 4191–4214, https://doi.org/10.1016/j.jfranklin.2018.12.014

[34] F. Tooryan, E. R. Collins, Optimum size and placement of distributed generators in microgrid based on reliability concept, Proceedings of 2018 IEEE Power and Energy Conference at Illinois (PECI), (2018), pp. 1–6, https://doi.org/10.1109/PECI.2018.8334992

[35] S. Saremi, S. Mirjalili, A. Lewis, Grasshopper optimisation algorithm: theory and application, Adv. Eng. Softw. 105 (2017) 30–47, https://doi.org/10.1016/j.advengsoft.2017.01.004

[36] M. W. Khan, J. Wang, M. Ma, L. Xiong, P. Li, F. Wu, Optimal energy management and control aspects of distributed microgrid using multi-agent systems, Sustain. Cities Soc. 44 (2019) 855–870, https://doi.org/10.1016/j.scs.2018.11.009

[37] F. Tooryan, S. M. Tafreshi, S. Bathaee, H. Hamidhassanzadeh-Fard, Distributed energy resources optimal sizing and placement in a microgrid, Int. Electr. Eng. J. 4 (2013) 1059–1070.

[38] Bertsch V, Geldermann J, Lühn T. What drives the profitability of household PV investments, self-consumption and self-sufficiency?; 2017.

[39] Weniger J, Tjaden T, Quaschning V. Sizing of residential PV battery systems. Energy Procedia 2014; 46: 78–87. http://dx.doi.org/10.1016/j.egypro.2014. 01.160

[40] Brusco G, Burgio A, Menniti D, Pinnarelli A, Sorrentino N. The economic viability of a feed-in tariff scheme that solely rewards self-consumption to promote the use of integrated photovoltaic battery systems. Appl Energy 2016; 183: 1075–85. http://dx.doi.org/10.1016/j.apenergy.2016.09.004

[41] Castillo-Cagigal M, Caamaño-Martín E, Matallanas E, Masa-Bote D, Gutiérrez A, Monasterio-Huelin F, et al. PV self-consumption optimization with storage and Active DSM for the residential sector. Sol Energy 2011; 85: 2338–48. http://dx.doi.org/10.1016/j.solener.2011.06.028

[42] Linssen J, Stenzel P, Fleer J. Techno-economic analysis of photovoltaic battery systems and the influence of different consumer load profiles. Appl Energy 2017; 185: 2019–25. http://dx.doi.org/10.1016/j.apenergy.2015.11.088

[43] Ratnam EL, Weller SR, Kellett CM. Scheduling residential battery storage with solar PV: Assessing the benefits of net metering. Appl Energy 2015; 155: 881–91. http://dx.doi.org/10.1016/j.apenergy.2015.06.061

[44] Kanteh Sakiliba S, Sani Hassan A, Wu J, Saja Sanneh E, Ademi S. Assessment of stand-alone residential solar photovoltaic application in sub-Saharan Africa: A CASE STUDY of Gambia. J Renew Energy 2015; 2015: 1–10. http://dx.doi.org/10.1155/2015/640327

[45] Spiers D. Batteries in PV Systems. Practical Handbook Photovolt 2012: 721–76. http://dx.doi.org/10.1016/B978-0-12-385934-1.00022-2

[46] Barros J, Leite H. Feed-in tariffs for wind energy in Portugal: Current status and prospective future. In: Electrical power quality and utilisation (EPQU), 2011 11th International Conference on, IEEE; 2011, p. 1–5.

[47] Berrada A, Loudiyi K. Operation, sizing, and economic evaluation of storage for solar and wind power plants. Renew Sustain Energy Rev 2016; 59: 1117–29. http://dx.doi.org/10.1016/j.rser.2016.01.048

[48] Corcuera S, Estornés J, Menictas C. Advances in batteries for medium and large-scale energy storage. Elsevier; 2015 http://dx.doi.org/10.1016/B978-1-78242-013-2.00002-9

[49] Vassallo AM. Advances in Batteries for medium and large-scale energy storage. Elsevier; 2015. http://doi.org/10.1016/B978-1-78242-013-2.00017-0

[50] Pyrgou A, Kylili A, Fokaides PA. The future of the Feed-in Tariff (FiT) scheme in Europe: The case of photovoltaics. Energy Policy 2016; 95. http://dx.doi.org/10.1016/j.enpol.2016.04.048

[51] Li R, Wang Z, Gu C, Li F, Wu H. A novel time-of-use tariff design based on Gaussian Mixture Model. Appl Energy 2016; 162: 1530–6. http://dx.doi.org/10.1016/j.apenergy.2015.02.063

[52] Ruth M, Pratt A, Lunacek M, Mittal S, Wu H, Jones W. Effects of home energy management systems on distribution utilities and feeders under various market structures 2015; 15(18).

[53] Ayón X, Gruber JK, Hayes BP, Usaola J, Prodanovic ́M. An optimal day-ahead load scheduling approach based on the flexibility of aggregate demands. Appl Energy 2017; 198: 1–11. http://dx.doi.org/10.1016/j.apenergy.2017.04.038

[54] Hanna R, Kleissl J, Nottrott A, Ferry M. Energy dispatch schedule optimization for demand charge reduction using a photovoltaic-battery storage system with solar forecasting. Sol Energy 2014; 103. http://dx.doi.org/10.1016/j.solener.2014.02.020

[55] Stadler M, Groissböck M, Cardoso G, Marnay C. Optimizing Distributed Energy Resources and building retrofits with the strategic DER-CAModel. Appl Energy 2014; 132: 557–67. http://dx.doi.org/10.1016/j.apenergy.2014.07.041

[56] Beck T, Kondziella H, Huard G, Bruckner T. Optimal operation, configuration and sizing of generation and storage technologies for residential heat pump systems in the spotlight of self-consumption of photovoltaic electricity. Appl Energy 2017; 188: 604–19. http://dx.doi.org/10.1016/j.apenergy.2016.12.041

[57] Olaszi BD, Ladanyi J. Comparison of different discharge strategies of grid connected residential PV systems with energy storage in perspective of optimal battery energy storage system sizing. Renew Sustain Energy Rev 2017; 75: 710–8. http://dx.doi.org/10.1016/j.rser.2016.11.046

[58] Carlos A. Coello Coello, David A. Van Veldihuizen, and Gary B. Lamont, Evolutionary Algorithms for Solving Multi-Objective Problems, Kluwer Academic Publishers, New York 2002.