الجمهورية الجزائرية الديمقراطية الشعبية

People's Democratic Republic of Algeria

وزارة التعليم العالي والبحث العلمي

Ministry of Higher Education and Scientific Research

جامعة غرداية

University of Ghardaia

كلية العلوم والتكنولوجيا

Faculty of Science and Technology

قسم الآلية والكهروميكانيك

Department of Automatics and Electromechanics

Registration No

…./……./……

Final Thesis Submitted in partial fulfillment of the requirements for the degree of Master, within the framework of ministerial decree 1275 – Final year diploma – Startup.

Field of Study: Science and Technology

Major: Electrical engineering

Specialization: Renewable Energy in electrical engineering

Title

Power Forecasting to Enable Peak Shaving in a Gas Turbine–Based Standalone Microgrid with PV Integration

Presented by:

BOUDJERADA Ahmed Abderrahmane

MOULAY OMAR Abdelouahab

Defended publicly on: 21/06/2026

Board of Examiners:

FERKOUS Khaled	MCA	Univ. Ghardaïa	**President**
KIFOUCHE Abdessalam	MCA	Univ. Ghardaïa	**Examiner**
BOUCHAKOUR Abdelhak	D.R	URAER	**Examiner**
MOSBAH Charaf Abdelkarim	MCB	Univ. Ghardaïa	**Supervisor**
SKAYARE Soundous	E.V	Univ. Ghardaïa	**Co-supervisor**

Academic Year: 2025 / 2026

الجمهورية الجزائرية الديمقراطية الشعبية

République Algérienne Démocratique et Populaire

وزارة التعليم العالي والبحث العلمي

Ministère de l'Enseignement Supérieur et de la Recherche Scientifique

جامعة غرداية

Université de Ghardaïa

كلية العلوم والتكنولوجيا

Faculté des Sciences et de la Technologie

قسم الآلية والكهروميكانيك

Département de d'automatique et d'électromécanique

N° d'enregistrement

…./……./……

Mémoire de fin d'étude, en vue de l'obtention du diplôme Master, dans le cadre de l'arrêté ministériel 1275 – Diplôme de fin d'études – Startup.

Domaine: Sciences et Technologies

Filière: Electrotechnique

Spécialité: Énergie renouvelable en électrotechnique

Thème

Power Forecasting to Enable Peak Shaving in a Gas Turbine–Based Standalone Microgrid with PV Integration

Présenté par :

BOUDJERADA Ahmed Abderrahmane

MOULAY OMAR Abdelouahab

Soutenue publiquement le: 21/06/2026

Devant le jury composé de:

FERKOUS Khaled	MCA	Univ. Ghardaïa	**Président**
KIFOUCHE Abdessalam	MCA	Univ. Ghardaïa	**Examinateur**
BOUCHAKOUR Abdelhak	D.R	URAER	**Examinateur**
MOSBAH Charaf Abdelkarim	MCB	Univ. Ghardaïa	**Encadreur**
SKAYARE Soundous	E.V	Univ. Ghardaïa	**Co-encadreur**

Année universitaire: 2025 / 2026

Acknowledgments

First and foremost, we express our profound gratitude to Allah, the Most Merciful, for granting us the strength, patience, and determination to accomplish this humble work. We would like to extend our sincere thanks to our supervisor, Dr. Mosbah Charaf Abdelkarim, for his trust, continuous support, and insightful guidance, which were essential to the success of this project.

We are also especially grateful to our co-supervisor, Ms. Sekayar Soundous, for her valuable guidance, availability, and constructive feedback.

I also wish to express my gratitude to all the people who, in one way or another, encouraged and helped me to complete this work.

To my dear parents, I dedicate these sincere words to thank you for your presence, your light, every day.

ملخص

تعتمد الشبكات الصغيرة المستقلة في المناطق المعزولة غالبًا على التوربينات الغازية لتوفير الكهرباء بشكل موثوق ومستمر. ولكن عندما يزداد الطلب على الطاقة خلال فترات معينة، تضطر التوربينات الغازية إلى العمل تحت أحمال مرتفعة، وهذا قد يؤدي إلى زيادة استهلاك الوقود، وتسريع تقادم المعدات، ورفع تكاليف الصيانة. لذلك، يقترح هذا المشروع طريقة تعتمد على التنبؤ بالطاقة من أجل تقليل ذروة الطلب في شبكة صغيرة مستقلة تعتمد على توربين غازي مع دمج الطاقة الشمسية الكهروضوئية. تعتمد هذه الطريقة على استخدام بيانات التشغيل السابقة للتنبؤ بإجمالي الطاقة المنتجة في الشبكة، ثم تحديد الفترات التي يمكن أن تحدث فيها ذروات في الطلب. وبناءً على هذه الذروات المتوقعة، يتم اختيار الحجم المناسب لمحطة الطاقة الشمسية حتى تتمكن من المساهمة في تغطية جزء من الطلب خلال الفترات الحرجة. بهذه الطريقة، تساعد الطاقة الشمسية في تقليل الحمل الواقع على التوربين الغازي أثناء فترات الذروة. ويساهم هذا النهج في تقليل تشغيل التوربين تحت ظروف صعبة، مما يساعد على إطالة عمره التشغيلي، وخفض تكاليف الصيانة، والحفاظ على موثوقية تزويد الكهرباء. لذلك، فإن الجمع بين التنبؤ بالطاقة وتحديد الحجم المناسب لمحطة الطاقة الشمسية يمكن أن يكون حلاً فعالًا لتحسين الأداء التقني والاقتصادي للشبكات الصغيرة المستقلة.

الكلمات المفتاحية: نظام الشبكة المصغرة؛ تخفيف ذروة الأحمال؛ نظام الطاقة الكهروضوئية؛ نظام تخزين طاقة البطاريات؛ تقنية تخفيف ذروة الأحمال؛ التنبؤ بالطاقة.

Abstract

Standalone microgrids in isolated areas often use gas turbines to provide reliable electricity. However, when the power demand becomes very high, the gas turbine must work under heavy load conditions. This can increase fuel consumption, speed up equipment aging, and raise maintenance costs. This project proposes a method based on power forecasting to reduce peak loads in a standalone microgrid that uses a gas turbine and photovoltaic (PV) energy. The method uses historical operating data to predict the total power output of the microgrid and identify the periods when peak demand may occur. After detecting these expected peak periods, the suitable size of the PV plant can be selected so that solar energy can help supply the load during critical times. In this way, the PV system contributes to peak shaving and reduces the power stress on the gas turbine. By limiting the operation of the gas turbine under extreme load conditions, this approach can help extend its lifetime, reduce maintenance costs, and keep the electricity supply reliable. Therefore, combining power forecasting with proper PV sizing can improve both the technical and economic performance of standalone microgrids.

Keywords: microgrid system; peak load shaving; photovoltaic system; battery energy storage system; peak shaving technique;power forecasting

Résumé

Dans les zones isolées, les micro-réseaux autonomes utilisent souvent des turbines à gaz pour assurer une alimentation électrique fiable. Cependant, lors de pics de consommation, la turbine à gaz doit fonctionner à pleine charge, ce qui peut accroître la consommation de carburant, accélérer le vieillissement des équipements et augmenter les coûts de maintenance. Ce projet propose une méthode de prévision de la consommation pour réduire les pics de charge dans un micro-réseau autonome utilisant une turbine à gaz et l'énergie photovoltaïque (PV). La méthode exploite les données d'exploitation historiques pour prédire la production totale du micro-réseau et identifier les périodes de forte demande. Une fois ces pics identifiés, la taille optimale de la centrale PV est déterminée afin que l'énergie solaire contribue à l'alimentation lors des pics critiques. Ainsi, le système PV contribue à l'écrêtement des pointes de consommation et réduit la sollicitation de la turbine à gaz. En limitant le fonctionnement de la turbine à gaz en cas de forte charge, cette approche permet d'allonger sa durée de vie, de réduire les coûts de maintenance et de garantir la fiabilité de l'approvisionnement en électricité. Par conséquent, la combinaison de la prévision de la consommation et d'un dimensionnement approprié du système PV permet d'améliorer les performances techniques et économiques des micro-réseaux autonomes.

Mots-clés : système de micro-réseau ; écrêtement des pointes de consommation ; système photovoltaïque ; système de stockage d'énergie par batterie ; technique d'écrêtement des pointes ; prévision de la production d'énergie

Table of Contents

List of Figures

List of Tables

List of Abbreviations

PV : Photovoltaic

MPPT : Maximum Power Point Tracking

DC : Direct current

AC : Alternative current

EMS : Energy Management System

CHP systems : Combined Heat and Power systems

SCADA : Supervisory Control and Data Acquisition

BESS : Battery energy storage system

MPC : Model Predictive Control

CNN : Convolutional Neural Network

LSTM : Long Short-Term Memory

GRU : Gated Recurrent Unit

MAE : Mean absolute error

RMSE : Root Mean Squared Error

MSE : Mean Squared Error

MAPE : Mean Absolute Percentage Error

AI : Artificial Intelligence

UCSD: University of California San Diego

SDG&E : San Diego Gas & Electric

IMG : Isolated Microgrid

General Introduction

The demand for reliable, sustainable, and low-cost electrical energy is increasing in many parts of the world. This has encouraged the development of hybrid power systems, which combine conventional energy sources with renewable energy sources such as solar or wind power [1], [2]. These systems are especially important in isolated microgrids, where electricity must be produced, controlled, and consumed locally without direct support from a large external power grid [2], [3]. In such areas, the continuity of power supply is a major concern because any failure in generation can directly affect homes, industries, and essential services [3]. Gas turbines are often used as the main source of electricity in isolated microgrids because they are flexible, can start and respond quickly, and are able to follow changes in electrical demand [4]. However, the power demand is not always constant. During certain periods of the day or year, electricity consumption can rise suddenly and create peak loads. These peak loads force gas turbines to operate under difficult conditions, which can increase thermal and mechanical stress on the equipment. As a result, the turbine may consume more fuel, require more maintenance, and suffer from faster degradation over time [5]. For this reason, managing and reducing peak loads has become an important operational task in isolated microgrids. Good peak-load management can improve system reliability, reduce fuel consumption, lower operating costs, and extend the lifetime of the gas turbine while maintaining a stable power supply for consumers [6].

This thesis is organized into three chapters. Chapter 1 presents standalone hybrid microgrids and their main components. Chapter 2 discusses peak demand challenges and mitigation strategies. Chapter 3 presents the proposed forecasting-based methodology, PV sizing strategy, and simulation results.

Chapter 1

Standalone Hybrid Microgrids: Architecture, Components, and Operation

1.1 Introduction

Reliable electricity is essential for modern life and development because it supports homes, schools, hospitals, industries, transport, communication, and public services. Utility companies must ensure that electricity demand is supplied continuously to keep the power system stable and reliable. The balance between electricity generation and consumption is very important, since any mismatch can affect system reliability [7] and create technical problems in the network. An unstable electricity supply can disturb daily life, delay industrial production, increase business losses, and affect essential services. Therefore, access to reliable electricity has a direct impact on the social and economic progress of society. However, producing enough electricity is not the only important objective. The method used to generate electricity must also be considered because it can influence environmental impacts, energy costs, and the long-term sustainability of the power system.

An electric power system is a large technical network used to generate, transmit, distribute, and deliver electrical energy to consumers. It is an essential infrastructure in modern society because electricity is needed in homes, industries, hospitals, transportation, communication, education, and many daily activities. The main purpose of a power system is to supply electricity in a safe, reliable, continuous, and economical way. A conventional power system is generally divided into three main parts: generation, transmission, and distribution. The generation part produces electricity from sources such as fossil fuels, hydropower, nuclear energy, solar energy, and wind energy. After generation, the voltage is increased by step-up transformers to reduce losses during long-distance transmission. The transmission network carries large amounts of power through high-voltage lines to load centers. Near consumers, substations reduce the voltage using step-down transformers, and the distribution system delivers electricity at lower voltage levels to residential, commercial, and industrial users.

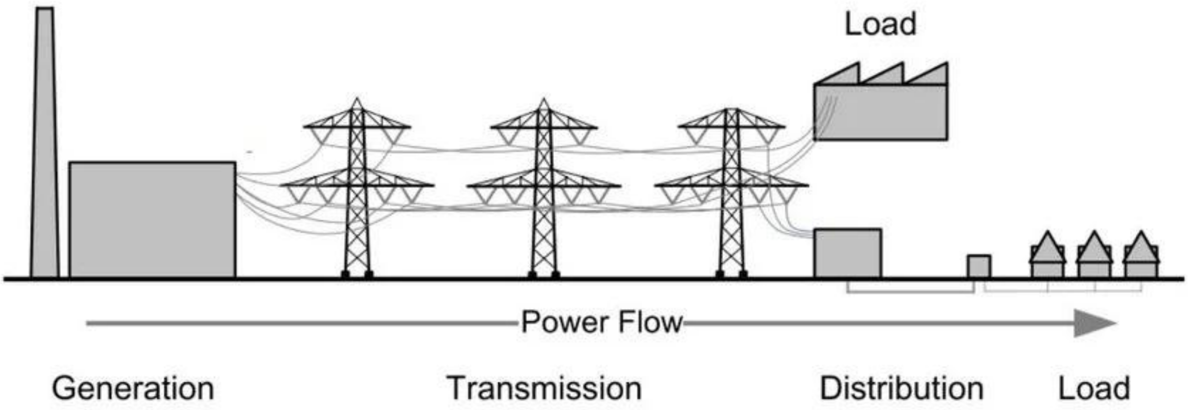


Figure 1: The electrical power system

Table 1: The electrical power system major parts.

Part of the power system	**Main function**	**Main objective**
Generation	Produces electrical energy from primary energy sources.	Convert different energy sources into electrical power and supply the required demand.
Transmission	Transfers of electrical power over long distances at high voltage.	Transport electricity efficiently from generation stations to main load centers while reducing losses.
Distribution	Delivers electricity to final consumers at medium and low voltage levels.	Supply safe and reliable electricity to residential, commercial, industrial, and public consumers.

The operation of an electric power system requires a continuous balance between electricity generation and electricity demand. Since electrical energy is difficult to store in large quantities without special storage systems, the generated power must follow the load demand at every moment. Any imbalance can cause power interruptions and affect the continuity of electricity supply. It also creates serious challenges for system operators, who must quickly restore balance and protect the network. Frequent imbalance and peak-load operation can increase thermal and mechanical stress on generators, accelerate equipment aging, and raise maintenance costs. This can lead to higher technical and financial losses for electricity companies. Therefore, operators must continuously monitor voltage, frequency, load variations, and equipment conditions to maintain system stability and reliability. Today, power systems are becoming more complex because of renewable energy sources, distributed generation, smart grids, and energy storage systems.

1.2 Concept of Microgrids

A microgrid is a small-scale power system that includes local generation units, energy storage systems, loads, and control devices within a defined electrical area. It can operate as one controllable system with respect to the main utility grid [7], [8]. A microgrid can work in grid-connected mode, where it exchanges power with the main grid, or in islanded mode, where it supplies local loads independently. This concept was developed to improve the integration of distributed energy resources into distribution networks. Instead of depending only on large centralized power plants, microgrids use local sources such as PV panels, wind turbines, diesel generators, gas turbines, fuel cells, and battery storage systems [9]. These sources are installed near the consumers, which reduces the distance between generation and consumption. This local structure can help reduce transmission losses and improve the efficiency of electricity supply. Therefore, microgrids are considered an important solution for modern, flexible, and reliable power systems.

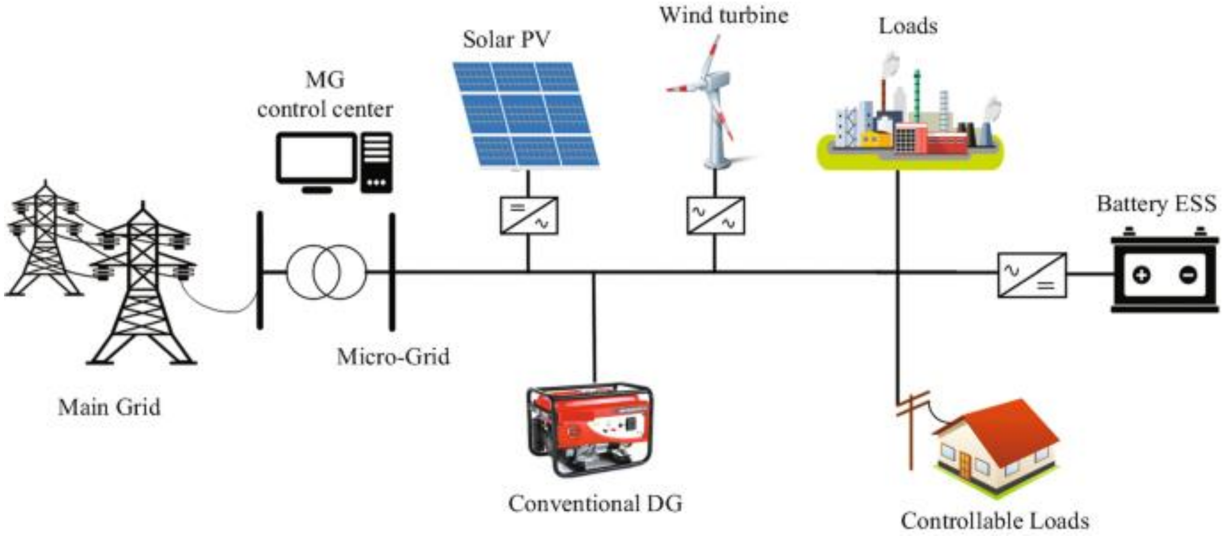


Figure 2: The basic architecture of a microgrid and its interaction with distributed energy resources and loads

Microgrids are especially useful in remote areas, isolated communities, campuses, hospitals, military bases, industrial sites, and critical infrastructures. In these applications, the microgrid can improve power reliability by continuing to supply electricity during disturbances or outages in the main grid. When a fault or disturbance occurs in the upstream network, the microgrid can disconnect from the main grid and continue operating in islanded mode if it has enough local generation and storage capacity [8], [10].

Microgrids are useful in remote areas, isolated communities, campuses, hospitals, military bases, industrial sites, and critical infrastructures because they can improve electricity reliability. During faults or outages in the main grid, a microgrid can disconnect and continue supplying local loads in islanded mode if enough local generation and storage are available [8], [10]. However, microgrid operation requires advanced control and energy management to coordinate generation units, storage systems, and loads while keeping voltage and frequency within acceptable limits. This task is more difficult in islanded mode because generation and demand must be balanced locally. For this reason, different control methods are used, such as droop control, hierarchical control, model predictive control, and multi-agent systems [11], [12]. Microgrids also help integrate renewable energy sources, but solar and wind power are intermittent because they depend on weather conditions. Therefore, storage systems and dispatchable generators are needed to reduce renewable variability and maintain power balance [11], [13]. In general, microgrids support reliable, flexible, and intelligent power systems, but they still face challenges related to protection, control complexity, storage sizing, economic optimization, and stable operation.

Table 2: Main characteristics and advantages of microgrids

Characteristic	**Description**	**Main advantage**
Local generation	Electricity is produced close to the consumers using distributed energy resources such as PV, wind, gas turbines, diesel generators, or fuel cells.	Reduces dependence on distant centralized power plants and can reduce network losses.
Clearly defined electrical boundary	The microgrid operates within a specific local electrical area, such as a campus, village, hospital, industrial site, or isolated community.	Makes the system easier to monitor, control, and manage as one local energy system.
Grid-connected operation	The microgrid can operate while connected to the main utility grid and exchange power with it.	Allows energy import when local generation is insufficient and energy export when there is surplus generation.
Islanded operation	The microgrid can disconnect from the main grid and operate independently.	Improves reliability and keeps important loads supplied during grid outages or disturbances.

Integration of renewable energy	Renewable sources such as solar PV and wind can be connected inside the microgrid.	Reduces fuel consumption, emissions, and operating costs.
Energy storage	Batteries or other storage systems can store excess energy and release it when needed.	Helps smooth renewable energy fluctuations and supports power balance.
Advanced control system	A microgrid controller coordinates generation, storage, loads, and grid connection.	Maintains voltage, frequency, stability, and optimal energy use.
Load management	Some loads can be controlled, shifted, or prioritized according to system conditions.	Improves energy efficiency and protects critical loads.
Improved reliability and resilience	The microgrid can continue supplying electricity during main-grid failures if enough local resources are available.	Reduces the impact of power interruptions on essential services.
Flexibility and scalability	New distributed generators, storage systems, or loads can be added progressively.	Allows gradual development according to energy demand and budget.

1.3 Types of Microgrids

Microgrids can be classified in different ways depending on their mode of operation, electrical structure, energy sources, and application area, there is no single fixed classification because microgrids can be designed for many purposes, such as rural electrification, renewable energy integration, industrial power supply, military facilities, hospitals, campuses, and critical infrastructure. The most common types of microgrids are presented below.

1.3.1 Grid-Connected Microgrids

A grid-connected microgrid operates while connected to the main utility grid through a point of common coupling. In this mode, it can exchange electricity with the main grid according to local generation and demand. When local generation is not enough, the microgrid imports electricity from the main grid. When local generation is higher than local demand, it can export the excess power. This type of microgrid is commonly used in urban areas, campuses, commercial buildings, and industrial sites. Its main advantage is that it can improve energy efficiency and reduce electricity costs while still receiving support from the utility grid. However, it requires advanced control systems to manage power exchange, voltage regulation, protection, and synchronization [7]. Therefore, grid-connected microgrids are useful solutions for improving local energy management and system flexibility.

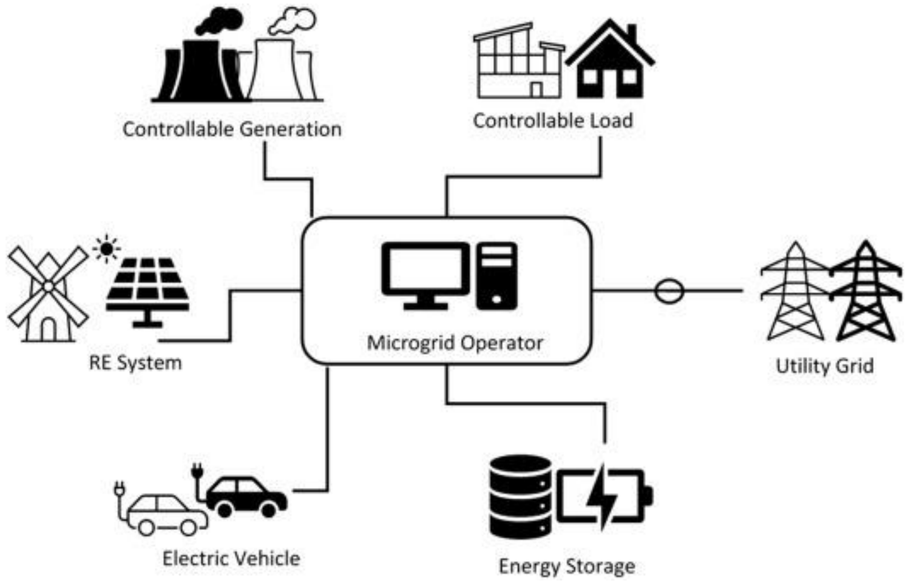


Figure 3 : grid-connected microgrid configuration

1.3.2 Standalone Microgrids

An islanded microgrid, also called a standalone microgrid, operates independently from the main grid. This type is very important for remote areas, isolated communities, islands, desert regions, mining sites, and military bases where access to the national grid is difficult or impossible. In islanded operation, the microgrid must supply all local loads using its own generation sources and energy storage systems. Therefore, the balance between generation and demand is more critical. If the generated power is lower than the load demand, power interruptions may occur. For this reason, standalone microgrids often use dispatchable generators, such as diesel generators or gas turbines, together with renewable energy sources and batteries [8], [9].

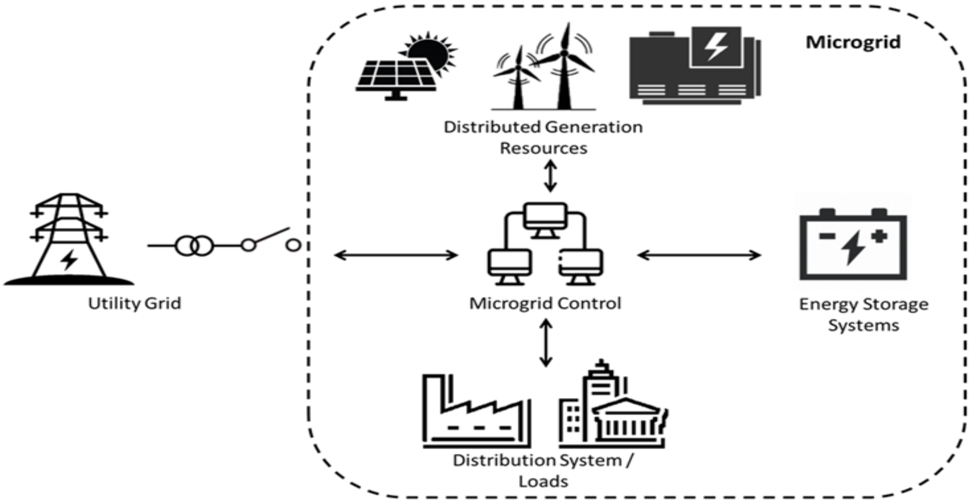


Figure 4 : showing an isolated microgrid supplying local loads without utility grid support

1.3.3 Hybrid Microgrids

Hybrid microgrids are microgrids that combine renewable energy sources with conventional non-renewable energy sources in the same local power system. Renewable sources may include photovoltaic panels, wind turbines, biomass units, or small hydropower systems, while non-renewable sources usually include diesel generators, gas turbines, or microturbines. This combination is commonly used to improve power supply reliability, especially in isolated or standalone microgrids where connection to the main utility grid is weak, unavailable, or technically difficult [7], [11].

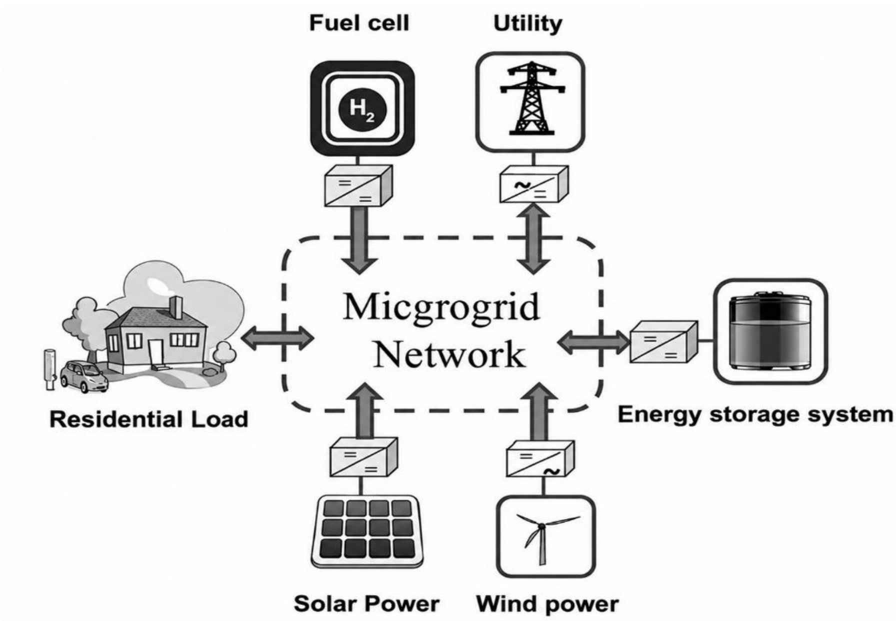


Figure 5 : hybrid microgrid integrating renewable and conventional generation sources

Table 3: a comparison table between grid-connected, standalone, and hybrid microgrids below.

	Grid-connected microgrid	**Standalone microgrid**	**Hybrid microgrid**
Main concept	Connected to the main utility grid.	Operates independently from the main grid.	Combines renewable and non-renewable energy sources.
Energy sources	Main grid, PV, wind, batteries, local generators.	Local generators, PV, wind, batteries.	PV/wind with diesel generator, gas turbine, or battery storage.
Main advantage	Can import or export power with the grid.	Suitable for remote and isolated areas.	Improves reliability and reduces fuel consumption.
Main challenge	Requires grid synchronization and protection control.	Must balance generation and load locally.	Requires good energy management between different sources.
Typical use	Campuses, hospitals, industries, smart buildings.	Villages, islands, desert areas, remote sites.	Isolated microgrids, oil and gas sites, farms, industrial areas.

1.4 Main Components of a Microgrid

A microgrid is composed of several elements that work together to generate, control, store, and deliver electrical energy to local loads. The main components usually include distributed energy resources, energy storage systems, power electronic converters, protection devices, control systems, and electrical loads. In renewable-based microgrids, energy sources such as solar photovoltaic systems, wind turbines, biomass units, and small hydropower plants can be used to reduce fuel consumption and improve energy sustainability. However, because many renewable sources are variable, they are often combined with energy storage systems or backup generators to maintain power reliability [8], [11].

1.4.1 Renewable Energy Sources

Renewable energy sources are energy resources that are naturally replenished and can be used to generate electricity with lower environmental impact compared with fossil-fuel-based generation. In microgrids, renewable energy sources are important because they can reduce fuel dependence, decrease greenhouse gas emissions, and improve local energy autonomy. The most common renewable energy technologies used in microgrids are solar photovoltaic systems, wind energy systems, biomass energy systems, and small hydropower systems.

Solar Photovoltaic Systems

Solar photovoltaic (PV) systems convert sunlight directly into electrical energy using photovoltaic cells. When solar radiation reaches the PV modules, the semiconductor material produces direct-current (DC) electricity. This DC power can be used directly in DC microgrids or converted into alternating-current (AC) electricity using an inverter for AC loads and grid connection. In microgrids, PV systems are widely used because they are modular, easy to install, and suitable for distributed generation. A typical PV generation system includes PV modules, a DC combiner box, a maximum power point tracking (MPPT) controller, an inverter, protection devices, and sometimes a battery energy storage system. The battery is useful when PV generation is higher than load demand or when solar radiation is not available. However, PV systems are intermittent because their output depends on solar irradiance, temperature, shading, and weather conditions.

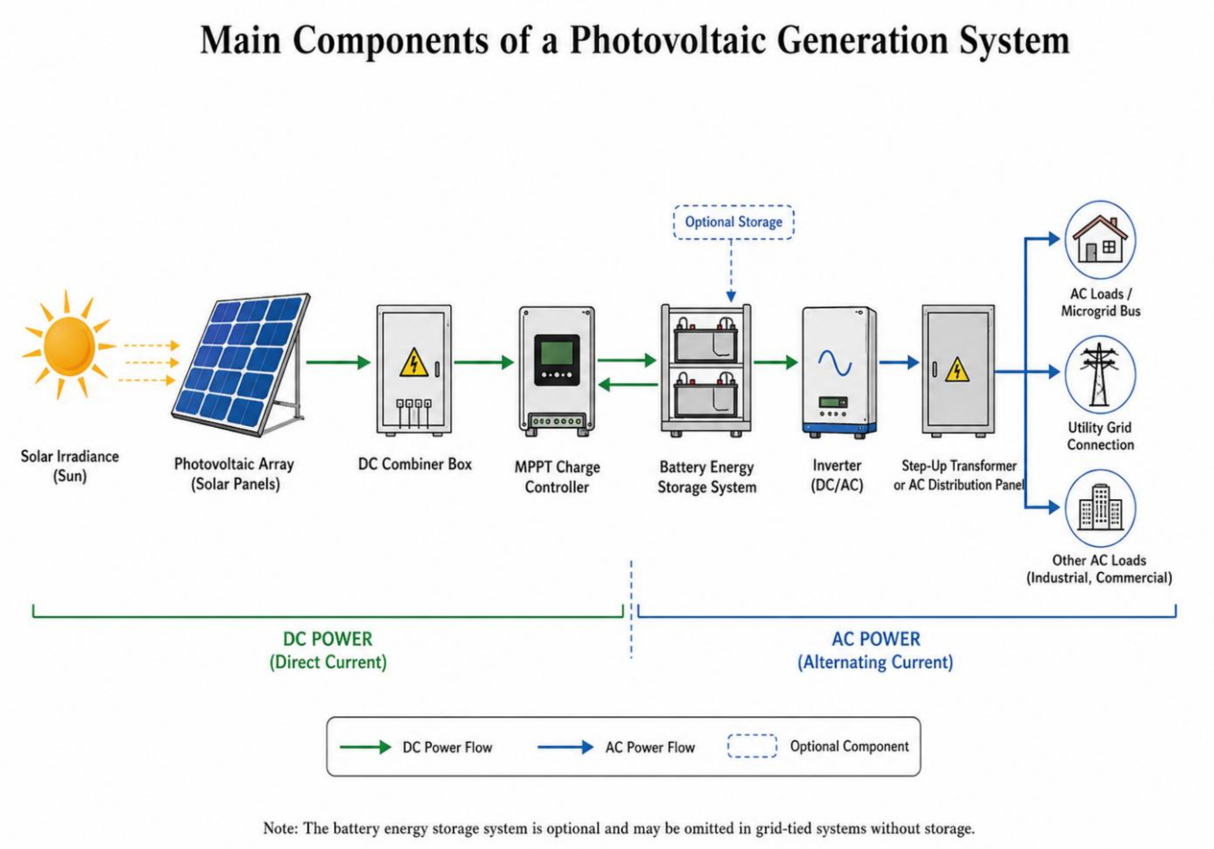


Figure 6 : the main components of a photovoltaic generation system

Table 4: Summarizing the advantages and limitations of PV systems.

Advantages	**Limitations**
Use solar energy, which is clean, renewable, and widely available.	Power production depends on solar irradiance and weather conditions.
Produce electricity without direct greenhouse gas emissions during operation.	Manufacturing, transportation, and end-of-life recycling still have environmental impacts.
Modular and easy to install in small or large-scale systems.	Require suitable space and proper orientation to achieve good performance.
Have low operating and maintenance requirements compared with conventional generators.	Dust, shading, and high temperature can reduce efficiency.
Suitable for distributed generation and can reduce dependence on fossil fuels.	Intermittent output may require batteries or backup sources to maintain reliability.
Can reduce long-term electricity costs after installation.	Initial investment cost can still be high, especially when batteries are included.

1.4.2 Conventional Distributed Generation Units

Conventional distributed generation units are controllable power sources installed close to the load in microgrids. They are mainly used to improve reliability, support renewable energy sources, supply peak demand, and provide backup power during grid disturbances or renewable energy shortages. Unlike solar PV and wind systems, these units can usually be controlled according to load demand [3], [14], which makes them important for standalone and hybrid microgrids that require continuous electricity supply. The main technologies include diesel generators, gas turbines, microturbines, and fuel cells. Each technology has different characteristics related to efficiency, emissions, fuel needs, operating cost, response time, and reliability [15]. Therefore, selecting the suitable generation unit depends on the microgrid size, load profile, fuel availability, environmental limits, and economic conditions.

1.4.3 Diesel Generators

Diesel generators are among the most common conventional generation units used in standalone and remote microgrids. A diesel generator consists of a diesel internal combustion engine coupled to an electrical generator. The diesel engine converts the chemical energy of fuel into mechanical energy, while the generator converts this mechanical energy into electrical energy. Diesel generators are widely used because they are commercially available, reliable, relatively easy to install, and able to start quickly. They are often used as backup sources, emergency power supplies, or main generation units in isolated areas where the utility grid is not available. In hybrid microgrids, diesel generators are commonly combined with renewable energy sources and battery storage to reduce fuel consumption and improve supply reliability [16]. However, diesel generators have important limitations. They consume fossil fuel and produce carbon dioxide, nitrogen oxides, and particulate emissions. Their operating cost can also be high because of fuel prices, fuel transportation, and maintenance requirements. In addition, poor maintenance can reduce their reliability during long power outages. For this reason, diesel generators should be properly sized and operated with an energy management strategy to avoid unnecessary fuel consumption and equipment stress [16], [17].

1.4.4 Gas Turbines

Gas turbines are conventional generation units that produce electricity by burning fuel in a combustion chamber and using the resulting hot gases to rotate a turbine connected to a generator. They are commonly used in applications where medium or high power capacity is required. In distributed generation and microgrid applications, gas turbines can provide dispatchable power during high-demand periods or when renewable energy generation is not sufficient. Gas turbines can operate using natural gas or other suitable fuels. When natural gas is available, they generally produce lower particulate emissions than diesel generators. They can also be used in combined heat and power systems, where exhaust heat is recovered for heating, cooling, or industrial processes. This can increase the overall efficiency of the energy system. However, the main disadvantages of gas turbines are their dependence on fuel, carbon dioxide emissions, and sensitivity to operating conditions. Their efficiency can decrease at partial load and under high ambient temperatures. Therefore, gas turbines require careful sizing and proper dispatch control when they are used in microgrids [18].

1.4.5 Microturbines

Microturbines are small gas turbine systems used for distributed generation. They are generally smaller than conventional gas turbines and are suitable for small commercial, industrial, and remote applications. A typical microturbine includes a compressor, combustor, turbine, generator, recuperator, and power electronic interface. Microturbines are attractive for microgrids because they are compact, have relatively low vibration, and can operate with different fuels such as natural gas, biogas, or other gaseous fuels. They can also be used in combined heat and power applications, where both electricity and useful heat are produced. This makes them suitable for buildings, hospitals, small industries, and hybrid microgrids that require both electrical and thermal energy [18], [19]. However, microturbines usually have lower electrical efficiency than large gas turbines and some reciprocating engines. Their economic performance depends strongly on fuel price, thermal energy use, operating hours, and maintenance requirements. Therefore, microturbines are more attractive when the recovered heat can be used effectively [17].

1.4.6 Fuel Cells

Fuel cells are electrochemical generation units that convert the chemical energy of a fuel directly into electrical energy. Unlike diesel generators, gas turbines, and microturbines, fuel cells do not depend on a conventional combustion process to produce electricity. A fuel cell system usually includes a fuel cell stack, fuel processor, power conditioning unit, and auxiliary systems. Fuel cells are attractive for microgrid applications because they can provide high electrical efficiency, low noise, low vibration, and low local emissions. They can also provide high-quality power, which makes them suitable for critical loads such as hospitals, data centers, telecommunication systems, and sensitive industrial facilities [20]. However, the main limitations of fuel cells are their high initial cost, fuel supply requirements, and sensitivity to fuel quality. Some fuel cell technologies require hydrogen, while others can operate using natural gas or biogas after fuel reforming. Fuel cell stack lifetime and replacement cost are also important economic factors. Therefore, fuel cells are generally more suitable for applications where low emissions, high efficiency, and power quality are more important than low initial investment [20].

Table 5 : a comparison table of conventional distributed generation technologies based on efficiency, emissions, operating cost, and reliability

Technology	Efficiency	Emissions	Operating cost	Reliability and role in microgrids
Diesel generator	Medium to high, depending on size and loading condition.	High CO_2, NOx, and particulate emissions compared with cleaner technologies.	Medium to high because of fuel consumption, fuel transport, and maintenance.	Reliable if well maintained; suitable for backup power, black start, and remote microgrids.
Gas turbine	Medium to high, especially at larger sizes or	Lower particulate emissions than diesel when using	Medium, depends strongly on fuel	Suitable for dispatchable power,

	with heat recovery.	natural gas, but still produces CO_2 and NOx.	price and operating conditions.	peak-load support, and CHP applications.
Microturbine	Medium, generally lower than large gas turbines and some reciprocating engines.	Relatively low emissions when using natural gas or clean gaseous fuels.	Medium to high per kWh if heat recovery is not used.	Suitable for small-scale CHP, commercial sites, and hybrid microgrids.
Fuel cell	High compared with many combustion-based technologies.	Very low local emissions,emissions depend on the fuel source.	High initial cost; operating cost depends on fuel, stack lifetime, and maintenance.	Suitable for critical loads, low-noise operation, and low-emission microgrids.

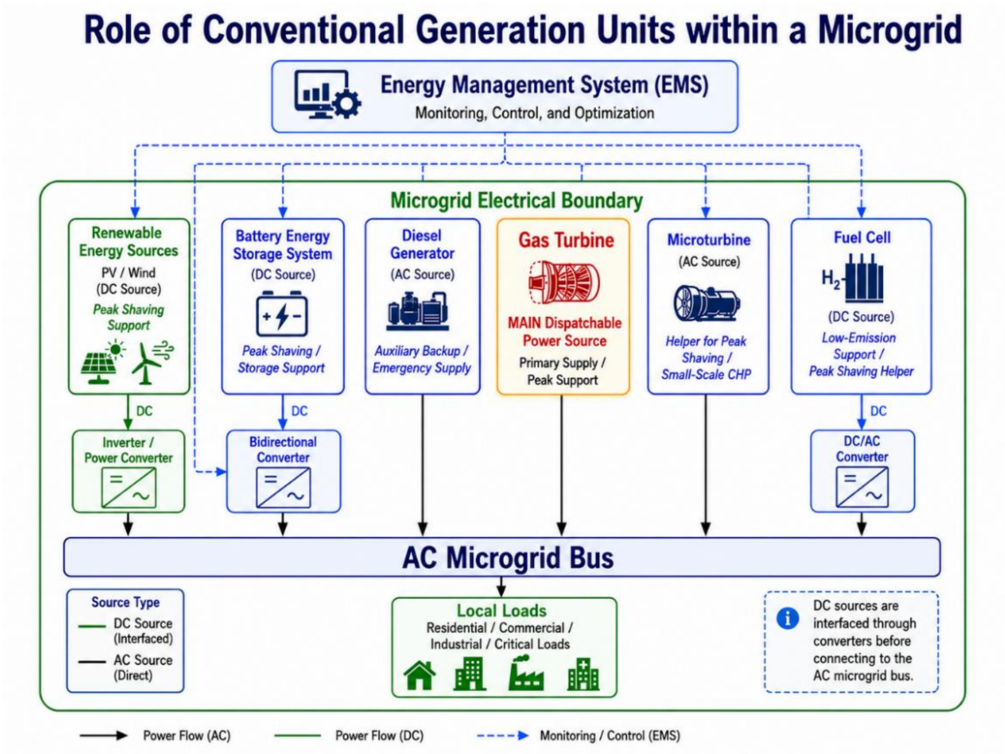


Figure 7 : The role of conventional generation units within a microgrid

1.5 Gas Turbine Technology

Gas turbines are important conventional generation units in power systems and microgrids because they provide dispatchable power, fast start-up, high power density, and reliable operation. In standalone and hybrid microgrids, they often work as the main controllable source used to balance generation and demand. However, during peak-load periods, gas turbines may operate under high stress, which can increase fuel consumption and maintenance needs. To reduce this stress, renewable energy sources such as solar PV and wind systems can be integrated into the microgrid. These sources can supply part of the required power during high-demand periods, helping to reduce the load on the gas turbine. This contribution supports peak shaving, lowers fuel consumption, and improves the overall efficiency of microgrid operation. A gas turbine converts fuel energy into mechanical energy and then into electrical energy using a generator. Its main components are the compressor, combustion chamber, turbine, and generator, and its operation is generally based on the Brayton cycle.

1.5.1 Working Principle of Gas Turbines

The working principle of a gas turbine is based on a continuous thermodynamic process that includes air compression, fuel combustion, gas expansion, and electrical power generation. First, ambient air is drawn into the compressor, where both its pressure and temperature are increased. The compressed air is then directed to the combustion chamber, where fuel is injected and burned at approximately constant pressure. This combustion process produces hot, high-pressure gases that expand through the turbine blades. During this expansion, the turbine converts the thermal energy of the gases into mechanical energy. Part of the mechanical power produced by the turbine is used to drive the compressor, while the remaining useful power is transmitted to the electrical generator to produce electricity. In a simple open-cycle gas turbine, the exhaust gases are released directly into the atmosphere after leaving the turbine. However, in a combined-cycle configuration, these hot exhaust gases are recovered using a heat recovery steam generator to produce steam, which drives a steam turbine and increases the total efficiency of the power plant [20]. From a thermodynamic point of view, the ideal gas turbine operates according to the Brayton cycle, which consists of four main processes: isentropic compression, constant-pressure heat addition, isentropic expansion, and constant-pressure heat rejection. In real gas turbines, these processes are not perfectly ideal because of energy losses in the compressor, combustion chamber, turbine, and exhaust system.

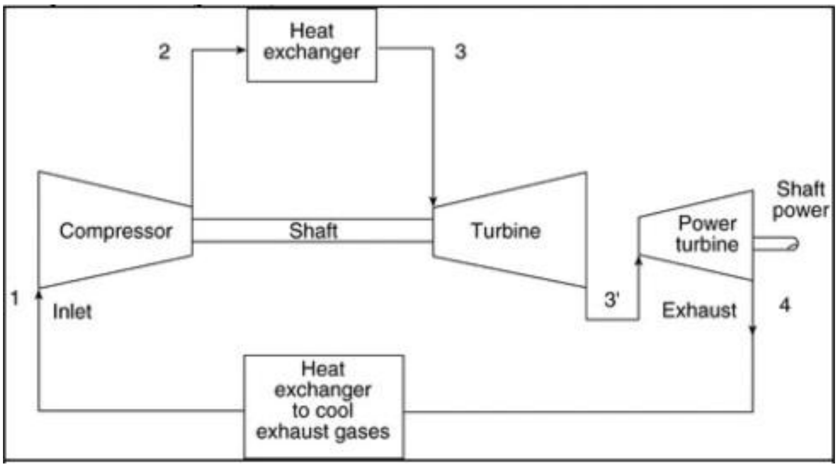


Figure 8 : Brayton Cycle

1.5.2 Types of Gas Turbines

Gas turbines can be classified according to their cycle configuration, size, and application. The most common types used in power generation and microgrid applications are open-cycle gas turbines, combined-cycle gas turbines, and micro gas turbines.

1.5.2.1.1 Open-cycle gas turbines

Open-cycle gas turbines, also called simple-cycle gas turbines, use only the gas turbine cycle. They are relatively simple, fast to start, and suitable for peak-load support. However, they have lower efficiency because the exhaust heat is not recovered.

1.5.2.1.2 Combined-cycle gas turbines

Combined-cycle gas turbines use both a gas turbine cycle and a steam turbine cycle. The exhaust heat from the gas turbine is recovered to produce steam in a heat recovery steam generator. This steam drives a steam turbine and produces additional electricity. For this reason, combined-cycle gas turbines are more efficient than open-cycle units, but they are more complex and more expensive.

1.5.2.1.3 Micro gas turbines

Micro gas turbines are small gas turbine units designed for distributed generation and small-scale combined heat and power applications. They are compact, have low vibration, and can operate with different fuels such as natural gas or biogas. However, their electrical efficiency is usually lower than that of larger gas turbines unless heat recovery is used.

Table 6 : a table comparing open-cycle gas turbines, combined-cycle gas turbines, and micro gas turbines

Type	Configuration	Efficiency	Advantages	Limitations	Applications
Open-cycle gas turbine	Compressor, combustor, turbine, and generator. Exhaust gases are discharged directly.	Medium; commonly about 33–43% at maximum load.	Fast start-up, simple structure, suitable for peak load and backup operation.	Lower efficiency, high fuel consumption at part load, exhaust heat is not recovered.	Peak-load plants, emergency support, grid balancing, standalone microgrids.
Combined-cycle gas turbine	Gas turbine plus heat recovery steam generator and steam turbine.	High, around 60% in modern systems.	High, better fuel utilization, lower CO_2 per kWh than simple-cycle operation.	More complex, higher capital cost, slower start-up than simple-cycle units.	Utility power plants, industrial power supply, large microgrids, CHP systems.
Micro gas turbine	Small gas turbine with compressor, combustor, turbine, recuperator, generator, and power electronics.	Medium, commonly lower than large gas turbines in electrical-only mode.	Compact, low vibration, suitable for distributed generation and CHP.	Higher cost per kW, lower electrical efficiency, performance depends on heat recovery use.	Buildings, hospitals, remote sites, small industrial microgrids.

1.5.3 Performance Characteristics of Gas Turbines

The performance of a gas turbine depends on several operating and design parameters, including pressure ratio, turbine inlet temperature, compressor efficiency, turbine efficiency, fuel type, ambient temperature, part-load operation, and maintenance condition. In general, a higher pressure ratio and a higher turbine inlet temperature can improve gas turbine efficiency and specific power output, but they also increase material strength requirements and cooling needs. Gas turbine output is also strongly affected by ambient temperature. When the ambient temperature increases, air density decreases, which reduces the mass flow rate entering the compressor. As a result, turbine power output and efficiency may decrease. This issue is particularly important in hot climates and desert regions, where gas turbines often operate under high-temperature conditions. In microgrid applications, gas turbines are important because they can provide dispatchable and controllable power. However, frequent start-stop operation, partial-load operation, and peak-load operation can increase thermal and mechanical stress on the machine. Therefore, gas turbines must be properly sized and controlled to reduce fuel consumption, emissions, equipment stress, and maintenance costs.

1.6 Energy Storage Technologies

Energy storage technologies are important elements in modern microgrids because they help balance the difference between electricity generation and load demand. In microgrids that include renewable energy sources, such as photovoltaic and wind systems, energy storage is especially important because renewable generation is intermittent and depends on weather conditions. Storage systems can absorb excess energy when generation is higher than demand and release stored energy when generation is lower than demand. In this way, energy storage systems improve microgrid reliability, power quality, operational flexibility, and stability. They can also support several important functions, including peak shaving, frequency regulation, voltage control, backup power supply, and the integration of renewable energy sources. Different storage technologies are available for microgrid applications, and each technology has specific characteristics related to energy density, power density, response time, lifetime, efficiency, and cost [21]. The most common energy storage technologies used or studied in microgrids include battery energy storage systems, flywheel energy storage systems, supercapacitors, and hydrogen energy storage systems.

1.6.1 Battery Energy Storage Systems

Battery energy storage systems store electrical energy in chemical form and convert it back into electrical energy when needed. A typical battery system includes battery cells or modules, a battery management system, power converters, protection devices, thermal management equipment, and control units. In microgrids, batteries are widely used because they provide fast response, good efficiency, and flexible operation. They can be charged when renewable generation is high and discharged when load demand increases or when renewable generation decreases. Batteries are also useful for peak shaving, load shifting, backup power supply, and smoothing photovoltaic or wind power fluctuations. Different battery technologies can be used in microgrid applications, including lithium-ion, lead-acid, sodium-sulfur, nickel-based, and flow batteries. Among these technologies, lithium-ion batteries are widely adopted because of their relatively high energy density, high efficiency, and decreasing cost. However, battery systems also have some limitations, such as aging, limited cycle life, thermal management requirements, safety concerns, and replacement cost [22].

1.6.2 Flywheel Energy Storage Systems

Flywheel energy storage systems store energy in the form of rotational kinetic energy. During charging, an electric motor accelerates a rotating mass, while during discharging, the rotating mass drives a generator to produce electrical energy. Modern flywheel systems often use magnetic bearings, vacuum enclosures, and power electronic converters to reduce losses and improve overall performance. Flywheels are suitable for applications that require high power, very fast response, and frequent charge-discharge cycles. They are commonly used for power quality improvement, frequency regulation, voltage support, and short-duration backup power. One of their main advantages is their long cycle life, since they do not depend on electrochemical reactions like batteries [23]. However, flywheels generally have lower energy density than batteries and are therefore more suitable for short-duration energy storage. Their cost can also be high, especially for advanced high-speed systems equipped with magnetic bearings and vacuum containment. For this reason, flywheel energy storage systems are mainly used when fast response and high power capability are more important than long energy duration [21], [23].

1.6.3 Supercapacitors

Supercapacitors, also called ultracapacitors, store energy through electrostatic charge separation at the electrode–electrolyte interface. They differ from batteries because they store energy physically rather than through chemical reactions, which gives them very fast charge and discharge capability. Supercapacitors have very high power density, very fast response time, and very long cycle life. They are suitable for short-duration applications such as power smoothing, transient support, voltage stabilization, regenerative braking, and high-power pulses. In microgrids, they can be combined with batteries to form a hybrid energy storage system. In this configuration, the supercapacitor supplies fast power variations, while the battery supplies longer-duration energy [24]. However, the main limitation of supercapacitors is their low energy density compared with batteries. This means that they can deliver high power for a short time, but they cannot store large amounts of energy for long periods. Their cost per unit of stored energy is also relatively high. Therefore, supercapacitors are mainly used for short-term power support rather than long-duration energy supply [24].

1.6.4 Hydrogen Energy Storage

Hydrogen energy storage is a chemical storage technology that stores energy in the form of hydrogen. In a renewable-based microgrid, excess electricity can be used by an electrolyzer to split water into hydrogen and oxygen. The produced hydrogen is then stored in tanks or other suitable storage systems. When electricity is needed, the stored hydrogen can be converted back into electrical energy using a fuel cell or a hydrogen-fueled generator. Hydrogen storage is useful for long-duration and seasonal energy storage because hydrogen can store large amounts of energy for extended periods. It can help microgrids with high renewable energy penetration by storing surplus solar or wind energy and using it later during periods of low renewable generation [24], [25]. However, hydrogen energy storage also has several challenges. It requires an electrolyzer, hydrogen storage system, fuel cell or generator, compression or another storage technology, and appropriate safety systems. Its round-trip efficiency is generally lower than that of battery storage because energy is lost during electrolysis, compression, storage, and conversion back into electricity. Hydrogen systems also have high initial costs and require strict safety measures because hydrogen is highly flammable. Therefore, hydrogen storage is more suitable for long-duration applications where batteries may become too expensive or technically limited.

1.7 Energy Management Systems in Microgrids

An Energy Management System (EMS) is a key part of a modern microgrid because it monitors, controls, and optimizes distributed energy resources, storage systems, conventional generators, and electrical loads. Its main objective is to ensure reliable, economical, and efficient microgrid operation under different conditions [26], [27]. The EMS must continuously balance power generation and load demand, especially when solar PV and wind energy are used. This task becomes more complex because renewable energy output changes with weather conditions. Therefore, the EMS uses real-time measurements, forecasts, control actions, and optimization methods to coordinate the available resources [28], [29]. It can operate in both grid-connected and islanded modes. In grid-connected mode, it manages electricity import and export with the main grid. In islanded mode, it must maintain the local power balance by coordinating renewable sources, batteries, conventional generators, and controllable loads[26], [29].

1.7.1 Functions of Energy Management Systems

The functions of an energy management system (EMS) depend on the size, type, and complexity of the microgrid. However, its main functions generally include data acquisition, generation scheduling, storage management, load management, economic dispatch, renewable energy forecasting, and protection coordination. First, the EMS collects data from different parts of the microgrid, such as voltage, current, frequency, active power, reactive power, battery state of charge, renewable generation, fuel consumption, and load demand. These data are used to evaluate the real-time operating condition of the microgrid. Second, the EMS controls the operation of generation units by deciding how much power should be produced by each source according to load demand, fuel cost, renewable generation, and technical constraints. For example, when photovoltaic production is high, the EMS can reduce the output of conventional generators or charge the battery. When renewable production is low, it can start dispatchable generators or discharge the storage system. Third, the EMS manages energy storage systems by determining when batteries should be charged or discharged according to the power balance, electricity price, peak demand, and battery operating limits. Proper battery management is important because excessive cycling or deep discharge can accelerate battery degradation. Fourth, the EMS can perform load management by shifting, reducing, or disconnecting some loads during critical periods. This function is especially important in islanded microgrids, where the available generation may not always be sufficient to supply all loads. In such cases, critical loads are usually given priority over non-critical loads. Finally, the EMS supports the economic and reliable operation of the microgrid by minimizing fuel consumption, reducing operating cost, improving renewable energy utilization, reducing emissions, and maintaining voltage and frequency within acceptable limits [27], [30].

1.7.2 Supervisory Control and Data Acquisition (SCADA)

Supervisory Control and Data Acquisition, commonly known as SCADA, is a system used for monitoring and controlling industrial and electrical systems. In a microgrid, SCADA provides the communication and supervision layer between field devices and the control center. It collects real-time data from sensors, meters, relays, inverters, generators, circuit breakers, and energy storage systems, and displays these data to the operator through a human-machine interface. A typical SCADA system includes remote terminal units, programmable logic controllers, communication networks, servers, databases, and operator interfaces. Remote devices collect measurements from the field, while the central system processes the data and allows the operator or the energy management system to send control commands. In microgrid applications, SCADA is important because it gives operators a clear view of the system status. It can display voltage, frequency, power flow, generator status, breaker position, battery state of charge, alarms, and historical trends. It can also support fault detection, event recording, remote control, and maintenance planning. However, SCADA does not replace the energy management system. SCADA mainly collects and displays data and sends control commands, while the EMS uses these data to make operational and optimization decisions. Therefore, SCADA and EMS are complementary systems in modern microgrids [31].

1.7.3 Optimization and Scheduling Functions

Optimization and scheduling are essential functions of the EMS because they define the best operating plan for the microgrid over short-term or day-ahead periods. They decide when generators should operate, how much power they should produce, when batteries should charge or discharge, and how power should be exchanged with the main grid. The main objectives are to reduce fuel cost, limit emissions, increase renewable energy use, reduce peak demand, and maintain system reliability. In hybrid microgrids, this task is important because renewable sources are clean but variable, conventional generators are controllable but consume fuel, and batteries have capacity and lifetime limits. For this reason, the EMS must coordinate all resources carefully to balance generation and demand. Different optimization methods can be used, including linear programming, mixed-integer linear programming, model predictive control, stochastic optimization, heuristic algorithms, and artificial intelligence methods [30]. Forecasting also plays an important role because predictions of load demand, solar irradiance, wind speed, renewable generation, and electricity price help the EMS prepare better decisions. Poor forecasting can cause fuel waste, battery overuse, renewable energy curtailment, or power imbalance. In practice, SCADA provides real-time monitoring and data acquisition, while the EMS uses these data with forecasting, optimization, and scheduling to improve reliability, reduce costs, support peak shaving, and maintain voltage and frequency stability [28].

1.8 Challenges of Standalone Hybrid Microgrids

Standalone hybrid microgrids supply local loads without relying on the main utility grid. They usually combine renewable sources, such as PV and wind systems, with conventional generators, such as diesel generators or gas turbines, and energy storage systems [32], [33]. This combination can improve electricity reliability and reduce fuel consumption, especially in remote and isolated areas. However, their operation is more difficult because generation and demand must be balanced locally at every moment. Unlike grid-connected microgrids, standalone systems cannot import power from the main grid when local generation is not enough. Therefore, any mismatch between generation and load demand can directly affect voltage, frequency, power quality, and supply continuity. The main challenges include renewable energy intermittency, load variability, voltage and frequency stability, and peak demand management. For this reason, standalone hybrid microgrids require careful design, reliable control, and effective energy management.

1.8.1 Renewable Energy Intermittency

Renewable energy intermittency is a major challenge in standalone hybrid microgrids because solar and wind generation depend on changing weather conditions. Solar PV output is affected by solar irradiance, temperature, cloud cover, and day-night cycles, while wind power depends mainly on wind speed [32]. As a result, renewable generation is not constant and may not always match the load demand. When renewable production is higher than demand, the excess energy must be stored in batteries or curtailed. When renewable production is lower than demand, storage systems or conventional generators must supply the missing power. If these backup resources are not sufficient, load shedding or power interruptions may occur. Therefore, standalone microgrids require accurate forecasting, proper storage sizing, and efficient energy management [32], [33]. These strategies help balance generation and demand, reduce renewable energy curtailment, and improve the reliability of microgrid operation.

1.8.2 Load Variability

Load variability refers to the continuous change in electricity demand over time. In standalone microgrids, the load can vary according to the time of day, season, weather conditions, user behavior, industrial activity, agricultural operations, or the operation of specific equipment such as pumps, motors, cooling systems, and compressors. Load variability is more critical in standalone microgrids because these systems have limited generation capacity and cannot depend on the main grid for support. Sudden load increases may cause a power deficit, voltage drop, or frequency deviation, while sudden load decreases may create excess power, which can overcharge storage systems or force generators to operate under inefficient low-load conditions. In hybrid microgrids, load forecasting is very important because it helps the energy management system plan the operation of generators, renewable sources, and batteries. If the predicted load is lower than the actual demand, the microgrid may not prepare enough generation capacity, which can affect supply reliability. Conversely, if the predicted load is higher than the actual demand, the system may operate generators unnecessarily, increasing fuel consumption, emissions, and operating cost [32], [33].

1.8.3 Frequency and Voltage Stability

Frequency and voltage stability are essential requirements for the safe and reliable operation of standalone hybrid microgrids. Frequency is mainly affected by the balance between active power generation and active power demand. If the load becomes higher than the available generation, the frequency tends to decrease; conversely, if generation becomes higher than the load, the frequency tends to increase. In both cases, excessive frequency deviation can damage electrical equipment or activate protection systems. Voltage stability is strongly related to reactive power balance, load variations, line impedance, converter control, and the operation of distributed generators. In standalone microgrids, voltage control is more difficult because the system is smaller and weaker than the main utility grid. In addition, many renewable energy sources are connected through power electronic converters, which reduces the natural inertia of the system compared with conventional synchronous generators [34], [35]. Low inertia makes standalone microgrids more sensitive to sudden disturbances, such as a rapid decrease in photovoltaic generation or a sudden increase in load demand, which can cause fast frequency and voltage deviations. To address this problem, microgrids use control strategies such as droop control, virtual inertia control, battery energy storage support, reactive power compensation, and load shedding. These methods help maintain voltage and frequency within acceptable limits during both normal and disturbed operating conditions [34], [35].

1.8.4 Peak Demand Management

Peak demand occurs when the electrical load reaches its highest value during a specific period. In standalone hybrid microgrids, peak demand is a major challenge because the system must have enough local generation and storage capacity to supply the maximum load without support from the main grid. If the microgrid is not properly sized, peak demand can overload generators, deeply discharge batteries, increase fuel consumption, and reduce system reliability. Peak demand also increases the stress on conventional generation units such as diesel generators and gas turbines. Frequent operation near maximum capacity can increase thermal and mechanical stress, accelerate equipment aging, and raise maintenance costs. In remote microgrids, this problem becomes more critical because maintenance services and fuel transportation are often expensive and difficult. Peak demand management aims to reduce or shift the highest load periods using methods such as battery energy storage, demand response, load shifting, load prioritization, renewable generation scheduling, and predictive control. For example, batteries can discharge during peak periods, while non-critical loads can be shifted to periods of lower demand. In this way, peak demand management can reduce generator stress, improve fuel economy, and increase microgrid reliability [36], [37]. In summary, standalone hybrid microgrids are promising solutions for reliable and sustainable power supply in isolated areas. However, their successful operation depends on the ability to manage renewable intermittency, load variability, voltage and frequency stability, and peak demand. These challenges require accurate forecasting, efficient energy management, proper sizing of generation and storage systems, and advanced control strategies.

1.9 Conclusion

This chapter presented the fundamental concepts related to standalone hybrid microgrids and their role in modern power systems. It began with an overview of electrical power systems and the importance of maintaining a continuous balance between electricity generation and load demand. The concept of microgrids was then introduced as an effective solution for improving energy reliability, flexibility, and the integration of distributed energy resources. Different microgrid configurations, including grid-connected, standalone, and hybrid microgrids, were discussed, highlighting their characteristics, advantages, and typical applications.

The chapter also examined the main components of a microgrid, including renewable energy sources, conventional distributed generation units, energy storage technologies, and energy management systems. Particular attention was given to gas turbines, which play a critical role in standalone hybrid microgrids due to their ability to provide dispatchable and reliable power. The operating principles, classifications, and performance characteristics of gas turbines were presented, together with the challenges associated with their operation under varying load conditions. In addition, the importance of energy storage systems and advanced energy management strategies was emphasized, as these technologies contribute to improving system stability, reliability, and operational efficiency.

Overall, the chapter demonstrated that standalone hybrid microgrids represent a promising solution for supplying electricity in isolated and remote areas. However, their successful operation depends on the effective coordination of generation sources, storage systems, and control strategies. Among the most important operational challenges is the management of high-demand periods, during which conventional generation units may experience increased stress, reduced efficiency, and higher operating costs.

Chapter 2

Peak Demand Challenges and Mitigation Strategies in Power Systems

2.1 Introduction

Peak demand is a major challenge in power-system operation and planning because electricity demand changes during the day, across days, and between seasons. Since electricity generation must generally match consumption in real time, system operators must continuously adjust generation according to load demand. This task becomes more difficult during peak periods, when demand reaches its highest level and additional generation capacity is required. Peak demand can increase operating costs because expensive or less efficient units may be used for short high-demand periods. It can also create technical stress on generators, transformers, cables, and protection equipment. In standalone and hybrid microgrids, this problem is more critical because the system may not have support from the main grid during high-demand periods. Therefore, understanding load profiles and peak-demand behavior is necessary before applying solutions such as demand response, energy storage, renewable support, and forecasting-based energy management [38], [39]. This chapter explains load variations, peak-demand causes, and their impacts on standalone microgrids.

2.2 Load Characteristics and Demand Profiles

Electric load represents the electrical power consumed by users at a specific time. It changes continuously because of human activity, weather conditions, work schedules, industrial processes, and the use of electrical equipment. For this reason, electricity demand usually follows repeated patterns over different time scales. Studying load profiles is important because it helps operators and planners identify periods of low, normal, and high consumption. This information is useful for scheduling generation units, sizing energy storage systems, planning maintenance activities, and reducing fuel consumption. Load-profile analysis also helps detect peak periods and prepare suitable energy management strategies. The most common types of load profiles are daily, weekly, and seasonal profiles.

2.2.1 Daily Load Profiles

A daily load profile shows how electricity demand changes during a 24-hour period. In general, electricity consumption is low at night because most residential, commercial, and industrial activities are reduced. Demand starts to increase in the morning when people wake up, use lighting and appliances, and when business and industrial activities begin. During the day, the load usually remains moderate or high because of industrial operation, commercial activity, cooling systems, lighting, and other electrical equipment. In many power systems, the highest demand occurs in the late afternoon or early evening [38], when people return home and domestic electricity use increases. The shape of the daily load profile depends on the type of consumers connected to the system. Residential areas often have clear morning and evening peaks, while industrial areas may show a more stable demand during working hours. Weather also strongly affects daily demand, especially through air-conditioning in summer and electric heating in winter.

2.2.2 Weekly Load Profiles

A weekly load profile shows how electricity demand changes from one day to another during the week. In many power systems, demand is higher from Monday to Friday because commercial, educational, administrative, and industrial activities are more active . During these working days, many electrical loads operate during regular hours, which increases total consumption. On weekends, electricity demand is usually lower because many offices, schools, and industrial facilities reduce or stop their activities. However, this pattern can change in areas dominated by residential loads, tourism, hospitals, or continuous industrial processes. In these cases, weekend demand may remain high or close to weekday demand. Weekly load profiles are useful for planning generator operation, scheduling maintenance, and preparing for expected demand changes [3], [39]. In microgrids, this information helps manage generation and storage capacity according to the expected weekly demand pattern.

2.2.3 Seasonal Load Profiles

A seasonal load profile shows how electricity demand changes during the year. This variation is mainly caused by weather and temperature changes. In hot regions, demand often increases in summer because of air-conditioning and cooling systems, while in cold regions it may increase in winter when electric heating is used. Spring and autumn usually have lower demand because heating and cooling needs are reduced, and these periods are often called shoulder seasons. During these seasons, the load is more moderate and the stress on generation and distribution equipment is lower. Seasonal load profiles are important for long-term planning because they help estimate annual peak demand, prepare fuel resources, schedule maintenance, and decide if more generation or storage capacity is needed. In standalone microgrids, seasonal variation is especially important because demand and renewable generation can change at the same time. For example, solar production and cooling demand may both increase in summer, while winter conditions may reduce solar output and increase some loads.

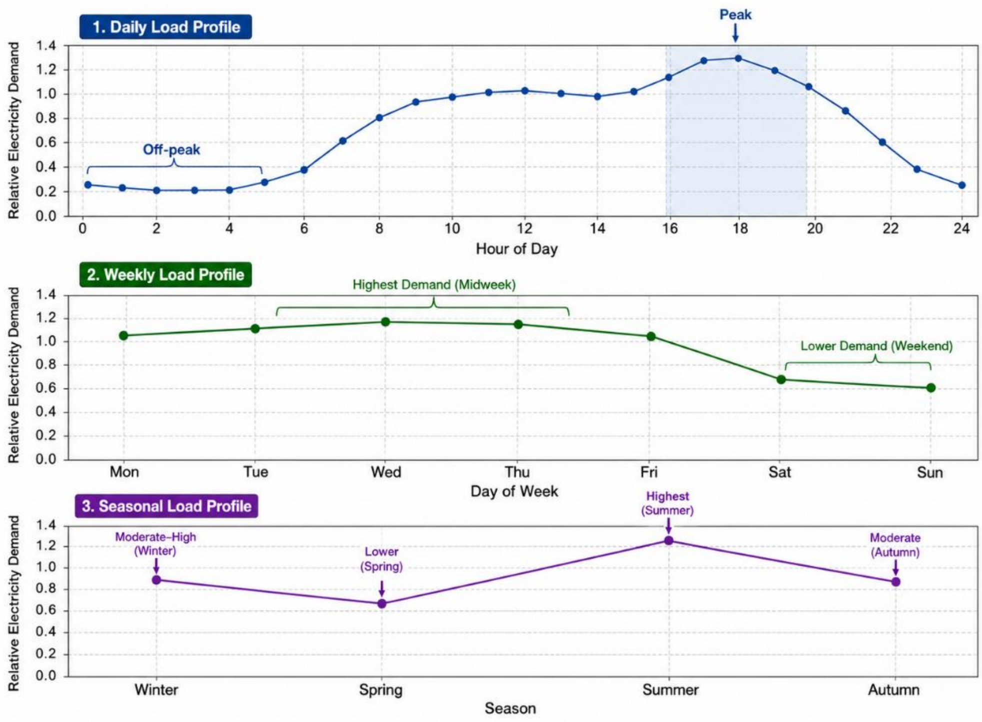


Figure 9 : typical daily, weekly, and seasonal electricity demand profiles

Table 7 : The main characteristics of each load profile type

Load profile type	**Time scale**	**Characteristics**	**Influencing factors**	**Main use in power system studies**
Daily	24 hours	Shows low demand during night, increasing demand in the morning, high demand during working hours, and peak demand in the evening or afternoon.	Human activity, working hours, lighting, heating, cooling, industrial operation.	Short-term operation, peak detection, generator scheduling, and battery control.
Weekly	7 days	Shows higher demand during weekdays and lower demand during weekends in many systems.	Work schedules, school activity, commercial operation, industrial production, weekend behavior.	Weekly generation planning, maintenance scheduling, and load management.

Seasonal	Months or seasons	Shows demand variation across the year, often higher in summer or winter and lower in spring and autumn.	Temperature, humidity, air conditioning, heating, tourism, agricultural activity.	Long-term planning, capacity sizing, fuel planning, and seasonal peak estimation.

2.3 Peak Demand Phenomenon

Peak demand is the highest electrical load reached by a power system during a specific period, such as a day, week, month, season, or year. It is an important indicator because it defines the maximum capacity that the system must be able to supply. Peak demand usually occurs only during short periods when many users consume electricity at the same time. Even if these periods last only a few hours, they strongly affect the design and operation of the power system. Power plants, transformers, cables, and protection devices must be sized to support these maximum load values. Peak demand also increases operating costs because expensive or less efficient generators may be needed during high-demand periods. In isolated systems, it can increase fuel consumption and accelerate equipment aging [39]. Therefore, reducing peak demand is an important strategy to improve the technical and economic performance of power systems and microgrids.

2.3.1 Definition of Peak Demand

Peak demand is the highest level of electrical power demand recorded during a specific time interval. It represents the maximum load that the power system must be able to supply. For example, a daily peak is the highest load reached during one day, while an annual peak is the highest load reached during one year. Peak demand is usually measured in kilowatts, megawatts, or gigawatts, depending on the size of the system. In small microgrids, it is often expressed in kilowatts, while in large power systems it is expressed in megawatts or gigawatts. From an operational point of view, peak demand is important because it determines the required generation capacity and reserve margin. If enough power is not available during peak periods, problems such as voltage drops, frequency deviations, load shedding, or power interruptions may occur. Therefore, accurate peak-demand prediction is necessary to support reliable power-system operation.

2.3.2 Causes of Peak Demand

Peak demand is mainly caused by the simultaneous use of many electrical loads. In residential areas, it can occur when people return home and use lighting, cooking appliances, air conditioning, heating, and other domestic equipment at the same time. In commercial areas, demand often increases during working hours because of lighting, computers, elevators, ventilation, and cooling systems . Weather also has a strong effect on peak demand, especially during hot days when air-conditioning use rises or during cold periods when electric heating is needed. Industrial and agricultural activities can also create peaks when large motors, pumps, compressors, furnaces, production lines, or irrigation systems operate simultaneously. In standalone microgrids, even a few large loads can produce a significant peak because the total system capacity is limited [39]. Sudden changes, such as the simultaneous start-up of motors or cooling units, may also cause rapid load increases and lead to voltage or frequency disturbances [39]. Therefore, understanding the causes of peak demand is important for reliable system operation and effective energy management.

2.3.3 Peak Demand in Standalone Microgrids

Peak demand is more critical in standalone microgrids than in large interconnected systems because all electricity demand must be supplied by local generators and storage units [3], [39]. Unlike grid-connected systems, standalone microgrids cannot easily import additional power from the main grid during high-demand periods. When peak demand occurs, diesel generators or gas turbines may operate near their maximum capacity, which increases fuel consumption, emissions, and mechanical stress. Frequent peak operation can also accelerate generator aging and increase maintenance costs. Battery energy storage can reduce peak demand by supplying part of the load, but it has limited capacity and must be carefully managed to avoid deep discharge and degradation[39] . If renewable generation is low during peak periods, the microgrid depends more on conventional generators. Sudden load increases can also affect voltage and frequency stability if generation does not respond quickly. Therefore, peak-demand management, supported by forecasting-based energy management, is essential to improve reliability, reduce fuel use, decrease generator stress, and lower operating costs.

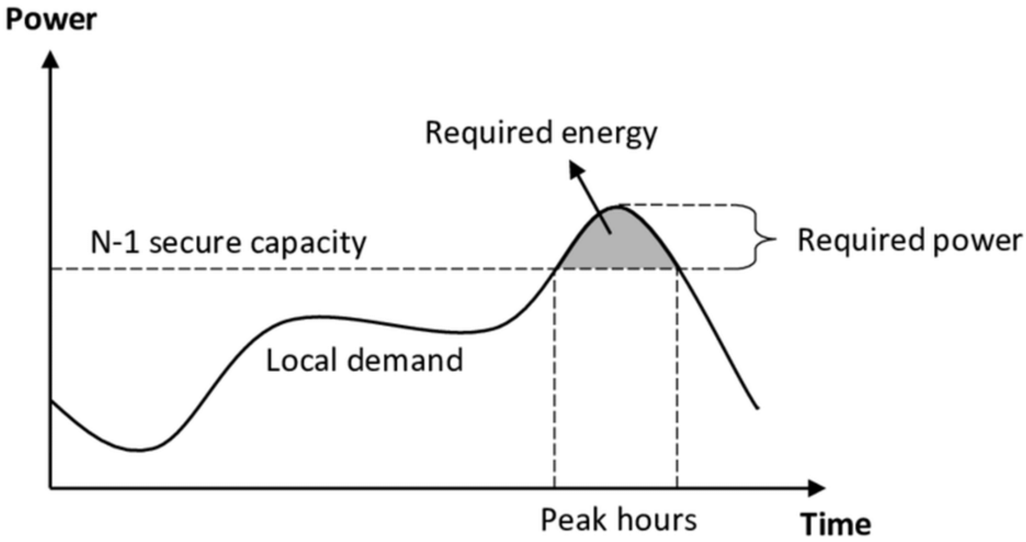


Figure 10: a load curve showing peak and off-peak periods

2.4 Impacts of Peak Demand

Peak demand has important effects on the technical, economic, and environmental performance of power systems. During peak periods, the system must supply a high amount of power in a short time, which can increase operating costs and stress the electrical infrastructure. In standalone and hybrid microgrids, these impacts are more critical because all the required energy must be supplied locally by generators, renewable sources, or storage systems.

2.4.1 Economic Impacts

Peak demand increases the cost of electricity supply because system operators may need to use expensive and less efficient generation units during high-demand periods. These units are often used for a short time, but they must be available to guarantee system reliability. In addition, peak demand can increase fuel consumption, maintenance costs, and the required investment in generation, storage, transformers, and cables. In microgrids, frequent peak periods may force diesel generators or gas turbines to operate near their maximum capacity, which increases fuel cost and accelerates equipment aging.

2.4.2 Operational Impacts

From an operational point of view, peak demand creates stress on generators, transformers, cables, converters, and protection devices. If demand rises quickly and the generation does not respond fast enough, the system may experience voltage drops, frequency deviations, or even load shedding. In standalone microgrids, this problem is more serious because there is no main grid to support the system during sudden load increases. Therefore, peak demand requires accurate forecasting, sufficient reserve capacity, fast control response, and proper scheduling of generators and energy storage systems.

2.4.3 Environmental Impacts

Peak demand can also increase environmental impacts because high-demand periods may require the use of fossil-fuel-based backup or peaking generators. These units can produce higher emissions of carbon dioxide, nitrogen oxides, and other pollutants, especially when diesel generators or inefficient thermal units are used. Reducing peak demand through energy storage, demand response, load shifting, and renewable energy support can help reduce the operation of high-emission generators and improve the environmental performance of the power system.

Table 8 : The consequences of peak demand on system operation and economics

Impact category	Consequences	Effect on system operation	Economic effect
Generation stress	Conventional generators may operate near their rated capacity during peak periods.	Increases thermal and mechanical stress on diesel generators and gas turbines.	Higher fuel consumption, higher maintenance cost, and faster equipment aging.
Network loading	Transformers, cables, converters, and protection devices may carry high current.	Increases the risk of overload, voltage drops, and protection activation.	May require larger transformers, cables, and protection equipment.
Reliability risk	Available generation or storage may be insufficient during peak periods.	Can lead to load shedding, voltage instability, frequency deviations, or power interruptions.	Causes service interruption losses and reduces supply reliability.
Operating cost	Expensive or less efficient generators may be needed to meet the peak load.	Increases dependence on backup or peaking units.	Raises electricity production cost and fuel expenses.
Maintenance requirements	Frequent peak-load operation accelerates component wear.	Reduces the lifetime of generators, storage systems, and power electronic converters.	Increases preventive and corrective maintenance costs.

Environmental impact	Fossil-fuel-based units may be used more frequently during peak demand.	Increases fuel combustion during high-demand periods.	Raises CO_2, NOx, and pollutant emissions, especially in diesel- or gas-turbine-based systems.
System planning	The system must be sized according to the maximum demand, even if it occurs for a short time.	Requires higher installed capacity and larger reserve margin.	Increases capital investment in generation, storage, and network infrastructure.

2.5 Peak Demand Indicators

Peak demand indicators are used to describe the form and behavior of an electrical load profile. They help engineers know if the load is stable, changing, or concentrated during short high-demand periods. These indicators are important in power-system planning, generator sizing, energy management, demand response, and peak-shaving studies. In power systems and microgrids, the most useful indicators are the Peak-to-Average Ratio, Load Factor, and Demand Factor. These indicators are simple, but they give important information about how well the installed generators and network capacity are used. When a system has a high peak demand but a low average demand, it usually needs larger equipment, more reserve power, and higher operating costs. In contrast, a system with a smoother load profile is usually easier, safer, and less expensive to operate [40], [41].

2.5.1 Peak-to-Average Ratio (PAR)

The Peak-to-Average Ratio, usually written as PAR, is an important indicator used to compare the maximum power demand with the average power demand over a selected period. It is commonly used in demand-side management and smart-grid studies to measure how strong the demand peak is compared with the normal load level [42], [43]. A high PAR means that the load profile has large peaks and poor load distribution. This situation can increase stress on generators, transformers, cables, and energy storage systems. It can also require larger system capacity to supply short periods of high demand. In contrast, a low PAR means that the load is more balanced and easier to manage. Reducing PAR is therefore an important objective in peak shaving, load shifting, and demand-response strategies[42]. This helps improve system operation and reduce the technical and economic impacts of peak demand.

2.5.2 Load Factor

The Load Factor is the ratio between the average load and the maximum demand during a selected period. It is used to evaluate how efficiently the available electrical system capacity is used. A high load factor means that the load remains close to the maximum demand for a large part of the time, which indicates better use of generators and network equipment. A low load factor means that the system has high demand peaks but relatively low average consumption [44], [45]. This is important because many power-system components must be sized according to the maximum demand, even if it occurs only for a short time. Improving the load factor can reduce the need for oversized generators, transformers, cables, and storage systems. In demand-response studies, improving the load factor is often combined with reducing consumer energy costs [44], [46]. Therefore, load factor is an important indicator for improving system efficiency and reducing the impact of peak demand.

2.5.3 Demand Factor

The Demand Factor is the ratio between the maximum demand of a system and the total connected load. The connected load is the sum of the rated powers of all electrical devices connected to the system. Since all devices rarely operate at full power at the same time, the demand factor is usually less than or equal to one [36]. This indicator is useful in electrical design because it helps engineers avoid oversizing generation and distribution equipment. If the connected load is high but only part of it operates at the same time, the real maximum demand will be lower than the total connected load. In microgrids, demand factor is important for selecting the capacity of generators, inverters, transformers, cables, and energy storage systems. A high demand factor means that many loads may operate simultaneously, requiring larger system capacity. A low demand factor allows more efficient sizing because the connected load is not fully used at the same time.

2.6 Peak Shaving Techniques

Peak shaving techniques are used to reduce the maximum power demand during peak periods by lowering high-demand peaks or shifting part of the load to off-peak hours. Their main objective is to make the load curve smoother and easier to manage. In power systems and microgrids, peak shaving can reduce operating costs, limit the use of expensive peaking generators, and decrease stress on generators, transformers, cables, and storage systems [6], [36]. This is especially important in microgrids because generation and storage capacities are limited, and the balance between local generation and demand must be maintained continuously.

Common peak shaving methods include demand response, battery energy storage, distributed generation, renewable energy integration, and electric vehicle-based strategies [36], [47]. These methods can be applied separately or combined within an energy management system. As a result, peak shaving helps improve reliability, reduce costs, and support more efficient microgrid operation.

2.7 Demand Response Programs

Demand response is a peak shaving technique that reduces or shifts electricity consumption during critical periods instead of increasing generation. It allows system operators to encourage users to reduce, delay, or reschedule part of their load when demand is high. This can be done through time-of-use tariffs, direct load control, interruptible load contracts, incentive programs, or real-time pricing [41]. Demand response is useful because it can reduce peak demand without the need to install new generation units. Non-critical loads, such as air conditioning, water heating, pumping systems, and some industrial processes, can be moved to off-peak periods. This helps flatten the load curve, reduce operating costs, and improve system reliability. However, the effectiveness of demand response depends on customer participation, communication systems, control infrastructure, and suitable financial incentives [40], [41].

2.7.1 Battery Energy Storage Systems

Battery Energy Storage Systems (BESS) are effective technologies for peak shaving because they can store energy during off-peak periods and discharge it during peak-demand periods. The battery can be charged using low-cost electricity, surplus generation, or renewable energy, then used to supply part of the load when demand is high [37], [48]. This reduces the power required from the main grid or from conventional generators. In microgrids, BESS can provide fast response, load smoothing, renewable energy support, and backup power. It can also reduce the need to operate diesel generators or gas turbines near their maximum capacity. However, battery-based peak shaving requires proper sizing and control. An undersized battery may not reduce the peak effectively, while an oversized battery can increase investment costs. Battery aging, depth of discharge, state of charge limits, and replacement cost must also be considered [37], [49] during system design and operation.

2.7.2 Distributed Generation

Distributed generation can be used for peak shaving by producing electricity close to the load during high-demand periods. These generators may include diesel generators, gas turbines, microturbines, fuel cells, biomass generators, or combined heat and power units. During peak periods, they can supply part of the local demand and reduce the power required from the main grid or from the main microgrid generator [36]. The main advantage of distributed generation is that many of these units are dispatchable, especially conventional generators. This means they can provide firm power when renewable sources or batteries are not sufficient. However, fossil-fuel-based distributed generation can increase fuel consumption, emissions, noise, and maintenance costs. Therefore, distributed generation should be operated carefully and coordinated with renewable energy sources and storage systems. This coordination helps improve peak shaving while reducing technical, economic, and environmental impacts.

2.7.3 Renewable Energy Integration

Renewable energy integration can support peak shaving when renewable production occurs during high-demand periods. For example, solar PV can help reduce daytime peaks caused by cooling loads, commercial activity, or industrial operation. Wind energy can also contribute to peak reduction when wind power is available during periods of high demand [50]. However, renewable-based peak shaving is limited because solar and wind generation are intermittent and depend on weather conditions. Solar PV cannot reduce evening or night peaks unless it is combined with energy storage. Similarly, wind generation may not always match the time of peak demand. For this reason, renewable energy becomes more effective for peak shaving when it is combined with batteries, forecasting, demand response, and energy management systems [50]. This combination improves the use of renewable energy and helps reduce the stress on conventional generators.

2.7.4 Electric Vehicle-Based Peak Shaving

Electric vehicles can support peak shaving through controlled charging and vehicle-to-grid operation. In controlled charging, EV charging is shifted from peak hours to off-peak hours to avoid increasing electricity demand during critical periods. In vehicle-to-grid operation, EV batteries can discharge power back to the grid or microgrid during peak-demand periods [51]. This makes EVs a promising flexible energy resource, especially when many vehicles are connected at the same time. However, EV-based peak shaving requires smart chargers, communication infrastructure, user participation, suitable pricing methods, and protection of battery lifetime. If EV charging is not properly controlled, it can increase peak demand instead of reducing it [52]. Therefore, EV charging and discharging must be managed by an intelligent scheduling or energy management system. This helps reduce peak load and improve the flexibility of power systems and microgrids.

2.8 Forecasting for Peak Demand Management

Forecasting is an essential tool for peak demand management because it helps predict future electricity consumption before peak periods occur. In power systems and microgrids, accurate load forecasting allows operators to prepare generation units, schedule battery storage, manage demand response, and reduce unnecessary fuel consumption [53], [54]. Without forecasting, the system may react too late to sudden load increases, which can lead to higher operating costs, generator stress, voltage deviations, or load shedding. Forecasting is especially important in standalone hybrid microgrids because they cannot depend on the main utility grid during peak periods. The local controller must know in advance whether renewable generation, battery storage, and conventional generators can satisfy the expected demand. Forecasting-based energy management can therefore improve reliability, reduce peak-load stress, and support optimal microgrid operation [55], [56]. It also helps operators make better decisions before critical conditions appear.

2.8.1 Load Forecasting Fundamentals

Load forecasting is the process of predicting future electricity demand using historical load data, weather information, calendar variables, and other related factors. Its main objective is to estimate the amount of power required during a future time interval. Forecasting models may use inputs such as previous load values, temperature, humidity, hour of the day, day of the week, holidays, and seasonal information [53]. Different methods can be applied, including regression models, time-series models, exponential smoothing, and autoregressive models. More advanced approaches include artificial neural networks, support vector machines, random forests, gradient boosting, deep learning, and hybrid models . These modern methods are useful because they can describe nonlinear relationships between demand, weather, and time-related variables. For peak demand management, forecast accuracy is very important because underestimation may leave the system without enough generation or storage capacity, while overestimation may cause unnecessary generator operation [57]. Therefore, effective load forecasting should reduce prediction errors, especially during high-demand periods, to support reliable and economical system operation.

2.8.2 Forecasting Horizons

Load forecasting can be classified according to the prediction horizon. The forecasting horizon refers to how far into the future the model predicts the load demand. The most common categories are short-term, medium-term, and long-term load forecasting. Each horizon has different objectives, input data requirements, and applications in power-system operation and planning [53], [58].

2.8.3 Short-Term Load Forecasting

Short-term load forecasting predicts electricity demand from a few minutes ahead to several hours or days ahead, and in some studies it can extend up to one week. It is mainly used for real-time operation, unit commitment, economic dispatch, battery scheduling, demand response, and peak shaving [53], [57]. In microgrids, this type of forecasting is important because it helps the energy management system make better operational decisions. It can guide when generators should start or stop, when batteries should charge or discharge, and when non-critical loads should be reduced or shifted. For example, if an evening peak is expected, the controller can charge the battery during the day and use it later to support the load [55], [56]. This reduces generator stress during peak periods and improves the reliability of microgrid operation. Therefore, short-term load forecasting is an essential tool for efficient and flexible energy management.

2.8.4 Medium-Term Load Forecasting

Medium-term load forecasting predicts electricity demand over several weeks to several months. It is mainly used for maintenance planning, fuel planning, energy purchasing, monthly operation planning, and resource scheduling [58], [59]. This type of forecasting helps utilities and microgrid operators understand expected demand trends before high-demand periods. In hybrid microgrids, it can support fuel supply planning for diesel generators or gas turbines and help prepare the available generation resources. It can also assist in planning battery operation and evaluating renewable energy availability. Medium-term forecasting is useful for identifying months when demand may increase because of cooling, heating, agricultural pumping, or industrial activity. This information allows operators to prepare the microgrid in advance. Therefore, medium-term load forecasting supports reliable, economical, and organized microgrid operation.

2.8.5 Long-Term Load Forecasting

Long-term load forecasting predicts electricity demand over one year or several years. It is mainly used for power-system expansion planning, investment decisions, generation capacity planning, transmission and distribution reinforcement, and long-term energy policy [58], [59]. Unlike short-term forecasting, it is not focused on real-time operation but on estimating future electricity demand growth. In microgrids, long-term forecasting is important during system design or expansion because it helps determine future needs for PV capacity, battery storage, conventional generators, transformers, and distribution lines. It is also useful for isolated microgrids serving growing communities, industrial sites, agricultural farms, or remote facilities. By estimating future demand, operators and planners can avoid undersizing or oversizing the system. Therefore, long-term forecasting supports reliable planning, better investment decisions, and sustainable microgrid development.

2.8.6 Renewable Power Forecasting

Renewable power forecasting is the process of predicting the future output of renewable energy sources, mainly solar PV and wind systems. It is important in microgrids because renewable generation is variable and depends strongly on weather conditions. Accurate forecasting helps the energy management system prepare batteries, schedule conventional generators, reduce fuel consumption, and avoid power imbalance during peak-demand periods [60], [61]. In standalone hybrid microgrids, renewable forecasting is directly linked to peak demand management. If renewable generation is expected to be low during a peak period, the controller can prepare the battery or start a backup generator in advance. If renewable generation is expected to be high, the controller can reduce the use of conventional generators and charge the storage system [62], [63]. In this way, renewable forecasting improves the coordination between renewable sources, storage units, and dispatchable generators. It also supports more reliable and economical microgrid operation.

2.8.7 Solar Power Forecasting

Solar power forecasting predicts the future output of a photovoltaic system using variables such as solar irradiance, temperature, cloud cover, time of day, season, and historical PV power data. Solar irradiance is the most important input because PV generation depends directly on the sunlight received by the panels, while high temperature can reduce PV efficiency [60], [61]. Forecasting methods may include physical models, statistical models, machine-learning models, and hybrid approaches. Physical models use solar geometry, weather forecasts, and PV system parameters, while statistical and machine-learning models learn from historical data. Artificial intelligence techniques, such as neural networks, support vector machines, random forests, gradient boosting, and deep learning, are widely used for PV forecasting [60], [61], [64]. For peak demand management, short-term solar forecasting is especially useful because it shows whether PV generation will be available during daytime peaks. If PV production is expected to be high, the microgrid can reduce the use of diesel generators or gas turbines. If cloud cover is expected to reduce PV output, the EMS can prepare battery discharge or backup generation in advance [62], [64].

2.8.8 Wind Power Forecasting

Wind power forecasting predicts the future electrical output of wind turbines using variables such as wind speed, wind direction, air density, turbine characteristics, and historical wind-power data. Wind speed is the most important factor because wind power is strongly related to the cube of wind speed, so small wind-speed errors can cause large forecasting errors [65], [66]. Compared with solar forecasting, wind forecasting is often more difficult because wind speed changes quickly and varies strongly with time and location. Forecasting methods include physical models based on numerical weather prediction, statistical time-series models, machine-learning models, and hybrid approaches. Recent studies use methods such as random forests, support vector regression, convolutional neural networks, and long short-term memory networks to capture nonlinear wind patterns [65], [66], [67]. In microgrids, wind forecasting helps schedule batteries, reduce generator operation, and prepare reserve power. If wind power is expected to decrease during a peak period, dispatchable generation or storage support must be prepared [63], [67]. Therefore, combining wind and solar forecasting with load forecasting improves energy management, reduces peak stress, and supports reliable microgrid operation.

2.9 Artificial Intelligence Techniques for Forecasting

Artificial Intelligence techniques are important tools for load and renewable power forecasting because they can learn complex and nonlinear relationships from historical data. In peak demand management, AI-based forecasting helps predict future high-load periods, allowing the EMS to prepare generators, schedule batteries, shift flexible loads, and reduce fuel consumption [54], [59]. This is especially useful in standalone hybrid microgrids, where generation and demand must be balanced locally without support from the main grid. AI models use inputs such as historical load, temperature, humidity, solar irradiance, wind speed, calendar information, and previous peak events. Before training, data preprocessing, normalization, feature selection, missing-data treatment, and outlier detection are needed to improve accuracy [57], [68]. Common machine-learning methods include neural networks, support vector regression, random forests, gradient boosting, and ensemble models. Deep-learning and hybrid models, such as LSTM, CNN, GRU, and CNN-LSTM, are also used to extract temporal patterns from load and renewable energy data [68], [69]. For solar and wind forecasting, AI can use irradiance, temperature, cloud cover, wind speed, wind direction, and historical power data [60], [70]. However, AI models require good-quality data, proper validation, and suitable error metrics such as MAE, RMSE, and MAPE to balance accuracy, speed, simplicity, and interpretability.

2.10 Forecast-Based Peak Shaving Strategies: Literature Review

Forecast-based peak shaving strategies combine forecasting models with energy management and scheduling algorithms to reduce the maximum demand in power systems and microgrids. The main idea is to predict future load demand and renewable generation, then use this information to control batteries, flexible loads, and conventional generators before peak periods occur [6], [71]. This approach is more effective than reactive control because the system can prepare its resources in advance instead of responding after the peak appears. In microgrids, these strategies are commonly applied with PV systems, wind generation, battery storage, diesel generators, gas turbines, and controllable loads. Forecasting can improve economic operation, reduce fuel consumption, limit battery stress, and decrease the need for expensive peak generation [6], [32]. However, the success of this approach depends on the accuracy of load and renewable forecasts. It also depends on the quality of the optimization model and the ability of the controller to update decisions when real conditions differ from predictions.

2.10.1 Forecast-Based Energy Management Approaches

Forecast-based energy management uses predicted information to choose the best operating strategy for a microgrid. These forecasts may include load demand, PV power, wind power, electricity price, battery state of charge, and weather variables. Based on this information, the EMS decides how much power should come from renewable sources, batteries, and conventional generators during each time interval [54], [71]. Predictive EMS structures have been proposed in several studies, including the work of Durán et al., where an LSTM model was used to forecast PV power and load demand for a PV-dominated microgrid [71]. Forecast-based EMS can improve renewable energy use and reduce unnecessary generator operation when the forecasts are accurate [6], [60]. Model Predictive Control is a common approach because it uses forecasts, solves an optimization problem, applies the first control action, and updates the decision when new data are available [72], [73]. This makes it suitable for microgrids with variable load and renewable generation. Forecast-based EMS can also minimize fuel cost, battery degradation cost, electricity purchase cost, or total operating cost while respecting technical constraints such as battery limits, generator limits, ramp rates, and power balance [32], [74]. Therefore, it is especially important in standalone hybrid microgrids, where power balance must be maintained locally.

2.10.2 Forecast-Based Peak Shaving in Microgrids

Forecast-based peak shaving in microgrids uses predicted load demand and generation information to reduce the highest demand periods. Instead of reacting after the peak occurs, the controller predicts when the peak is expected and prepares the available resources in advance [6], [74]. For example, the battery can be charged before the peak and discharged during the high-demand period, while flexible loads can be shifted to off-peak hours. Dispatchable generators can also be scheduled only when needed, which helps reduce fuel consumption and generator stress. Battery Energy Storage Systems are widely used for this purpose because they respond quickly and can supply power during peak periods. Peak forecasting improves battery scheduling by identifying the highest-demand hours and using the battery more effectively [75]. In islanded microgrids, this strategy is especially important because there is no main grid support during sudden demand increases [37]. Forecast-based peak shaving can also use renewable power forecasts to decide whether PV or wind generation can support the expected peak [60], [71]. This improves peak shaving reliability and reduces unnecessary generator operation.

2.10.3 Forecast-Based Scheduling of Conventional Generators

Forecast-based scheduling of conventional generators is an important strategy in standalone and hybrid microgrids because diesel generators, gas turbines, and microturbines should operate only when needed. These generators can support the system when renewable generation and battery storage are not sufficient, but they also increase fuel consumption, emissions, maintenance cost, and mechanical stress [32], [74]. For this reason, generator scheduling should be based on predicted load demand, renewable energy availability, and reserve requirements. This process is usually treated as a unit commitment and economic dispatch problem, where the EMS decides which generators should be ON or OFF and how much power each online generator should produce [74], [76]. The optimization must respect technical limits such as generator capacity, ramp rates, minimum up/down time, start-up cost, and fuel cost. Forecast uncertainty is important because underestimating demand may leave the microgrid without enough generation, while overestimating it may cause unnecessary generator operation [76]. During expected peak periods, the EMS can start generators in advance and coordinate them with battery discharge to reduce voltage or frequency problems. Therefore, forecast-based scheduling supports peak shaving, reduces fuel use and generator stress, improves renewable energy utilization, and increases the reliability of standalone hybrid microgrids.

2.11 Research Gap and Motivation

The reviewed literature shows that important progress has been made in peak shaving, microgrid energy management, and forecasting techniques. Many studies have examined demand response, battery storage, renewable integration, and optimization-based scheduling to reduce peak demand. Other works have focused on load forecasting, renewable power forecasting, and predictive control for better microgrid operation. However, these topics are often studied separately, with limited focus on integrated frameworks that directly link forecasting results to peak shaving decisions in standalone hybrid microgrids [6], [72]. In addition, many studies mainly target cost minimization or energy balancing rather than reducing peak stress on conventional generators such as gas turbines. Some hybrid microgrid studies also focus on optimal sizing and techno-economic design, while fewer studies propose operational methods that use forecasted demand to guide PV contribution for peak reduction. Therefore, this gap supports the development of a forecast-driven PV–gas turbine peak shaving framework that combines forecasting, peak identification, and operational decision-making [32], [76], [77].

2.11.1 Limitations of Existing Peak Shaving Strategies

Existing peak shaving strategies can reduce peak demand, but each method has important limitations. Demand response depends strongly on user participation, suitable incentives, and communication infrastructure. Battery-based peak shaving is effective, but its performance depends on proper sizing, state-of-charge management, and battery degradation limits. Distributed generation and renewable energy integration can also support peak reduction, but their effectiveness depends on fuel availability, renewable intermittency, and coordination with other microgrid resources [6], [36]. Another limitation is that many peak shaving methods are reactive instead of predictive. In many cases, the control system responds only after the load has already increased, which can reduce the effectiveness of peak mitigation. This problem is more critical in standalone microgrids, where local resources must be prepared quickly. Moreover, some methods focus only on reducing the electrical peak, without fully considering generator stress such as repeated start-stop cycles, operation near rated power, and accelerated aging [6], [36], [72].

2.11.2 Limitations of Existing Forecast-Based Approaches

Forecast-based approaches improve microgrid decision-making by predicting future load demand and renewable generation, but they still have several limitations. Forecast uncertainty is one of the main problems because errors in load or renewable prediction can cause poor scheduling, unnecessary generator operation, battery misuse, or failure to meet peak demand [32], [76]. In addition, many forecast-based EMS studies focus mainly on economic dispatch or grid-connected operation rather than peak-focused control in standalone hybrid microgrids [71], [72]. Another limitation is that several studies do not clearly combine peak detection, peak-period classification, and generator stress reduction in the control objective. In many cases, forecasting is used to improve general scheduling, but not specifically to reduce peak loading on conventional generators. Some predictive microgrid studies also focus on PV-battery coordination or generic unit commitment without directly considering the role of gas turbines during forecasted peak-demand periods [71], [76], [78]. Therefore, more integrated approaches are needed to connect forecasting, peak identification, and gas turbine stress reduction in standalone hybrid microgrids.

2.11.3 Motivation for a Forecast-Driven PV–Gas Turbine Peak Shaving Framework

The motivation of this work is to develop a forecast-driven framework that reduces peak stress on a gas turbine in a standalone hybrid microgrid. The main idea is to forecast the total microgrid power demand, detect expected peak periods, and use photovoltaic generation to support these critical intervals [71], [77]. In this approach, the PV system is not only treated as a renewable energy source, but also as an active peak shaving resource. This is important because gas turbines are reliable and dispatchable, but repeated operation during peak-load periods increases fuel consumption, thermal stress, maintenance needs, and operating cost. PV generation can reduce part of the daytime load on the gas turbine, but its contribution must be planned because solar power is intermittent. In standalone microgrids, peak demand must be managed locally because there is no permanent support from the main grid [39], [77], [78]. Therefore, a forecast-driven PV–gas turbine framework can improve reliability, reduce generator stress, increase renewable energy utilization, and support more economical operation.

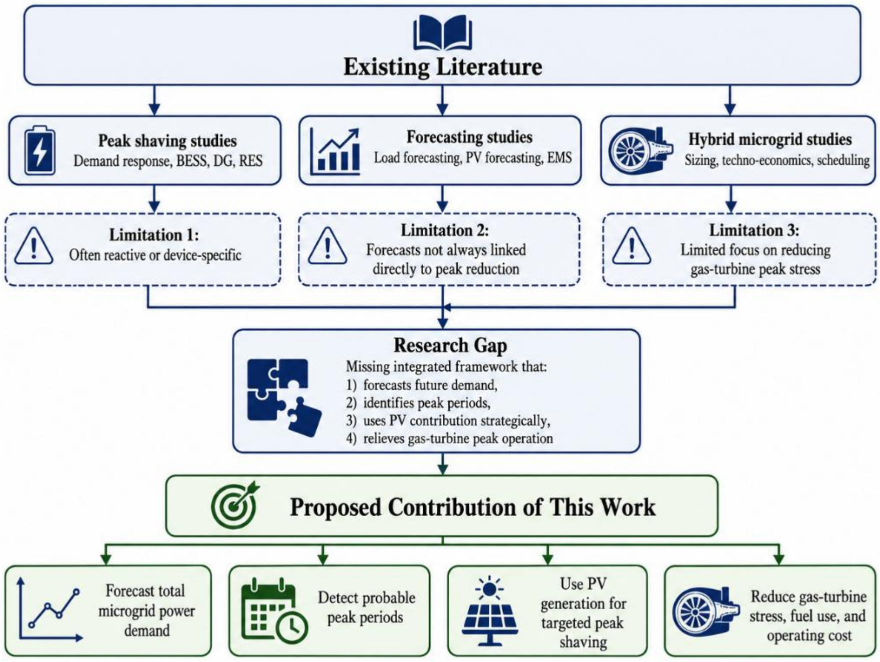


Figure 11 : The identified research gap and the proposed contribution of this work

2.12 Conclusion

This chapter discussed peak demand challenges and mitigation strategies in power systems, with particular attention to standalone hybrid microgrids. It first explained load characteristics and demand profiles, including daily, weekly, and seasonal variations, then presented the peak demand phenomenon, its causes, and its technical, economic, and environmental impacts. The chapter also introduced key peak demand indicators such as the Peak-to-Average Ratio, Load Factor, and Demand Factor, which help evaluate the severity and efficiency of load profiles. Several peak shaving techniques were reviewed, including demand response, battery energy storage, distributed generation, renewable energy integration, and electric vehicle-based strategies. In addition, forecasting methods and artificial intelligence techniques were discussed as important tools for predicting load demand and renewable power generation. Finally, the chapter identified the research gap related to the limited integration of forecasting, PV contribution, and gas-turbine peak stress reduction, which motivates the development of a forecast-driven PV–gas turbine peak shaving framework in the following chapter.

Chapter 3

Forecast-Driven Peak Shaving Framework for Gas Turbine Stress

3.1 Introduction

This chapter presents the methodology developed to transform historical microgrid measurements into forecasting-based peak-shaving decisions. The proposed method combines data preprocessing, historical peak analysis, short-term load forecasting, long-term daily-peak forecasting, photovoltaic (PV) power representation, battery energy storage system (BESS) dispatch, and PV sizing. The main objective is not only to forecast future power demand, but also to use the predicted critical periods to evaluate how PV generation and BESS support can reduce the residual load imposed on the gas-turbine source.

The methodology is built around a real open-source microgrid dataset instead of a theoretical or synthetic load profile. The working case is derived from the University of California, San Diego (UCSD) microgrid dataset released by Silwal et al. [75]. This dataset is suitable for the present study because it contains multi-year measurements of power consumption, on-campus generation, grid import, PV generation, and storage-related resources in a real advanced campus microgrid. Therefore, it provides a realistic basis for testing forecasting and peak-shaving algorithms.

It is important to clarify that the UCSD microgrid is not treated here as a purely standalone microgrid. It is a real grid-connected campus microgrid that self-generates a large part of its electricity and exchanges the remaining power with San Diego Gas & Electric (SDG&E). In this dissertation, the dataset is used as a realistic experimental case for a gas-turbine-based standalone or weak-grid operating scenario. The total campus load is used as the demand signal to be forecasted, while the available PV measurements and the simulated BESS strategy are used to evaluate peak-shaving support.

3.2 Dataset Source and Study Case Description

The data used in this chapter are based on the article “Open-source multi-year power generation, consumption, and storage data in a microgrid,” published in the Journal of Renewable and Sustainable Energy by Silwal, Mullican, Chen, Ghosh, Dilliott, and Kleissl [75]. The article reports open-source, quality-controlled microgrid data from the UCSD campus. According to the source, the UCSD microgrid includes a central natural-gas-fired combined heat and power plant with two 13.5 MW gas turbines and a 3 MW steam turbine, distributed solar PV generators, a 2.8 MW fuel cell, a 2.5 MW battery energy storage system, chilled thermal energy storage, electric-vehicle charging stations, and monitored campus buildings.

For the present implementation, The processed file contains the main fields needed for this study, including the timestamp, total load and the measurements are expressed in kW, and therefore the analysis keeps the same unit structure: kW for power, kWh for energy, and kWp for installed PV capacity.

3.3 Gas-Turbine Load Assumption

An important methodological assumption is required because the working dataset does not provide a separate measured time series for the electrical power generated only by the gas turbines. The measured demand variable used in the forecasting model is the total campus load, while the available on-campus generation variable represents an aggregate of several resources and cannot be interpreted as pure gas-turbine production.

Therefore, for the purpose of applying the proposed gas-turbine peak-shaving framework, the total load is assumed to represent the equivalent load supplied by the gas-turbine source in the considered standalone or weak-grid operating scenario. Consequently, the terms forecast load, residual gas-turbine power, and gas-turbine burden used in the following sections refer to modeled quantities derived from the total load, not to directly measured gas-turbine output. This assumption is necessary to adapt the UCSD dataset to the objective of this work while keeping the interpretation methodologically clear.

3.4 Overall Methodological Framework

The proposed framework follows a sequential procedure that connects historical data analysis, forecasting, peak detection, PV contribution, BESS dispatch, and PV sizing. The general workflow is presented as follows: UCSD microgrid dataset, data preprocessing, historical peak detection, feature engineering, short-term load forecasting, future peak detection, PV power representation, BESS dispatch simulation, PV sizing scan, and finally peak-shaving indicators with best PV size selection.

The first stage prepares the dataset by cleaning the time series, selecting the appropriate columns, and resampling the data to an hourly resolution. The second stage detects historical peaks and extracts useful information about the timing and severity of high-load events. The third stage builds forecasting features from calendar variables, lagged values, and rolling statistics. Then, machine-learning models are trained to forecast short-term hourly load and long-term daily peak demand. The predicted load is analyzed to detect future critical periods.

Finally, PV and BESS support are simulated to evaluate the reduction in gas-turbine stress for different PV sizes.

3.5 Data Preprocessing and Time-Series Preparation

The preprocessing stage transforms the raw dataset into a regular time-series structure suitable for peak detection and forecasting. The Python implementation first reads the uploaded CSV or Excel file, verifies that the selected time, load, PV power, or solar irradiance columns are present, converts the timestamp field to a datetime format, converts numerical columns to numeric values, removes invalid timestamp or load rows, and sorts the observations chronologically.

Because public microgrid datasets may contain sub-hourly measurements and duplicate timestamps, the script first aggregates duplicate timestamps using the mean of numerical values, then resamples the data to the selected working resolution. In the reported results, the working resolution is hourly. This resolution is suitable for the objective of this dissertation because peak-shaving decisions depend on the timing of high-load intervals, while the objective is not to model second-by-second electrical transients.

Missing load values after resampling are filled using interpolation followed by backward and forward filling. The same logic is applied to optional temperature, solar irradiance, and PV power columns when they are available. The resulting dataset is a continuous and homogeneous time series that can be used for forecasting and for constructing peak-shaving indicators.

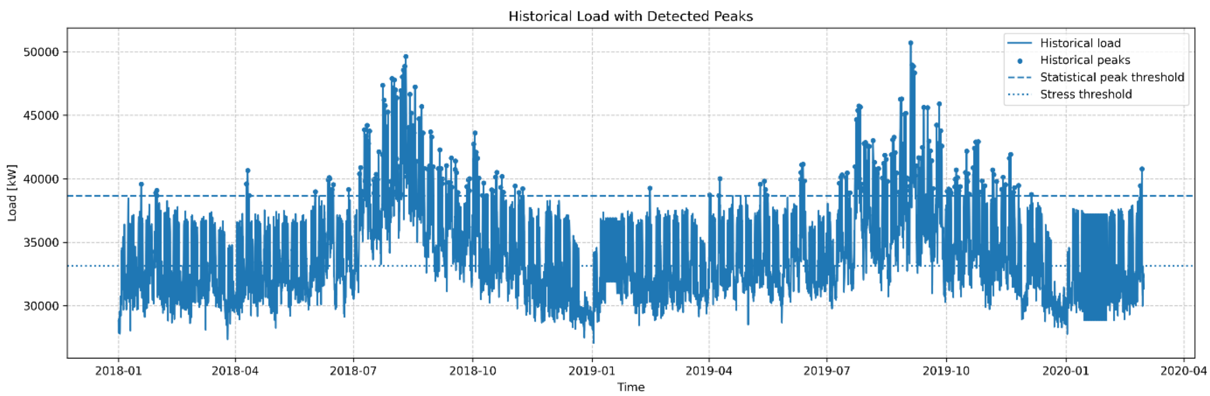


Figure 12 : Historical load profile with detected peaks

3.6 Historical Peak Detection and Exploratory Peak Analysis

Historical peak detection is performed before forecasting because it provides a baseline description of the system stress pattern. A statistical peak threshold is computed as the 90th percentile of the historical load distribution. Local maxima above this threshold are then detected using a minimum distance between peaks and a prominence criterion. This avoids counting small oscillations as separate high-demand events.

In parallel, an operational gas-turbine stress threshold is introduced as a fraction of an assumed rated generation capacity. In this work, because gas-turbine output is not available as an independent measured column, the stress threshold is applied to the assumed gas-turbine-supplied load represented by the total load signal. Therefore, the peak-shaving indicators are scenario-based indicators rather than direct measurements of gas-turbine operation.

The stress threshold is calculated as Pstress = fstres x PGT,rated, where Pstress is the gas-turbine stress threshold, fstres is the stress fraction, and PGT,rated is the rated gas-turbine power. In the implemented case, the rated gas-turbine power is 51,000 kW and the stress fraction is 0.65.

The historical analysis is extended by extracting the daily maximum load, monthly maximum load, hour of occurrence of daily peaks, weekday distribution of peaks, monthly count of peak events, and average peak value by month. These indicators are important because they show whether peak demand is random or structured. The results show that peak demand follows daily and seasonal patterns, which supports the use of forecasting for anticipating future critical periods.

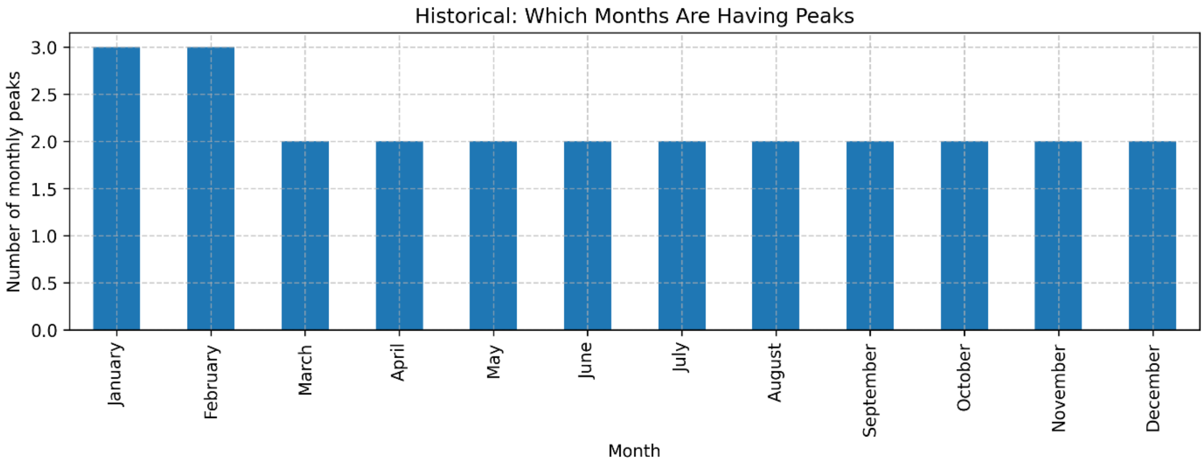


Figure 13 : Historical monthly peak count.

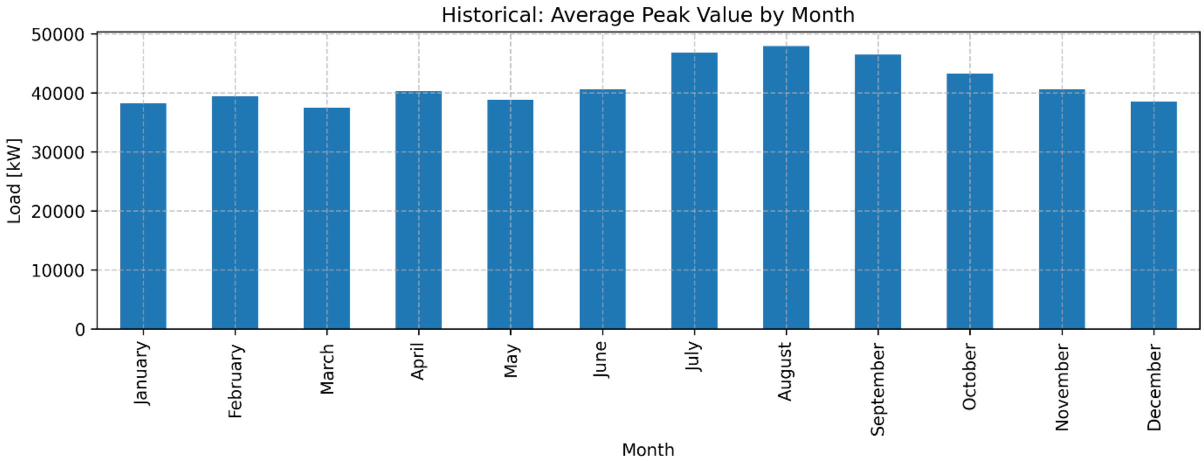


Figure 14 : Historical average peak value by month

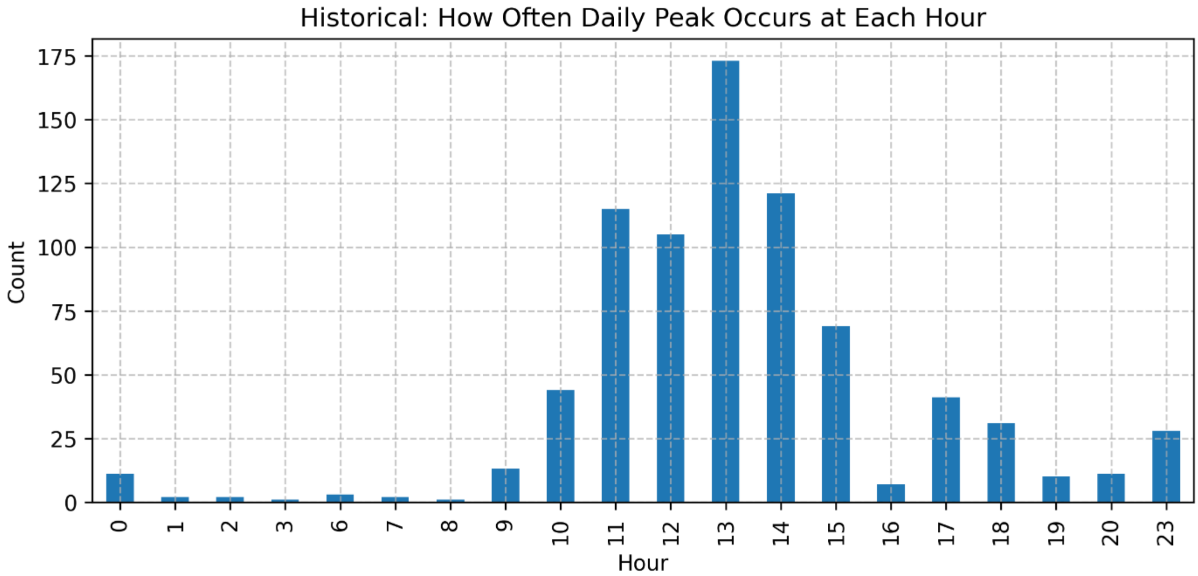


Figure 15 : Historical distribution of the hour at which the daily peak occurs

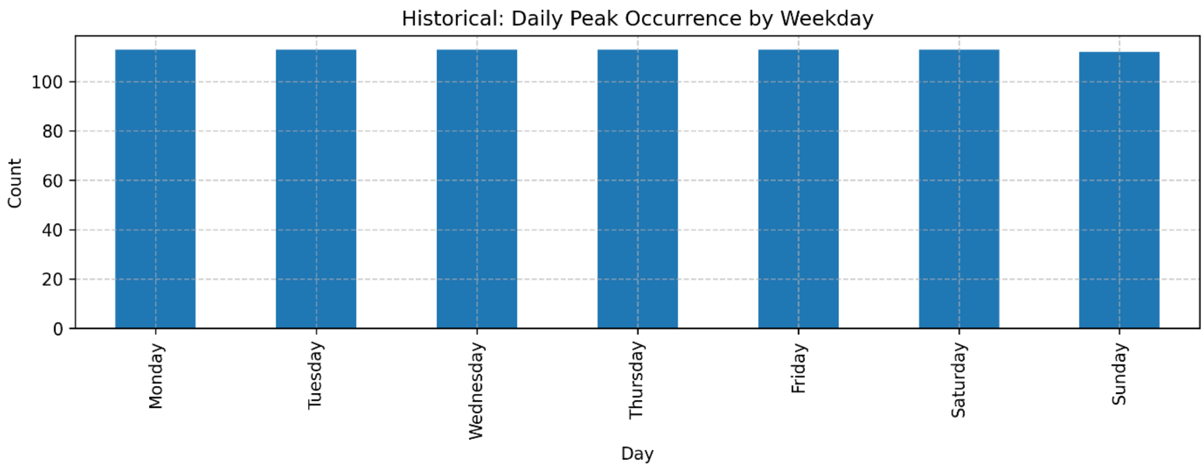


Figure 16 : Historical daily peak occurrence by weekday.

3.7 Forecasting Feature Engineering

The forecasting framework relies on engineered features that describe the temporal structure of the load. For the hourly model, the script creates calendar features such as hour of day, day of week, month, day of year, and a weekend indicator. These variables allow the model to represent daily routines, weekly differences, and seasonal effects.

In addition to calendar information, the model uses lagged values and rolling statistics. The hourly lags include one hour, twenty-four hours, forty-eight hours, and one hundred sixty-eight hours. These represent short-term persistence, yesterday-at-the-same-hour recurrence, two-day memory, and weekly recurrence. Rolling means and rolling standard deviations over twenty-four and one hundred sixty-eight hours summarize the recent level and variability of the load.

Cyclical encoding is also used for periodic time variables. The hour of the day and day of the year are transformed using sine and cosine functions so that their periodic nature is preserved. This is important because hour 23 and hour 0 are close in the real daily cycle, although they are numerically far apart in a simple integer representation.

The same feature-engineering logic is used for renewable-power forecasting when a PV power or solar-irradiance column is available. The script can operate in two PV input modes: irradiance-based and synthetic. A historical solar irradiance is used if its available and if not,a synthetic clear-sky PV profile is generated.

3.8 Prediction Method: Histogram-Based Gradient Boosting Regression

The prediction stage of this work is based on a supervised machine-learning regression method called Histogram-Based Gradient Boosting Regression. In the Python implementation, this method is applied using the HistGradientBoostingRegressor algorithm. This model belongs to the family of ensemble learning methods, where several decision-tree learners are built sequentially. Each new tree attempts to reduce the errors produced by the previous trees. Through this progressive correction process, the final model can learn nonlinear relationships between the input variables and the target variable.

This method was selected because it is suitable for nonlinear time-series regression problems and can efficiently handle large datasets. It also requires limited preprocessing compared with some other machine-learning methods and can capture interactions between calendar variables, lagged load values, rolling statistics, and renewable generation indicators. These characteristics are useful for microgrid forecasting because load demand and PV production are affected by nonlinear relationships between time, previous operating values, weather-related behavior, and seasonal patterns.

The general forecasting problem can be written as P_hat(t) = f(Xt), where P_hat(t) is the predicted power at time t, f is the trained regression model, and Xt is the feature vector containing calendar features, lagged values, rolling statistics, and optional weather or PV-related variables.

The model performance is evaluated using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE measures the average absolute difference between measured and predicted values, while RMSE gives more weight to larger errors. These indicators are useful for evaluating whether the model can reproduce the amplitude and timing of load variations.

3.9 Model and Peak Detection Parameters

The forecasting and peak detection parameters used in the implementation are summarized in Table 10. These values define the peak detection sensitivity, forecasting horizon, gas-turbine stress threshold, and PV sizing search range.

Table 9 : Forecasting and optimization parameters

Parameter	**Value**	**Description**
Peak quantile	0.9	Statistical threshold for historical peak detection
Peak distance	4 h	Minimum distance between detected peaks
Historical prominence	300 kW	Minimum prominence for historical peak detection
Future prominence	150 kW	Minimum prominence for future peak detection
Hourly test period	30 days	Chronological test period for hourly model evaluation

Hourly forecast horizon	30 days	Short-term recursive forecast horizon
Daily peak forecast horizon	12 months	Long-term daily peak forecasting horizon
GT rated power	51,000 kW	Assumed gas-turbine rated power
GT stress fraction	0.65	Fraction used to define the stress threshold
PV size minimum	1,000 kWp	Lower bound of the PV sizing scan
PV size maximum	30,000 kWp	Upper bound of the PV sizing scan
PV size step	1,000 kWp	Increment used in the PV sizing scan

3.10 Short-Term Hourly Load Forecasting Results

The first forecasting layer concerns short-term hourly load prediction. The historical dataset is divided chronologically into training and testing periods. The model is trained on the historical training data and then evaluated on unseen test data using MAE and RMSE. This chronological split is important because it preserves the temporal order of the data and avoids using future information during training.

After validation, the trained model is used recursively to forecast the next 30 days. In this recursive procedure, each predicted hourly value is added to the previous sequence and reused to calculate the next prediction. This produces a continuous future load profile.

The comparison between measured and predicted load shows that the model follows the actual load profile closely during the test period. This is important because the objective is not only to estimate the average demand, but also to preserve the timing and amplitude of high-load periods. A forecasting model that excessively smooths the peaks would underestimate the future burden imposed on the gas-turbine source and could lead to an underdesigned peak-shaving strategy.

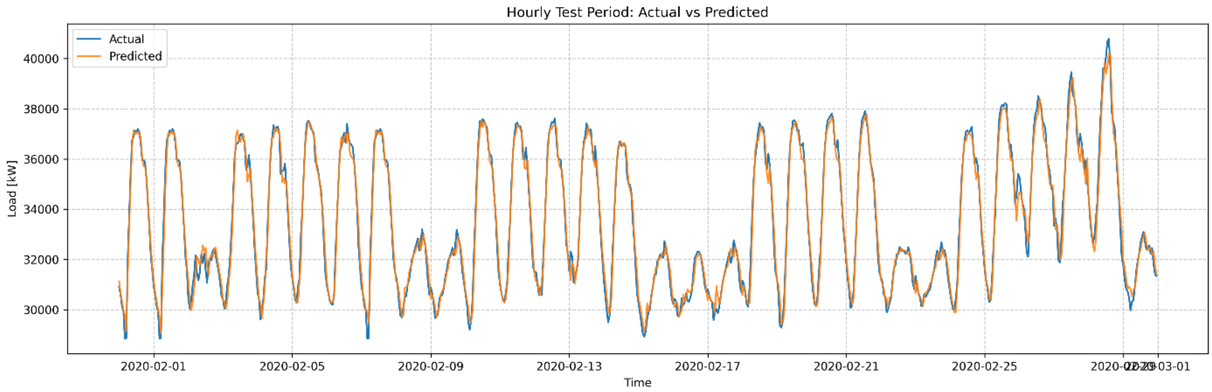


Figure 17 : Hourly test period: actual versus predicted load.

3.11 Thirty-Day Recursive Forecast and Future Peak Detection

After validation, the hourly model is used recursively to generate a thirty-day forecast. The resulting forecast is analyzed by the peak-detection module. The script first attempts to detect future peaks using the historical statistical threshold. If no peaks are detected, it applies an adaptive forecast-based threshold. If the forecast is too smooth for local maxima to be detected, the daily maximum fallback marks the maximum forecasted load of each day. This prevents the future-peak curve from being empty and makes the future peak information usable for decision-making.

The thirty-day forecast shows a clear daily structure and identifies expected future peak periods. These peaks define the operating intervals during which the gas-turbine source is likely to experience the highest burden. In the proposed methodology, future peaks are not treated only as predicted values; they become target intervals for evaluating PV and BESS contribution. This creates the main link between forecasting and peak shaving in the proposed framework.

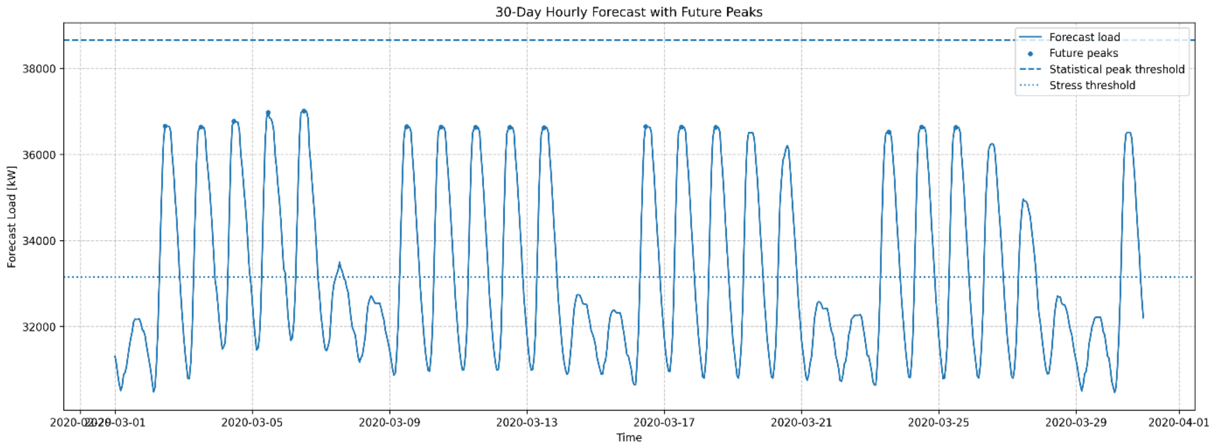


Figure 18 : Thirty-day hourly forecast with future peaks.

3.12 Long-Term Daily Peak Forecasting

The second predictive layer focuses on the daily maximum load. The hourly load series is converted into a daily peak series by taking the maximum load value of each day. A separate gradient-boosting model is then trained using daily calendar features, lagged daily peak values, and rolling statistics over weekly and monthly windows.

This model does not aim to reconstruct the full hourly curve. Instead, its purpose is to provide a strategic view of future critical days over a longer planning horizon. The twelve-month forecast of daily peak demand allows the identification of months with sustained high-load operation. From this forecast, the script calculates monthly stress-day counts and monthly average daily peaks. These outputs are useful for planning because they identify not only individual peak events, but also periods with repeated high operating burden.

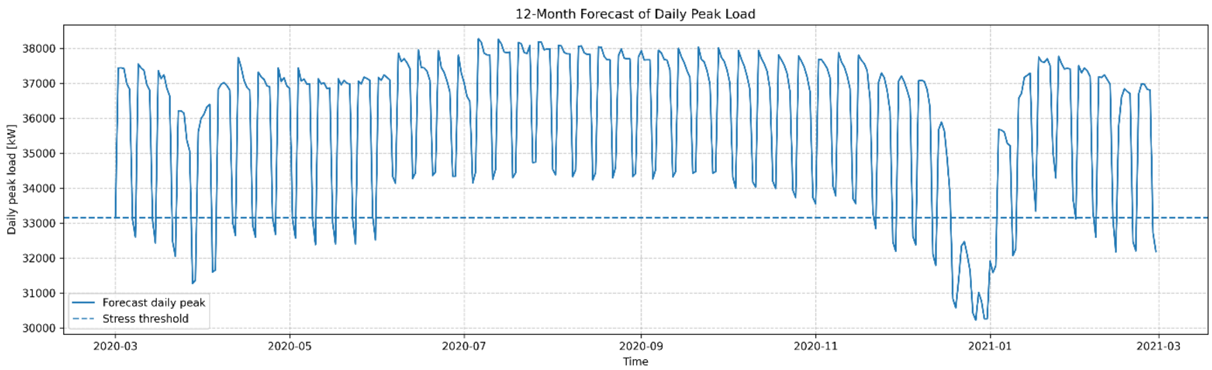


Figure 19 : Twelve-month forecast of daily peak load

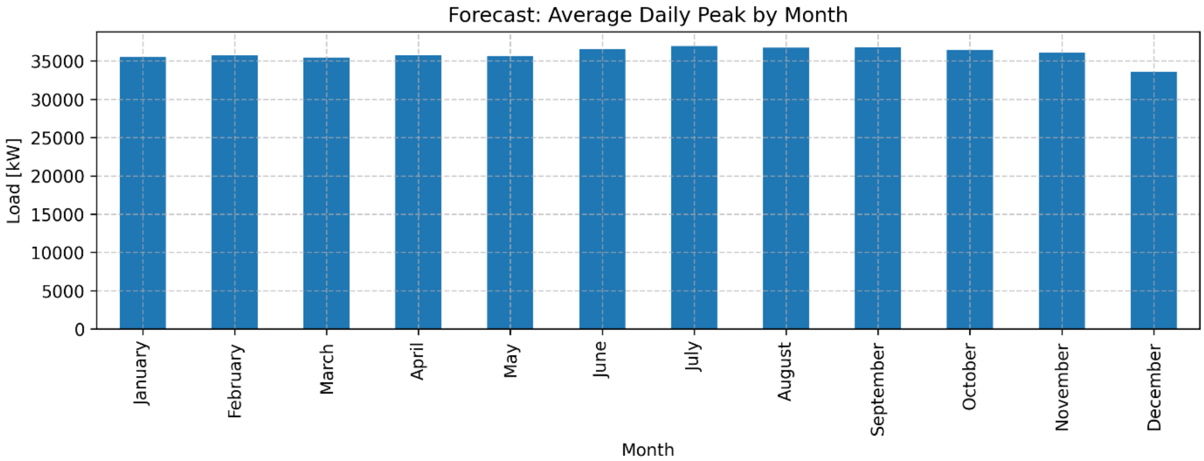


Figure 20 : Forecast average daily peak by month

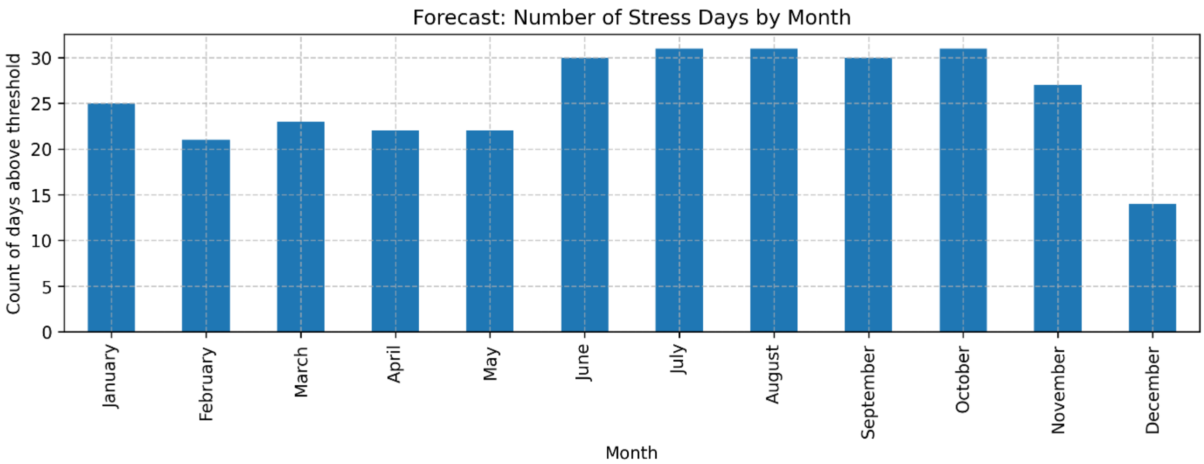


Figure 21 : Forecast number of stress days by month

3.13 Photovoltaic Power Representation from the UCSD Dataset

The PV representation is adapted to the available input data. Instead of relying only on a generic solar profile, the implementation can use a historical solar irradiance column when such a column exists. The script forecasts or repeats the PV power behavior depending on data availability, then normalizes the PV source power by a reference capacity to obtain a dimensionless PV factor. This PV factor is multiplied by each candidate PV capacity in the sizing scan. The PV power for a candidate size can be calculated as PPV,t = PVsize x FPV,t, where PPV,t is the PV power at time t, PVsize is the candidate installed PV capacity, and FPV,t is the normalized PV factor.

The PV profile is zero during the night and increases during daytime, with a maximum around midday. The comparison between forecast load and PV power is important because it shows the limitation of PV-only peak shaving. When the load peak occurs during daylight, PV can contribute directly. However, when high demand occurs during the evening or night, PV alone cannot reduce the gas-turbine burden unless it is combined with storage. For this reason, the BESS layer is introduced in the methodology.

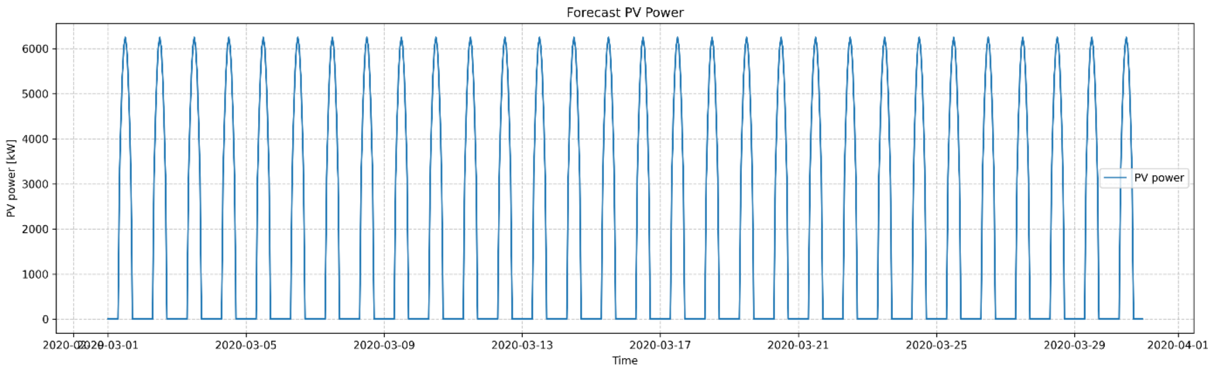


Figure 22 : Forecast PV power

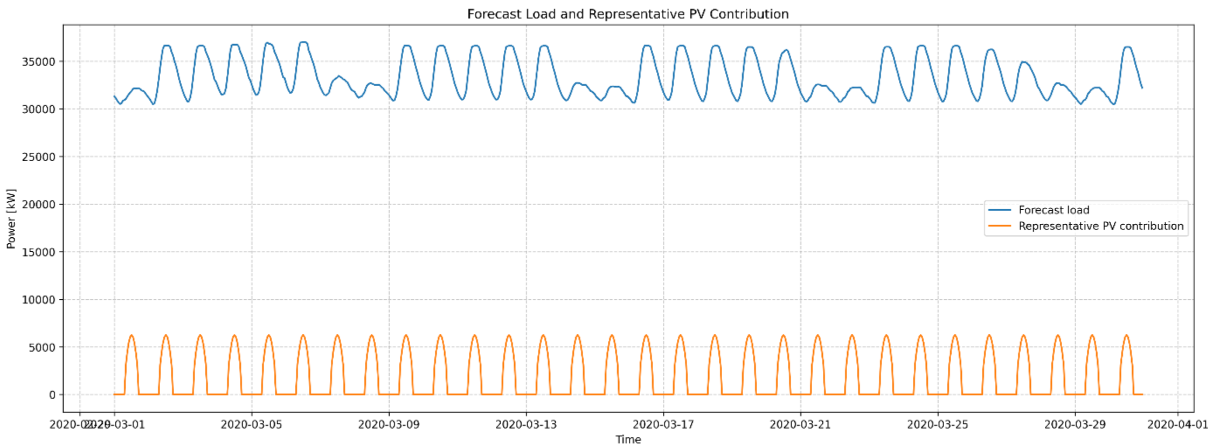


Figure 23 : Forecast load and representative PV contribution

3.14 Battery Energy Storage System Dispatch Strategy

The BESS is introduced to complement the PV contribution. In the implemented control logic, the battery charges when PV production is available and discharges during no-PV or low-PV periods in peak periods. The day/night decision is based mainly on the PV factor rather than the absolute PV power. This is important because very small positive PV values may appear around sunrise or sunset. Therefore, a PV-factor threshold is used to classify low-PV periods as no-light intervals.

The BESS operation is limited by energy capacity, power capacity, initial state of charge, minimum SOC, maximum SOC, charging efficiency, and discharging efficiency. During PV availability, a configured fraction of PV power is reserved for charging the battery. During no-PV or low-PV periods, the BESS supplies part of the load, subject to power and SOC constraints. This strategy is simple but operationally clear: daytime PV charges the battery, and the stored energy is then used when solar power is not available.

Table 10 : BESS dispatch parameters

Parameter	Value	Description
BESS energy capacity	20,000 kWh	Total battery energy capacity
BESS power capacity	5,000 kW	Maximum charge/discharge power
Initial SOC	80%	Initial state of charge
Minimum SOC	20%	Lower operating limit
Maximum SOC	95%	Upper operating limit
Charge efficiency	0.95	Battery charging efficiency
Discharge efficiency	0.95	Battery discharging efficiency
Charge fraction of PV	0.5	Fraction of PV power reserved for charging
Night GT target fraction	0.8	Target fraction of GT stress threshold at night
Night load support fraction	0.2	Fraction of night load supplied by BESS
PV day threshold for BESS	0.3	Threshold below which PV is treated as low/no-PV

The residual gas-turbine power after PV is computed by subtracting the PV power from the forecast load. After BESS support, the residual gas-turbine power is computed by subtracting both PV power and battery discharge power from the forecast load. The state of charge evolves according to the charging power, discharging power, battery capacity.

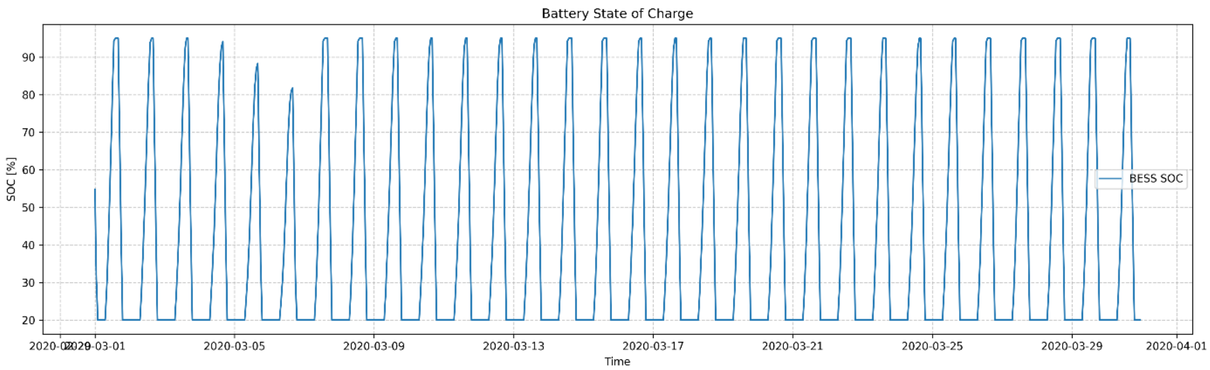


Figure 24 : Battery state of charge

3.15 PV Sizing Scan and Peak-Shaving Indicators

The PV sizing scan evaluates several candidate PV capacities and computes the resulting stress indicators. For each candidate size, the normalized PV factor is multiplied by the installed PV capacity to obtain the forecast PV power. The residual gas-turbine power after PV is then calculated by subtracting the PV contribution from the forecast load. The BESS dispatch is also simulated for each candidate size, producing a second residual profile after both PV and BESS support.

The method therefore evaluates two scenarios for each PV size: PV-only support and PV+BESS support. The main performance indicators are the number of stress hours, the overload energy above the stress threshold, the maximum residual gas-turbine power, the PV energy, the BESS charge energy, the BESS discharge energy, and the minimum and maximum SOC reached during the simulation.

The best PV size is selected by minimizing the remaining overload energy after PV+BESS, then minimizing the remaining stress hours and the maximum residual power. This ranking is more appropriate for the present problem than selecting PV size based only on total PV energy because the central objective is to reduce high-load stress on the gas-turbine source.

In the reported case, the script identifies 10,000 to 30,000 kWp as the best PV size within the scanned range. This value should be interpreted as a scenario result within the selected search interval and assumptions, not as a final investment recommendation. A complete engineering design would additionally require economic optimization, land availability, inverter sizing, battery degradation analysis, and uncertainty analysis.

.

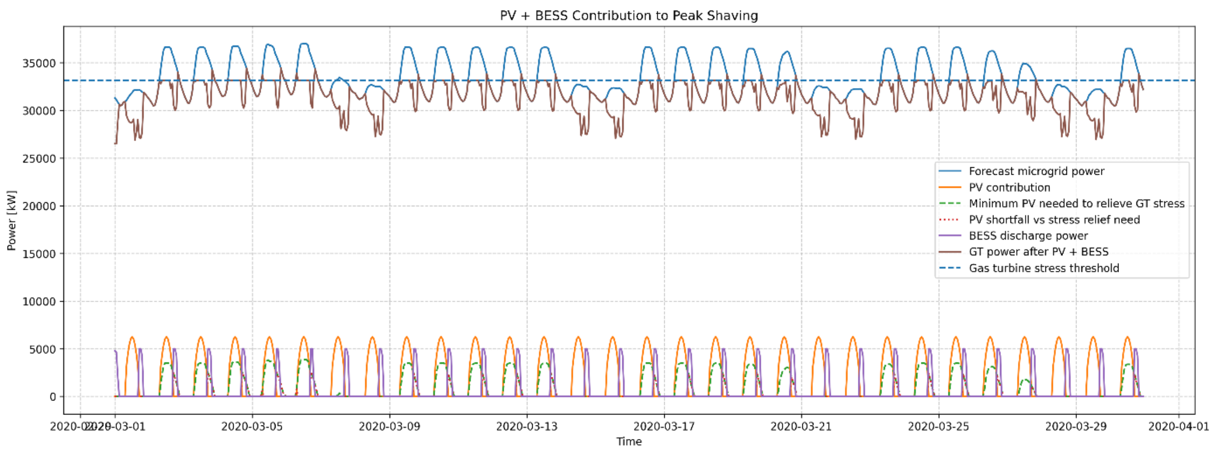


Figure 25 : PV and BESS contribution to peak shaving

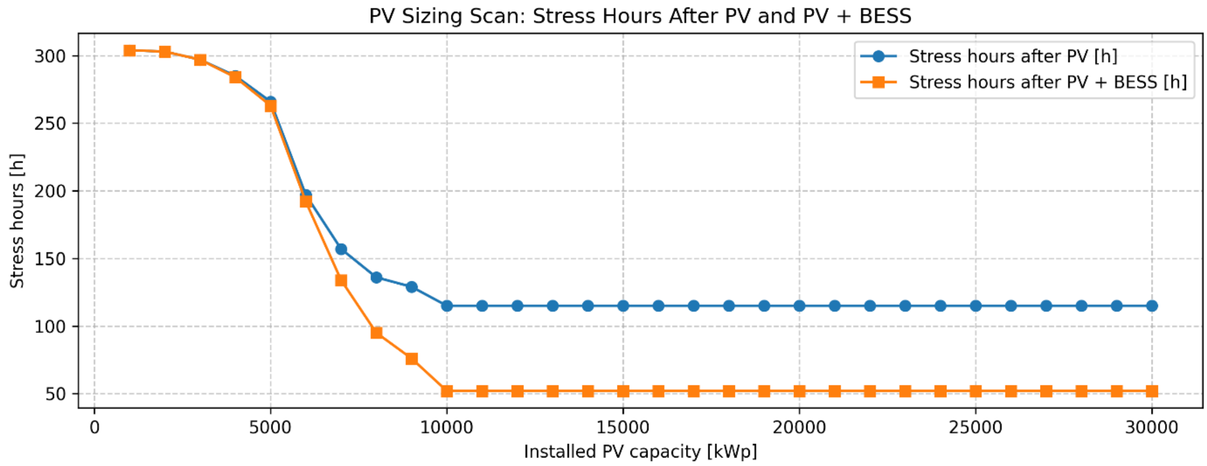


Figure 26 : sizing scan: stress hours after PV and PV+BESS

3.16 Discussion of the Main Results

The results obtained from the UCSD dataset support the central idea of this dissertation that forecasting can be used to identify future critical load periods, and these periods can guide the sizing and operation of PV and BESS resources for peak shaving. The historical load curve demonstrates that high-demand periods are not isolated random anomalies but follow identifiable daily and seasonal structures. This confirms that peak detection and forecasting are useful tools for preparing energy resources before critical operating conditions occur.

The hourly forecasting model reproduces the measured test profile with close agreement, which makes it suitable for generating a short-term operating scenario. The future forecast then converts the learned load structure into expected peak intervals that can be used for operational assessment. This is important because the proposed method does not use forecasting as a separate prediction exercise, but as an input for peak-shaving decision-making.

The PV and BESS results show that renewable support is most useful when it is interpreted through the residual gas-turbine burden rather than only through generated energy. PV reduces daytime load, while BESS extends the usefulness of PV by shifting part of the stored energy to no-light or low-PV periods. The SOC curve confirms that the storage system is actively charged and discharged across the forecast horizon. The PV sizing scan further shows that the combined PV+BESS scenario reduces stress hours more effectively than PV alone.

The results should nevertheless be interpreted according to the nature of the dataset. The UCSD microgrid is a grid-connected campus microgrid, while the dissertation problem concerns gas-turbine stress reduction in a standalone or weak-grid context. For this reason, the dataset is used as a realistic experimental case rather than as a direct isolated-site measurement because the unavailability of data. The gas-turbine stress threshold is also a modeling parameter, and the proposed PV size is a scenario output. These assumptions do not invalidate the method; instead, they clearly define the scope of the numerical experiment.

3.17 Limitations and Assumptions

Several limitations must be clearly stated. First, the UCSD dataset represents a real advanced campus microgrid, but it is not a purely standalone microgrid. Therefore, the methodology uses the dataset as a realistic proxy for microgrid demand and resource behavior. Second, the gas-turbine stress threshold is defined as a fraction of an assumed rated capacity and is not calibrated using manufacturer maintenance data. Third, the PV sizing scan is bounded by the user-defined minimum, maximum, and step size; therefore, the selected PV capacity is optimal only within the explored range.

Fourth, the BESS dispatch strategy is rule-based and does not yet include economic dispatch, battery aging cost, degradation modeling, or model predictive optimization. Fifth, the forecast results depend on the selected features, the selected model, and the quality of the historical data. Finally, uncertainty in load and renewable forecasts is not explicitly propagated through the sizing decision.

Despite these limitations, the methodology is appropriate because it creates a complete framework that can solve the proposed problem. It uses a real open-source dataset, applies transparent preprocessing, trains forecasting models, identifies future critical intervals, simulates PV and BESS support, and evaluates stress-oriented indicators. This makes the chapter consistent with the research gap identified in Chapter 2, where forecasting, renewable contribution, and gas-turbine peak-stress reduction were presented as elements that should be linked in one framework.

3.18 Conclusion

This chapter presented a forecasting-based PV-BESS peak-shaving methodology using the UCSD open-source microgrid dataset as the experimental basis. Since the dataset does not provide a separate measured gas-turbine power signal, the total campus load was used as the equivalent gas-turbine burden in a standalone or weak-grid scenario. This assumption allowed the study to evaluate gas-turbine stress reduction while maintaining a clear methodological interpretation.

The preprocessing stage converted the measurements into a regular hourly time series and preserved the kW, kWh, and kWp unit structure of the original data. Historical peak detection showed the temporal organization of high-load intervals, while the hourly and daily forecasting models provided both operational and strategic views of future demand. The PV representation was adapted to the available PV source data, and a BESS dispatch strategy was added to support low-PV and no-PV periods. Finally, the PV sizing scan demonstrated how forecasted peaks can be translated into stress-hour and overload-energy indicators for gas-turbine peak-shaving analysis. The chapter therefore provides a dataset-consistent and source-appropriate methodology for connecting power forecasting, PV integration, BESS operation, and gas-turbine stress reduction.

General Conclusion

This thesis addressed the challenge of peak demand management in standalone hybrid microgrids, with particular emphasis on reducing the operational stress experienced by gas turbines. The study began by presenting the fundamental concepts of electrical power systems, microgrids, and standalone hybrid configurations, highlighting their importance in supplying reliable electricity to isolated regions. The main components of these systems, including gas turbines, photovoltaic power plants, energy storage technologies, and energy management systems, were discussed to provide a comprehensive understanding of their operation. Particular attention was given to gas turbines because of their crucial role in ensuring power reliability and system stability. However, their operation during high-demand periods can lead to increased fuel consumption, higher operating costs, and accelerated equipment aging. These considerations demonstrate the importance of developing effective strategies capable of improving system efficiency while maintaining a reliable power supply.

The work then focused on peak demand challenges and forecasting-based mitigation strategies. A forecasting framework was developed using historical power generation data to predict future demand and identify potential peak-load periods. The forecast results were subsequently used to evaluate the contribution of photovoltaic generation as a peak-shaving resource capable of reducing the load imposed on the gas turbine during critical operating conditions. The obtained results showed that integrating forecasting with photovoltaic generation can significantly reduce peak stress periods, increase renewable energy utilization, and support more economical microgrid operation. Therefore, the proposed approach represents a practical and effective solution for enhancing the performance of standalone hybrid microgrids while contributing to fuel savings and improved operational sustainability. Future research may extend this work through the integration of battery energy storage systems, advanced machine learning forecasting techniques, and real-time optimization algorithms to further improve system reliability and energy management capabilities.

References

[1] P. Bajpai and V. Dash, “Hybrid renewable energy systems for power generation in stand-alone applications: A review,” *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 2926–2939, Jun. 2012, doi: 10.1016/j.rser.2012.02.009.

[2] A. H. Fathima and K. Palanisamy, “Optimization in microgrids with hybrid energy systems – A review,” *Renewable and Sustainable Energy Reviews*, vol. 45, pp. 431–446, May 2015, doi: 10.1016/j.rser.2015.01.059.

[3] A. Hirsch, Y. Parag, and J. Guerrero, “Microgrids: A review of technologies, key drivers, and outstanding issues,” *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, Jul. 2018, doi: 10.1016/j.rser.2018.03.040.

[4] R. Banihabib and M. Assadi, “The Role of Micro Gas Turbines in Energy Transition,” *Energies*, vol. 15, no. 21, p. 8084, Oct. 2022, doi: 10.3390/en15218084.

[5] M. A. Gonzalez-Salazar, T. Kirsten, and L. Prchlik, “Review of the operational flexibility and emissions of gas- and coal-fired power plants in a future with growing renewables,” *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 1497–1513, Feb. 2018, doi: 10.1016/j.rser.2017.05.278.

[6] M. M. Rana, M. Atef, M. R. Sarkar, M. Uddin, and G. Shafiullah, “A Review on Peak Load Shaving in Microgrid—Potential Benefits, Challenges, and Future Trend,” *Energies*, vol. 15, no. 6, p. 2278, Mar. 2022, doi: 10.3390/en15062278.

[7] D. T. Ton and M. A. Smith, “The U.S. Department of Energy’s Microgrid Initiative,” *The Electricity Journal*, vol. 25, no. 8, pp. 84–94, Oct. 2012, doi: 10.1016/j.tej.2012.09.013.

[8] N. Hatziargyriou, H. Asano, R. Iravani, and C. Marnay, “Microgrids,” *IEEE Power and Energy Mag.*, vol. 5, no. 4, pp. 78–94, Jul. 2007, doi: 10.1109/MPAE.2007.376583.

[9] R. H. Lasseter and P. Paigi, “Microgrid: a conceptual solution,” in *2004 IEEE 35th Annual Power Electronics Specialists Conference (IEEE Cat. No.04CH37551)*, Aachen, Germany: IEEE, 2004, pp. 4285–4290. doi: 10.1109/PESC.2004.1354758.

[10] Y. Xu, Z. Shi, J. Wang, and P. Hou, “Discussion on the Factors Affecting the Stability of Microgrid Based on Distributed Power Supply,” *EPE*, vol. 05, no. 04, pp. 1344–1346, 2013, doi: 10.4236/epe.2013.54B254.

[11] D. E. Olivares *et al.*, “Trends in Microgrid Control,” *IEEE Trans. Smart Grid*, vol. 5, no. 4, pp. 1905–1919, Jul. 2014, doi: 10.1109/TSG.2013.2295514.

[12] J. M. Guerrero, J. C. Vasquez, J. Matas, L. G. De Vicuna, and M. Castilla, “Hierarchical Control of Droop-Controlled AC and DC Microgrids—A General Approach Toward Standardization,” *IEEE Trans. Ind. Electron.*, vol. 58, no. 1, pp. 158–172, Jan. 2011, doi: 10.1109/TIE.2010.2066534.

[13] S. Parhizi, H. Lotfi, A. Khodaei, and S. Bahramirad, “State of the Art in Research on Microgrids: A Review,” *IEEE Access*, vol. 3, pp. 890–925, 2015, doi: 10.1109/ACCESS.2015.2443119.

[14] M. H. Saeed, W. Fangzong, B. A. Kalwar, and S. Iqbal, “A Review on Microgrids’ Challenges & Perspectives,” *IEEE Access*, vol. 9, pp. 166502–166517, 2021, doi: 10.1109/ACCESS.2021.3135083.

[15] M. Shafiullah *et al.*, “Review of Recent Developments in Microgrid Energy Management Strategies,” *Sustainability*, vol. 14, no. 22, p. 14794, Nov. 2022, doi: 10.3390/su142214794.

[16] F. Conte, F. D’Agostino, G. Mosaico, F. Silvestro, and S. Grillo, “An Efficiency-Based Power Management Strategy for an Isolated Microgrid Project,” in *2022 IEEE Power & Energy Society General Meeting (PESGM)*, Denver, CO, USA: IEEE, Jul. 2022, pp. 1–5. doi: 10.1109/PESGM48719.2022.9916899.

[17] J. Marqusee, S. Ericson, and D. Jenket, “Emergency Diesel Generator Reliability and Installation Energy Security,” NREL/TP-5C00-76553, 1659892, MainId:7227, Apr. 2020. doi: 10.2172/1659892.

[18] R. De Robbio, “Micro Gas Turbine Role in Distributed Generation with Renewable Energy Sources,” *Energies*, vol. 16, no. 2, p. 704, Jan. 2023, doi: 10.3390/en16020704.

[19] A. H. S. Weerakoon and M. Assadi, “Micro Gas Turbines in the Global Energy Landscape: Bridging the Techno-Economic Gap with Comparative and Adaptive Insights from Internal Combustion Engines and Renewable Energy Sources,” *Energies*, vol. 17, no. 21, p. 5457, Oct. 2024, doi: 10.3390/en17215457.

[20] D. Akinyele, E. Olabode, and A. Amole, “Review of Fuel Cell Technologies and Applications for Sustainable Microgrid Systems,” *Inventions*, vol. 5, no. 3, p. 42, Aug. 2020, doi: 10.3390/inventions5030042.

[21] X. Luo, J. Wang, M. Dooner, and J. Clarke, “Overview of current development in electrical energy storage technologies and the application potential in power system operation,” *Applied Energy*, vol. 137, pp. 511–536, Jan. 2015, doi: 10.1016/j.apenergy.2014.09.081.

[22] O. Schmidt, A. Hawkes, A. Gambhir, and I. Staffell, “The future cost of electrical energy storage based on experience rates,” *Nat Energy*, vol. 2, no. 8, p. 17110, Jul. 2017, doi: 10.1038/nenergy.2017.110.

[23] X. Li and A. Palazzolo, “A review of flywheel energy storage systems: state of the art and opportunities,” *Journal of Energy Storage*, vol. 46, p. 103576, Feb. 2022, doi: 10.1016/j.est.2021.103576.

[24] A. G. Olabi, Q. Abbas, A. Al Makky, and M. A. Abdelkareem, “Supercapacitors as next generation energy storage devices: Properties and applications,” *Energy*, vol. 248, p. 123617, Jun. 2022, doi: 10.1016/j.energy.2022.123617.

[25] S. Dai, P. Shen, W. Deng, and Q. Yu, “Hydrogen Energy in Electrical Power Systems: A Review and Future Outlook,” *Electronics*, vol. 13, no. 17, p. 3370, Aug. 2024, doi: 10.3390/electronics13173370.

[26] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, “Microgrids energy management systems: A critical review on methods, solutions, and prospects,” *Applied Energy*, vol. 222, pp. 1033–1055, Jul. 2018, doi: 10.1016/j.apenergy.2018.04.103.

[27] “Microgrid Energy Management: Classification, Review and Challenges,” *CSEE JPES*, 2023, doi: 10.17775/CSEEJPES.2021.09150.

[28] S. F. Rafique and Z. Jianhua, “Energy management system, generation and demand predictors: a review,” *IET Generation Trans & Dist*, vol. 12, no. 3, pp. 519–530, Feb. 2018, doi: 10.1049/iet-gtd.2017.0354.

[29] J. Comden and J. Wang, “An Innovative Energy Management System for Microgrids with Multiple Grid-Forming Inverters,” in *2024 IEEE Power & Energy Society General Meeting (PESGM)*, Seattle, WA, USA: IEEE, Jul. 2024, pp. 1–5. doi: 10.1109/PESGM51994.2024.10689231.

[30] A. Cabrera-Tobar, A. Massi Pavan, G. Petrone, and G. Spagnuolo, “A Review of the Optimization and Control Techniques in the Presence of Uncertainties for the Energy Management of Microgrids,” *Energies*, vol. 15, no. 23, p. 9114, Dec. 2022, doi: 10.3390/en15239114.

[31] X. Zhaoxia, G. Zhijun, J. M. Guerrero, and F. Hongwei, “SCADA system for islanded DC microgrids,” in *IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society*, Beijing: IEEE, Oct. 2017, pp. 2669–2674. doi: 10.1109/IECON.2017.8216449.

[32] S. Vinothine, L. N. Widanagama Arachchige, A. D. Rajapakse, and R. Kaluthanthrige, “Microgrid Energy Management and Methods for Managing Forecast Uncertainties,” *Energies*, vol. 15, no. 22, p. 8525, Nov. 2022, doi: 10.3390/en15228525.

[33] H. Zhang, “Application of day-ahead optimal scheduling model based on multi-energy micro-grids with uncertainty in wind and solar energy and energy storage station,” *Int. J. Renew. Energy Dev.*, vol. 13, no. 5, pp. 873–883, Sep. 2024, doi: 10.61435/ijred.2024.60218.

[34] N. Khosravi, D. Çelik, H. Bevrani, and S. Echalih, “Microgrid stability: A comprehensive review of challenges, trends, and emerging solutions,” *International Journal of Electrical Power & Energy Systems*, vol. 170, p. 110829, Sep. 2025, doi: 10.1016/j.ijepes.2025.110829.

[35] E. Rokrok, M. Shafie-khah, and J. P. S. Catalão, “Review of primary voltage and frequency control methods for inverter-based islanded microgrids with distributed generation,” *Renewable and Sustainable Energy Reviews*, vol. 82, pp. 3225–3235, Feb. 2018, doi: 10.1016/j.rser.2017.10.022.

[36] S. S. Hussain Rizvi, K. T. Chaturvedi, and M. Lal Kolhe, “A review on peak shaving techniques for smart grids,” *AIMSE*, vol. 11, no. 4, pp. 723–752, 2023, doi: 10.3934/energy.2023036.

[37] M. Uddin, M. F. Romlie, M. F. Abdullah, C. Tan, G. Shafiullah, and A. H. A. Bakar, “A novel peak shaving algorithm for islanded microgrid using battery energy storage system,” *Energy*, vol. 196, p. 117084, Apr. 2020, doi: 10.1016/j.energy.2020.117084.

[38] A. Hirsch, Y. Parag, and J. Guerrero, “Microgrids: A review of technologies, key drivers, and outstanding issues,” *Renewable and Sustainable Energy Reviews*, vol. 90, pp. 402–411, Jul. 2018, doi: 10.1016/j.rser.2018.03.040.

[39] M. F. Zia, E. Elbouchikhi, and M. Benbouzid, “Microgrids energy management systems: A critical review on methods, solutions, and prospects,” *Applied Energy*, vol. 222, pp. 1033–1055, Jul. 2018, doi: 10.1016/j.apenergy.2018.04.103.

[40] P. Palensky and D. Dietrich, “Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads,” *IEEE Trans. Ind. Inf.*, vol. 7, no. 3, pp. 381–388, Aug. 2011, doi: 10.1109/TII.2011.2158841.

[41] P. Siano, “Demand response and smart grids—A survey,” *Renewable and Sustainable Energy Reviews*, vol. 30, pp. 461–478, Feb. 2014, doi: 10.1016/j.rser.2013.10.022.

[42] A.-H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, “Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid,” *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 320–331, Dec. 2010, doi: 10.1109/TSG.2010.2089069.

[43] Y. Liu, C. Yuen, S. Huang, N. Ul Hassan, X. Wang, and S. Xie, “Peak-to-Average Ratio Constrained Demand-Side Management With Consumer’s Preference in Residential Smart Grid,” *IEEE J. Sel. Top. Signal Process.*, vol. 8, no. 6, pp. 1084–1097, Dec. 2014, doi: 10.1109/JSTSP.2014.2332301.

[44] W.-Y. Chiu, J.-T. Hsieh, and C.-M. Chen, “Pareto Optimal Demand Response Based on Energy Costs and Load Factor in Smart Grid,” *IEEE Trans. Ind. Inf.*, vol. 16, no. 3, pp. 1811–1822, Mar. 2020, doi: 10.1109/TII.2019.2928520.

[45] M. H. Albadi and E. F. El-Saadany, “A summary of demand response in electricity markets,” *Electric Power Systems Research*, vol. 78, no. 11, pp. 1989–1996, Nov. 2008, doi: 10.1016/j.epsr.2008.04.002.

[46] N. G. Paterakis, O. Erdinc, A. G. Bakirtzis, and J. P. S. Catalao, “Optimal Household Appliances Scheduling Under Day-Ahead Pricing and Load-Shaping Demand Response Strategies,” *IEEE Trans. Ind. Inf.*, vol. 11, no. 6, pp. 1509–1519, Dec. 2015, doi: 10.1109/TII.2015.2438534.

[47] B. N. Silva, M. Khan, and K. Han, “Futuristic Sustainable Energy Management in Smart Environments: A Review of Peak Load Shaving and Demand Response Strategies, Challenges, and Opportunities,” *Sustainability*, vol. 12, no. 14, p. 5561, Jul. 2020, doi: 10.3390/su12145561.

[48] A. Oudalov, R. Cherkaoui, and A. Beguin, “Sizing and Optimal Operation of Battery Energy Storage System for Peak Shaving Application,” in *2007 IEEE Lausanne Power Tech*, Lausanne, Switzerland: IEEE, Jul. 2007, pp. 621–625. doi: 10.1109/PCT.2007.4538388.

[49] D. Kucevic, L. Semmelmann, N. Collath, A. Jossen, and H. Hesse, “Peak Shaving with Battery Energy Storage Systems in Distribution Grids: A Novel Approach to Reduce Local and Global Peak Loads,” *Electricity*, vol. 2, no. 4, pp. 573–589, Nov. 2021, doi: 10.3390/electricity2040033.

[50] S. Mishra and P. Palanisamy, “Efficient Power Flow Management and Peak Shaving in a Microgrid-PV System,” in *2018 IEEE Energy Conversion Congress and Exposition (ECCE)*, Portland, OR, USA: IEEE, Sep. 2018, pp. 3792–3798. doi: 10.1109/ECCE.2018.8558312.

[51] Y. Li and K. Li, “Incorporating Demand Response of Electric Vehicles in Scheduling of Isolated Microgrids With Renewables Using a Bi-Level Programming Approach,” *IEEE Access*, vol. 7, pp. 116256–116266, 2019, doi: 10.1109/ACCESS.2019.2936487.

[52] V. Sultan, A. Aryal, H. Chang, and J. Kral, “Integration of EVs into the smart grid: a systematic literature review,” *Energy Inform*, vol. 5, no. 1, p. 65, Dec. 2022, doi: 10.1186/s42162-022-00251-2.

[53] G. Gross and F. D. Galiana, “Short-term load forecasting,” *Proc. IEEE*, vol. 75, no. 12, pp. 1558–1573, 1987, doi: 10.1109/PROC.1987.13927.

[54] T. Hong and S. Fan, “Probabilistic electric load forecasting: A tutorial review,” *International Journal of Forecasting*, vol. 32, no. 3, pp. 914–938, Jul. 2016, doi: 10.1016/j.ijforecast.2015.11.011.

[55] U. B. Tayab, A. Zia, F. Yang, J. Lu, and M. Kashif, “Short-term load forecasting for microgrid energy management system using hybrid HHO-FNN model with best-basis stationary wavelet packet transform,” *Energy*, vol. 203, p. 117857, Jul. 2020, doi: 10.1016/j.energy.2020.117857.

[56] A. Moradzadeh, S. Zakeri, M. Shoaran, B. Mohammadi-Ivatloo, and F. Mohammadi, “Short-Term Load Forecasting of Microgrid via Hybrid Support Vector Regression and Long Short-Term Memory Algorithms,” *Sustainability*, vol. 12, no. 17, p. 7076, Aug. 2020, doi: 10.3390/su12177076.

[57] S. Akhtar *et al.*, “Short-Term Load Forecasting Models: A Review of Challenges, Progress, and the Road Ahead,” *Energies*, vol. 16, no. 10, p. 4060, May 2023, doi: 10.3390/en16104060.

[58] S. R. Khuntia, J. L. Rueda, and M. A. M. M. Van Der Meijden, “Forecasting the load of electrical power systems in mid- and long-term horizons: a review,” *IET Generation Trans & Dist*, vol. 10, no. 16, pp. 3971–3977, Dec. 2016, doi: 10.1049/iet-gtd.2016.0340.

[59] N. Ahmad, Y. Ghadi, M. Adnan, and M. Ali, “Load Forecasting Techniques for Power System: Research Challenges and Survey,” *IEEE Access*, vol. 10, pp. 71054–71090, 2022, doi: 10.1109/ACCESS.2022.3187839.

[60] A. Mellit, A. Massi Pavan, E. Ogliari, S. Leva, and V. Lughi, “Advanced Methods for Photovoltaic Output Power Forecasting: A Review,” *Applied Sciences*, vol. 10, no. 2, p. 487, Jan. 2020, doi: 10.3390/app10020487.

[61] R. A. Rajagukguk, R. A. A. Ramadhan, and H.-J. Lee, “A Review on Deep Learning Models for Forecasting Time Series Data of Solar Irradiance and Photovoltaic Power,” *Energies*, vol. 13, no. 24, p. 6623, Dec. 2020, doi: 10.3390/en13246623.

[62] W. Tercha, S. A. Tadjer, F. Chekired, and L. Canale, “Machine Learning-Based Forecasting of Temperature and Solar Irradiance for Photovoltaic Systems,” *Energies*, vol. 17, no. 5, p. 1124, Feb. 2024, doi: 10.3390/en17051124.

[63] V. R. Patel, H. S. Cakar, and M. Jamil, “Short-Term Solar and Wind Power Forecasting Using Machine Learning Algorithms for Microgrid Operation,” *Energies*, vol. 19, no. 2, p. 550, Jan. 2026, doi: 10.3390/en19020550.

[64] X. Jiao and W. Xiao, “Review of Data-Driven Approaches Applied to Time-Series Solar Irradiance Forecasting for Future Energy Networks,” *Energies*, vol. 18, no. 21, p. 5823, Nov. 2025, doi: 10.3390/en18215823.

[65] R. J. Bessa, V. Miranda, A. Botterud, J. Wang, and E. M. Constantinescu, “Time Adaptive Conditional Kernel Density Estimation for Wind Power Forecasting,” *IEEE Trans. Sustain. Energy*, vol. 3, no. 4, pp. 660–669, Oct. 2012, doi: 10.1109/TSTE.2012.2200302.

[66] Y. Yang, H. Lou, J. Wu, S. Zhang, and S. Gao, “A survey on wind power forecasting with machine learning approaches,” *Neural Comput & Applic*, vol. 36, no. 21, pp. 12753–12773, Jul. 2024, doi: 10.1007/s00521-024-09923-4.

[67] W.-H. Lin, P. Wang, K.-M. Chao, H.-C. Lin, Z.-Y. Yang, and Y.-H. Lai, "Wind Power Forecasting with Deep Learning Networks: Time-Series Forecasting," *Applied Sciences*, vol. 11, no. 21, p. 10335, Nov. 2021, doi: 10.3390/app112110335.

[68] Y. Eren and İ. Küçükdemiral, "A comprehensive review on deep learning approaches for short-term load forecasting," *Renewable and Sustainable Energy Reviews*, vol. 189, p. 114031, Jan. 2024, doi: 10.1016/j.rser.2023.114031.

[69] A. Gasparin, S. Lukovic, and C. Alippi, "Deep learning for time series forecasting: The electric load case," *CAAI Trans on Intel Tech*, vol. 7, no. 1, pp. 1–25, Mar. 2022, doi: 10.1049/cit2.12060.

[70] N. E. Benti, M. D. Chaka, and A. G. Semie, "Forecasting Renewable Energy Generation with Machine Learning and Deep Learning: Current Advances and Future Prospects," *Sustainability*, vol. 15, no. 9, p. 7087, Apr. 2023, doi: 10.3390/su15097087.

[71] F. Durán, W. Pavón, and L. I. Minchala, "Forecast-Based Energy Management for Optimal Energy Dispatch in a Microgrid," *Energies*, vol. 17, no. 2, p. 486, Jan. 2024, doi: 10.3390/en17020486.

[72] A. Parisio, E. Rikos, and L. Glielmo, "A Model Predictive Control Approach to Microgrid Operation Optimization," *IEEE Trans. Contr. Syst. Technol.*, vol. 22, no. 5, pp. 1813–1827, Sep. 2014, doi: 10.1109/TCST.2013.2295737.

[73] J. Hu, Y. Shan, J. M. Guerrero, A. Ioinovici, K. W. Chan, and J. Rodriguez, "Model predictive control of microgrids – An overview," *Renewable and Sustainable Energy Reviews*, vol. 136, p. 110422, Feb. 2021, doi: 10.1016/j.rser.2020.110422.

[74] W. Hu, Ping Wang, and H. B. Gooi, "Towards optimal energy management of microgrids with a realistic model," in *2016 Power Systems Computation Conference (PSCC)*, Genoa, Italy: IEEE, Jun. 2016, pp. 1–7. doi: 10.1109/PSCC.2016.7540954.

[75] A. Soman, A. Trivedi, D. Irwin, B. Kosanovic, B. McDaniel, and P. Shenoy, "Peak Forecasting for Battery-based Energy Optimizations in Campus Microgrids," 2020, doi: 10.48550/ARXIV.2005.13517.

[76] L. Alvarado-Barrios, Á. Rodríguez Del Nozal, J. Boza Valerino, I. García Vera, and J. L. Martínez-Ramos, "Stochastic unit commitment in microgrids: Influence of the load forecasting error and the availability of energy storage," *Renewable Energy*, vol. 146, pp. 2060–2069, Feb. 2020, doi: 10.1016/j.renene.2019.08.032.

[77] A. Al-Quraan, B. Al-Mharat, A. Koran, and A. G. Radaideh, "Performance Improvement of a Standalone Hybrid Renewable Energy System Using a Bi-Level Predictive Optimization Technique," *Sustainability*, vol. 17, no. 2, p. 725, Jan. 2025, doi: 10.3390/su17020725.

[78] M. Atef, T. Khatib, M. F. Abdullah, and M. F. Romlie, "Optimization of a Hybrid Solar PV and Gas Turbine Generator System Using the Loss of Load Probability Index," *Clean Technol.*, vol. 2, no. 3, pp. 240–251, Jul. 2020, doi: 10.3390/cleantechnol2030016.

الجمهورية الجزائرية الديمقراطية الشعبية
République Algérienne Démocratique et Populaire
وزارة التعليم العالي والبحث العلمي
Ministère de l'Enseignement Supérieur Et de La Recherche Scientifique
جامعة غرداية

Faculté des sciences et Technologies
Département d'automatique et d'électromécanique

كلية العلوم والتكنولوجيا
قسم الآلية والكهروميكانيك

Université de Ghardaïa

غرداية في : 2026/06/11

إذن بطباعة مذكرة ماستر

بعد الاطلاع على محتوى المذكرة المنجزة من طرف الطلبة التالية أسماؤهم:

1. الطالب : بوجرادة أحمد عبدالرحمان
2. الطالب : مولاي عمر عبدالوهاب

تخصص : طاقات متجددة في الكهروتقني

نأذن بإيداع مذكرة الماستر المعنونة بـ:

Power Forecasting to Enable Peak Shaving in a Gas Turbine–Based Standalone Microgrid with PV Integration

مصباح شرف عبدالكريم

الجمهورية الجزائرية الديمقراطية الشعبية
وزارة التعليم العالي والبحث العلمي

جامعة غرداية
كلية العلوم والتكنولوجيا
قسم :الآلية والكهروميكانيك

Université de Ghardaïa
Faculté des Sciences
et de la technologie

شعبة : الكهروتقني
تخصص: طاقات متجددة في الكهروتقني

غرداية في : 2026/07/20

شهادة ترخيص بالتصحيح والايداع:

انا الاستاذ : فركوس خالد
بصفتي المشرف المسؤول عن تصحيح مذكرة تخرج ماستر المعنونة بـ:

Power Forecasting to Enable Peak Shaving in a Gas Turbine–Based Standalone Microgrid with PV Integration

من انجاز الطلبة:

بوجرادة أحمد عبد الرحمان

مولاي عمار عبد الوهاب

التي نوقشت بتاريخ : 2026/06/21

اشهد ان الطلبة قد قاموا بالتعديلات والتصحيحات المطلوبة من طرف لجنة المناقشة وقد تم التحقق من ذلك من طرفنا وقد استوفت جميع الشروط المطلوبة.

امضاء المسؤول عن التصحيح

فركوس خالد

مصادقة رئيس القسم

رئيس قسم الآلية والكهروميكانيك
عزاوي محمد

الجمهورية الجزائرية الديمقراطية الشعبية
وزارة التعليم العالي والبحث العلمي
جامعة غرداية
حاضنة أعمال جامعة غرداية

رقم: 144/ ح.أ.ج.غ/2026

شهادة توطين مشروع مبتكر وفق القرار008 المعدل والمتمم للقرار1275

أنا الممضي أسفله، السيد: **د/ طالب أحمد نور الدين**

مسير حاضنة الأعمال: **جامعة غرداية**

المقر الاجتماعي/ العنوان: **المنطقة العلمية، ص ب 455، غرداية، 47000، الجزائر**

رقم علامة الحاضنة: **1004253146** بتاريخ: **2025/04/10**

طبيعة المشروع: **مؤسسة ناشئة**

أشهد أن الطالب(ة) / الطلبة التالية أسماؤهم:

الإسم واللقب	الطور الدراسي	التخصص	الكلية
أحمد عبد الرحمان بوجرادة	M2	طاقات متجددة في الهندسة الكهربائية	كلية العلوم والتكنولوجيا
عبد الوهاب مولاي عمار	M2	طاقات متجددة في الهندسة الكهربائية	كلية العلوم والتكنولوجيا

تحت إشراف الأستاذ(ة)/الأساتذة التالية أسماؤهم:

الإسم واللقب	الرتبة	التخصص	الكلية
عبد الكريم مصباح	أستاذ محاضر ب	آلية	كلية العلوم والتكنولوجيا

تم توطينه على مستوى حاضنة أعمال جامعة غرداية - بمشروع تحت اسم:

Power forecasting to enable peak shaving in a gas turbine-based standalone microgrid with PV integration.

خلال السنة الجامعية: **2026/2025**

سلمت هذه الشهادة بطلب من المعني للإدلاء بها في حدود ما يسمح به القانون.

حرر في غرداية بتاريخ: 2026/04/26

مدير الحاضنة

وزارة التعليم العالي و البحث العلمي
حاضنة الأعمال
مسؤول حاضنة الأعمال
طالب أحمد نور الدين

جدول نموذج الأعمال BMC

شرائح العملاء (CS)
- مهندسون وفِرَق الطاقة
- مشغلو الشبكات الصغيرة والمرافق
- الباحثون والطلاب المتقدمون

العلاقة مع العملاء (CR)
- خدمة ذاتية مؤتمتة بالكامل
- فترة تجريبية مجانية
- الدعم الفني المتدرج والمخصص

قنوات التوزيع (CH)
- المنصة الرقمية المباشرة
- التسويق الرقمي المهني والموجه
- ملفات التقارير التصديرية

القيم VP(
- منصة متكاملة كخدمة
- تقليص الإجهاد التشغيلي للمعدات
- دقة هندسية موثوقة .

الأنشطة الرئيسية (KA)
- التطوير البرمجي
- تنقية ومعالجة البيانات
- إدارة المبيعات والتسويق والدعم

الموارد الرئيسية (KR)
- البنية التكنولوجية والموقع الإلكتروني
- الملكية الفكرية والخوارزميات
- البنية السحابية التحتية

الشركاء الرئيسيون (KP)
- مزودو خدمات الاستضافة السحابية
- مزودو بوابات الدفع الإلكتروني
- المعاهد البحثية والمكاتب الهندسية الاستشارية

مصادر الدخل والإيرادات(RS)
- باقات الاشتراكات الشهرية المتكررة
- باقة المبتدئين(Starter - $19/mo)
- الباقة المهنية (Professional - $49/mo)
- الاشتراكات المخصصة للمؤسسات

(هيكل التكاليف CS)
- تكاليف تشغيل البنية التحتية السحابية
- تكاليف التطوير والصيانة البرمجية
- تكاليف المبيعات والتسويق وبوابات الدفع

-1 شرائح العملاء**(Customer Segments - CS)**

- مهندسون وفِرَق الطاقة: الاستشاريون والمهندسون في المكاتب الهندسية ومجموعات العمل المتخصصة في دراسات استدامة الطاقة وتحسين كفاءة الشبكات.
- مشغلو الشبكات الصغيرة والمرافق :(Microgrid Operators & Utilities)الجهات والهيئات المسؤولة عن إدارة محطات التوليد الهجينة والمعزولة التي تدمج التوربينات الغازية التقليدية مع مصادر الطاقة المتجددة.
- الباحثون والطلاب المتقدمون :الأكاديميون والباحثون في كليات الهندسة ومراكز تطوير تقنيات الطاقة الذين يركزون على استشراف الأحمال ودمج الطاقة الشمسية الكهروضوئية.

-2 القيم المقترحة**(Value Propositions - VP)**

- منصة متكاملة كخدمة :(All-in-One SaaS)تحويل ملفات البيانات الخام (CSV) إلى لوحات تحكم تحليلية تفاعلية وقرارات استراتيجية جاهزة للتنفيذ دون حاجة لبرمجيات معقدة.
- تقليص الإجهاد التشغيلي للمعدات :خفض ساعات العمل الشاقة (GT Stress Hours) على التوربينات الغازية وحمايتها من التغيرات المفاجئة في الأحمال عبر الإدارة الذكية وتحديد الحجم المثالي للخلايا الشمسية.(PV Sizing)
- دقة هندسية موثوقة: تزويد فِرَق العمل بمؤشرات أداء دقيقة وصارمة للتنبؤ بالأحمال (مثل RMSE وMAE) مع مرونة كاملة في استخدام وتغيير وحدات قياس القدرة (ميجاواط، كيلواط، واط).
- كفاءة استثمارية وزمنية: توفير مئات الساعات من التحليلات اليدوية وبناء النماذج الرياضية، وتقديمها بأسعار مرنة وفي متناول الفئات المستهدفة مقارنة بالأدوات الاحترافية الاحتكارية.

-3 قنوات التوزيع**(Channels - CH)**

- المنصة الرقمية المباشرة :(eneroptix.online)هي القناة الأساسية والواجهة الرسمية للوصول وتجربة الخدمات، التسجيل المباشر، والاشتراك بالباقات.
- التسويق الرقمي المهني والموجه :استهداف صناع القرار والمهندسين والباحثين عبر المنصات المهنية مثل LinkedIn والمجتمعات التقنية المتخصصة بمجالات نظم القوى والميكروجريد.

- ملفات التقارير التصديرية :(ZIP/JSON Reports)تعمل التقارير المستخرجة والقابلة للمشاركة بين أعضاء الفريق كأداة تسويق مرجعية غير مباشرة تؤكد جودة واحترافية الخدمة.

4- العلاقة مع العملاء**(Customer Relationships - CR)**

- خدمة ذاتية مؤتمتة بالكامل :(Automated Self-Service)تجربة مستخدم انسيابية تتيح للعميل رفع البيانات والتحكم في إعدادات المحاكاة وقراءة الرسوم البيانية التفاعلية بشكل مستقل ومباشر.
- فترة تجريبية مجانية :(2-Day Free Trial)تقديم وصول كامل ومجاني لمدة يومين لبناء الثقة الكاملة في قدرات الخوارزميات ومحرك التنبؤ قبل دفع أي رسوم اشتراك.
- الدعم الفني المتدرج والمخصص :توفير دعم مخصص وسريع للمشتركين في الباقات المهنية، مع توفير خدمات إدارة حسابات، تخصيص نماذج المحاكاة، والتدريب للمؤسسات الكبرى.(Enterprise)

5- مصادر الدخل والإيرادات**(Revenue Streams - RS)**

باقات الاشتراكات الشهرية المتكررة :(SaaS Monthly Subscriptions)

- باقة المبتدئين :(Starter - $19/mo) مصممة للطلاب والباحثين والمشاريع التجريبية الصغيرة، وتمنح 10 تحليلات شهرياً.
- الباقة المهنية :(Professional - $49/mo)موجهة لفِرَق الهندسة والاستشارات، وتتيح 100 تحليل شهرياً مع ميزات متقدمة للتخصيص والتصدير الفوري.
- الاشتراكات المخصصة للمؤسسات :(Enterprise - Custom Pricing)عقود واتفاقيات تجارية سنوية أو شهرية مرنة للشركات والمرافق الكبرى لتقديم تحليلات غير محدودة ونماذج Python مخصصة بالكامل تتماشى مع طبيعة مشاريعهم.

6- الموارد الرئيسية **(Key Resources - KR)**

- البنية التكنولوجية والموقع الإلكتروني: الكود البرمجي للمنصة ، أنظمة الواجهات والواجهات الرسومية التفاعلية لعرض البيانات.
- الملكية الفكرية والخوارزميات :محرك التنبؤ والتحليل المبني بلغةPython ، الخوارزميات المسؤولة عن معالجة البيانات، حساب الفروقات الرياضية، وتقييم إجهاد التوربينات.(GT Stress Analysis)
- البنية السحابية التحتية: الخوادم وقواعد البيانات الآمنة المخصصة لمعالجة ملفات الطاقة الكبيرة وتخزين بيانات المشاريع بأعلى معايير الحماية والاستقرار.

7- الأنشطة الرئيسية (Key Activities - KA)

- التطوير البرمجي المستمر: صيانة وتحديث المنصة بانتظام، تسريع محركات التحليل الرياضي، وتطوير الأدوات التفاعلية وعناصر التحكم في الرسوم البيانية.
- تنقية ومعالجة البيانات :(Data Validation)ضمان خلو الخوارزميات من الأخطاء أثناء تدقيق ومعالجة ملفات الـ CSVالمرفوعة للشبكة.
- إدارة المبيعات والتسويق والدعم :إدارة عمليات التسجيل والاشتراكات، ربط بوابات الدفع، وحل المشكلات الفنية والهندسية التي تواجه المستخدمين.

8- الشركاء الرئيسيون(Key Partners - KP)

- مزودو خدمات الاستضافة السحابية :شركات البنية التحتية السحابية) مثل AWS أو Digital Ocean)لضمان الأداء الفائق والقدرة على معالجة العمليات الحسابية المعقدة في ثوانٍ معدودة.
- مزودو بوابات الدفع الإلكتروني :المنصات المسؤولة عن معالجة المدفوعات والاشتراكات بشكل آمن (PayPal,Stripe,SATIM)
- المعاهد البحثية والمكاتب الهندسية الاستشارية: الشراكات الاستراتيجية لتقييم كفاءة خوارزميات التنبؤ وتقديم التغذية الراجعة لتطوير النماذج الرياضية بشكل مستمر.

9- هيكل التكاليف(Cost Structure - CS)

- تكاليف تشغيل البنية التحتية السحابية: نفقات استضافة السيرفرات، معالجة البيانات السحابية (Cloud Computing)، وحفظ وتأمين قواعد بيانات المشتركين.
- تكاليف التطوير والصيانة البرمجية :الاستثمار في الكوادر البشرية من مطورين ومهندسي بيانات المشرفين على استقرار وتحديث الشيفرات البرمجية والخوارزميات.
- تكاليف المبيعات والتسويق وبوابات الدفع: الميزانيات المخصصة للحملات الإعلانية الرقمية الموجهة، ورسوم اقتطاع العمليات المالية والاشتراكات عبر الشبكة.

10- العلامة التجارية :

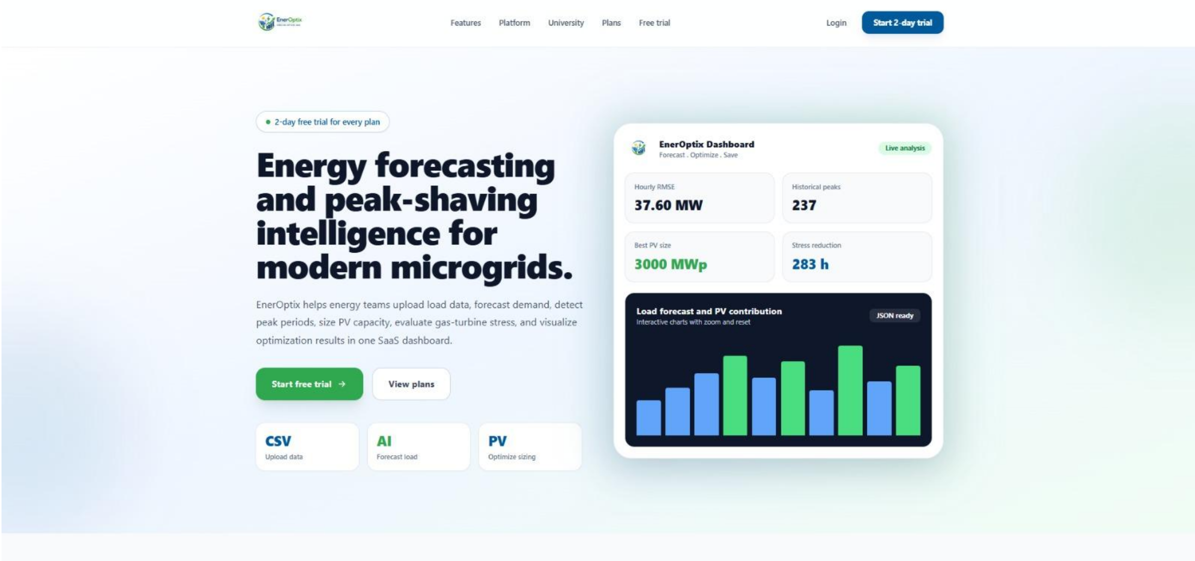
EnerOptix

FORECAST. OPTIMIZE. SAVE.

EnerOptix : هذا الاسم مستنبط من عدة كلمات الطاقة, (energy) , التحسين (optimze) , التحليل (Analysis)

دلالات الشعار :

يعبر الشعار الى استغلال مصادر الطاقة المتجددة وحلول التخزين الذكي من أجل توليد كهرباء نظيفة و تحسين الأداء والعوائد الاقتصادية , من خلال دمج تكنولوجيا المعلومات و بيانات الإحصاء مع مصادر الطاقة بهدف التنبؤ الدقيق بالاستهلاك الانتاج لتحسين المنظومة لتحقيق اقصى كفاءة و أعلى نسبة توفير ممكنة .



ترتكز هذه المنصة الرقمية الذكية على :

1. التنبؤ بالطاقة(Energy Forecasting)

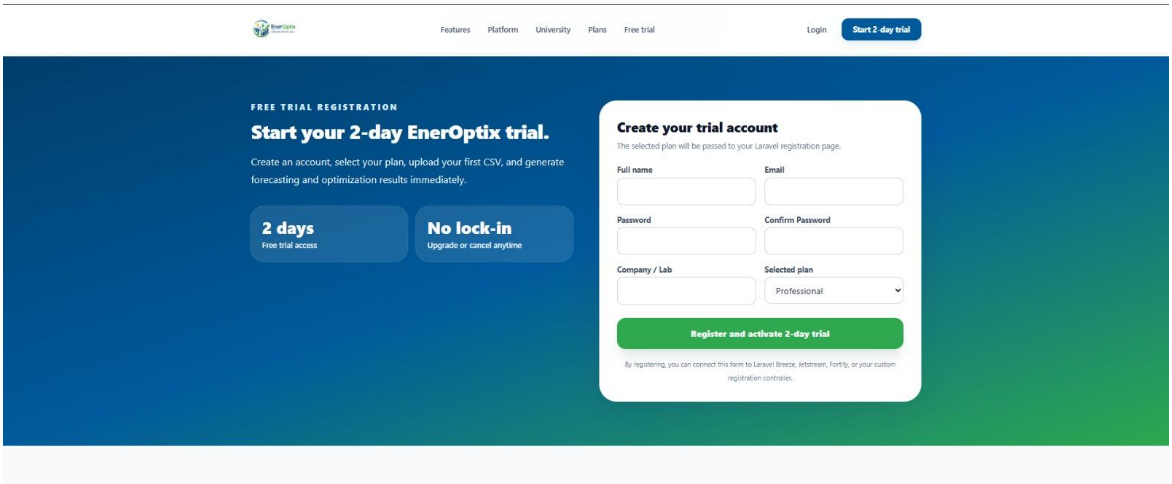
هو عملية تقدير وتوقع كميات الطلب (الاستهلاك) أو الإنتاج المستقبلي للطاقة الكهربائية بدقة، بناءً على تحليل البيانات التاريخية والظروف الجوية والمتغيرات التشغيلية.

- **في سياق المنصة :**يتم استخدام الذكاء الاصطناعي (AI) لتحليل بيانات الأحمال المرفوعة بصيغة CSV لتوقع الطلب المستقبلي.

2. تخفيض ذروة الطلب(Peak-Shaving)

هي استراتيجية لإدارة الأحمال الكهربائية تهدف إلى خفض كمية الطاقة المستأجرة من الشبكة أو من المولدات الرئيسية خلال فترات "الذروة" (التي يرتفع فيها الاستهلاك إلى حده الأقصى). يتم ذلك عادةً عن طريق الاستعانة بمصادر طاقة بديلة أو محلية خلال هذه الساعات الحرجة.

- **في سياق المنصة:** تهدف العملية إلى تحديد الحجم الأمثل لمحطات الطاقة الشمسية الكهروضوئية (**Best PV size**)لدمجها في الشبكات المصغرة (Microgrids). يساعد هذا التخفيض في تخفيف الإجهاد التشغيلي عن التوربينات الغازية المستمرة في العمل (**Gas-turbine stress**)، مما يقلل من فترات الضغط العالي عليها .



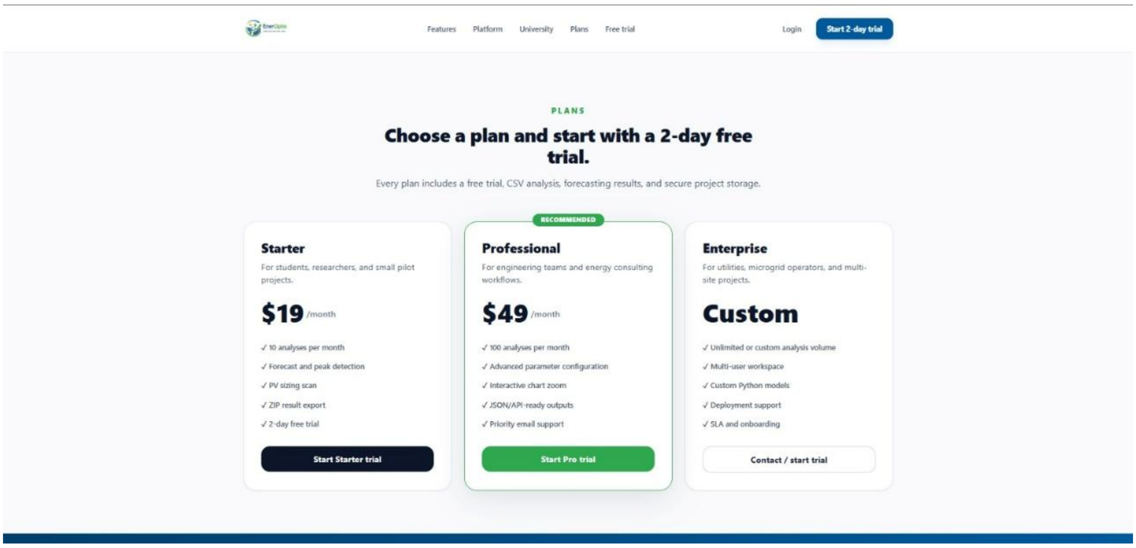
طبيعة المنصة وهدفها الأساسي :

المنصة مخصصة للمهندسين والمختصين في مجال الطاقة، حيث تتيح للمستخدم:

- رفع ملفات البيانات بصيغة CSV.
- توليد توقعات دقيقة وتحليلات لتحسين الأداء (Generate forecasting and optimization results).

تفاصيل العرض التجريبي

- المدة :فترة تجريبية مجانية لمدة يومين (2-day trial) بدون أي التزام طويل الأمد (No lock-in)، مع إمكانية الترقية أو الإلغاء في أي وقت.



خطط الاشتراك المتاحة :

تنقسم الخيارات في الصفحة إلى ثلاثة مستويات رئيسية تناسب فئات مختلفة من المستخدمين:

- **خطة المبتدئين - (Starter) بسعر 19$ شهرياً:**
  - **الفئة المستهدفة :**الطلاب، الباحثون، والمشاريع التجريبية الصغيرة.
  - **أبرز الميزات :**10 تحليلات شهرياً، التنبؤ وتحديد ذروة الاستهلاك، فحص حجم الأنظمة الكهروضوئية(PV sizing scan) ، وتصدير النتائج بصيغة.ZIP
- **الخطة الاحترافية - (Professional) بسعر 49$ شهرياً (موصى بها):**
  - **الفئة المستهدفة :**الفرق الهندسية وسير عمل استشارات الطاقة.
  - **أبرز الميزات :**100 تحليل شهرياً، إعدادات متقدمة للمتغيرات، تكبير تفاعلي للمخططات البيانية، مخرجات جاهزة لواجهة برمجة التطبيقات(JSON/API) ، ودعم فني ذو أولوية عبر البريد الإلكتروني.
- **خطة الشركات - (Enterprise) سعر مخصص:(Custom)**
  - **الفئة المستهدفة :**شركات المرافق الخدمية، مشغلو الشبكات الصغيرة(Microgrid) ، والمشاريع متعددة المواقع.
  - **أبرز الميزات :**حجم تحليلات غير محدود أو مخصص، مساحة عمل متعددة المستخدمين، نماذج بايثون مخصصة.(Custom Python models)

آلية عمل المنصة :

- **الرفع :(Upload)** يقوم المستخدم برفع بيانات الأحمال الكهربائية بصيغة ملفات ملفات CSV وتحديد أسماء الأعمدة الخاصة بالبيانات.

- **الإعداد :(Configure)** يتم تحديد وحدة القياس، الآفاق الزمنية للتنبؤ(Forecast horizons) ، عتبات الذروة(Peak thresholds) ، استطاعة التوربينات الغازية(GT power) ، ونطاق الطاقة الشمسية الكهروضوئية.(PV range)

- **التحليل :(Analyze)** يعتمد الموقع على محرك تنبؤ مبرمج بلغة **بايثون (Python)** لتوليد التوقعات، وتحديد أوقات الذروة، وحساب الحجم الأمثل للمحطة الشمسية الكهروضوئية (PV sizing)، بالإضافة إلى تقديم ملخص بصيغة .JSON

- **اتخاذ القرار :(Decide)** تعرض لوحة التحكم النتائج في شكل رسوم بيانية تفاعلية، مع إمكانية.

ابرز الميزات والخدمات :

1. إدارة وتحليل بيانات الأحمال (CSV upload workflow)

- تتيح المنصة رفع ملفات البيانات التي تحتوي على التوقيت الزمني (timestamp) وأعمدة الأحمال الكهربائية.

- تقوم المنصة تلقائياً بعمليات المعالجة الأولية والتحقق من صحة البيانات (preprocessing and validation).

2. التنبؤ بالأحمال (Load forecasting)

- توليد توقعات يومية وساعية لذروة الطلب على الطاقة.

- حساب مقاييس دقة التنبؤ الهندسية الأساسية مثل: **MAE** (متوسط الخطأ المطلق) و **RMSE** (جذر متوسط مربع الخطأ).

3. رصد فترات الذروة (Peak detection)

- تحديد فترات الذروة التاريخية والمستقبلية في الشبكة.

- إمكانية ضبط وتخصيص إعدادات "عتبة الإجهاد" (stress threshold) ومقاييس التباعد والبروز لتحديد القمم بدقة.

4. دراسة حجم الطاقة الشمسية (PV sizing scan)

- اختبار نطاقات وسعات مختلفة من الطاقة الشمسية الكهروضوئية (PV).

- تحديد التكوين الأمثل الذي يساهم بشكل مباشر في **تقليل ساعات الإجهاد على التوربينات الغازية** (gas-turbine stress hours) وخفض طاقة الحمل الزائد.

5. مرونة واجهة التحكم (Interactive charts & Configurable units)

- **تخصيص الوحدات:** تتيح اختيار وحدات قياس القدرة المناسبة للمشروع سواء كانت واط (W)، كيلوواط (kW)، أو ميجاواط (MW)، مع إدخال معاملات التوربينات الغازية والطاقة الشمسية بناءً عليها.
- **مخططات تفاعلية:** عرض الرسوم البيانية للأحمال التاريخية، التنبؤات، مساهمة الطاقة الشمسية، وذروة الطلب الشهري مع ميزات التكبير والتحكم.