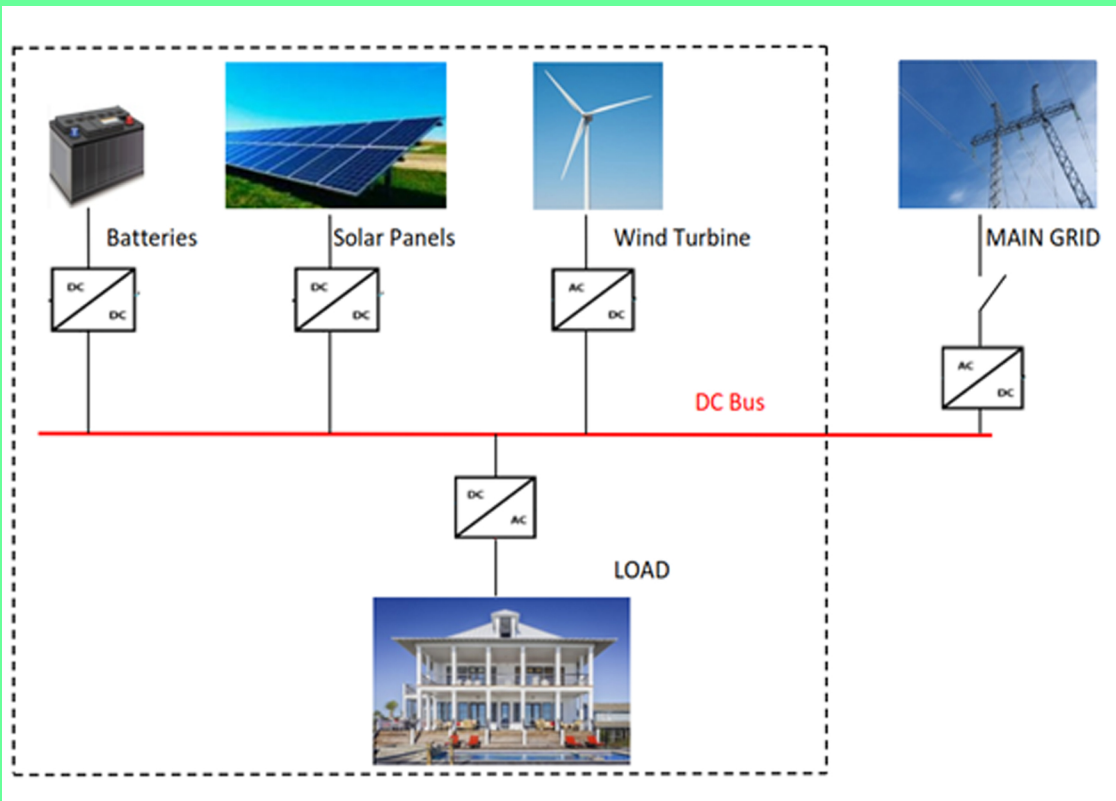


Microgrids – optimization, management and operation



Microgrids – optimization, management and operation

“Obrazovanie i Poznanie”

2025

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1. Introduction to microgrids. Concepts, definition, classification

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Abstract

Microgrids arise as a response to the need for more flexible, reliable and sustainable energy systems [1, 2, 3], especially in conditions of increasing consumption and integration of Renewable Energy Sources (RES). They are localized energy systems that can operate both connected to the main electricity grid and autonomously. Their main role is to ensure uninterrupted power supply, increase energy security and enable efficient use of renewable energy sources such as sun and wind. Microgrids are particularly useful for remote areas, critical infrastructure and industrial enterprises with high reliability requirements. Their development prospects foresee extended integration of artificial intelligence, inclusion of energy storage systems and participation in decentralized energy markets.

1.1. A new approach to energy production and consumption

The era of industrialization of mankind has brought great technical progress, but it is also associated with the emergence of new challenges. One of them is the release of large amounts of harmful emissions (carbon dioxide (CO₂) and other toxic gases) into the atmosphere. Another harmful effect resulting from human activity is the pollution of soil, seas and freshwater basins with chemicals and

difficult to degrade products such as plastic waste. Environmental pollution leads to climate changes such as “global warming” and the associated droughts and forest fires (see the special report entitled “Energy and Climate Change”, 2015 [4]). The use of fossil fuels for electricity generation has had a detrimental effect over the years, requiring the need for alternative energy sources. To overcome the listed harmful effects, a new approach to energy production and consumption is required. Policies have been developed to balance energy efficiency and climate change [5]. In China, the goal of energy policy by 2030 is 35% of the energy produced to come from renewable energy sources (RES) (see [6]). The US Department of Energy [8] and the European Commission [7] are aiming for 27% of the energy used to be produced from renewable sources by 2030. The Organisation for Economic Co-operation and Development (OECD) has set a primary goal of mitigating global climate change by achieving a low-carbon economy [4]. Microgrids, based on the concept of using clean renewable energy sources, have gained much importance in recent years as an alternative, as they use advances in information and communication technologies (ICT) to increase the quality and efficiency of services and distributed energy resources (DER) for the purpose of environmental sustainability. Microgrids play a major role in changing energy production and consumption. In them, energy losses caused by energy transmission are avoided. Most important is that they significantly reduce the pollution or do not pollute the environment. By operating independently of the main electricity distribution grid (in “island” mode), they reduce the load on it and make the global energy system more resilient. (i.e., resistant to natural disasters and capable of rapid recovery in the event of accidents or military actions). In “grid-connected” mode (or “hybrid” mode), microgrids can also use energy from the main grid. In general, microgrids are very flexible and reliable [9].

In recent years, there has been great progress in new technologies such as the Internet of Things (IoT), the Internet of Everything (IoE),

and Artificial Intelligence (AI) [10]. They are used to improve (optimize) the consumption of energy and resources in modern cities, which is known as the “Green Transformation”. In this regard, ideas are being developed and implemented to make the home and the entire city “smart”. Microgrids should also function in a “smart” way, applying the mentioned new technologies and optimizing energy consumption. That is why they are of interest to many researchers. Mathematical models are formulated for them, and optimization techniques are applied.

[1.2. What is a microgrid ?](#)

Definition: A **microgrid** is a localized (decentralized) low-voltage power system that can produce, store, and distribute electrical energy **independently of** or **in sync with** the main electricity distribution grid (national or regional grid). It includes various energy sources (e.g. solar, wind, diesel, fuel cell, batteries), loads [11] (consumers – a small number of buildings, electric vehicle charging stations, etc.), and a control system [12]).

Main features:

- **Island mode** – the microgrid operates autonomously, independently of the main grid.
- **Grid-connected mode** – the microgrid operates in sync with the main grid.
- **Local control** – the microgrid has its own intelligent control and management system (see [12]).
- **Increased reliability** – in the event of an interruption in the power supply from the main grid, the microgrid can continue to supply power to its local consumers.

[1.3. Microgrid classification](#)

Microgrids can be classified according to several criteria:

1.3.1. By type of energy sources

- **Traditional** – diesel generators, natural gas, etc.
- **Renewable (RES-based)** – solar panels (Photovoltaics (PV)), wind turbines, small hydroelectric power plants, etc.
- **Hybrid** – a combination of renewable and traditional sources.

1.3.2. By connection method

- **Connected to the main network (Grid-connected)** – can exchange energy with the main grid.
- **Autonomous (Isolated / Stand-alone)** – fully autonomous, often used in remote areas.

1.3.3. By scale

- **Nanogrids** – много малки системи (например за едно домакинство).
- **Microgrids** – localized networks for campuses, hospitals, factories, small neighborhoods, small villages.
- **Minigrids** – larger than microgrids, but smaller than the main electricity distribution grid.

1.3.4. By management

- **Centralized management** – one centralized device or platform manages the entire microgrid.
- **Decentralized / distributed management** – individual components have independent decision-making and coordination.

Microgrid management generally involves coordinating energy sources, consumers, and energy storage to achieve an optimal energy balance. It requires intelligent real-time monitoring and control systems that respond to changes in production and consumption. Optimization algorithms and artificial intelligence are used to make decisions that ensure the efficiency, reliability, and sustainability of the system.

Some databases store statistical data on energy consumption in buildings, as well as on energy production from renewable energy sources. These data can be used to optimize the operation of microgrids using appropriate mathematical models and optimization algorithms. Examples of publicly available databases containing statistical information on energy production and consumption are EBSCO [13] and EMIS [14].

Energy & Power Source (EBSCO) [13] is the leading full-text database of content related to the energy and power industry. It provides leading journals focused on oil, natural gas, electricity, coal, nuclear, and renewable energy. It also includes metrics and best practices from leading industry players in the world.

Energy management information system (EMIS) [14] is a large energy management information system in Moldova.

Another major energy information system is the National Energy Information System siePaís [15]. It is a modern computer tool developed by the Latin American Energy Organization (OLADE) that integrates, processes and disseminates statistical, prospective, socio-economic, legal and documentary information on the energy sector of the 12 OLADE member countries, including Brazil, Guyana, Ecuador,

Paraguay, Panama, Honduras, etc. It is based on standardized methodologies and concepts that allow the consolidation of information at the national level. OLADE, together with its 27 member countries from Latin America and the Caribbean, provides free access to information on economic-energy statistics from 1970 to the present. It addresses issues related to energy balances, greenhouse gases, economic-energy indicators, demand and supply, prices, reserves, potential and energy infrastructure (see [16]).

In the United States, there is an agency called the U.S. Energy Information Administration [17], on whose website relevant energy statistics can be found. More information on energy information systems is given in [18].

[1.3.5. A microgrid example](#)

Let the following microgrid setup be available:

- A small number of buildings (a remote hamlet of 2-3 houses or a university campus of 3-4 blocks);
- Solar panels on the roofs;
- A small wind turbine;
- An energy storage system (batteries);
- An intelligent system for controlling energy consumption and production;
- An alternative own energy source (e.g. a diesel generator);
- The ability to disconnect from the main grid in case of an accident and operate autonomously in island mode.

A simple diagram of such a microgrid is shown in Fig. 1.1. The elements of the microgrid are stylized. In addition, this diagram does not show all the connections to the control system (input and output signals).

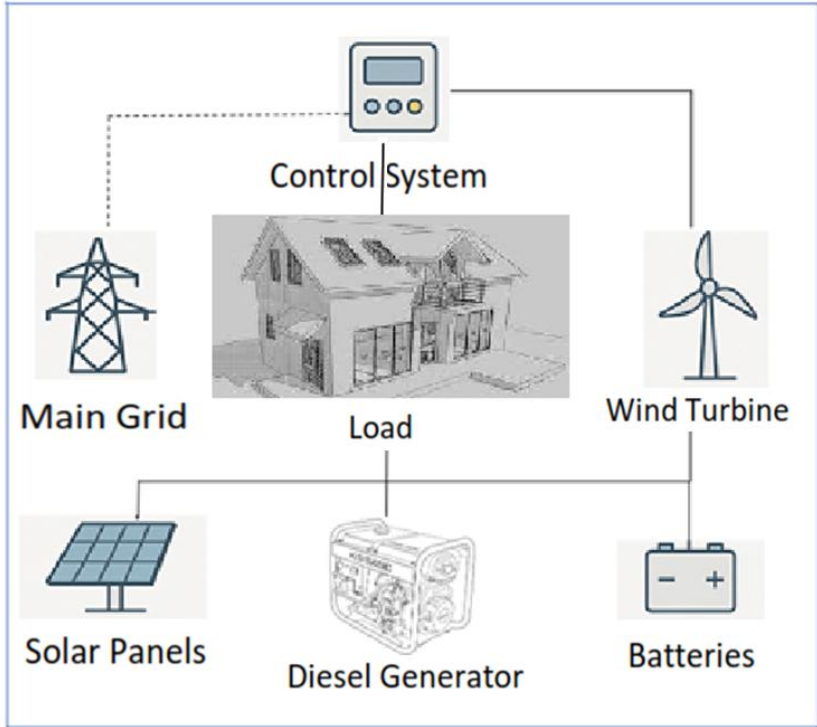


Fig. 1.1. A microgrid schema

A more detailed schema of a microgrid is presented in Fig. 1.2. During operation, the subsystems Solar Panels, Wind Turbines, and Energy Storage System send data about their current state (output voltage and output current) to the Control System. It also receives data from the main grid. After processing the received data, control signals S1, S2, S3, and S4 are generated. They are fed from the Control System (Energy Management System (EMS)) to the corresponding subsystems in the microgrid (see Fig. 1.3).

Other microgrid architectures are considered and discussed in the following chapters.

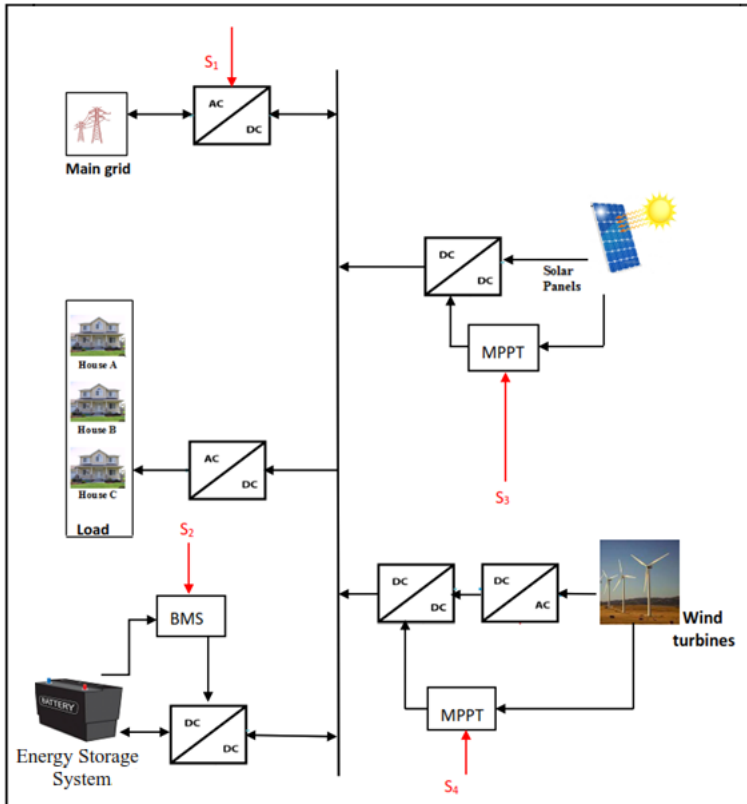


Fig. 1.2. A more detailed microgrid schema

In the above schema, DC/AC denotes an inverter that converts direct current into alternating current. Accordingly, AC/DC is an inverter that converts alternating current into direct current. MPPT mode denotes the Maximum Power Point Tracking mode. BMS (Battery Management System) is used to denote the battery mode management system (charging, discharging, passive state). The input

and output signals of the Energy Management System are presented in Fig. 1.3.

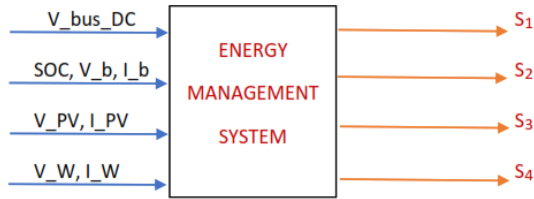


Fig. 1.3. The Energy Management System

Here, V_{bus_DC} means the voltage value of the DC bus, SOC denotes the state of charge value of the batteries in the Energy Storage System. V_b and I_b are the voltage and current values of the Energy Storage System. Other input data are V_{PV} and I_{PV} , which contain the voltage and current values of the photovoltaic system. Finally, V_W and I_W are the voltage and current values of the wind turbines.

The output signals of the Energy Management System are input signals for the corresponding devices and subsystems of the microgrid, as shown in Fig. 1.2.

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2. Microgrid cluster operations management

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Abstract

Microgrid clusters are interconnected groups of individual microgrids that coordinate their work to increase the reliability and efficiency of the energy supply. They enable the sharing of resources, such as electricity and storage capacity, between different participants in the system. This improves resilience against local failures and optimizes the use of renewable sources. Clusters facilitate the participation of microgrids in decentralized energy markets and create opportunities for new business models. They play a key role in the transition to smart and low-carbon energy systems of the future.

2.1. Introduction

With the increasing use of renewable energy sources, decentralized energy systems, known as microgrids, have become an important part of modern energy infrastructures. When multiple microgrids are interconnected and/or coordinated by a centralized or decentralized control system, they form a cluster of microgrids. Such clusters improve the resilience, reliability, efficiency, and flexibility of energy systems, especially in urban areas and critical infrastructures such as hospitals, universities, and industrial parks [1], [2].

2.2. Main characteristics of microgrid clusters

A microgrid cluster is a coordinated group of independent microgrids that share resources and information and can:

- Exchange energy with each other;
- Respond collectively to events such as power outages or peak loads;
- Participate in energy markets as a single unit;

This collaboration allows for **better load management, energy distribution, and cost optimization** than if each microgrid were to act independently [3].

2.3. Management architecture

Different types of microgrid cluster architectures are discussed in [4].

2.3.1 Centralized management

In this architecture, a central control unit (e.g., an **energy dispatcher** or **control center**) receives data from all microgrids in the cluster and makes decisions for optimal energy distribution, load balancing, and coordinated disaster response [5]. This facilitates:

- Global optimization;
- Centralized participation in energy markets;
- Storage and analysis of large volumes of data.

Disadvantages: The centralized structure is vulnerable to failures of the central controller and requires reliable communication links. This approach allows for global optimization, but is risky in the event of a failure of the central system.

2.3.2 Decentralized management

In this approach, each microgrid makes its own decisions based on local information and coordination with other microgrids through a communication infrastructure [6]. The following are used:

- Multi-agent systems (MAS);
- Peer-to-peer (P2P) models;
- Local energy sharing protocols.

In the MAS model, each microgrid has its management agent that coordinates its actions with the others through a communication protocol. This increases the resilience and scalability of the cluster.

Advantages: Higher resilience, flexibility, and less load on the communication network.

2.4. Operational strategies and optimization

Microgrid cluster management requires the application of optimization algorithms and intelligent strategies to ensure reliable and cost-effective operation. The key aspects include:

2.4.1 Energy optimization

- Balancing local production and consumption;
- Choosing when and how much energy to store or give to other microgrids;
- Optimal use of batteries and renewable sources.

[2.4.2 Energy exchange between microgrids](#)

Peer-to-peer trading mechanisms are used, in which microgrids negotiate energy volumes and prices [7]. For this purpose, the following are often used:

- **Blockchain technologies** for security and transparency;
- **Real or virtual market mechanisms** for price determination.

[2.4.3 Reservation and resilience](#)

Microgrid clusters can dynamically manage reserves that are used in the event of:

- Failures and outages;
- Peak loads;
- Transition to islanding.

[2.4.4 Forecasting and machine learning](#)

Artificial intelligence (AI) and machine learning (ML) methods are used (see [8]) for:

- Energy consumption forecasting;
- Renewable energy generation forecasting;
- Adaptive optimization based on weather data and user behavior.

[2.5. Technologies used](#)

[2.5.1 Internet of Things \(IoT\)](#)

The concept of the Internet of Things (IoT) was introduced by Kevin Ashton at the end of the 20th century [9]. Its main idea is to use

multiple types of electronic systems and sensors, interconnected in a network, to collect, store, and analyze data, as well as to exchange information and provide optimized services. IoT technology allows for optimizing energy consumption in buildings. Its implementation can turn the relevant buildings into “smart”. In this way, energy costs and the release of thermal energy into the atmosphere can be significantly reduced. Sensors and interconnected devices [10] collect and transmit data on:

- Energy production and consumption;
- Equipment status;
- Presence of people (energy consumers) in the building;
- Availability of renewable resources (e.g., sun, wind);
- Atmospheric conditions (humidity, cloudiness, etc.).

2.5.2 Artificial Intelligence (AI)

Artificial Intelligence (AI) emerged as a scientific field in the 1950s, with the first attempts to create machines capable of solving logical problems and imitating human intelligence. Modern AI uses various approaches, including machine learning, neural networks, logic programming, heuristics, and evolutionary algorithms. In microgrid management, AI plays a key role by forecasting energy demand and production, optimizing resource dispatch, managing energy storage, and making real-time decisions. Thanks to its ability to adapt to dynamic and uncertain environments, AI improves the efficiency, flexibility, and autonomy of microgrids. This makes it an indispensable tool for implementing smart and sustainable energy systems.

Artificial intelligence is used (see [11], [12]) for:

- Optimal load distribution;
- Intelligent management of energy storage;
- Event prediction and real-time adaptation.

2.5.3 Cloud and Edge Computing

Cloud platforms [13] provide storage and centralized analysis of large volumes of data, storage, and management of complex algorithms for microgrid optimization and forecasting. Edge devices [14] perform local processing in real time, allowing rapid responses to changes in load or production. The joint operation of cloud platforms and edge devices provides efficient, flexible, and scalable management of distributed energy resources.

2.5.4 Blockchain

This technology serves to provide a secure and transparent platform for energy trading [15]. Blockchain is an advanced technology that, together with the Internet of Things (IoT), Artificial Intelligence (AI), and Cloud and Edge Computing, is entering the development and evolution of microgrids, making them intelligent. Blockchain technology can be used to generate decentralized energy systems, where energy trading between users is allowed. In doing so, several challenges must be overcome, such as scalability, compliance with regulatory systems, and integration with existing energy systems (see [16]).

2.6. Challenges and directions for future research

2.6.1 Cybersecurity

With increasing connectivity, protection against cyberattacks becomes critically important [17]. Techniques such as:

- Encryption of communications;
- Blockchain for commercial transactions;
- Anomaly detection using machine learning is being used.

The security of communications in microgrids is essential to prevent cyberattacks and ensure the reliable operation of power systems. The IEC 61850 and IEC 62351 standards provide guidelines for ensuring secure communication between microgrid components [18]. The

paper [19] discusses the application of the IEC 62351 standard to protect communications in microgrids. This standard recommends the use of Transport Layer Security (TLS) to ensure the confidentiality and integrity of messages, especially when using protocols such as GOOSE (Generic Object Oriented Substation Event) and MMS (Manufacturing Message Specification) within the framework of IEC 61850. TLS uses cryptographic algorithms such as AES-256 and SHA-256, as described in the IEC 62351-4 standard, for participant authentication, key exchange, encryption, and message authentication, thereby protecting critical data and commands in microgrids. For GOOSE messages, RSA digital signing and SHA-256 hashing are used to ensure data authenticity and integrity [19].

Furthermore, for resource-constrained systems, lightweight cryptographic solutions are proposed, such as the use of Datagram TLS (DTLS) with pre-shared keys and AES-CCM, which provide low latency and are suitable for real-time applications in microgrids [20].

[2.6.2 Regulations and standards](#)

The lack of unified standards and regulations makes integration between microgrids difficult, especially in international cooperation.

[2.6.3 Economic sustainability](#)

The creation of efficient business models for the cost-effective operation of microgrids and clusters is an ongoing area of active research [21].

[2.7. Conclusion](#)

Microgrid clusters represent the future of the decentralized energy system. They combine the advantages of individual microgrids with the possibility of coordinated management and mutual assistance, leading to higher resilience, efficiency, and intelligence of energy

systems. Using modern technologies such as IoT, AI, and Blockchain, as well as cloud and edge computing, creates new opportunities for optimization and autonomous management of microgrid clusters. Their further development and application are expected to be intensified.

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3. Economic management of microgrid operation

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Abstract

Economic management and operation of microgrids are necessary to ensure optimal use of available energy resources and minimal costs for consumers. Through intelligent planning and control, a balance can be achieved between energy production, storage, and consumption, avoiding expensive peak loads and inefficiency losses. This management allows microgrids to sell excess energy on the market or store it at low prices, which increases their profitability. Efficient operation also prolongs the lifespan of components such as batteries and inverters by managing loads and regulating charge-discharge cycles. Economic models play a crucial role in supporting decision-making connected with investments in new technologies and capacity expansion. Moreover, well-managed microgrids enhance energy independence for consumers and reduce dependence on the main (central) grid, which is particularly significant in the context of rising energy prices and increasing climate challenges. The economic efficiency of microgrids makes them more attractive to businesses and municipalities, promoting their widespread implementation. This, in turn, contributes to building a sustainable and decentralized energy system that aligns with the global sustainable development goals.

3.1. Introduction

The economic exploitation of electrical microgrids involves optimizing their design, operation, and integration to maximize financial benefits while ensuring their reliability and sustainability. This encompasses various strategies and mathematical models tailored to address unique challenges and opportunities presented by microgrids.

The pursuit of maximum financial returns from the deployment and operation of microgrids is an increasingly expanding area of research. The main goal is to optimize the use of Distributed Energy Resources (DER), including renewable energy sources and energy storage, to minimize costs or maximize profits under market and regulatory constraints.

3.2. Strategies for economic exploitation of microgrids

3.2.1 Costs minimization

Objective: To reduce the operating and capital costs of the microgrid.

Method: To plan the operation of distributed energy sources (DER), energy storage, and load scheduling to minimize the energy bought from the main grid.

Optimal energy management in a hybrid microgrid is discussed in [1]. The methodology in this study is based on the optimal energy flow and day-ahead energy consumption forecasts. The microgrid includes RES: photovoltaic panels and wind turbines. A mathematical model is formulated to minimize the energy consumption from the main national grid. The optimization is performed in a MATLAB environment by applying and comparing three different algorithms.

An optimization problem is solved using real climate data for the city of Almeria (Spain).

Microgrids are of two types: 1) Microgrids connected to the main (national) energy grid, and 2) Microgrids operating independently (independently of the main grid).

Example of planning the operation of a microgrid: Shifting (redistributing) the load over time, reducing peak loads, and optimally planning the battery operation schedule.

3.2.2 Получаване на максимални приходи

Objective: Selling excess energy to the main grid or participating in ancillary services markets (e.g., frequency regulation).

Method: Forecasting market prices and adjusting energy production/exports accordingly.

Tools: Bidding strategies adapted to the energy price.

3.2.3 Multi-objective (multi-criteria) optimization

Economic objectives (criteria) are combined with environmental (e.g., minimizing CO₂ emissions) or technical (e.g., maximizing reliability) objectives.

3.2.4 Demand response and energy trading

Microgrids participate in local energy markets, peer-to-peer trading, or aggregator-based models.

They can serve as consumers (producers + consumers), optimizing economic returns through blockchain-based trading or transactional energy systems.

3.3. Mathematical models for economic optimization of microgrid operation

3.3.1 Mixed integer linear programming (MILP)

Popular for: Optimal operation and planning of microgrids with discrete solutions (e.g. ON/OFF state of generators) [2], [3].

Strengths: Deterministic, solvable with commercial solvers (CPLEX, Gurobi).

3.3.2 Stochastic optimization

When used: Volatility (uncertainty) in load(s), renewable energy production and market energy prices.

Models: Two-stage or multi-stage stochastic programs have been developed (see [4]).

3.3.3 Robust optimization

It considers **worst-case scenarios** [5].

This type of optimization is more conservative than stochastic, but does not require probability distributions.

3.3.4 Game theory

It is applied to **multi-agent microgrids**, in particular with competing owners of distributed energy resources or in peer-to-peer markets [6].

3.3.5 Reinforced Learning (RL)

It does not require specific models, i.e. it is model-free. It studies economic allocation and bidding strategies through interaction with the environment.

It finds increasing application with the increasing participation of microgrids in the real market [7], [8].

Physically informed convolutional neural networks (CNN) have been developed for real-time economic management, combining data-driven approaches with physical system constraints to improve decision-making accuracy [9].

3.3.6 Other economic models

- Models aiming for minimum battery degradation costs: Economic models increasingly incorporate battery aging.
- Policy and regulation: Feed-in tariffs, time-of-use pricing, and incentives shape economic strategies.
- Carbon pricing: Environmental taxation models add another economic dimension.
- Model predictive control (MPC): MPC frameworks predict future system states to make informed control decisions, optimizing performance over a moving time horizon [10]. Economic MPC is specifically aimed at minimizing the costs of microgrid operations [11].
- Heuristic and metaheuristic algorithms: Techniques such as the butterfly optimization algorithm and bacterial feeding optimization address complex, nonlinear optimization problems in microgrid control [12].
- Convex optimization problem models: Nonlinear convex cost models account for factors such as energy storage degradation, allowing more accurate and efficient economic solutions for dispatching control [13].

3.3.7 Economic modeling tools and platforms

Several tools and platforms have been developed to facilitate economic modeling and optimization of microgrids:

XENDEE: A comprehensive microgrid design and economic optimization platform for developers and financiers [14].

DER-CAM: Developed by Lawrence Berkeley National Laboratory, this tool supports the optimal selection and operation of distributed energy resources (DER) in microgrids.

HOMER: This microgrid and energy resource platform (see [15]) assesses the technical and economic feasibility of microgrid configurations (projects).

EnergyPLAN: A simulation tool for analyzing the energy, environmental, and economic impacts of various energy systems, including microgrids.

[3.3.8 Examples of mathematical models and tasks for optimal economic management of microgrid operation:](#)

3.3.8.1 Economic model

In [16], an economic model of the following microgrid operating autonomously – in island mode (isolated from the main grid) is proposed (Fig. 3.1).

The components that make up the microgrid are:

- *Houses.* Some parameters are fixed, such as the floor area, the cooling and heating systems, and their set values. The GridLab-D simulation tool used in this study has the advantage of having default values for the systems used in the house simulation; therefore, for all parameters that are not explicitly defined, the default value is used. Here, a group of three houses is used, each of which is connected to one phase of the transmission system; this approach is used to reduce the load imbalance between the phases of the microgrid.

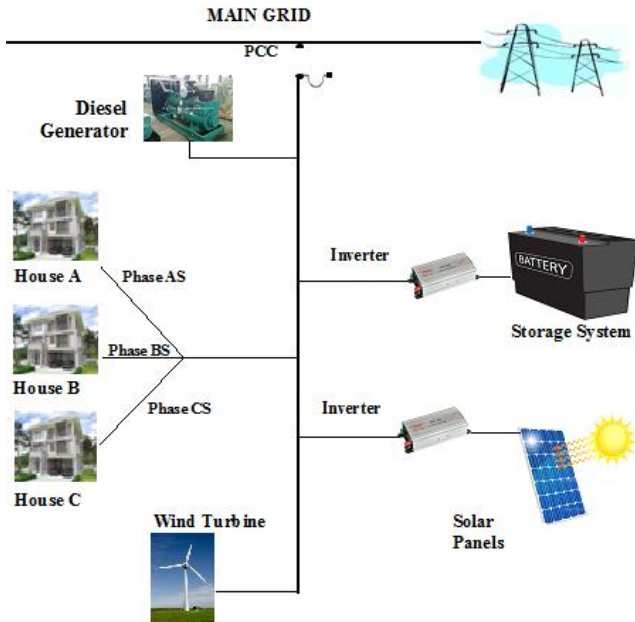


Fig. 3.1. Microgrid in island mode

- *Photovoltaic system.* The photovoltaic power system consists of solar panels and an inverter (to connect the system to the AC grid with the loads). The parameter that has the greatest influence on the energy production is the area of the entire photovoltaic system. In this case, the area of all solar panels is set to 1500 ft² (square feet). This value corresponds to a peak power output of about 25-30 kW (the value was obtained from the simulations).
- *Batteries.* The battery bank is not included in the simulations, since the behavior of the battery system is unknown and the battery schedule must be calculated by a Matlab solver by solving the corresponding optimization problem. The battery system consists of a battery bank (with a maximum stored energy of 100 kWh) and an inverter for charging/discharging the battery (with a power of 10 kW).

- *Diesel generator.* In this case, a KOHLER Systems 35kW/44kVA diesel generator (engine type: 3029TF120, class G3) was used. This diesel generator has a nominal power of 38 kW and a nominal voltage of 400/230 V (see <http://www.kohlerpower.com.sg/industrial/detail.htm?sectionNumber=13261&categoryNumber=11961&prodnum=248461>).

The behavior of renewable energy sources and the load is simulated from historical climate data for a specific geographical location: Seattle (USA). The data on solar radiation and wind speed, as well as on energy consumption in houses, are real data for a given winter day. They are taken as forecast data. The energy security tolerances used to cover the uncertainty of the forecast data are discussed in [17].

Given this, the following values are assumed in the defined optimization model: Wind turbine: (−30%); Photovoltaic: (−37%); Houses: (+25%); Diesel generator: (+20%). This means that (the energy produced by the diesel generator + the battery discharge energy) must be equal to 120% of the energy needed to cover the difference between 125% of (the forecast for houses + the energy for battery charging) and (70% of the wind forecast + 63% of the solar forecast) to cover the energy fluctuations due to forecast uncertainty that could eventually occur.

With the correct forecast data for the RES production and the consumption of houses a day before, it will be possible to optimize the behavior of the microgrid for the whole year, solving one day ahead the corresponding schedule optimization problem for the next

day. The analyzed time interval (one day and one night) is divided into 24 time steps, each with a length of 1 hour. The formulated optimization problem has the form: The balance power P_B of the studied microgrid must satisfy the following equations (see [18]):

$$P_{RES} + P_B = P_L \quad (1)$$

$$P_B = P_{Bat_d} + P_{DG} , \quad (2)$$

where P_{RES} is the output power of the renewable energy sources, P_B is the balanced power, P_{Bat_d} is the discharging power of the battery system, P_{DG} is the output power of the diesel generator, and P_L is the microgrid load, equal to the energy consumption of the houses plus the energy for charging the battery system.

The parameters and solution variables used in the proposed formulation are presented in Table 3.1.

Table 3.1. Parameters.

Parameter	Description
CC	Capital costs for 1 hour interval
OM	Operational maintenance costs for 1 hour
RC	Replacement costs (of the battery/batteries)
FC	Fuel costs for the interval of 1 hour
EC	Emission costs for 1 hour interval
CRF	Capital recovery factor for 1 hour
SFF	Sinking fund factor for 1 hour

The objective function that is minimized consists of the cost of the microgrid's balance power.

Objective function:

$$F = \sum_{t=1}^{24} (C_t \cdot P_{Bt}) = \sum_{t=1}^{24} CC_{DG}(t) + OM_{DG}(t) + FC_{DG}(t) + EC_{DG}(t) + \sum_{t=1}^{24} OM_{Bat}(t) + RC_{Bat}(t) + CC_{Inv}(t) \quad (3)$$

where P_{Bt} is the balance power for hour t , and C_t is the price of this power. C_t includes the depreciation costs (capital costs) of each element (unit) of energy production of the microgrid, the operating costs of the individual units, the costs of the fuel consumed by the diesel generator, and the costs of emissions. It should be noted that the photovoltaic area, the power of the wind turbine, and the energy consumption in the houses cannot be optimized, since their schedules are independent. F is calculated only for the hours when the diesel generator is operating and when the battery system is charging/discharging.

Formulas for calculating the corresponding annual values are given in [19, 20]. Therefore, the hourly capital costs for microgrid units that do not need replacement during the project life cycle, such as a diesel generator and an inverter, are calculated as follows:

$$CC_{DG} = \frac{C_{cap_{DG}} \cdot CRF(i, y)}{5375}, \quad (4)$$

Assuming that the diesel generator is used for an average of 15 hours per 24-hour period, the denominator is equal to the number of hours the diesel generator will run in 1 year: $5375 = 15 \times 365$;

Here, $C_{cap_{DG}}$ is the cost of capital (in US\$), y is the duration of the project, and i is the annual interest rate.

$$CRF(i, y) = \frac{i \cdot (1+i)^y}{(1+i)^y - 1} \quad (5)$$

In formula (5) $CRF(i, y)$ is the capital recovery rate for 1 year.

The annual interest rate is calculated as follows (see [21]):

$$i = \frac{i' - f}{1 + f} \quad (6)$$

where: i' is the loan interest rate (%), and f is the annual inflation rate (%).

The operational maintenance costs per hour are:

$$OM = \frac{Ccap_{DG} \cdot (1 - \lambda)}{5375 \cdot y} \quad (7)$$

for the diesel generator, and

$$OM = \frac{Ccap_{Bat} \cdot (1 - \lambda)}{6570 \cdot y} \quad (8)$$

for the battery, where: λ is the reliability of the respective unit.

Assuming that the battery is used for an average of 18 hours in a 24-hour period (i.e. $365 \times 18 = 6570$ hours per year), the cost of replacing a battery for one hour is:

$$RC = \frac{Crep_{Bat} \cdot SFF(i, y_{rep})}{6570} \quad (9)$$

where: $Crep_{Bat}$ is the battery replacement cost and SFF is the sinking fund factor, which is calculated as follows [21]:

$$SFF = \frac{i}{(1+i)^y - 1} \quad (10)$$

The cost of diesel generator fuel per hour (for hour t) is:

$$FC = Cf \cdot G(t) \quad (11)$$

where: Cf is the fuel price per liter and $G(t)$ is the hourly consumption of the diesel generator. $G(t)$ is calculated according to [19, 20, 22, 23] as follows:

$$G(t) = (0,246P_{DG}(t) + 0,08415 \cdot P_R) \quad (12)$$

where: $P_{DG}(t)$ is the power of the diesel generator at time t , and P_R is the nominal power of the diesel generator.

The hourly cost of harmful emissions (CO₂ emissions) is:

$$EC(t) = \frac{E_f \cdot E_{cf} \cdot P_{DG}(t)}{1000} = 0,0187 \cdot P_{DG}(t) \quad (13)$$

where: E_f is the emission function (kg/kWh). The parameter E_{cf} is the emission cost factor (US \$/ton).

Economic data are given in Table 3.2:

Table 3.2. Economic data for the microgrid.

Description	Value
Interest rate i' (%)	3
Inflation rate (%)	1,6
Inverter life span (years)	20
Battery life span (years)	10
Inverter reliability (%)	98
Battery reliability (%)	98
Diesel generator reliability (%)	90
Diesel generator cost (US\$/KW)	500
Battery cost (US\$/KWh)	200
Inverter cost (US\$/KW)	1000
Fuel price (C_f) (US\$/l)	0,75
Emissions function (kg/kWh)	0,34
Emission cost factor (US\$/ton)	55

Other parameters that need to be defined are the threshold value of the energy for charging and discharging the batteries P_{bt_max} , fixed at 10 kW per hour, and the maximum capacity of the batteries E_{bt_max} , fixed at 100 kWh.

The data in Table 3.2 are taken from [19], only the fuel price value is taken from [20]. Since $PR = 38$ kW, therefore $C_{cap_{DG}} = \$ 19,000$. In [18] it is stated that a high-speed (3,600 r/min) air-cooled diesel generator can be used for about 20,000 hours. Therefore, γ in equations (5), (7) and (8) is: $\gamma = 3.721$. The annual interest rate $i = 0.53846154$. Therefore, $CRF(i, \gamma) = 0.6742$. $CC_{DG} = \$2.38/h$. $OM_{DG} = \$0.095/h$. $OM_{Bat} = \$0.0061/h$. The cost of the batteries $C_{rep_{Bat}} = \$20,000$. $SFF = 0.1357$. $RC = \$0.413/h$. $C_{cap_{Inv}} = 10,000$ W. The hourly capital cost for the inverter is: $CC_{Inv} = \$1/hr$.

Therefore, equation (3) of the objective function takes the form:

$$F = \sum_{t=1}^{24} 2,38.P_{DG}(t) + 0,095.P_{DG}(t) + 0,1845.P_{DG}(t) + 2,398.P_{DG}(t) + \dots (14)$$

$$+ 0,0187.P_{DG}(t) + \sum_{t=1}^{24} 0,274.P_{Bat}(t) + 0,413.P_{Bat}(t) + 1.I_{mv}(t)$$

The constraints relating to the diesel generator are [24]:

$$0.3.P_R \leq P_{DG}(t) \leq P_R \quad (15)$$

Taking into account the adopted tolerances for energy security, the following constraint is obtained:

$$P_{DG}(t) = \begin{cases} 1,2.(1,25.P_L - 0,63.P_{PV} - 0,7.P_{WT} - P_{Bat_d}) & \text{if } 0,63.P_{PV} + 0,7.P_{WT} + P_{Bat_d} < 1,25.P_L \\ 0. & \text{otherwise} \end{cases} \quad (16)$$

where: $P_L(t)$ is the power absorbed by the houses during the hour “ t ” [kW]; $P_{PV}(t)$ is the power delivered by the photovoltaic panels during the hour “ t ” [kW]; $P_{WT}(t)$ is the power delivered by the wind turbine during the hour “ t ” [kW]; $P_{Bat_d}(t)$ is the power delivered by the battery pack (discharging) during the hour “ t ” [kW]

The battery system constraints are:

$$-P_{BT_MAX} \leq P_{BAT}(T) \leq +P_{BT_MAX} \quad (17)$$

$$SOC_{MIN} \leq SOC(t) \leq SOC_{MAX} \quad (18)$$

$$\sum_{t=1}^{24} P_{Bat}(t) = 0; \quad t = 1, \dots, 24; \quad (19)$$

P_{BT_max} is the maximum power that the battery system can deliver/absorb [kW]; $SOC(t)$ is the state of charge of the battery at time “ t ” [%] SOC_{min} = lower limit for the state of charge of the battery [%] SOC_{max} = upper limit for the state of charge of the battery [%].

Finally, taking into account the energy balance of the microgrid (see equations (1)-(2)), the following constraint is obtained:

$$P_{Bat}(t) + P_{DG}(t) \geq P_H(t) - P_{PV}(t) - P_{WT}(t), \quad t = 1, \dots, 24; \quad (20)$$

where $P_H(t)$ is the energy consumption in the houses. The energy $P_{Bat}(t)$ is considered positive when the batteries are discharging and negative when they are charging. Therefore, equation (17) represents the limit of power that can be delivered or absorbed by the inverter connected to the batteries; the system cannot provide or absorb power greater than PBT_max .

The state of charge (SOC) of the battery represents the amount of energy stored in the battery. Therefore, equation (18) means that for each time step, the SOC must be between a minimum and a maximum value, depending on the system used to store the energy, and corresponds to the physical limit for a maximum SOC of 100%. In this case, the minimum and maximum SOC levels are fixed at 20% and 100%, respectively.

The battery charge depends on the value of $P_{Bat}(t)$. For each time step, the relationship between these variables is shown below [25]:

$$SOC(t) = SOC(t-1) - \frac{P_{Bat}(t)}{E_{bt_max}} \cdot \Delta t \quad (21)$$

where: Δt is the time step [1 h], $SOC(0)$ = the initial charge of the batteries (this is the input value of the task). In this optimization task, the initial value of SOC is fixed at 50%. This means that at the beginning of the optimization, the batteries are charged to half of their full charge.

The constraint shown in equation (19) is used to obtain the same SOC value at the end of the 24-hour period as at the beginning of the period. Therefore, this value can be used as input for the optimization task the next day.

Climatic data for a typical winter day in Seattle, USA, was obtained from an external file with the ".TMY2" extension. TMY stands for "Typical Meteorological Year," and this data was used as forecast information in this study – see <https://sourceforge.net/p/gridlab-d/code/4252/tree/course/>

[ThreeDayCourse_v22/Day2/Demos/4.4%20Generator%20Examples/](#).

The graphs of changes in climatic data (temperature, solar radiation and wind speed) are shown in Fig. 3.2.

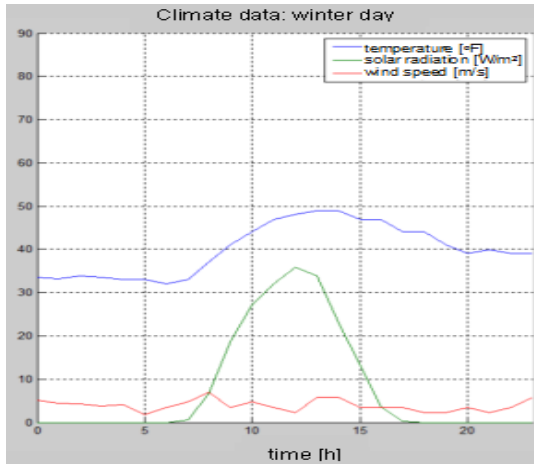


Fig. 3.2. Trend in climate data (temperature, solar radiation and wind speed) on a typical winter day

The energy consumption of houses, as well as the energy production from solar panels and wind turbines, was simulated using the GridLab-D software. This tool is designed for simulating complex, multiphysics, and distributed systems, such as microgrids. GridLab-D was developed by the U.S. Department of Energy (DOE) at the Pacific Northwest National Laboratory (PNNL) with funding from the Office of Electric Power, in collaboration with industry and academia. It is an open-source tool that supports multidomain modeling (including energy, time, and market) and the simulation of energy systems, particularly for distribution grids, using a discrete event-based computing model. The graphs illustrating the energy consumption of the houses, the energy produced by photovoltaics, and the energy generated by the wind turbine are presented in Figure 3.3..

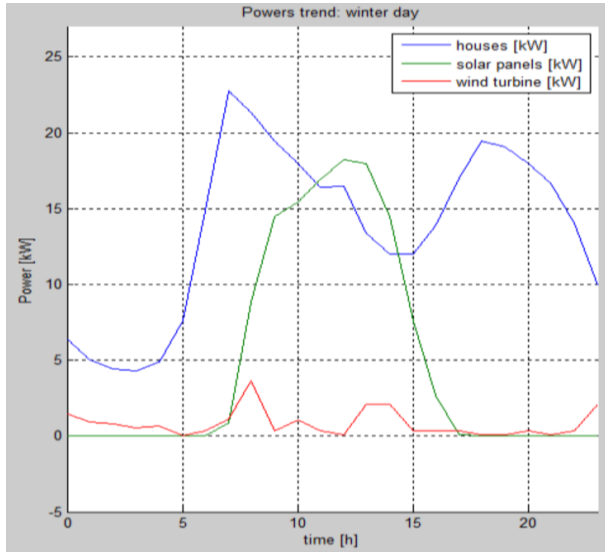


Fig. 3.3. Energy consumption by houses and energy production from solar panels and wind turbines on a winter day.

Optimization results:

Equations (16)-(20) have 48 variables: $P_{DG}(t)$ and $P_{Bat}(t)$, $t=1, \dots, 24$; The Matlab solver *fmincon* was used to solve this optimization problem. The "Help" menu in Matlab [27], under "Optimization tools", provides a description and explanation of how to perform the optimization.

fmincon: Finds the minimum of a nonlinear multidimensional constrained problem, takes a vector x as input and returns a scalar f as output.

This solver can utilize several algorithms to optimize the problem, including the interior point algorithm and the active set constraint algorithm (which is specifically for optimization problems with linear inequality constraints). In this instance, the active set constraint algorithm was employed. After 18 iterations, the optimal value of the objective function (14), which represents the costs of the diesel

generator and the battery system (including the inverter), expressed in US dollars (US\$), is:

$$F^* = 205\,037.$$

The results of running “*fmincon*” for a winter day using the “*optimtool*” interface in Matlab are shown in Fig. 3.4.

The total number of objective function calculations is shown, as well as the value of the objective function at each iteration.

The best point found (the optimal solution) is shown in the variable space.

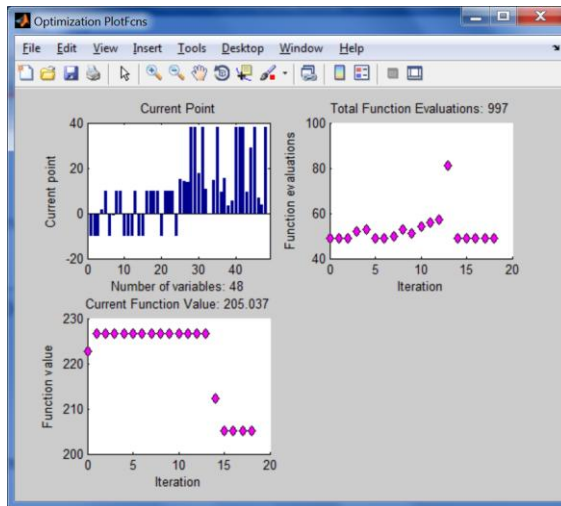


Fig. 3.4. Optimization results using the *fmincon* solver

The first 24 variables in Fig. 3.4 represent the battery operation schedule, while the next 24 variables correspond to the diesel generator operation schedule.

The optimization results indicate that the total cost for a 24-hour period during a winter day, based on the objective equation (14), is $F = 205.037$. In contrast, the initial battery schedule — without optimization — results in an objective function value of $F = 226.717$.

Therefore, the simultaneous optimization of both the battery schedule and the diesel generator schedule achieves a cost reduction of approximately 10.574%

The solution to the optimization problem outlined in equations (14) to (21) accomplishes two key objectives: 1) It ensures that the load is met with a sufficient energy reserve. 2) This optimization results in a remarkable reduction of 10,574% in the total operational costs of the microgrid.

The corresponding graphs of the energy consumption, as well as the battery system and the diesel generator operation are presented in Fig. 3.5:

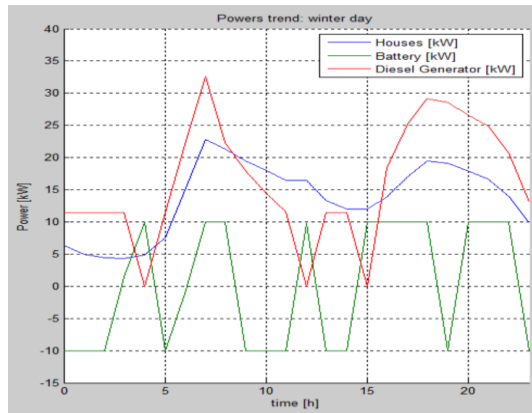


Fig. 3.5. Graphs of the house consumption, optimized battery schedule and optimized diesel generator schedule

The results obtained demonstrate that by optimizing the schedules for batteries and the diesel generator, a significant safety margin is achieved concerning the system load. Furthermore, this optimization leads to a substantial reduction in costs for the end user. By minimizing the objective function, fuel consumption of the diesel generator is also reduced, resulting in lower fuel expenses. Additionally, this approach mitigates the harmful impact on the

environment. Therefore, formulating and solving such optimization problems is crucial.

3.3.8.2 Determining the optimal capacity of the energy storage system in a microgrid operating in island mode

In [28], eight scenarios for the microgrid were examined, each featuring different battery system capacities, as discussed in [16] in the previous section. The optimization results for a similar economic model indicate that the maximum cost reduction occurs with a battery pack capacity of 100 kWh. If we consider the reduced costs over a 24-hour period in winter as an average, we can estimate the total sum (TS) of reduced costs over the project's life cycle of 3,653 years. This estimation is based on optimizing both the battery pack schedule and the diesel generator schedule. A comparison with the capital cost of the battery pack (CC_{Bat}) is provided in Table 3.3.

Table 3.3. Comparison between TS and CC_{Bat}

Сценарий №	E_{bt_max} [kWh]	TS [\$]	CC_{Bat} [\$]	$TS - CC_{Bat}$ [\$]
1	10	3746,70	2000	+1746,70
2	25	5746,72	5000	+746,72
3	50	9000,08	10000	-999,92
4	100	22306,86	20000	+2306,86
5	150	21120,18	30000	-8879,82
6	200	19933,51	40000	-20066,49
7	250	18746,83	50000	-31253,17
8	500	12813,45	100000	-87186,55

Increasing the battery pack capacity above 100 kWh for the studied microgrid results in a decrease in the percentage of cost reduction. The comparison presented in Table 3.3 indicates that the total cost reduction over the project's life cycle is less than the capital costs for the battery pack in all instances where the maximum battery capacity

(*Ebt_max*) exceeds 100 kWh. Consequently, increasing battery capacity leads to higher daily electricity costs for the end user. If a larger battery pack capacity is still necessary, there are two potential solutions to maintain daily energy costs:

1) *Extend the project's life cycle*: It is important to note that daily charging and discharging of batteries shortens their lifespan. To enhance the project's life cycle, a limit can be established in the mathematical model for the number of battery discharges and charges allowed in a single day..

2) *Develop more affordable batteries*: This would enable the use of a larger capacity battery pack without significantly increasing costs.

A third option for reducing costs is having the microgrid operate in conjunction with the main grid. In this scenario, any excess energy produced by renewable sources—which cannot be consumed by the microgrid's loads or stored in the batteries—can be sold to the main grid at the relevant prices during day and night periods.

3.3.8.3 Multi-criteria model for optimization of microgrid operation

In [29], a three-criteria microgrid model with the same components as in [16] and [28], but operating non-autonomously in a mode connected to the main grid, is presented. In addition to the economic criterion (14), a sum of emission costs criterion is introduced:

$$\min F_2 = \sum_{t=1}^{24} EC(t) = \sum_{t=1}^{24} \frac{E_f \cdot E_{cf} \cdot P_{DG}(t)}{1000}, \quad (22)$$

as well as a criterion of the difference between the value of energy purchased from the main grid and the value of energy sold to the main grid:

$$\min F_3 = Ep_d + Ep_n - Es, \quad (23)$$

where Ep_d represents the amount of energy purchased from the main grid during the day, while Ep_n denotes the energy purchased

from the main grid at night. Es is the total energy sold to the main grid over a 24-hour period. The purchase price is divided into two categories: a daytime price (from 06:00 to 22:00) and a nighttime price (from 22:00 to 06:00). Based on data from [30], the daytime price is set at \$0.124 per kWh, whereas the nighttime price is \$0.062 per kWh. Additionally, the selling price from the microgrid to the main grid is fixed at \$0.0787 per kWh, according to data from [31].

Fig. 3.6 shows the microgrid scheme:

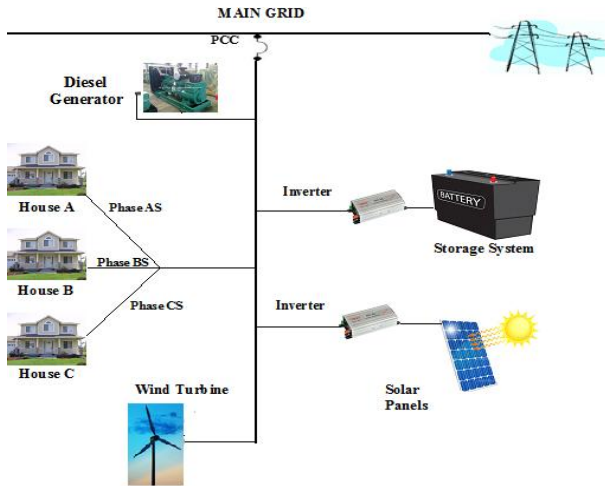


Fig. 3.6. A microgrid, connected to the main grid

To address the multi-criteria problem described above, all objective functions are combined into a scalarization function, allowing the problem to be treated as a single-objective problem. The weighted sum function is selected as the scalarization method, where each objective is assigned a weight w_i , where $i = 1, \dots, 3$; based on the preferences of the decision-maker (DM):

$$f(x) = \sum_{i=1}^3 w_i F_i(x) \quad \dots(24)$$

This multi-criteria optimization problem was addressed using a genetic algorithm developed in the MATLAB environment. To

evaluate the results, we compared them with the MATLAB solver gamultiobj, which is designed for multi-criteria nonlinear optimization under constraints. A population size of 50 was selected for the genetic algorithm. All the obtained compromise solutions showed that the objective function (24) produced negative values, indicating that the microgrid sells energy to the main grid at a price higher than that of the energy it purchases.

3.3.8.4 Study of the return on investment of a photovoltaic system in a microgrid

The performance of a photovoltaic system installed at Maungaraki School in Wellington, New Zealand, was investigated as part of the Dynamis project. This system consists of two 5 kW power converters with communication capabilities and 40 photovoltaic panels. The total cost of the project is NZ\$28,000 (approximately US\$19,600), which encompasses the system itself, additional equipment, installation, the installer's margin, and overhead costs. During periods of low energy demand, such as holidays and weekends, any excess energy generated is exported to the main grid. This system has been in operation since 2014 and has been evaluated for performance parameters in accordance with the International Energy Agency Photovoltaic Power Systems Program (IEA PVPS), the Clean Energy Council industry guide, and the IEC standard.

The annual performance ratio (PR) of the system is 78%. It is estimated that the total energy consumption from the main network has been reduced by 32% over the year. The calculated simple payback period for the system is 6.4 years. In monetary terms, the school has effectively reduced its electricity bill by 45%, resulting in savings of approximately NZ\$4,700 in 2014. This aligns with the simple payback period determined by the SAM financial model.

3.4 Conclusion

The economic exploitation of microgrids is a multifaceted endeavor that uses strategic planning, advanced mathematical modeling, and specialized tools to optimize performance and profitability. Ongoing research and technological advances continue to refine these approaches, contributing to the wider adoption and integration of microgrids into modern energy systems. Economic exploitation ensures the cost minimization for consumers and the optimal use of available energy resources. In addition, it increases the energy independence of consumers and reduces dependence on the central grid. This makes microgrids increasingly attractive for both individual consumers and industrial enterprises. In addition, the created decentralized energy system with many microgrids and clusters of microgrids increases the energy system's resilience as a whole. This is extremely important, especially when overcoming the consequences of natural disasters, wars, and technical failures.

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4. Energy management systems in microgrids. Optimal dispatching.

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Abstract

Effective management and dispatch of energy in microgrids is essential for achieving energy efficiency, reliability, and sustainability. This approach allows for the intelligent allocation of available resources, such as solar and wind power, as well as stored energy in batteries, to meet energy consumption needs while minimizing losses and costs. By dynamically adjusting to fluctuations in energy demand and production, system stability is maintained, preventing overloads and shortages. Optimal dispatch also facilitates the integration of renewable energy sources, which reduces dependence on the main grid and fossil fuels. This management strategy provides greater flexibility, enabling microgrids to respond effectively to changing external conditions, including market prices and emergency situations. Ultimately, it fosters the development of a more sustainable, economical, and autonomous energy system. This is why it is a focus of intensive scientific research and continuous improvement.

4.1. Microgrid energy management systems

Energy Management Systems (EMS) are essential for managing microgrids. They optimize energy production, consumption, and storage while reducing operating costs and environmental impacts [1].

The implementation of efficient energy management systems (EMS) is essential due to the instability and uncertainty associated with renewable energy sources (RES) and the controllable nature of microgrid components. These components include various types of power generation sources, energy storage systems, electric vehicle charging systems, and heating and cooling systems. Recent studies have extensively utilized multi-agent systems (MAS) and model predictive control (MPC) approaches, as both offer solutions to many of the challenges faced by EMS. The strength of these methods lies in the independent characteristics of MAS, the predictive capabilities of MPC, and their ability to ensure affordable, flexible, and secure operation of microgrids.

A modern review of the classification of microgrid control and optimization methods and their objectives is presented in [2]. This work helps to understand the operational challenges of microgrids and EWS from the perspective of the energy trilemma (flexibility, availability, and security).

4.1.1 Main functions of EMS:

- Real-time energy flow monitoring;
- Optimization of renewable energy use;
- Battery charging and discharging management;
- Integration with load and generation forecasting data;
- Control of grid interaction.

EMS employs a combination of classical optimization algorithms—such as linear and nonlinear programming — and modern techniques, including artificial intelligence, metaheuristic algorithms, genetic algorithms, and reinforcement learning, to manage resources adaptively. Decentralized strategies are crucial for enhancing the resilience and efficiency of electrical grids.

4.1.2 Hierarchical structure of EMS:

EMS is usually organized into three levels:

- **Field level:** control of local devices – inverters, batteries, generators.
- **Control level:** coordination between local units.
- **Supervisory level:** strategic optimization, interaction with external networks, forecasting.

4.2. Optimal dispatching

Optimal dispatching involves distributing generated energy among available sources and consumers to minimize costs and/or harmful emissions while adhering to technical constraints.

4.2.1 Objective functions:

- Minimizing the costs of energy production and purchase;
- Minimizing carbon dioxide emissions (and other harmful gases such as SO₂, SO₃, NO₂, CO, CH₄, etc.);
- Minimizing network losses.

4.2.2 Constraints:

- Generator power limitations;
- Battery capacity limitations;
- Voltage and frequency maintenance requirements.

4.2.3 Optimization methods:

- Linear/Nonlinear Programming (LP/NLP);
- Mixed Integer Linear Programming (MILP);
- Stochastic Optimization;
- Metaheuristic Algorithms: Particle Swarm Optimization (PSO), Genetic Algorithms (GA);
- Artificial Intelligence Algorithms (AI Algorithms): Deep Reinforcement Learning (DRL) [3, 4].

4.2.4 Examples:

The paper [5] provides an overview of technologies and techniques for managing renewable energy, considering the variability in renewable energy generation and fluctuations in energy demand. Additionally, the comprehensive review [6] explores the integration of renewable energy sources into microgrids and the challenges arising from their intermittent nature. It discusses various artificial intelligence techniques employed to tackle these challenges, including integration schemes, communication issues, and energy management strategies.

A proposed algorithm for optimal energy management in a "smart" home utilizes deep reinforcement learning (DRL) to efficiently dispatch energy within a microgrid that includes distributed generators, such as solar and wind power, as well as an energy storage system comprising either lead-acid or lithium-ion batteries and a home energy management system (HEMS). The primary goal is to minimize energy costs, which is framed as a Markov decision-making process. This algorithm is built on deep deterministic policy gradients (DDPG) and is robust, meaning it remains effective regardless of uncertainties

in energy generation from renewable sources or variations in the home's thermal dynamics. Simulation results demonstrate the algorithm's effectiveness.

The review [7] discusses how artificial intelligence techniques can be applied to the management and operation of microgrids. It highlights the potential of artificial intelligence to enhance the reliability of smart microgrids. In the study [8], the use of AI is explored through a multi-agent system (MAS) that is incorporated into an energy management strategy for a hybrid microgrid. In this system, renewable energy sources (RES) operate in Maximum Power Point Tracking (MPPT) mode. The components of the system are modeled using MATLAB/Simulink. Additionally, the work [9] addresses the modeling of power converters in MATLAB/Simulink.

The paper [10] explores advanced machine learning algorithms, specifically Support Vector Regression (SVR), with the goal of enhancing the efficiency and reliability of grid-connected microgrids.

In [11], a neural network-based energy management system is proposed for islanded AC microgrids that are powered by photovoltaic (PV) panels and a battery energy storage system.

The study in [12] focuses on improving the stability of energy flows within a hybrid microgrid. Additionally, an energy management system (EMS) for optimal energy control in microgrids is presented in [13]. Overall, it can be concluded that the implementation of an EMS is consistently beneficial, leading to reductions in both costs and energy consumption.

Extensive reviews on optimal energy management strategies in microgrids are presented in [14] and [15].

4.2.5 Improving energy efficiency in Durres Port Authority buildings

An Internet of Things (IoT) approach to improve energy efficiency in the Port Authority buildings located in Durres, Albania, is discussed in [16]. Comprehensive reviews of various IoT strategies aimed at enhancing the energy efficiency of buildings can be found in [17, 18]. In [16], the energy consumption of a microgrid consisting of ten administrative buildings at the Port of Durres is analyzed. The proposal includes a specific IoT implementation designed to transform these buildings into smart structures that will comply with the Nearly Zero Energy Buildings (NZEB) standards established by the EU Directive 2018/844 [19]. The microgrid integrates a combination of renewable energy sources, including a Photovoltaic System (PVS) based on solar panels and an Energy Storage Unit (ESU), as well as a Building Energy Management System (BEMS). The energy capacity of the ESU is optimized to match the capacity of the PV system. Furthermore, various sensors are installed both inside and outside the buildings, allowing for remote control of the Heating, Ventilation, and Air Conditioning (HVAC) systems.

The microgrid comprises 10 administrative buildings of the Durres Port Authority (DPA) in Albania. They are designated as follows:

- 1) ADM 1,
- 2) ADM 3,
- 3) ADM 4,
- 4) ADM 6 Environment and Security,
- 5) ADM 9 (Fire Brigade),

- 6) GMD (General Maritime Directorate (Captainship)),
- 7) Guardia di Finanza (Finance Guard),
- 8) ASC – Albanian Stevedoring Company,
- 9) Lighthouse Office, and
- 10) HTM – HTM Company building.

The port of Durres is large and includes a yacht harbor, a fishing port and a port for large ships, as well as a long quay for loading and unloading with cranes (see Fig. 4.1).



Fig. 4.1. Photo of the port of Durres, Albania
(<https://www.durresport.al/index.php/en/port/>)

All the buildings are relatively new and do not require special renovations. They experience minimal heat loss. Additionally, the administrative buildings have flat roofs, which, combined with the favorable climatic conditions in Durres—characterized by a high number of sunny days each year—make them suitable for installing solar panels. This installation can lead to a significant reduction in electricity consumption from the main electricity grid. The energy consumption data for these buildings over the past five years was provided by the Durres Port Authority.

In the Port of Durres, the photovoltaic system (PVS) has an area of 2,500 m². The energy storage unit consists of lithium-ion batteries, and simulation calculations indicate that its maximum optimal energy storage capacity is 1,500 kWh. This Battery Energy Storage (BES) unit is connected to the energy system of the buildings via 15 bidirectional AC/DC inverters, which facilitate battery charging and discharging. Each inverter is capable of handling a charging/discharging capacity of 10 kW per hour. The energy produced by the PV system, in conjunction with the BES, covers approximately 50% of the buildings' energy consumption during the summer period and about 30-35% during the winter months. To maximize energy efficiency, the Building Energy Management System (BEMS) calculates an optimal charging and discharging schedule for the BES. This ensures that the energy consumption of the buildings within the microgrid is met to the greatest extent possible, rendering these buildings intelligent.

In [21], an IoT-based energy management system for buildings is considered. It performs control of electronic devices (actuators), but does not optimize the BMS schedule. A variant of a microgrid energy management system is proposed in [22]. It does not include forecasting of energy production and consumption. The Building Energy Management System (BEMS) in the Port of Durres is more complex. It combines a forecasting module and an optimization module.

The forecasting module in the Building Energy Management System (BEMS) predicts energy consumption for buildings by utilizing available statistical data on daily usage and weather forecasts. The generated forecast is continuously compared with real-time data from building sensors and is adjusted

accordingly. A combination of internal and external sensors, along with infrared sensors, detects human presence in various areas of the building. This information is relayed to the BEMS, which can then turn off power in unoccupied spaces and manage the LED lighting system accordingly. Additionally, "smart sockets" are implemented, and heating, ventilation, and air conditioning (HVAC) systems can be controlled remotely to optimize energy consumption.

Figure 4.2 illustrates the control of the BES via the Building Energy Managements System:

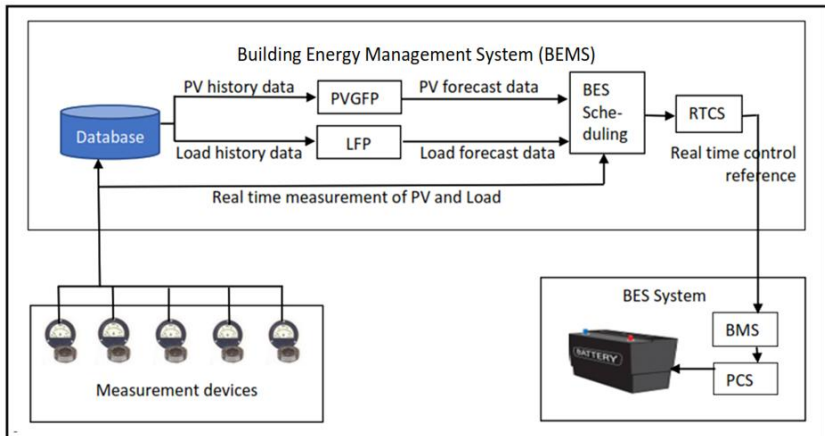


Fig. 4.2 Scheme of BES management through EMS

Here, PVGFP is designated as "Photovoltaic generation forecast program" for the energy generated by the PVS, LFP is designated as "load forecast program", BMS is the "Battery management system", and PCS is the "power conditioning system".

The forecasting module in the Building Energy Management System (BEMS) predicts the energy consumption of buildings using available statistical data for a specific day, along with

weather forecasts. This prediction is compared in real time with data from external sensors installed in the buildings, allowing for adjustments as needed.

The optimization module of the BEMS is designed to address the following tasks:

1. Optimize the costs associated with the installation and maintenance of essential IoT equipment, which includes sensors, photovoltaic systems, and energy storage units.
2. Minimize energy consumption from the main power grid by optimizing the charging and discharging schedules of the energy storage unit. This optimization takes into account estimated energy consumption of the buildings and the expected energy production from the photovoltaic system. The optimization is performed continuously at short intervals to correct any inaccuracies in the forecasts.

By implementing this IoT-based BEMS, the buildings are transformed into smart buildings. Eventually, these buildings aim to achieve nearly zero energy consumption from the main power grid.

4.2.6 Microgrid optimal energy management, assisted by artificial intelligence (AI)

Below is an example of an application of optimal energy flow management, where data from each component of the microgrid (IoT data) is collected by sensors and fed to an Energy Management System (EMS), where the data is processed using artificial intelligence (AI).

The microgrid includes a group of houses (Load), a photovoltaic system (PVS), wind turbines (WT), an energy storage system

(ESS), and an energy management system (EMS). The microgrid scheme is presented in Chapter 1 - Fig. 1.2, and the EMS scheme is in Chapter 1 in Fig. 1.3.

Optimization problems are formulated to minimize the energy costs associated with a microgrid during a typical winter day. This 24-hour period is divided into 24 one-hour time steps. Figure 4.3 illustrates the total energy generated by the photovoltaic system (PVS) and the wind turbines (WT), as well as the energy consumed by the load.

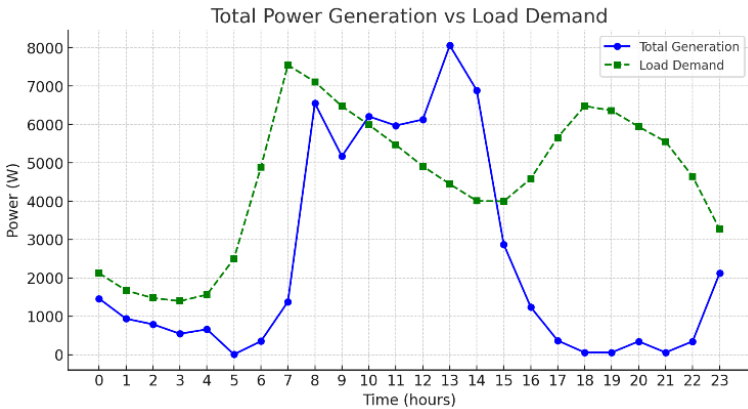


Fig. 4.3 Total Power generation and Load Demand (in a 24-hour period)

Fig. 4.4 shows a diagram of the Balance energy.

The optimization process is organized in two stages. First, a bicriteria optimization model is proposed to determine the optimal charging/discharging schedule of the energy storage system. The goal is to reduce peak energy consumption and achieve a gentle operating mode of the energy storage system.

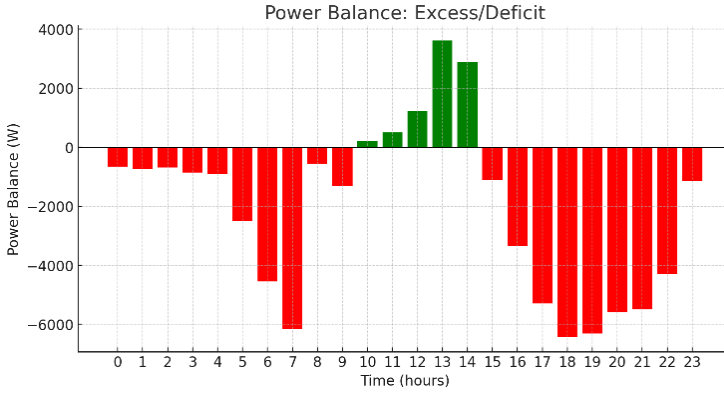


Fig. 4.4 Balance power diagram

A reinforcement learning model has been proposed to optimize the Maximum Power Point Tracking (MPPT) mode, similar to the model discussed in [8]. The aim of this model is to provide real-time adjustments to compensate the fluctuations in energy generated from photovoltaic (PV) and wind turbine (WT) sources.

A. Bicriteria optimization model

The additional power required from the main grid is denoted by PMG and is divided into two parts:

$$PMG = Pd + Pn , \quad (25)$$

Here, Pd is the energy delivered during the day (in the interval 6:00 a.m. - 10:00 p.m.), and Pn is the energy consumed at night (in the interval 10:00 p.m. - 6:00 a.m.).

- *Objective functions:*

Two objective functions must be minimized simultaneously. The first one is:

$$\min F_1 = \sum_{i=0}^{24} (P_L(i) - P_{PV}(i) - x(i)) \cdot Pr(i) + OM_{ESS} + RC_{ESS} + CC_{Inv} , \quad (26)$$

Here, OM_{ESS} is the operation and maintenance cost of the energy storage system (ESS), RC_{ESS} is the replacement cost of the ESS, and CC_{Inv} is the capital cost of the inverters. Furthermore, $Pr(i)$ is the price of energy purchased/sold from/to the main grid at the i -th hour of the day.

Based on the data from [23], the daytime energy price (from 06:00 a.m. to 10:00 p.m.) is:

$$Pr(i) = 0,124 \text{ \$/kWh for } 6 \leq i < 22; \quad (27)$$

and the price of nighttime energy (from 10:00 p.m. to 06:00 a.m.) is:

$$Pr(i) = 0,062 \text{ \$/kWh for } i < 6 \text{ or } i \geq 22; \quad (28)$$

The second objective function has the form:

$$\min F_2 = \sum_{i=0}^{24} |z(i)| \quad (29)$$

where $z(i) = 1$, when the energy storage system ESS has changed its operating mode (from $(i-1)$ th to i -th hour: 1) transition from charging to passive state or discharge; 2) transition from passive state to charge/discharge; 3) transition from discharge to passive state or charge;), $z(i) = 0$, when the ESS remains in the same operating mode in the i -th hour as in the $(i-1)$ th hour. Minimizing the number of transitions from one operating mode to another ensures a longer ESS life and gentle operation of the batteries.

- *Constraints:*

The ESS system must satisfy the same set of constraints (15)-(21) as in Chapter 3.

The minimum State of charge (SOC) level is denoted by SOC_{min} and is fixed at 20% of the maximum capacity of the ESS. The

maximum SOC level is denoted by SOC_{max} and is fixed at 100% respectively. The constraints for the state of charge are (18) and (21) respectively.

B. Reinforcement learning model (RL model)

A model is proposed to optimize maximum power point tracking (MPPT) for both photovoltaic (PV) systems and wind turbines within a microgrid. Reinforcement learning techniques can be utilized for continuous learning and optimization of the tracking process. Given that MPPT optimization involves real-time adjustments of duty cycles or control parameters, the actor-critic approach is particularly suitable. The **Soft Actor-Critic (SAC) method** is ideal for continuous control tasks such as MPPT, as it effectively balances exploration and exploitation. Therefore, SAC has been chosen for adjusting the duty cycles and control parameters in this study.

Continuous control variables:

- Photovoltaic system: Duty cycle (DDD) regulation of the DC-DC converter.
- Wind turbines: Generator load resistance regulation.

- Reward function:

The reward function R to be maximized is a sum of penalties taken with a negative sign. The first term of the penalty is the squared deviation from the forecasted consumption from the main grid. To calculate the second term of the penalty, a vector v is created. Let $PESS_{max}$ be the maximum power [kW] that the energy storage system can deliver/absorb. In case the balancing power $PB(i)$ is negative and the ESS is charging at

hour i , then $v(i) = \text{PESS_max}$; In case the balancing power $\text{PB}(i)$ is positive and the ESS is discharging at hour i , then $v(i) = \text{PESS_max}$; In other cases $v(i) = 0$. The second term of the penalty is equal to the sum of the squares of the $v(i)$ -components, $i = 1, \dots, 24$; The function R has the form:

$$R = -\sum_{t=1}^{24} \lambda [P_{MG}(t) - P_{PrMG}(t)]^2 + \gamma [v(t)]^2 \quad (30)$$

The **“Reinforcement Learning toolbox”** is used to implement the Soft Actor-Critic (SAC) agent for MPPT optimization in the MATLAB environment.

The steps in the MATLAB script are as follows:

1. Define the environment (MPPT simulation for photovoltaic systems and wind turbines).
2. Configure the SAC agent settings (actors, critical networks).
3. Train the SAC agent using the MATLAB training function.
4. Memorize and deploy the trained agent.

The environment functions used are as follows:

- `mppt_step(action)`: Simulates the PV/wind system and returns the new state and reward.
- `mppt_reset()`: Resets the environment to its initial state.

The Soft Actor-Critic (SAC) agent with reinforcement learning (RL) is trained for 1000 episodes, which means that the agent interacted with the environment 1000 times, learning how to optimize the maximum power point tracking (MPPT) for the microgrid in Fig. 1.2.

Each episode consists of 24 time steps (1 hour each), where the SAC agent:

1. Observes the system state (battery charge and power balance).
2. Chooses an action (battery charge/discharge decision).
3. Receives a reward based on how well it matches the optimal MPPT schedule.
4. Updates its internal model using the Soft Actor-Critic algorithm to improve future decisions.

The SAC agent needs to be trained further. Real-time sensor data can be used for this training. Finally, the trained agent is saved for deployment.

The training process of the SAC agent is shown in Fig. 4.5.

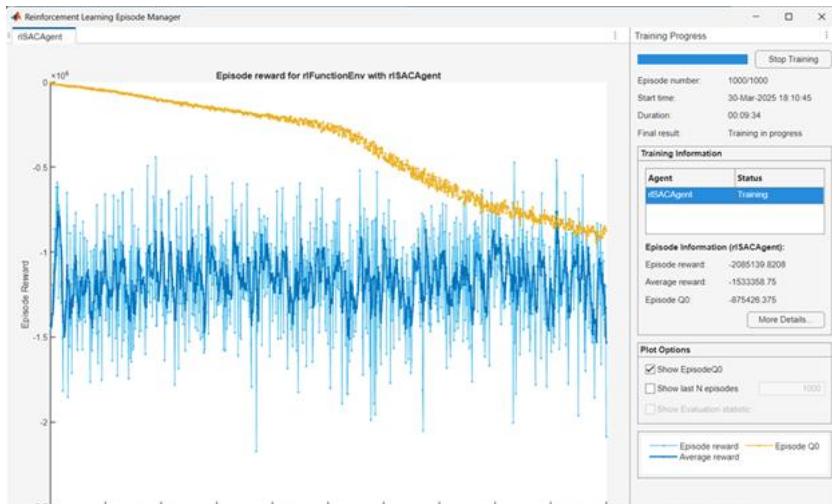


Fig. 4.5 SAC agent training process for 1000 episodes

Since the training has reached the maximum number of episodes, it is essential to analyze the agent's performance to determine if it has converged to an effective policy. The trained agent is deployed in the environment for one episode to

evaluate its performance. It runs a full 24-hour simulation and provides the agent's actions, observations (specifically, the state of charge evolution), and reward values. The results obtained are very promising. Now, the trained SAC agent can be implemented on a microcontroller for Maximum Power Point Tracking (MPPT) optimization in real-world conditions.

C. Results of energy management optimization using artificial intelligence

Renewable energy production is modeled using historical climate data for Seattle, USA. The AI in the Energy Management System is utilized for the following purposes:

1) Intelligent Battery Management

- **Forecasting Energy Consumption and Production:** The AI analyzes historical data alongside weather forecasts to predict future energy consumption and production.
- **Charging Batteries at Low Prices:** Taking advantage of varying energy prices throughout the day, the AI charges the batteries during periods when electricity is cheaper.
- **Utilizing Stored Energy at High Rates:** The system discharges stored energy to power homes when electricity prices are high.
- **Optimizing Battery Wear:** The AI minimizes excessive charge and discharge cycles, helping to prolong the life and efficiency of the Energy Storage System.

2) Balancing own consumption and trading with the main grid

- Maximize use of locally produced energy – AI distributes generated solar and wind energy between the three houses to avoid purchases from the main grid.
- AI sells excess energy to the main grid – if the batteries are full and consumption is low, AI calculates when it is most profitable to sell the excess energy.

3) *Load Management (Demand Response)*

- Delayed consumption - AI manages smart appliances (boilers, heat pumps, heating/cooling systems), turning them on when excess energy is available.
- Preemptive load management - If the forecast shows an energy deficit, AI can suggest homeowners to reduce consumption at certain times.

4) *MPPT optimization*

For MPPT optimization, the AI implements the Reinforcement Learning model with a Soft Actor-Critic (SAC) agent. The MATLAB Reinforcement Learning toolbox is used. The AI continuously improves based on past results, optimizing the tracking for different environmental conditions.

For the Energy Storage System schedule optimization experiments, the bicriteria model is solved using the ***gamultiobj*** multicriteria optimization solver (with multiple objective functions) and constraints from the MATLAB Global Optimization toolbox.

The result shows that the use of AI in the energy management system leads to additional energy savings in the range of 10%

to 12%, depending on the intensity of energy consumption by the houses.

The generated optimal schedule of the Energy Storage System is shown in Fig. 4.6.

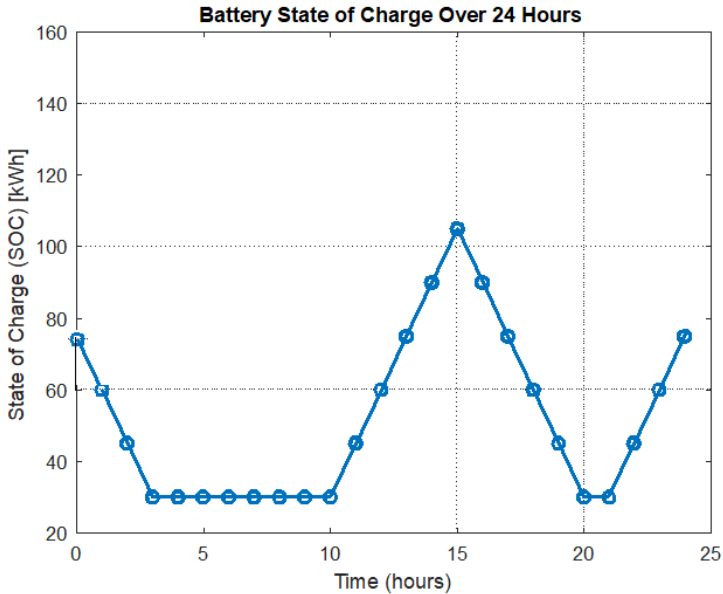


Fig. 4.6 Optimal ESS charging/discharging schedule in the 24-hour period

In the above example, the MPPT mode of the photovoltaic system is optimized. Similarly, the MPPT mode of the wind turbines is optimized. The charging/discharging schedule of the Energy Storage System is also optimized.

Conclusion: The application of artificial intelligence results in several significant benefits:

- i) Reduced energy costs through dynamic charging and efficient battery usage.

- ii) Optimal utilization of renewable energy sources without incurring losses.
- iii) Improved stability of the microgrid by effectively balancing supply and demand.
- iv) Extended battery life achieved through intelligent control of charge and discharge cycles.

Experiments have demonstrated that the optimization models developed are effective and can be applied to address real-world challenges in the management and operation of microgrids.

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5. Heuristic techniques and evolutionary algorithms in microgrid optimization tasks

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Abstract

Microgrids (MGs) have gained significant popularity as a means of electricity generation over the past ten years due to various factors, including the need to utilize renewable and environmentally friendly energy sources. A crucial aspect of designing and operating MGs is their optimization, ensuring they function efficiently under normal conditions and respond effectively to unexpected events, such as increased energy consumption or reduced electricity production. To address these challenges, numerous optimization methods are employed. This chapter reviews heuristic and evolutionary approaches to solving various optimization problems related to microgrids.

5.1. Introduction

Microgrids (MGs) represent a significant scientific and practical achievement in the modern world. They have elevated the quality of energy infrastructure. The creation and development of microgrids have been made possible through advancements in various fields, including engineering, information and communication technologies, mathematics, and more.

There are many definitions of microgrids. According to some authors [1, 2, 3], a microgrid is any clearly defined (sub)system consisting of power generators, energy storage devices, and energy consumers that operate under the control of a local management. An important feature of a microgrid is the ability to connect/disconnect to the main grid to maintain standard service during disturbances without compromising the integrity of the transmission network.

An important feature of microgrids is that they can operate autonomously (in island mode) or connected to the main grid. Other features of microgrids are: generation of energy for immediate local consumption, intelligent management using smart controllers.

The main components of microgrids are:

- ✓ energy storage devices;
- ✓ devices for converting energy from AC to DC and vice versa;
- ✓ energy distribution devices, such as transformers and switches;
- ✓ control devices – provide safety, reliability, flexibility (response according to demand);
- ✓ control and monitoring devices – for safety, reliability, coordination of the individual parts of the microgrid.

An example of a microgrid scheme with its main components is shown in Fig. 5.1.

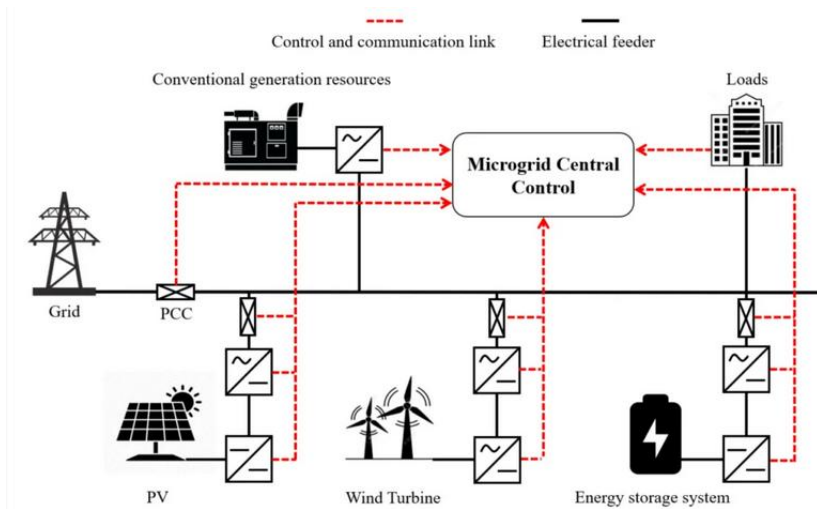


Fig. 5.1. Microgrid ¹

According to the type of current, MGs are divided into AC MGs (alternating current), DC MGs (direct current) and hybrid MGs. According to the connection method, MGs are divided into grid-connected and islanded. Akter et al. [4] consider 11 types of MGs according to scenario/purpose, source/type of electricity and mode of operation.

5.2. Optimization tasks for microgrids

Despite their name, microgrids (MGs) are intricate systems that can be quite expansive in terms of spatial dimensions, encompassing a wide range of components. This complexity presents several interesting challenges that need to be addressed to ensure effective operation [4-9].

In her monograph [10], Borissova discusses various approaches to decision-making and optimization in the design, operation, maintenance, and investment of wind farms. She also examines key

¹ <https://energyconsortium.org/an-introduction-to-microgrids-benefits-components-and-applications-for-a-sustainable-energy-future/>

issues such as balancing energy consumption and synchronizing with other energy sources. The text highlights solutions to specific challenges, including supplier selection, monitoring, predictive maintenance, and the production of components for wind turbines.

In this context, the following main tasks for microgrids can be identified:

5.2.1 Energy efficiency management task

This includes optimizing the types of electricity sources, such as utilizing renewable sources, minimizing losses during transmission, storage, and distribution of electricity, and reducing losses during electricity usage.

5.2.2 Energy availability management task in microgrids

This is done to ensure there is enough electricity available in case of failures in the main grid or the microgrid (MG). It also considers high-priority consumers who require a continuous supply of electricity. Additionally, this section addresses the management of electricity storage components within the MGs.

5.2.3 Microgrid reliability and resilience management task

The reliability of a microgrid ensures its trouble-free operation. Applying methods for predicting various emergency events and their avoidance is essential. The resilience of a microgrid guarantees its efficiency during peaks and troughs in electricity consumption and/or production.

5.2.4 Microgrid security management task

The security of a microgrid (MG) refers to its overall effectiveness in responding to natural disasters (such as earthquakes and floods), targeted attacks, and harmful impacts from various non-production factors that could damage the main grid or microgrids themselves. In this context, the location of the components within a microgrid is crucial. It is essential to consider all relevant factors during the design phase of the microgrid.

5.2.5 Cost optimization task

This includes the costs associated with building and maintaining a particular microgrid (MG), as well as expenses for electricity production, personnel, and more. Additionally, it is important to consider the intended use of the MG, whether it can be designed for a unified approach or specialized purposes, and in what format it will be implemented.

5.3. Heuristic techniques and evolutionary algorithms for microgrid optimization

In this section, we will review heuristic and evolutionary approaches to optimization problems related to microgrids (MGs). We will examine several stages of the MG life cycle: design, operation, and diagnostics/monitoring. Heuristic optimization methods, which are a type of approximate method, are employed when exact methods prove inefficient. This inefficiency can arise when a significant amount of time is required to find the optimal solution, or when no exact solution can be identified at all. The optimization of microgrids is classified as an NP problem, particularly when integer variables are included in the optimization models. This means that no algorithm can guarantee an exact solution in polynomial time.

Currently, over 540 heuristic algorithms have been created [11]. Before that, we will present a classification of heuristic and

evolutionary approaches according to Bhattacharyya et al. [12]– see Fig. 5.2.

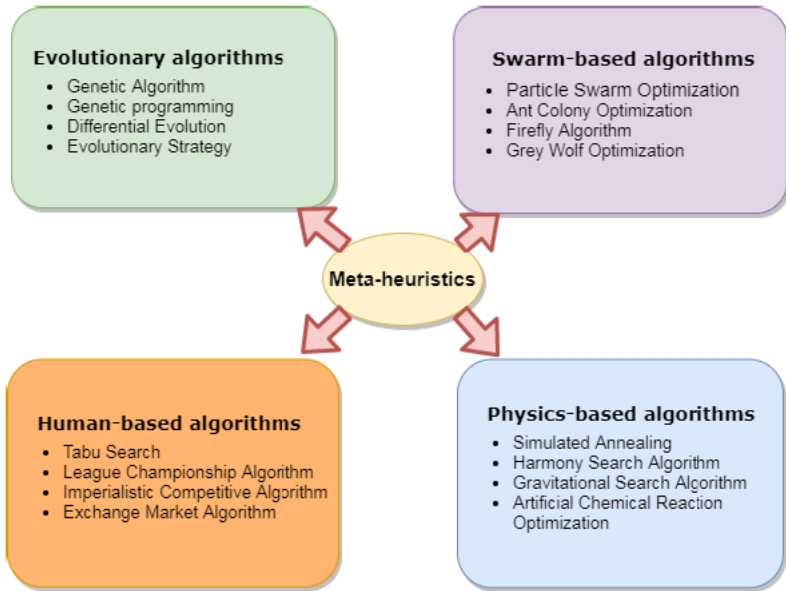


Fig. 5.2. Different groups of metaheuristic algorithms according to [12].

Heuristic and metaheuristic methods are commonly employed to address various issues related to microgrids (MGs). Between 2012 and 2022, the number of scientific studies focused on optimizing MGs increased by more than tenfold, as noted by Zheng et al. [13]. In this review, we examine several key types of MG problems that can be effectively solved using heuristic and evolutionary methods (HEM):

1. Implementation Phase in MG Control
 - MG sizing and component selection;
 - Configuration of MG parameters, including battery charging and discharging times and the angle of solar panels;
2. Operational Phase in MG Control

- optimal energy planning;
- real-time planning (short-term planning).

The types of MG optimization problems solved with HEM are also reviewed in Kassab et al. [14], Rezk et al. [15], Gamarra & Guerrero [16]. The papers by Vaish et al. [17], Suresh et al. [18], Thirunavukkarasu et al. [19] consider applications of heuristic approaches inspired by nature (such as simulated annealing method, intelligent water drop method, gravity search method, etc.) to solve MG optimization problems..

5.3.1. Sizing/design of microgrids

The sizing of microgrids is a crucial phase in their design and requires careful consideration of various factors to maximize efficiency and effectiveness. It is essential to determine the optimal balance between the power generated by energy sources and the capacity of storage components. Additionally, understanding the primary objectives of the specific microgrid—such as its operational modes and the types of electricity consumers it will serve—plays a vital role in ensuring its seamless and efficient performance. By addressing these key elements, we can guarantee that the microgrid will operate smoothly under all conditions. Numerous studies, including those by Kassab et al. [14] and Bilal et al. [20], emphasize the importance of this task in achieving reliable microgrid systems.

Elazab et al. [21] address the challenge of sizing and optimizing the operation of a microgrid under dynamic pricing conditions. This microgrid includes wind turbines, PV panels, storage batteries, and an AC-DC/DC-AC converter. The authors propose two optimization criteria: minimizing total annual costs and reducing harmful emissions produced during operation. To achieve this, they developed the Dandelion Algorithm (DA), an evolutionary algorithm. They also compared their results with other methods, including Particle Swarm Optimization (PSO), the Nutcracker Optimization Algorithm (NOA), and the Kepler Optimization Algorithm (KOA). Reich

[22] introduces a heuristic search method for sizing distributed energy resources, known as Network of microgrids (NMGs). This method is implemented on the open-source Microgrid Planner platform [23]. It can generate multiple potential solutions based on the preferences of the decision maker, who can then select the best option using a linear local search method.

Fioriti et al. [24] propose a consolidated heuristic approach for the design of MGs. The core of the heuristic is the particle swarm optimization (PSO) method. This method optimizes the MG according to the criterion of “Net present cost” (NPC), which must be minimized. The criterion includes investment costs, operating costs, and residual value at the end of the project cycle. The method can generate several solutions at each iteration. A real example of an MG built in Soroti, Uganda is solved.

Bilal et al. [20] propose a hybrid heuristic for designing an MG. The network is standalone and may or may not include renewable energy sources (solar PV panels, wind turbines WT). The components: diesel generators DG and energy storage batteries BES are mandatory. The number of components is unknown, and they participate as variables in the optimization. The hybrid heuristic includes the Particle Swarm method and the Whale Optimization Algorithm (WOA). Several criteria (multi-criteria task) are optimized: levelized electricity costs, total net current costs, and minimization of emissions from diesel generators. A comparison is made with the Particle Swarm, Whale Strategy, and Stochastic Fractal Search (SFSA) methods. A MG was designed for this task in the Chennai, India area.

An application for optimal energy consumption in a microgrid (MG) was conducted for a university campus, as described by Marinova et al. [25]. The microgrid includes photovoltaic (PV) panels, storage batteries, proton exchange membrane (PEM) fuel cells, and a converter designed for low-cost biohydrogen production. The parameters for the converter and fuel cells were optimized, and an

optimal schedule for the storage cells and the required biohydrogen was determined. The calculations were performed using MATLAB.

The role of the Energy Management System (EMS) for microgrids (MGs) is examined in the study by Guliashki and Marinova [26]. Initially, the economic costs without the use of an EMS were optimized, and subsequently, new energy schedules were developed with the EMS in place. The results indicated improved energy efficiency for microgrids. Additionally, Guliashki and Marinova [27] consider the energy efficiency of buildings within microgrids during the design phase. Key parameters such as the window-to-wall ratio (WWR), type of glazing, insulation levels, building orientation, and the use of shading devices (like shutters, sun blinds, and awnings) were optimized to enhance energy performance.

An accelerated genetic algorithm for energy flow control in MGs, called ASOGA, was proposed in Guliashki & Marinova [28]. A multi-criteria model with four criteria was also proposed, which, after scalarization, was solved by the genetic algorithm. A comparison with a classical genetic algorithm was made.

The optimization of storage battery capacity design in an island microgrid (MG) was conducted by Guliashki and Marinova [29]. They examined eight scenarios based on the least favorable conditions, specifically during a winter day. The study determined the optimal battery capacity by focusing on the goal of maximizing the reduction in energy costs.

The optimal design of various aspects of wind farms has been explored in numerous sources. In their study, Borissova and Mustakerov [30] examine the ideal placement of wind turbines and the integration of mixed-model management (MM) into the overall grid. They propose a mixed-integer nonlinear model for determining capacity and a linear model for calculating the distances to the connection point.

The issue of determining the type and number of wind turbines has been addressed by Borissova and Mustakerov [31]. They proposed a mixed-integer model with two criteria: maximizing energy production and minimizing costs. In their later work, Borissova and Mustakerov [32] examined the optimal design of wind farms, considering the specific characteristics of the terrain and incorporating restricted zones for turbine placement. They introduced a single-criterion mixed-integer nonlinear model along with an algorithm for solving it. Furthermore, Borissova and Mustakerov developed a web-based system for the preliminary assessment of wind farms [33]. This system accounts for various factors, including the required power, the number and type of turbines, their location, and associated costs.

5.3.2. Microgrid operation

The exploitation of MGs and its optimization in various aspects is discussed in [34] Suchetha & Ramprabhakar, [35] Gao et al. etc. The statistical data for renewable energy sources with rapid acceleration towards a sustainable microgrid are shown in Fig. 5.3 a,b.

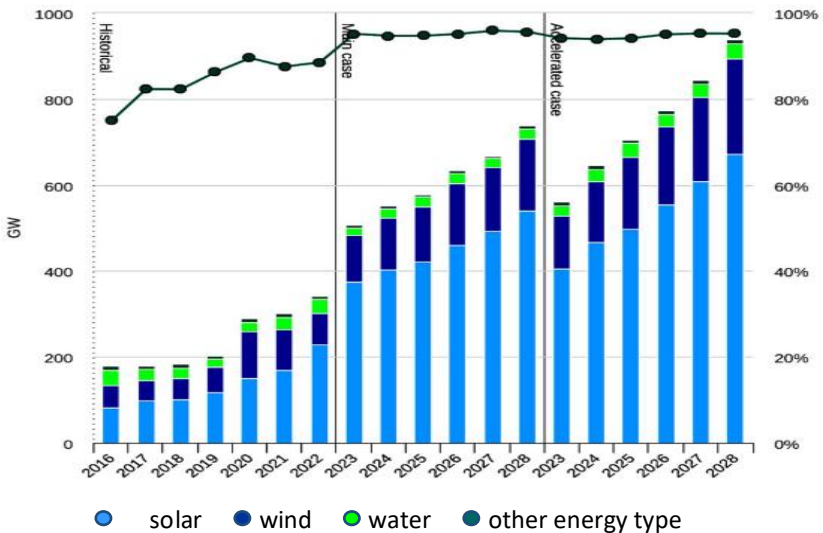


Fig. 5.3. a. Renewable energy growth by technology according to [36]

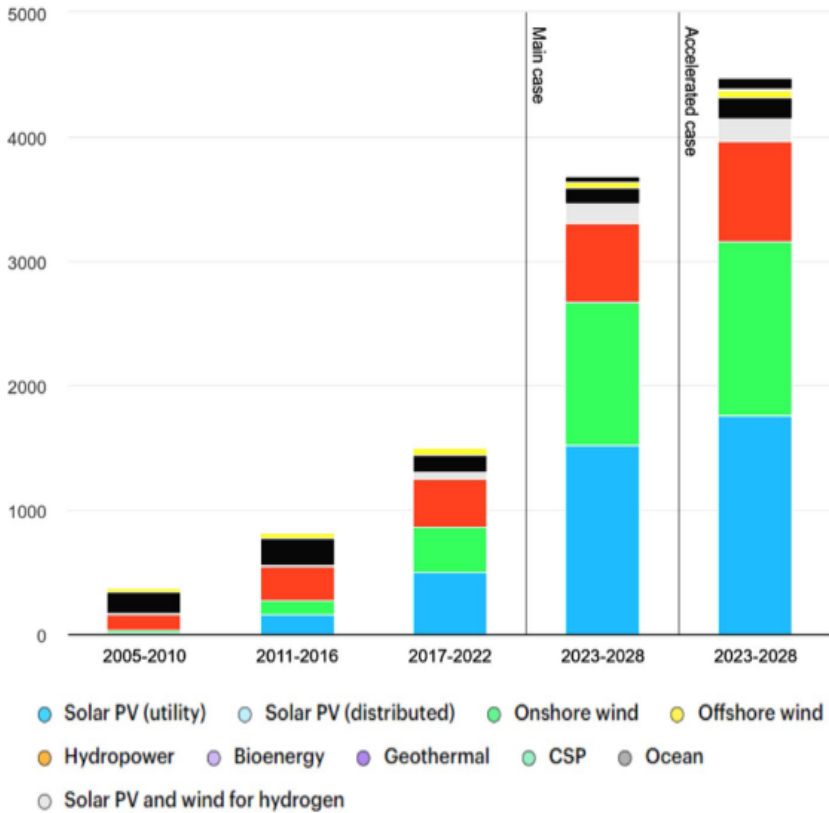


Fig. 5.3. b. Renewable energy growth by technology according to [36]

The development of publication activity for MGs by years is presented in Fig. 5.4.

Optimization of energy storage batteries for an MG in connected mode was done in Guliashki et al. [37]. MG consists of PV panels, batteries, and an inverter. Several scenarios for sunny and windy days are considered, respectively, with the goal of minimal use of energy from the main grid.

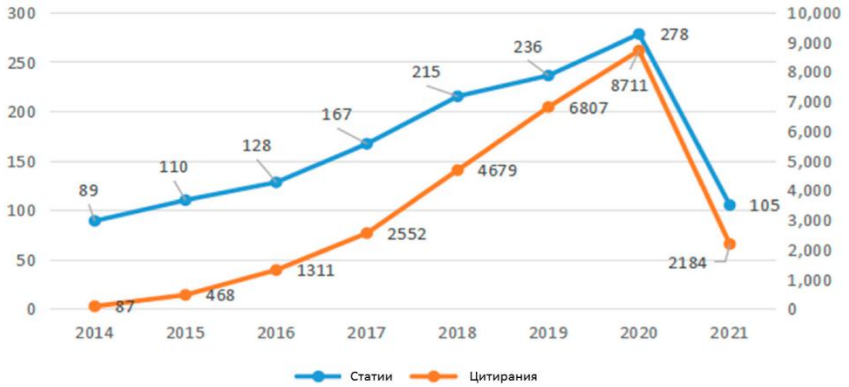


Fig. 5.4. Distribution by year of articles and number of citations for MGs for the period 2014 – 2021 according to [35]

A similar problem was studied in Marinova & Guliashki [38] for the case of an island MG. The MG includes PV panels, a wind turbine, and three houses. Two problems are solved: optimization of the battery schedule by the energy criterion and optimization of the battery schedule by the price criterion.

In [39], Tomoiaga et al. propose a fast heuristic algorithm for optimal control of the movement of electric energy flows in an island (stand-alone) MG (which is not connected to the general transmission network). A model with an objective function – minimum of the energy price within a 24-hour interval (48 half-hour intervals) is solved.

The microgrid (MG) consists of microturbines, photovoltaic panels, wind generators, storage devices, and both controllable and uncontrollable consumers. The minimum response time is half an hour. According to Hou et al. [40] and Colet-Subirachs et al. [41], to ensure long-term sustainable operation under varying loads, each microgrid must have a management and control system that enables different adjustments over time.

It is customary to work with three time frames in electrical power management:

- **Primary Correction:** This is implemented instantly and in a decentralized manner. The main goal is to prevent the automatic activation of load control devices when the frequency drops due to any fault.
- **Secondary Correction:** This is applied centrally for the entire microgrid (MG) and operates over a range of several minutes. The purpose of secondary correction is to maintain the nominal frequency and ensure that there is a reserve for primary correction. In practice, this involves adjusting the active energy produced by the currently operating sources. Additionally, secondary correction can facilitate a smooth transition of the MM from "island mode" to a state connected to the main grid.
- **Tertiary Correction:** This form of correction is also applied centrally but operates over a range of 15 to 30 minutes. It involves either starting or stopping energy sources, adjusting the active energy from the currently operating sources, and varying the active energy consumption.

The heuristic algorithm proposed by the authors essentially functions as a sorting algorithm. It organizes the energy sources in ascending order and compares their output against the energy requirement for a specific 30-minute time interval. A key aspect of the algorithm is the "key source," which is defined as the point where the produced energy equals the consumed energy for that time step. Therefore, any sources above this key source do not contribute during this interval. In summary, the authors introduce a **method for predictive control**.

A similar problem was addressed by Alahakoon et al. [42], who proposed a meta-heuristic approach. The MG considered, operates independently and represents the microgrid of marine vessels and

ships. It includes components such as fuel cells, solar photovoltaics, diesel generators, battery systems for energy storage, and various consumers. The meta-heuristic combines particle swarm optimization (PSO) and grey wolf optimization (GWO). This combination was chosen because PSO excels at exploring a wide range of potential solutions throughout the feasible set, while GWO is effective at identifying promising solutions in the vicinity of a given point. Overall, this method serves as a control strategy based on **meta-heuristic optimization**.

The optimal management of stored energy in batteries, known as the Battery Energy Storage System (BESS), for microgrids (MGs) is discussed in the work of Guliashki and Marinova [43]. A microgrid is connected to the main grid and consists of a small group of houses, a photovoltaic (PV) system, proton exchange membrane fuel cells (PEMFC), and a control system known as the Energy Management System (EMS). The microgrid also features three-phase current transmission. A **classical proportional-integral (PI) control approach** is proposed for managing the storage cells. The system is implemented using MATLAB, specifically through the Simulink and SimPowerSystems toolboxes. By optimizing the scheduling of the fuel cells, the system's operational time is extended.

A study on energy schedules for island microgrids (MGs) was conducted by Marinova and Guliashki [44, 45]. The microgrid comprises a storage system (batteries), photovoltaic (PV) panels, a diesel generator, and several households. The aim of the study is to minimize the cost of generated energy while optimizing the schedules for the storage system and the diesel generator. This optimization takes into account fluctuations in demand over time and various operational constraints.

Guliashki et al. [46] studied the energy efficiency of buildings included in the MM. The initial investment costs and energy costs are optimized while minimizing the environmental pollution of the MM. The resulting two-criteria model is solved using a genetic algorithm.

An IoT approach to improve energy efficiency in the buildings of the Port Authority of Durres, Albania, is proposed in [47] by Marinova et al. Various options for smart devices, sensor networks, and remote control tools for managing energy flows, monitoring, and reducing electricity consumption in buildings have been examined and evaluated.

5.3.3 Microgrid diagnostics/monitoring/maintenance

The effective operation of an MG is impossible without active monitoring and diagnostics of its components, including power sources and consumers. Not many heuristic and evolutionary approaches can be mentioned in this section.

Kuo and Lu [48] view microgrids (MGs) as distributed multi-agent systems and have developed intelligent real-time control for this purpose. Their system adheres to the specifications of the Java Agent Development Framework (JADE), which is designed by the Foundation for Intelligent Physical Agents (FIPA). However, the authors do not specify the methods implemented in the control system.

Guliashki et al. [49] propose a decision-making approach aimed at enhancing the stability of energy flow in microgrids (MGs) during natural disasters, wars, or critical situations. The microgrid consists of photovoltaic (PV) panels and wind turbines. They propose a bicriteria model focused on increasing stability and minimizing the number of consumers who could be left without energy. Additionally, they consider the carbon emissions associated with the use of diesel generators.

5.4 Conclusion

Microgrids are a relatively new concept that has gained significant traction over the past twenty years. Due to changes in living conditions, advancements in science and technology, and shifts in energy policies across many countries, microgrids are positioned to

play an increasingly important role in electricity generation. Essentially, microgrids are complex structures that present a variety of optimization challenges and warrant greater scientific interest. Currently, several models and methods have been developed for optimizing the operation of microgrids and their various components. A notable portion of these optimization methods utilizes evolutionary and heuristic approaches, as they are capable of finding nearly optimal solutions in a relatively short time frame.

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6. Real Time Optimization of Energy Flows in a University Campus Microgrid

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Abstract

In the recent years, many university campuses have been working to build and implement intelligent hybrid energy systems (microgrids) aiming to reduce energy consumption and corresponding costs. Various models and implementations of such microgrids are considered in the literature (see [1, 2]). This chapter presents a real-time optimization of energy flows in one university campus microgrid in Lipjan, Kosovo.

6.1. Introduction

With the rapid advancement in artificial intelligence and smart grid technologies, microgrid optimization has become a research area to improve energy efficiency, reliability, and sustainability. However, optimizing microgrid performance poses significant challenges due to the unpredictable nature of power generation, demand fluctuations, and network interactions. Heuristic techniques and evolutionary algorithms have emerged as powerful solutions to address these

challenges, offering flexibility, adaptability, and efficiency in optimizing various microgrid parameters. The Nature-inspired algorithms, including genetic algorithms, differential evolution, and swarm intelligence methods, mimic natural selection and collective behavior to find optimal solutions in a vast search space. This study explores how heuristic-based optimization models and evolutionary algorithms can be integrated into smart microgrid control systems, using artificial intelligence to improve predictive analysis, real-time decision-making, and energy efficiency in modern power grids.

Muhammad et al. [3] provided an in-depth review of microgrids, outlining their role in modern energy systems and identifying key challenges that hinder their widespread adoption. The study highlights that microgrid stability and reliability remain significant issues due to the intermittent nature of renewable energy sources, which necessitates advanced control strategies such as predictive power management and real-time optimization. The authors highlight that artificial intelligence-based energy management systems, including heuristic and evolutionary algorithms, have shown potential to optimize energy allocation, reduce operational costs, and improve grid resilience. They further identify that regulatory and standardization gaps create barriers to large-scale deployment, advocating for a unified policy framework to facilitate integration with conventional grids. The study also highlights the importance of optimizing distributed energy resources, concluding that the incorporation of adaptive algorithms can significantly improve load balancing and energy storage efficiency. Furthermore, their findings suggest that hybrid microgrid architectures that combine renewable energy with traditional energy sources offer a viable path to ensure

grid stability while supporting sustainability goals. The study ultimately highlights the need for real-time decision-making frameworks and the application of heuristic techniques and evolutionary algorithms to address microgrid optimization challenges, ensuring greater energy reliability and economic feasibility.

Akter et al. [4] conducted a comprehensive review of meta-heuristic techniques in microgrid optimization, highlighting their critical role in addressing operational challenges of distributed energy systems. The study identified that renewable energy outages and power quality issues significantly impact microgrid performance, necessitating advanced optimization mechanisms for stability and efficiency. The authors analyzed various meta-heuristic algorithms, including genetic algorithms (GA), particle swarm optimization (PSO), artificial bee colony (ABC), and ant colony optimization (ACO), and found that these techniques effectively improve microgrid energy management, cost optimization, and demand response. A key achievement of their research is the identification of hybrid meta-heuristic methods – such as combining PSO with differential evolution (DE) or integrating GA with machine learning techniques that significantly improve the convergence speed and solution accuracy for nonlinear microgrid optimization problems. Furthermore, the paper highlights the impact of security algorithms in preventing cyberattacks on microgrids, recommending the integration of AI-driven security frameworks for improved system protection. Their findings suggest that optimized energy storage sizing through meta-heuristic approaches can significantly reduce costs and improve system reliability, especially in scenarios with high renewable penetration. Furthermore, the study explores future research

directions, advocating the integration of deep learning with heuristic optimization, blockchain-based decentralized energy trading, and quantum computing for high-dimensional energy management problems. The authors conclude that while meta-heuristic optimization techniques have significantly improved microgrid performance, real-time adaptability, computational efficiency, and hybridization of multiple techniques remain key areas for future advances in microgrid optimization.

Zedong et al. [5] provide a comprehensive review of meta-heuristic techniques in microgrid (MG) control, focusing on their application in both the implementation and operational phases. The study highlights that traditional optimization methods struggle with the limitations of multiple devices, multiple strategies, and multiple modes, making meta-heuristics an effective alternative to address multi-dimensional and multi-objective optimization problems. The authors classify and evaluate various meta-heuristic techniques, including swarm intelligence methods (e.g., particle swarm optimization, ant colony optimization) and evolutionary computational approaches (e.g., genetic algorithms, differential evolution), evaluating their computational efficiency and convergence capabilities. A significant contribution of the paper is the identification of hybrid meta-heuristic techniques that integrate multiple algorithms to improve the solution accuracy and computational efficiency in real-time MG control. Furthermore, the study highlights the growing role of machine learning-assisted meta-heuristic optimization, where AI-driven models improve adaptability and resilience in dynamic MG environments. The authors recommend future research on cooperative optimization strategies, parallel search mechanisms, and real-time decision-making frameworks,

especially in uncertain and variable energy demand scenarios. They conclude that while meta-heuristic techniques have significantly improved the efficiency and reliability of MG, further advances in hybrid AI-based approaches and decentralized energy trading mechanisms will be crucial for the next generation of intelligent MG systems.

Wang and Li [6] propose a dual-objective optimization model to improve microgrid demand response by incorporating price-based and incentive-based strategies. The study highlights that conventional load control models do not consider incentive-driven demand response, resulting in low user satisfaction, ineffective peak-valley price adjustments, and poor demand response efficiency. To address these shortcomings, the authors developed a flexible load control strategy optimized using an improved chaotic particle swarm optimization (CPSO) algorithm. The simulation results demonstrated significant improvements: user satisfaction increased by 9.51%, microgrid provider operating costs decreased by 12,975/ten thousand yuan, peak-valley gap was reduced by 4.61%, and user demand response was improved by 27.24% (Wang & Li, 2024). The CPSO algorithm outperforms traditional methods by improving global search capabilities and solution diversity, preventing premature convergence to local optima. Furthermore, the study found that integrating real-time pricing with incentive-based mechanisms provides a more balanced relationship between supply and demand, providing higher energy efficiency and economic benefits for both consumers and suppliers. The paper concludes that advanced optimization techniques, such as AI-driven hybrid models, can further improve microgrid resilience, reduce reliance on distributed power, and achieve better load matching.

Majeed et al. [7] present a novel energy management system based on adaptive genetic algorithm (AGA) for grid-connected microgrids designed to optimize energy scheduling, reduce operating costs, and improve renewable energy utilization. The study emphasizes the integration of wind, photovoltaic (PV), diesel generators, and battery storage systems, ensuring reliable energy distribution while minimizing cost fluctuations. A key contribution of the paper is the improvement of load scheduling algorithms by using an adaptive genetic approach that dynamically adjusts energy import/export strategies based on real-time demand and renewable generation. Simulation results show that the proposed AGA method significantly reduces energy costs compared to traditional optimization techniques, achieving a cost of 52.53 cents per kWh, which is significantly lower than particle swarm optimization (88.63 cents per kWh) and the Firefly algorithm (670.77 cents per kWh). Furthermore, the authors demonstrate that real-time optimization of energy flow between distributed energy resources improves the economic and environmental sustainability of microgrids, with significant carbon emission reductions and fuel efficiency improvements. Furthermore, the system prioritizes the consumption of renewable energy, ensuring that excess energy is either stored in battery systems or exported to the grid when excess generation occurs. The study concludes by advocating for AI-driven hybrid approaches integrating machine learning techniques to improve real-time adaptability in microgrid energy management, ultimately contributing to a more resilient and cost-effective microgrid infrastructure.

Simulation and analysis approaches for the design of microgrid systems from a sustainable planning perspective are reviewed

in [8]. A comprehensive review of existing simulation tools and approaches used for the design of power generation technologies is presented. Traditional strategies and emerging trends in power system simulation are discussed and compared based on the software used, the type of problem to be solved, the input parameters provided, and the expected output. On this basis, a practical simulation framework for sustainable energy planning is introduced, which is based on the Socio-Technical-Economic-Environmental Policy (STEEP) model. This is a holistic sustainability model that takes into account key dimensions of power system planning compared to the traditional techno-economic model used in several existing simulation tools and analysis. The article points towards data-driven analysis and software applications for energy modeling.

The review [9] focuses on balancing economic, environmental, social and technical criteria to improve the performance and sustainability of renewable energy generation systems (using solar, wind, biomass, geothermal, hydro and tidal energy). The review explores state-of-the-art algorithms such as Multi-Objective Particle Swarm Optimization (MOPSO) and Non-Dominated Sorting Genetic Algorithm II (NSGA-II), along with Crow Search Algorithm (CSA), Gray Wolf Optimizer (GWO), Levy Flight-Salp Swarm Algorithm (LF-SSA), Mixed Integer Linear Programming (MILP) and tools such as HOMER Pro 3.12–3.16 and MATLAB 9.1–9.13. The authors highlight the growing role of advanced multi-energy storage technologies in stabilizing hybrid renewable energy systems (HRESs) and addressing the intermittency of renewable sources. Furthermore the role of integration of metaheuristic algorithms with machine learning is outlined. This approach enables dynamic adaptability and predictive optimization, paving the way for real-time energy

management. Designing HRESs to achieve cost-effectiveness, environmental sustainability, and operational reliability highlights the transformative potential of emerging technologies. This review provides critical insight into the evolving landscape of HRESs optimization, offering actionable recommendations for future research and practical applications to achieve global energy sustainability goals.

The paper [10] examines the use of artificial intelligence for the development and management of distributed renewable energy generation and how AI can be used to overcome the challenges arising from the use of distributed renewable energy sources such as solar and wind power. The opportunities, risks and applications of AI technology are assessed by applying Saunders' Research Onion framework to achieve methodological soundness. The authors conclude that AI has high potential and applicability for decentralized energy networks, but certain technical, operational and policy issues need to be addressed to achieve successful implementation. Therefore, the study points out the need for future research and collaboration between stakeholders to explore all the possibilities for applying AI in this area with concrete suggestions for future research directions and interdisciplinary collaboration. The idea is that by understanding the advantages and disadvantages of AI implementation, experts can solve problems related to improving grid reliability and the stable integration of renewable sources into the global energy infrastructure.

Microgrids are vulnerable to faults that affect their performance. In addition, they require the implementation of dynamic power flow management and optimization strategies.

The use of artificial intelligence (AI) is of key importance in this regard. The study [11] presents a comprehensive review of the applications of AI strategies on hybrid renewable microgrids for optimization, power quality improvement, and fault analysis in microgrids. The use of techniques such as machine learning (ML), genetic algorithms (GA), artificial neural networks (ANN), fuzzy logic (FL), particle swarm optimization (PSO), heuristic optimization, artificial bee colony (ABC), and others is considered. The applications of AI in microgrids are discussed along with their advantages, disadvantages, and future prospects. The coordination and use of renewable energy, solar photovoltaic, and wind energy in a hybrid microgrid is discussed in the event of faults.

The article [12] discusses the implementation of energy management systems (EMS) that utilize artificial intelligence (AI), referencing over 200 scientific articles. Key aspects of EMS optimization include energy production from both traditional and renewable sources, economic efficiency, and fulfilling customer expectations. The review critically examines the classification of energy management systems, their applications, and the challenges they face. A primary focus is on overcoming the variability of renewable energy sources. The article also discusses the advantages of different optimization techniques and analyzes the application of various artificial intelligence methods, in particular those involving unsupervised learning, semi-supervised learning, and supervised learning. Hierarchical control mechanisms for using artificial intelligence at three levels are explored as well. Conclusions drawn highlight the significance of deep learning for load forecasting and its potential to significantly enhance the reliability and efficiency of microgrids. The authors stress the importance of

leveraging distributed energy resources (DER) and optimizing EMS through artificial intelligence techniques, which can lead to substantial cost reductions and improved resilience in microgrid operations.

6.2. Microgrid System Overview

The microgrid system at the University for Business and Technology (UBT) campus in Lipjan, Kosovo, represents a tangible step toward embracing sustainable and decentralized energy technologies in educational and research institutions. Designed as a real-world implementation of smart energy infrastructure, the system not only supplies clean energy to part of the campus but also serves as a living laboratory for students, researchers, and engineers exploring the future of energy systems.

6.2.1. Solar Energy Infrastructure

At the heart of this microgrid is a carefully engineered photovoltaic (PV) system, covering a total area of 840.2 square meters. This extensive array of solar panels is strategically installed to capture optimal sunlight throughout the day and across different seasons. The panel model used in the installation is the HC450M, known for its high conversion efficiency and durability. These panels convert solar radiation into electrical energy, feeding the microgrid with clean, renewable power.

To convert the generated direct current (DC) electricity into alternating current (AC) suitable for grid use and local consumption, the system incorporates three high-efficiency KACO 50.TL3 [13] inverters. These inverters are well-known for

their robust performance, especially in medium- to large-scale solar installations. Their reliable conversion process ensures minimal energy loss, even under varying solar radiation and temperature conditions an important factor considering the seasonal climate shifts experienced in this region.

6.2.2. Energy Storage Capabilities

The UBT campus microgrid integrates a practical energy storage solution to enhance stability and enable continuous energy supply, even during periods of low solar production. The system uses Pylontech US3000C battery modules [14], chosen for their balance of performance, safety, and cost. Each module offers 3.55 kWh of nominal capacity, and the current setup includes 12 units, resulting in a total storage capacity of 42.6 kWh. This allows the microgrid to store excess solar energy generated during the day and supply it back when needed such as during cloudy weather or at night, thereby increasing system autonomy. The batteries offer over 6,000 life cycles at 90% depth of discharge (DoD), making them highly durable for long-term use.

6.2.3. Environmental and Geographic Context

The UBT microgrid is located in Lipjan, a municipality in the Republic of Kosovo, and lies within a Central European climatic zone. The region experiences four distinct seasons, each influencing solar energy generation in different ways. During the winter months, lower temperatures and frequent cloud cover typically reduce solar panel output. Conversely, the summer season provides extended daylight hours and high

solar irradiance, allowing the system to operate near peak capacity.

The microgrid benefits from moderate elevation and relatively clean air, especially during spring and early autumn, contributing to improved solar efficiency. These climatic characteristics make Lipjan an ideal location for studying the variability of photovoltaic performance under real environmental conditions.

The site's seasonal dynamics and weather variability are continuously monitored, offering valuable data to optimize system performance. This understanding informs both the day-to-day operational strategy and the long-term planning of future energy expansion, making the UBT microgrid a vital reference point for sustainable infrastructure development in the Western Balkans.

6.2.4. Integration and Scalability

Designed with modularity in mind, the UBT microgrid infrastructure is both scalable and adaptable. As energy demands increase or technological advancements emerge, the system can be expanded with additional solar panels, upgraded inverters, or increased battery storage. Moreover, the system architecture supports integration with other renewable energy sources such as wind or hydro, providing a path toward even greater energy independence and sustainability in the future.

6.2.5. Microgrid Architecture

The architecture of the UBT microgrid as shown in Figure 6.1 integrates essential components including photovoltaic solar panels, battery storage systems, the UBT Smart City campus [15], [16], and the central electrical grid. This interconnected

structure ensures reliable, efficient, and sustainable energy management and distribution.

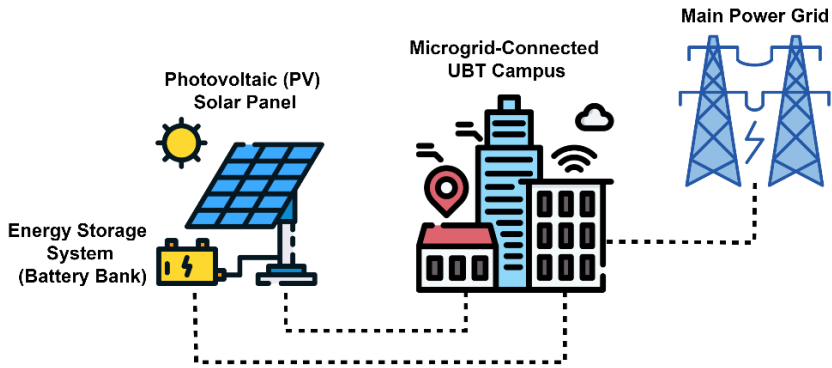


Fig. 6.1. UBT Microgrid Architecture

Photovoltaic Solar Panels: Solar panels constitute the primary renewable energy source within the microgrid system. Strategically installed to maximize exposure to sunlight, these panels convert solar irradiance into electrical energy, supporting daily campus operations and promoting sustainability.

Battery energy storage system: To mitigate the intermittent nature of solar energy, the architecture includes battery storage modules. These batteries store excess solar-generated electricity, which is utilized during periods of low solar irradiance, such as cloudy days or nighttime, ensuring continuous power supply and enhancing grid reliability.

UBT Smart City Campus: The campus serves as the central node of the microgrid, managing and utilizing the generated energy for educational, research, and operational purposes. Equipped

with advanced monitoring and control technologies, it actively optimizes energy consumption, distribution, and real-time response to operational demands.

Central Electrical Grid: The microgrid is interconnected with the central electrical grid, enabling flexible energy exchange. Excess renewable energy can be fed back to the central grid, contributing to broader energy sustainability. Conversely, the campus can draw power from the central grid when local generation and storage capacities are insufficient.

This holistic architecture, combining renewable generation, efficient storage, intelligent campus management [17], [18], and grid connectivity, embodies a resilient and sustainable approach to energy management, supporting both local and broader energy ecosystem objectives.

6.3. Data Collection and Preprocessing

Accurate and comprehensive data collection is essential when evaluating the performance of a solar-powered microgrid system, especially in regions with seasonal variability like Central Europe. For this study, a real-world dataset from the UBT campus microgrid in Lipjan, Kosovo, was compiled to capture a complete years' worth of operational and environmental information, enabling reliable modeling, analysis, and prediction of energy production dynamics.

6.3.1. Data Source and Recording Infrastructure

The dataset used in this case study is derived from real-world measurements collected daily throughout the year 2024 at the UBT campus microgrid located in Lipjan, Kosovo. Most of data are sourced from infrastructure physically installed at the microgrid site, enabling direct correlation between environmental conditions and system behavior.

The UBT microgrid provides detailed daily measurements of:

- Energy Production [kW],
- Operating Voltage [V],
- Generated Current [A].

These electrical parameters are directly collected from the microgrid's monitoring infrastructure, which continuously logs the performance of the solar panels and inverters. This ensures that all energy data reflects the actual performance of the photovoltaic (PV) system under real operating conditions.

Environmental parameters are measured in parallel using an officially registered weather station co-located with the PV installation. The weather station, registered as UBT - ILIPLJ1 on the Weather Underground platform (Figure 6.2), captures:

- Ambient temperature [°C],
- Relative humidity [%],
- Atmospheric pressure [hPa],
- Wind speed and direction,
- Dew point and UV index.

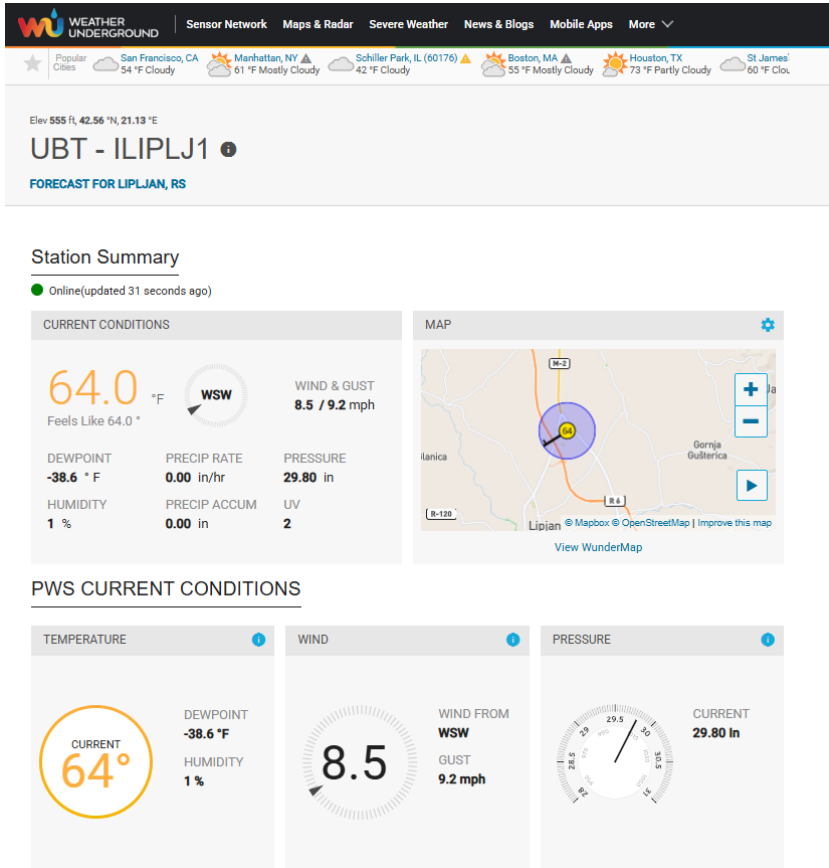


Fig. 6.2. UBT Station in Weather Underground

To complement local weather station data, cloud cover values are retrieved from the Open-Meteo platform as seen in Figure 6.3. This service provides historical cloud coverage specific to the city of Lipjan, ensuring regional relevance for solar energy forecasting and analysis.

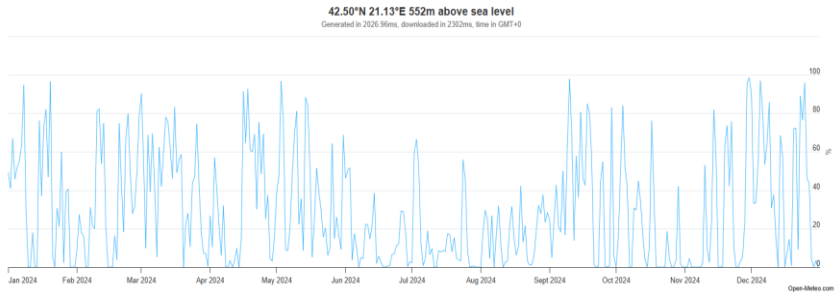


Fig. 6.3. Open Meteo Cloud Cover data for 2024.

By combining these sources, the resulting dataset provides a rich and localized view of both energy production and environmental context, which is crucial for conducting accurate modeling, forecasting, and optimization of the microgrid system.

6.3.2. Features and Dataset Composition

To enable a comprehensive analysis of the UBT microgrid’s performance, dataset was compiled and refined from continuous monitoring over the course of the year 2024. The dataset integrates energy production metrics taken from microgrid, in parallel, dataset integrates also key environmental parameters measured from the station which are accessible information through websites called Weather Underground and Open Meteo, forming a solid foundation for exploratory analysis, forecasting, and optimization tasks. Each data point represents a full-day snapshot of microgrid operation under varying weather and system load conditions. The selected features capture both the technical behavior of the photovoltaic (PV) infrastructure and the environmental influences specific to the UBT microgrid’s geographic setting.

The final dataset used in this case study includes the following features:

- Date – The specific calendar day on which the data was recorded.
- Production [kW] – Daily average of actual daily solar energy output produced by the PV system.
- Voltage [V] – Daily average operating voltage of the solar panels.
- Current [A] – Daily average electrical current generated by the system.
- Temperature [°C] – Daily average ambient air temperature measured locally at the microgrid site by an on-site weather station.
- Humidity [%] – Daily average relative humidity, also collected directly from the local measurement station located near the solar panels.
- Cloud Cover [%] – Daily average cloud coverage percentage.

6.3.3. Data Cleaning and Preprocessing Methodology

Before proceeding with any modeling or visual analysis, the dataset underwent a series of data cleaning and transformation steps to ensure its quality, consistency, and analytical integrity. Initially, invalid entries were removed, including rows containing missing sensor readings such as “--” placeholders found in the raw files as well as outliers or physically implausible values like negative energy production or extreme temperature readings beyond realistic operational limits. Following this, formatting was standardized across the dataset: dates were converted to a uniform YYYY-MM-DD format, and

numerical columns including energy production, voltage, and current were explicitly cast into floating-point data types for accurate computation. Finally, all data streams were synchronized to a daily frequency to ensure that each row in the dataset represents a unified snapshot of both environmental conditions and system performance at the same point in time. This multivariate alignment is essential for any time-series modeling or cross-feature correlation analysis performed later in the study.

6.3.4. Example Data Snapshot

The snapshot presented in Table 6.1 illustrates representative daily records extracted from the dataset, highlighting the influence of seasonal and meteorological variations on microgrid performance. As observed, winter conditions (e.g., December) are characterized by lower ambient temperatures and higher voltage values due to reduced thermal stress on photovoltaic components, whereas current values tend to be lower in response to diminished solar irradiance. In contrast, summer conditions (e.g., July) exhibit elevated current levels resulting from higher energy production, though voltage may slightly decrease due to increased ambient temperature. Additionally, variations in cloud cover, which directly impact irradiance levels, contribute to fluctuations in daily energy yield. These examples underscore the dynamic nature of solar power generation under real-world environmental conditions.

Table 6.1- Data Snapshot

Date	Production [kW]	Voltage [V]	Current [A]	Temperature [°C]	Humidity [%]	Cloud Cover [%]
2024-07-01	760.43	977.26	778.12	26.2	58	6.5
2024-12-18	278,73	958.9	290,68	2.0	90	44.42
2024-03-20	787.10	993.98	791.87	3.9	1	11.91

6.4. Exploratory Data Analysis (EDA)

This section presents a detailed exploratory data analysis (EDA) of the UBT microgrid dataset, with the goal of identifying seasonal behaviors, environmental dependencies, and data anomalies that can influence both forecasting accuracy and optimization effectiveness.

6.4.1. Seasonal Patterns in Solar Production

To observe the progression of solar energy generation throughout the year, a time-series visualization was created using daily energy production values. This graph reveals clear seasonal cycles, solar output increases during spring and peaks in summer when solar irradiance is high, before declining during autumn and reaching minimum levels in winter. These trends (Fig. 6.4) reflect the expected fluctuations of solar energy availability in the Central European climatic region.

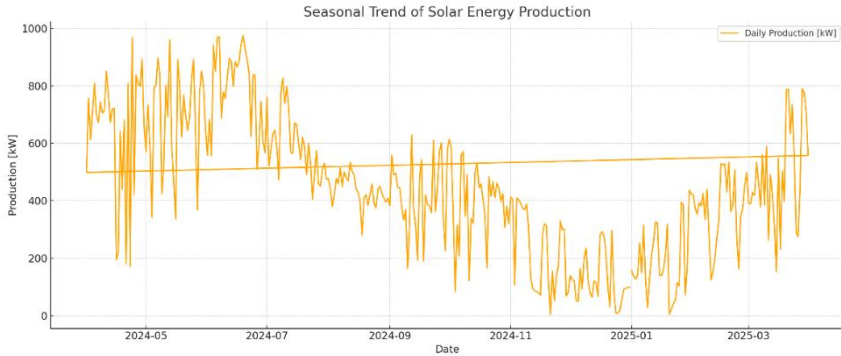


Fig. 6.4. Seasonal Trend of solar Energy Production

6.4.2. Correlation Analysis

A correlation matrix (Fig. 6.5) was constructed to quantify the linear relationships between production and environmental or electrical parameters. From this analysis, several insights emerged:

- Production and Current show a very strong positive correlation, which is expected since current scales directly with generated power.
- Temperature also positively correlates with production, though to a lesser extent, due to the moderating effects of panel efficiency under heat.
- Cloud Cover presents a clear inverse correlation with energy production—demonstrating that high cloudiness leads to reduced energy output.
- Voltage exhibits relatively low variability and weak correlation with other variables, as its fluctuations are less dynamic than current.

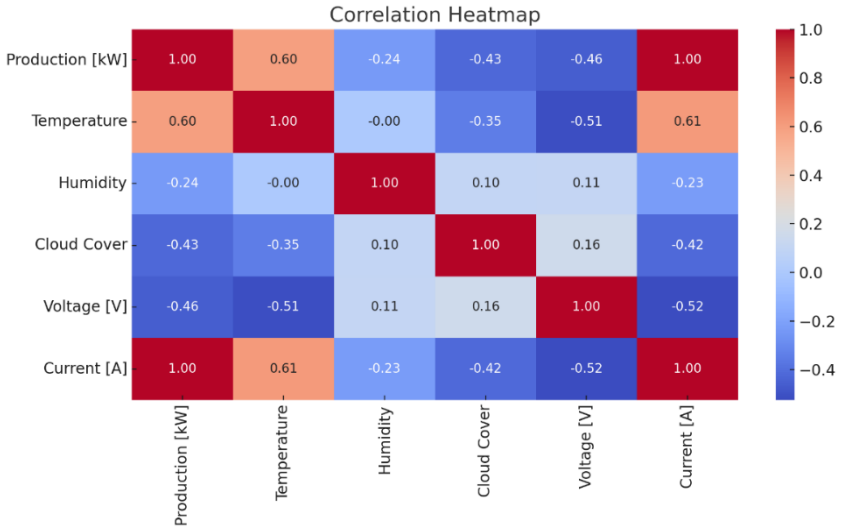


Fig. 6.5. Correlation Heatmap

6.4.3. Distribution and Outlier Detection

Figure 6.6 illustrates boxplots for six critical variables recorded by the UBT microgrid system in 2024: Voltage [V], Current [A], Production [kW], Temperature [°C], Humidity [%], and Cloud Cover [%]. These visualizations provide an intuitive understanding of the central tendency, dispersion, and presence of outliers within each dataset feature. The Production and Current plots reveal a right-skewed distribution, indicating that while most daily values are clustered around the lower-to-mid range, a smaller number of high-output days significantly increase the upper range typically associated with peak summer performance. Temperature data demonstrates a broad interquartile range due to seasonal fluctuations, while Humidity and Cloud Cover exhibit wider variability, which can influence solar irradiance and, consequently, energy yield. Voltage values remain relatively stable with fewer outliers,

reflecting consistent panel operation. Collectively, these boxplots serve as a foundation for identifying anomalies and understanding operational patterns in the microgrid's performance throughout the year.

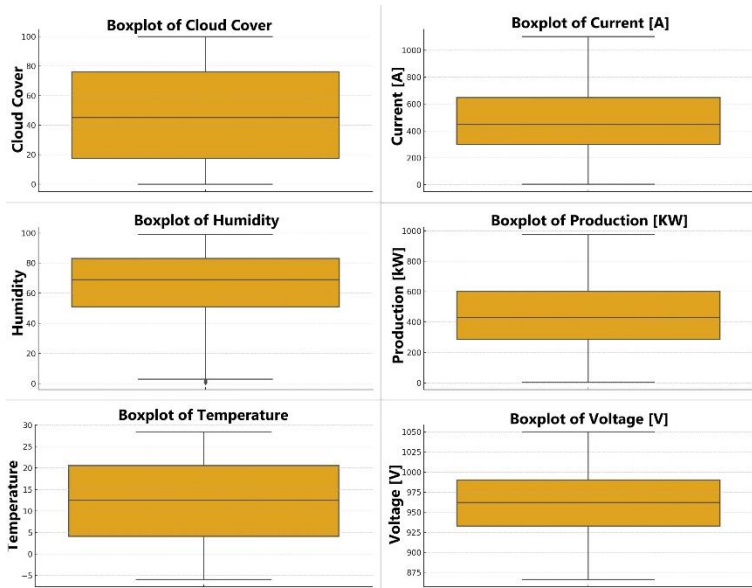


Fig. 6.6. Distribution and Outlier Detection

6.4.4. Scatterplot Analysis: Environmental Impact

To further explore the direct impact of weather conditions on energy yield (Fig. 6.7), scatterplots were generated for each of the following:

- Temperature vs. Production shows a moderate rise in output with increased temperature, though extreme heat can limit efficiency.

- Humidity vs. Production illustrates a slight negative correlation, higher humidity generally corresponds to lower solar generation.
- Cloud Cover vs. Production displays a strong inverse relationship, affirming cloudiness as one of the most impactful variables.

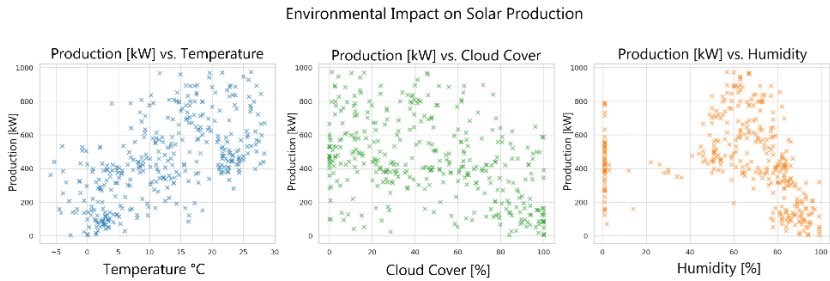


Fig. 6.7. Environmental impact on Solar Production

6.5. Forecasting Solar Energy Production Using LSTM and Weather Data

Following the comprehensive data acquisition and preprocessing pipeline described in Section 3, this section presents the design and implementation of a forecasting framework for predicting daily solar energy production at the UBT microgrid. The forecasting solution combines deep learning techniques, specifically Long Short-Term Memory (LSTM) networks with weather forecast data, making it possible to anticipate future energy availability. This predictive capability is critical for enhancing the operational efficiency of the microgrid, enabling load balancing, energy storage management, and strategic energy dispatch. Furthermore, by

integrating the backend model with a modern React-based user interface, the forecasting system becomes both actionable and user-friendly for researchers and operators.

6.5.1. Model Design and Training Strategy

The LSTM model was chosen for its strength in capturing temporal dependencies in multivariate time series, which is particularly important in solar energy systems affected by dynamic environmental conditions such as cloud cover, temperature, and humidity. As detailed in Section 3, the dataset was compiled using one year (2024) of daily observations from the UBT microgrid and corresponding weather data.

The model training strategy adopted a sliding window approach using a rolling sequence of the past 10 days (`window_size = 10`) to predict the next day's production. Each training sequence consisted of four key features:

- Daily Production (kW),
- Temperature (°C),
- Humidity (%),
- Cloud Cover (%).

The final model architecture, implemented using TensorFlow/Keras, comprises two LSTM layers with dropout regularization, followed by a dense output layer. Early stopping was employed to avoid overfitting.

```
model = Sequential()
model.add(LSTM(50, activation='relu',
return_sequences=True, input_shape=(10, 4)))
model.add(Dropout(0.2))
model.add(LSTM(30, activation='relu'))
model.add(Dropout(0.2))
model.add(Dense(1))
```

Initially, the model was trained and evaluated using the real-world dataset consisting of 365 daily records for the year 2024. This limited dataset resulted in suboptimal performance, with a Mean Absolute Error (MAE) of 122.02, a Root Mean Squared Error (RMSE) of 156.32, and a relatively low R-squared (R^2) value of 0.29. These metrics reflected the model's limited ability to generalize due to the small dataset size. To overcome the limitations of having real data only for the year 2024, additional data was created to cover the years 2000 to 2023. This synthetic dataset was generated using a Python script that followed recognizable seasonal patterns and added natural, random variations to reflect real-world conditions. As a result of retraining the model on the expanded dataset, the evaluation metrics improved significantly, achieving a Mean Absolute Error (MAE) of 53.51, a Root Mean Squared Error (RMSE) of 73.00, and an R-squared (R^2) value of 0.91, as shown in Figure 6.8, which displays the updated evaluation results captured directly from the terminal output after testing the model.

```
predictions = model.predict(X_test)
y_test_inv = scaler_y.inverse_transform(y_test)
predictions_inv = scaler_y.inverse_transform(predictions)
```

```
mae = mean_absolute_error(y_test_inv, predictions_inv)
rmse = np.sqrt(mean_squared_error(y_test_inv, predictions_inv))
r2 = r2_score(y_test_inv, predictions_inv)

print("\nModel Evaluation Metrics:")
print("Mean Absolute Error (MAE): {:.2f}".format(mae))
print("Root Mean Squared Error (RMSE): {:.2f}".format(rmse))
print("R-squared (R2): {:.2f}".format(r2))
```

```
Model Evaluation Metrics:
Mean Absolute Error (MAE): 53.51
Root Mean Squared Error (RMSE): 73.00
R-squared (R2): 0.91
```

Fig. 6.1 - Model Evaluation Metrics

6.5.2. Multi-Day Forecasting Approach

Unlike traditional single-step forecasting methods, this system was designed to perform multi-day forecasting using recursive inference. The forecasting loop begins with the last known 10-day sequence of historical data, and for each prediction step:

- 1) The next production value is predicted.
- 2) That prediction, combined with the day's forecasted weather features, forms the new input.
- 3) The updated sequence is fed into the model for the next day's prediction.

This process is repeated for the entire forecast horizon (e.g., 16 days), leveraging known future weather inputs while building upon model-predicted production outputs.

```
for i in range(len(temperature)):
    next_input = [predicted_production, temperature[i],
humidity[i], cloud_cover[i]]
    input_sequence = np.append(input_sequence[:, 1:, :],
[[next_input]], axis=1)
```

This recursive strategy allowed the system to simulate the evolving behavior of the solar production system under upcoming weather conditions.

6.5.3. Backend Application Programming Interface (API) for Forecast Inference

To facilitate integration with other systems and user interfaces, a RESTful API was developed using Flask. The /predict_production endpoint receives a JSON payload containing:

- Arrays for temperature, humidity, and cloud cover for future days.
- A recent_data matrix containing the last 10 days of historical data with all 4 features.

Upon receiving the payload, the backend loads the trained LSTM model and applies the recursive forecasting method, returning a list of daily production predictions.

```
{
  "temperature": [...],
  "humidity": [...],
  "cloud_cover": [...],
  "recent_data": [[production, temp, hum, cloud],
... ]
}
```

The API ensures lightweight, real-time inference capabilities that can be used not only by the frontend but also by third-party energy management applications.

6.5.4. Weather Data Aggregation via Open-Meteo API

The forecasting pipeline integrates seamlessly with real-time weather forecasts retrieved from the Open-Meteo API, configured for the exact coordinates of the UBT microgrid in Lipjan. Hourly data for: Temperature (°C), Relative Humidity (%) and Cloud Cover (%) are retrieved for a 16-day horizon and then aggregated into daily averages using custom logic:

```
const avgTemperature = temps.reduce((sum, val) => sum + val, 0) / temps.length;
```

The resulting daily weather data is formatted and passed to the model as future input.

6.5.5. Frontend Implementation: React-Based Visualization

To make the forecasts actionable and comprehensible for both technical and non-technical users, a responsive web interface was built using React. The frontend fetches weather data, sends it to the backend with historical sequences, and visualizes the resulting forecasts.

The first visualization is a dynamic table displaying, per day:

- Forecast Date,
- Predicted Solar Production (kW),
- Average Temperature (°C),
- Average Humidity (%),
- Cloud Cover (%).

The table integrates dynamic data fetched from the backend and aligns it with the weather forecast inputs, making it easier

for users to correlate the production forecast with expected environmental conditions. The final result is rendered as an elegant, responsive table where alternating row colors, subtle borders, and clear typography enhance visual hierarchy and usability. The styling also adapts gracefully to different screen sizes, making the interface accessible on both desktop and mobile devices. The Rendered Forecast Table (Table 6.2) shows the daily production predictions alongside temperature, humidity, and cloud cover. This real-time visual feedback makes the model's results actionable and interpretable by engineers, researchers, and decision-makers alike.

Table 6.2 – Rendered Forecast Table

Date	Predicted Production (kW)	Avg Temperature (°C)	Avg Humidity (%)	Avg Cloud Cover (%)
4/17/2025	241.64	16.00	77.00	72.00
4/18/2025	243.46	17.00	72.00	85.00
4/19/2025	251.86	14.00	67.00	62.00
4/20/2025	265.10	13.00	62.00	20.00
4/21/2025	281.54	14.00	71.00	62.00
4/22/2025	297.34	16.00	62.00	60.00
4/23/2025	314.30	15.00	64.00	84.00
4/24/2025	328.16	15.00	66.00	40.00
4/25/2025	345.96	15.00	55.00	29.00
4/26/2025	362.59	16.00	61.00	4.00
4/27/2025	376.91	17.00	65.00	41.00
4/28/2025	384.63	14.00	69.00	54.00
4/29/2025	389.33	11.00	72.00	64.00
4/30/2025	398.59	13.00	70.00	74.00
5/01/2025	412.18	15.00	72.00	71.00
5/02/2025	416.27	17.00	67.00	82.00

The second visualization component focuses on environmental inputs. It uses the Recharts library to render an interactive, responsive line chart displaying three key weather variables: temperature ($^{\circ}\text{C}$), humidity (%), and cloud cover (%) over the forecast period. By observing daily variations in these parameters, researchers and engineers can visually assess how atmospheric conditions may impact solar energy generation. The visual representation is particularly helpful in interpreting the relationship between environmental predictors and predicted production levels. The refined output is showcased in Figure 6.9, where each weather parameter is clearly color-coded and visually separated for intuitive understanding.

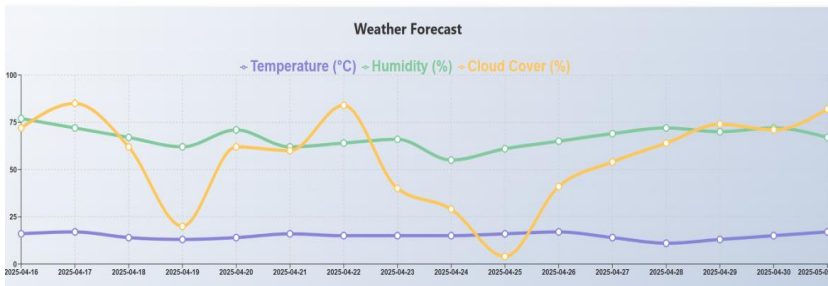


Fig. 6.9. Weather Forecast Chart

An example of the tooltip feature activated when hovering over a specific day is shown in Figure 6.10, clearly highlighting the exact temperature, humidity, and cloud cover values for May 17, 2025. This chart plays a crucial role in contextualizing the inputs used in the forecasting model and complements the prediction table by visually narrating the environmental story behind the numbers.

Following the visualization of weather parameters, the third component shifts focus to the predicted solar energy production over the forecast horizon. This chart provides a

clear and accessible representation of the LSTM model's output, showcasing how daily production is expected to evolve under the influence of forecasted weather conditions.

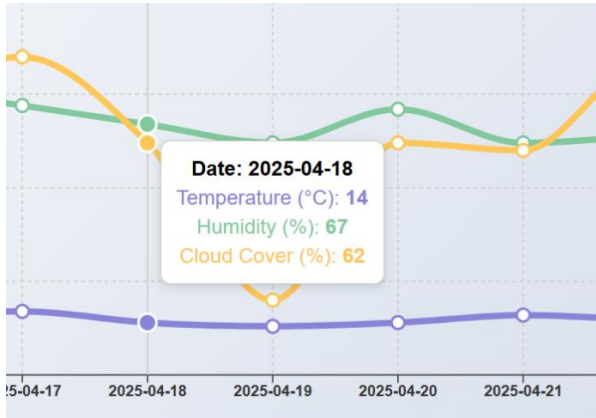


Fig. 6.10. The Tooltip Feature

The chart is implemented using Recharts, leveraging its customizable aesthetics and interactivity. Each predicted production value is plotted on a clean, gradient-enhanced background with rounded edges, creating a visually pleasant and readable interface. Users can hover over individual data points to display tooltips, revealing the exact predicted production (in kW) for each day, an essential feature for decision-makers monitoring microgrid operations.

An example of the forecasted production line chart is presented in Figure 6.11, where the system expects production to rise steadily during the forecast period. The tooltip on May 31, 2025, highlights a production value of 384.09 kW, demonstrating the precision and clarity of this visualization.

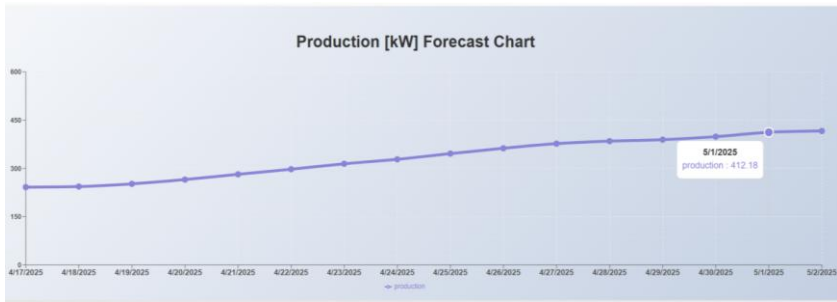


Fig. 6.11. Energy Production Forecast Chart

6.6. System Integration and Deployment Strategy

The forecasting system, weather service and login interface are designed as separate services, making the system modular and ready to operate in the cloud. It can be deployed as:

- A standalone forecasting service in smart microgrid control systems,
- A visual dashboard for energy operators and researchers,
- Or a microservice integrated with Internet of Things (IoT) platforms collecting live sensor data.

With additional enhancements such as adaptive learning and anomaly detection, the framework can be generalized to other renewable energy contexts.

6.7. Energy Production and Battery Performance Simulation

Building on the real-world infrastructure and predictive modeling described in previous sections, a simulation module was developed to emulate the dynamic behavior of solar

energy production and battery storage at the UBT microgrid system. The goal of this simulation was to create a controlled environment where synthetic, yet realistic, operational scenarios could be generated for validation, testing, and educational purposes. By capturing the time-dependent variability of solar generation and the energy buffering behavior of the battery system, this simulation enhances the system's applicability as a living laboratory and extends its utility for future research into microgrid optimization strategies.

The simulation module was implemented in Python and designed to mirror the diurnal and seasonal characteristics observed in real photovoltaic (PV) systems. Moreover, the battery dynamics were modeled to reflect the impact of fluctuating generation and consumption patterns on State-of-Charge (SoC) evolution.

6.7.1. Solar Energy Simulation

The simulation of solar output was constructed around the natural circadian and annual rhythms of solar irradiance. Daily variation is modeled using a sine function that peaks at solar noon (approximately 12:00 PM) and drops to zero outside active daylight hours (typically between 6:00 AM and 6:00 PM). This profile is consistent with observed solar production behaviors and ensures that the simulated output maintains temporal coherence with real-world solar cycles. To account for seasonal effects, the simulation incorporates a cosine-based modulation factor that varies with the day of the year. Maximum irradiance is centered around the summer solstice

(day 172), gradually decreasing toward the winter solstice, in accordance with the Earth's axial tilt and its impact on insolation levels. The resulting seasonal factor dynamically adjusts the amplitude of the daily sine wave, producing higher energy yields in summer and reduced yields in winter. Additionally, weather conditions are stochastically introduced to reflect atmospheric variability. Three categorical states clear, partly cloudy, and overcast are assigned probabilistically, with corresponding reduction factors on maximum potential output. Clear conditions preserve full irradiance, while overcast days significantly attenuate it, consistent with the behavior observed in empirical solar datasets. Random small perturbations are also added to emulate sensor noise and other minor environmental factors.

The final simulated solar power output at each time step is thus determined as a product of:

- Time-of-day dependency (sine wave),
- Seasonal modulation (cosine adjustment),
- Weather-driven attenuation (categorical probability model),
- Randomized noise (to introduce natural variance).

This multi-layered approach ensures that the solar production simulation is not merely synthetic, but statistically and behaviorally aligned with expected PV system performance under varying conditions.

6.7.2. Battery Charge Simulation

The battery subsystem was simulated to model energy storage dynamics in response to the balance between generated solar

energy and energy demand. The model assumes an initial battery charge of 50%, with a bounded operating range of 0% to 100% to reflect the physical constraints of lithium-ion battery technologies such as the Pylontech US3000C modules used in the UBT microgrid. At each simulation step, the net energy is computed as the difference between simulated solar output and a synthetic load profile. The load profile itself was designed to vary randomly within a plausible daily range, simulating realistic consumption patterns found in small institutional or residential microgrids.

The net energy is then scaled and applied to adjust the battery state of charge:

- A positive net energy (generation exceeds consumption) results in battery charging.
- A negative net energy (consumption exceeds generation) results in battery discharging.

The update equation ensures that battery overcharge and deep discharge are prevented, maintaining operational safety margins critical for long-term battery health. Additionally, the relatively modest scaling factor for energy adjustment introduces a smoothing effect, simulating the inertia observed in real battery systems due to limited charging and discharging rates.

By integrating this dynamic response into the simulation, the model accurately captures:

- The ability of the battery to store surplus solar energy during periods of high production,
- The battery's role in compensating for energy deficits during cloudy periods or nighttime,

- The cyclical nature of battery cycling under typical daily solar and load variability.

6.7.3. Simulation System State and Execution

The simulation maintains a shared global state, updated in real-time with each cycle of execution. Each iteration of the simulation (`simulation_step`) refreshes:

- Solar energy output,
- Weather condition,
- Load demand,
- Updated battery state of charge,
- Timestamp of the simulation event.

The modular nature of the simulation framework ensures that each component solar output, load, and battery response can be independently adjusted or extended in future studies. For instance, while the present focus excludes wind turbine dynamics, the underlying system was designed with extensibility in mind, allowing future integration of additional renewable sources or storage technologies without disrupting the core architecture.

The simulation model thus serves as both a validation environment for the forecasting system and a standalone tool for educational demonstrations and research explorations in microgrid dynamics.

6.8. Optimization Approach

A hybrid approach for microgrid optimization, involving heuristic techniques and evolutionary algorithms, with artificial intelligence (AI) control is proposed. It combines these three components (heuristic techniques, evolutionary algorithms, and artificial intelligence) to receive the final solution:

- Heuristic algorithms start the optimization process by providing intuitive and fast solutions.
- Evolutionary algorithms validate and improve these solutions using global search.
- Artificial intelligence provides adaptability and intelligent decision-making in real time by constantly improving the strategy through self-learning.

The performance of the hybrid approach for microgrid optimization is organized according the following Scenario:

1. Optimization objective: The main objective of this hybrid approach is to optimize the energy flows in the microgrid, minimizing energy consumption while ensuring the reliability and stability of the grid. This may include optimization of energy distribution, including the management of renewable energy sources (e.g. solar panels and wind turbines), batteries, and traditional energy sources.
2. Heuristic optimization techniques: Heuristic techniques can be used to initially solve the optimization problem, such as a resource-constrained search algorithm or local search algorithms. These methods will be used to quickly find solutions that are good, but not necessarily globally optimal. They can provide an intuitive and

adaptive approach that can quickly respond to dynamic microgrid conditions.

3. Evolutionary Algorithms (EA): To achieve a globally optimal solution, heuristic techniques can be combined with evolutionary algorithms such as genetic algorithms (GA) or differential evolution (DE). These algorithms mimic evolutionary processes and use populations of possible solutions that are combined, modified, and selected based on their fitness. For example:
 - Genetic algorithms can be used to optimize load distribution in a microgrid by combining battery energy management strategies, solar panel optimization, and wind turbine control.
 - Differential evolution can be used to optimize microgrid control parameters, such as generation unit shutdown or activation strategies and load management, while taking into account cost minimization and system resilience maximization.
4. Integration with Artificial Intelligence: Artificial Intelligence can be implemented to improve real-time decision making. For example, Reinforcement Learning can be used to train intelligent agents that adapt microgrid behavior based on rewards and punishments, while taking into account dynamic variables such as energy prices, consumption, and the availability of renewable sources.
 - Artificial intelligence can also be used to predict future loads and trends in energy production, allowing for optimization of resource allocation based on forecasts and current conditions.

6.9. Microgrid Cybersecurity

This section introduces a combined cybersecurity strategy designed to safeguard microgrids, incorporating machine learning-driven anomaly detection alongside data preprocessing methods. The proposed system integrates two main components, data preprocessing techniques and an autoencoder neural network to deliver robust cybersecurity measures:

- Data preprocessing methods initially refine sensor data to enhance the accuracy and reliability of the anomaly detection process.
- Autoencoder-based machine learning algorithms identify deviations from normal operational patterns, detecting anomalies that may indicate cyber threats on electrical components.

The effectiveness of the cybersecurity system for microgrid management is organized according to the following scenario:

1. **Cybersecurity Objective:** The main objective is to enhance microgrid resilience and security by continuously monitoring operational data and promptly identifying anomalies that could lead to failures or cyber incidents. This includes the protection of critical parameters such as current and voltage.
2. **Data Preprocessing Techniques:** Data preprocessing is essential for accurate anomaly detection. Techniques employed include:
 - Outlier removal using the Interquartile Range (IQR) method to filter abnormal values resulting from sensor malfunctions or noise.

- Data normalization via standard scaling ensures consistent data ranges, preventing biased results due to varying numerical scales among different sensor readings.
3. Autoencoder-Based Anomaly Detection: The anomaly detection component is built around an autoencoder neural network, trained on historical data to recognize standard operating patterns. This trained model then processes incoming real-time data to promptly detect deviations indicative of potential anomalies. This unsupervised learning model includes:
- An encoder that compresses data into lower-dimensional representations and a decoder that reconstructs data to detect deviations effectively.
 - Adaptive threshold methods based on statistical distribution analysis (mean, standard deviation, and percentiles) to determine anomaly thresholds dynamically, ensuring sensitivity and specificity in detection.

This integrated cybersecurity strategy substantially enhances microgrid resilience by promptly detecting anomalies, assessing their severity, and enabling rapid and well-informed responses to prevent disruptions and cyber incidents.

6.10. Discussion

The implementation of an AI-driven solar energy forecasting framework for the UBT microgrid system represents a significant advancement in the pursuit of intelligent, sustainable infrastructure within educational and research

environments. This study demonstrates how the integration of real-time weather data, historical solar production patterns, deep learning algorithms, and interactive web-based visualization can yield a forecasting solution that is both technically robust and practically applicable. The system was designed with the dual purpose of enhancing operational reliability and fostering experiential learning in the fields of artificial intelligence, energy informatics, and Internet of Things.

One of the most valuable outcomes of this forecasting system lies in its capacity to support predictive energy management within the microgrid. Through accurate multi-day forecasts of solar energy production, campus operators can make informed decisions about energy storage utilization, load balancing, and consumption prioritization. The recursive inference method, which builds forecasts day-by-day based on the last 10 days of operational data and upcoming weather variables, allows the system to capture the temporal evolution of solar production with a level of granularity suitable for both planning and control purposes. This method proved especially effective during stable seasonal periods, such as spring and summer, when atmospheric variability is lower and production patterns are more predictable.

In addition to operational benefits, the framework introduces substantial pedagogical value. At UBT, the microgrid not only powers physical infrastructure but also functions as a living laboratory where students and researchers can interact with real-world energy systems. This forecasting solution exemplifies how theoretical models such as LSTM neural networks can be contextualized through data-driven engineering projects. The

integration of machine learning with real-world sensor data cultivates a multidisciplinary learning environment where students can explore the convergence of data science, sustainability, and software development.

One of the key contributions of this work is the interpretability of model outputs. Rather than operating as a black-box prediction engine, the system emphasizes visual clarity through carefully designed user interfaces. The frontend displays production forecasts alongside their corresponding environmental parameters in both tabular and chart-based formats. This includes dynamic elements such as tooltips and data highlights that offer instant insight into the factors influencing predicted outputs. For instance, the production table (Figure 6.5) shows how production aligns with temperature, humidity, and cloud cover, while the line charts (Figures 6.6 and 6.7) provide intuitive trends and allow for deeper pattern recognition by non-expert users. This design philosophy centered around accessibility and insight ensures the usability of the platform across multiple stakeholder groups, including researchers, engineers, facility managers, and policy planners.

From a modeling perspective, the chosen LSTM architecture was well-suited to the time-series nature of solar energy data. Its capacity to capture sequential dependencies across days, without discarding context, enabled the system to account for gradual shifts in production that are influenced by weather variability and operational inertia. The inclusion of multiple input features especially cloud cover, which displayed a strong negative correlation with production substantially enhanced the model's predictive accuracy. Furthermore, the use of

dropout layers and early stopping helped avoid overfitting and ensured generalization to unseen conditions.

Equally important is the system's modular and extensible architecture. Each component backend model, API layer, and React-based frontend was designed as an independent module, allowing for easy adaptation and deployment. This modularity provides scalability along three critical dimensions. First, it allows for geographical transferability: the model can be retrained and redeployed in different regions with distinct weather profiles. Second, it supports functional extensibility: additional environmental predictors such as wind speed or solar irradiance can be added without significant structural changes. Third, the architecture is ready for real-time deployment in cloud or edge computing environments, enabling broader adoption in other microgrid or smart energy contexts.

The proposed forecasting framework exemplifies a real-world, scalable, and pedagogically enriching approach to AI-assisted energy management. It successfully bridges technical innovation with educational impact and paves the way for future research on adaptive energy systems in smart campuses and beyond.

6.11 Conclusions

This chapter presented an integrated hybrid approach to optimizing energy flows within a microgrid at the UBT campus, leveraging advanced heuristic techniques, evolutionary algorithms, and artificial intelligence-based control mechanisms. The synergy of these components significantly

improves real-time operational decision-making, optimizes energy distribution, and enhances the stability and reliability of the microgrid infrastructure.

The application of heuristic algorithms provided a rapid and adaptive response to dynamic operational conditions, laying a solid foundation for initial optimization efforts. Complementing these methods, evolutionary algorithms such as genetic algorithms and differential evolution effectively refined and validated solutions, ensuring global optimization objectives were met. Furthermore, artificial intelligence approaches, notably reinforcement learning and deep learning-based forecasting, added a critical layer of adaptability, enabling the microgrid to proactively adjust energy allocation based on real-time conditions and predictive analytics.

A critical aspect of this research involved enhancing cybersecurity through sophisticated anomaly detection strategies. Utilizing autoencoder neural networks combined with rigorous data preprocessing techniques, the system robustly identified and classified anomalies indicative of potential cyber threats or operational faults. This approach significantly bolstered the microgrid's resilience by enabling rapid and precise detection, assessment of anomaly severity, and swift, informed responses to mitigate cyber incidents.

Overall, the integrated optimization and cybersecurity methodologies detailed in this study highlight the substantial potential of artificial intelligence-driven solutions in improving the efficiency, reliability, and resilience of microgrid systems. Future research directions include exploring deeper integration with IoT technologies, real-time adaptability enhancements, and broader application across varying renewable energy

contexts, contributing to the sustainable advancement of intelligent energy systems.

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7. Conclusion

Research in the field of optimizing, managing, and operating microgrids is crucial for the development of sustainable, flexible, and intelligent energy systems. Microgrids integrate various energy sources, energy storage, and consumers within a localized system that can function independently or in synchronization with the main grid. Scientific and engineering efforts are focused on enhancing the efficiency, reliability, and profitability of microgrids by applying modern methods for control, dispatching, and economic optimization.

A primary area of research involves developing optimization algorithms that coordinate the operation of different components within the microgrid, such as photovoltaic panels, wind turbines, battery systems, and flexible loads. Techniques like linear and nonlinear programming, stochastic optimization, and heuristic methods—such as genetic algorithms, particle swarm optimization, and artificial neural networks—are employed. The objective is to minimize energy costs, reduce losses, and increase the utilization of renewable energy sources while considering system constraints and uncertainties in production and demand. Microgrid management prioritizes real-time monitoring, decision-making, and automation. Advances in the Internet of Things (IoT), cloud technologies, and edge devices have facilitated the creation of intelligent management platforms that collect and analyze data from multiple sensors and meters. These platforms can implement adaptive energy dispatch strategies that respond promptly to changes in production, consumption, or market energy prices. Furthermore, machine learning and artificial intelligence are

utilized for forecasting energy loads and production, optimizing energy storage, and managing risks.

Reliable, safe, and economically sustainable microgrid operation is essential, particularly over the long term. Research addresses challenges such as battery degradation, return on investment, and scenarios for operation during failures or disconnections from the main grid. Cybersecurity is also a significant concern, as microgrids depend on digital communications for control, making them susceptible to attacks. Therefore, the development of security protocols, encryption, and anomaly detection is a vital area of investigation. In conclusion, research in this field lays the groundwork for future energy systems that are not only technically efficient but also resilient against environmental and economic challenges. The optimization, management, and operation of microgrids will continue to be pivotal in the transition to a decentralized, smart, and low-carbon energy infrastructure.

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