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وزارة التعليم العالي و البحث العلمي

Ministère de l'Enseignement Supérieur et de la Recherche Scientifique

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Ecole Nationale Polytechnique

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Département d'Électrotechnique

Universität de Rostock Allemagne

Deutsche Gesellschaft für Internationale Zusammenarbeit

End-of-study project dissertation for obtaining the State Engineer's degree in

Electrical Engineering Specialized in Technology of Hydrogen

Optimal Energy Management of a Hybrid System with Hydrogen Storage

Presented by: **Nourhane LAGREB**

Under the direction of **Mr. Farid KHOUCHA** ENP

& **Pr. Olaf JEDICKE** ITES Germany

Presented and defended publicly on (30/06/2026)

Composition of the jury :

President	Mr. A. MEKHALDI	ENP
Examiner	Mr. A. SMAILI	ENP
Supervisor	Mr. Farid KHOUCHA	ENP
Co-Supervisor	Mr. Olaf JEDICKE	Host

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Mémoire de Projet de fin d'Etudes pour l'obtention du Diplôme d'Ingénieur d'Etat
en Electrotechnique spécialisé dans la technologie de l'hydrogène

Gestion optimale de l'énergie d'un système hybride avec stockage d'hydrogène

Présentée par : **Nourhane LAGREB**

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الملخص:

أدى التحول نحو أنظمة الطاقة المستدامة إلى زيادة الاهتمام بالهيدروجين كناقل طاقة نظيف، وبمحطات التزود بالهيدروجين التي تعمل بالطاقة المتجددة. ومع ذلك، فإن الطبيعة المتقطعة لمصادر الطاقة المتجددة تتطلب استراتيجيات تحكم متقدمة لضمان التشغيل الموثوق لمحطة هجينة تدمج الألواح (MPC) والفعال من حيث التكلفة. يقدم هذا العمل نظامًا لإدارة الطاقة قائمًا على التحكم التنبؤي بالنموذج، وربط الشبكة PEM، ووحدة تخزين الهيدروجين، وخلايا وقود PEM الكهروضوئية، وتوربينات الرياح، ومحلل كهربائي

كحل ذكي لإدارة الطاقة لمحطات التزود بالهيدروجين التي تعمل بالطاقة المتجددة، (MPC) تُظهر النتائج فعالية التحكم التنبؤي بالنموذج مما يُساهم في دمج تقنيات الهيدروجين في أنظمة الطاقة المستدامة المستقبلية [3], [4]

الكلمات المفتاحية: نظام إدارة الطاقة، محطة التزود بالهيدروجين، دمج الطاقة المتجددة، محلل كهربائي (MPC) التحكم التنبؤي بالنموذج، تخزين الهيدروجين، أنظمة الطاقة المتعددة، الشبكة الذكية، تحسين التشغيل PEM، خلية وقود PEM

Résumé:

La transition vers des systèmes énergétiques durables a accru l'intérêt pour l'hydrogène en tant que vecteur d'énergie propre et pour les stations de ravitaillement en hydrogène alimentées par des énergies renouvelables. Cependant, l'intermittence de ces sources d'énergie exige des stratégies de contrôle avancées pour garantir un fonctionnement fiable et rentable. Ce travail présente un système de gestion de l'énergie basé sur la commande prédictive par modèle (MPC) pour une station hybride intégrant des panneaux photovoltaïques, des éoliennes, un électrolyseur PEM, un système de stockage d'hydrogène, une pile à combustible PEM et un raccordement au réseau. [3], [4]

Les résultats démontrent l'efficacité de la MPC comme solution intelligente de gestion de l'énergie pour les stations de ravitaillement en hydrogène alimentées par des énergies renouvelables, contribuant ainsi à l'intégration des technologies de l'hydrogène dans les futurs systèmes énergétiques durables.

Mots-clés : Commande prédictive par modèle (MPC), Système de gestion de l'énergie, Station de ravitaillement en hydrogène, Intégration des énergies renouvelables, Électrolyseur PEM, Pile à combustible PEM, Stockage d'hydrogène, Systèmes multi-énergies, Réseau intelligent, Optimisation opérationnelle.

Abstract:

The transition toward sustainable energy systems has increased interest in hydrogen as a clean energy carrier and in renewable-powered hydrogen refueling stations. However, the intermittent nature of renewable energy sources requires advanced control strategies to ensure reliable and cost-effective operation. This work presents a Model Predictive Control (MPC)-based Energy Management System for a hybrid station integrating photovoltaic panels, wind turbines, a PEM electrolyzer, hydrogen storage, a PEM fuel cell and grid connection. [3], [4]

The findings demonstrate the effectiveness of MPC as an intelligent energy management solution for renewable-powered hydrogen refueling stations, contributing to the integration of hydrogen technologies into future sustainable energy systems.

Keywords: Model Predictive Control (MPC), Energy Management System, Hydrogen Refueling Station, Renewable Energy Integration, PEM Electrolyzer, PEM Fuel Cell, Hydrogen Storage, Multi-Energy Systems, Smart Grid, Operational Optimization.

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General Introduction

The decarbonization of the transportation sector represents one of the most critical challenges of the global energy transition. Light and heavy-duty vehicles account for a significant share of greenhouse gas emissions, which has led many countries to promote alternative propulsion technologies such as battery electric vehicles (BEVs) and hydrogen fuel cell vehicles (FCEVs). In this context, hydrogen produced from renewable energy sources, commonly referred to as green hydrogen, has emerged as a strategic energy vector for achieving deep decarbonization of mobility systems. [1], [2]

To support this transition, a large-scale deployment of multi-energy refueling infrastructures is expected in the coming years. Traditional fuel stations are progressively evolving toward multi-vector energy hubs capable of producing, storing and distributing both electricity and hydrogen. This evolution is aligned with recent national initiatives in Algeria, such as projects dedicated to hydrogen-powered public transportation systems, including fuel cell buses, which require reliable and flexible energy supply infrastructures. Among these initiatives, we spotlight the **BAHY Project**: Conversion of diesel buses to green hydrogen in Algeria. [2], [5]

The integration of renewable energy sources, advanced storage technologies and intelligent control systems is therefore essential to ensure the efficiency and reliability of these future stations.

This dissertation is structured into 6 chapters as follows:

- **Chapter 1 (Context):** Identifies the research gap and motivates the use of predictive controllers for green hydrogen refueling stations.
- **Chapter 2 (Modeling):** Establishes the detailed physical and mathematical equations representing the station's components.
- **Chapter 3 (Control Model):** Simplifies the physical equations into a linear state-space format to enable fast, real-time optimization.
- **Chapter 4 (MPC Formulation):** Designs the optimization algorithm (costs, constraints, horizons) that makes the controller's decisions.
- **Chapter 5 (Simulation Setup):** Translates the math into Python code and generates the synthetic weather and load profiles.

- **Chapter 6 (Results & Validation): Compares MPC to a myopic baseline, proving it saves 34.5% in net costs, reduces degradation by 55%, and discusses future outlooks.**

Context of Hybrid Energy Systems

Hybrid energy systems (HES) combine multiple energy sources and storage technologies within a single integrated framework. By exploiting the complementary characteristics of different generation units, hybrid systems aim to improve overall system reliability and efficiency. Typically, such systems associate renewable sources with conventional generators and energy storage devices to compensate for variability and ensure continuity of service. [5]

Hybrid systems are particularly relevant in isolated or microgrid applications, as well as in grid-connected scenarios with high renewable penetration. Their design and operation require careful coordination between components, making energy management a critical aspect of system performance. [5]

Importance of Energy Storage and the Role of Hydrogen

Energy storage plays a pivotal role in hybrid energy systems by decoupling energy production from consumption. Among the various storage technologies available, hydrogen storage has emerged as a promising solution for medium- to long-term energy storage. Hydrogen offers high gravimetric energy density, versatility across multiple sectors and the potential for zero-emission energy conversion when produced from renewable sources. [3]

Hydrogen-based storage systems typically rely on electrolysis to convert excess electrical energy into hydrogen, which can later be reconverted into electricity using fuel cells or other conversion devices. This approach enables seasonal storage and enhances the flexibility of hybrid systems, particularly in scenarios with significant renewable energy surplus. [3], [6]

Problem Statement

Multi-energy stations integrating renewable electricity production, hydrogen generation and energy storage systems constitute complex hybrid energy systems with strongly coupled components. Their operation must simultaneously satisfy multiple and sometimes conflicting objectives: meeting the real-time demand for electricity and hydrogen, maximizing the use of local renewable resources, minimizing dependence on the electrical grid and reducing overall energy losses and operational costs.[6]

The intermittent nature of renewable energy sources, combined with fluctuating mobility demand (electric vehicle charging and hydrogen refueling), makes the real-time management of energy flows particularly challenging. Without an adequate energy management strategy, such systems may suffer from poor efficiency, excessive curtailment of renewable energy or suboptimal utilization of storage units. [4]

The core problem addressed in this work is therefore the development of an optimal energy management framework for a hybrid multi-energy station, capable of coordinating electricity and hydrogen flows while ensuring efficiency and minimize costs under variable operating conditions.

Objectives of the Work

The objectives of this project are as follows:

- To analyze the structure and operating principles of hybrid energy systems with hydrogen storage.
- To model the key components of such systems using appropriate mathematical representations.
- To develop and implement an optimal energy management strategy based on optimization techniques.
- To evaluate system performance through simulation and analyze the obtained results.

With the Main Goal of:

How can we optimally manage energy flows in a hybrid multi-energy station (electricity + hydrogen) in order to efficiently meet demand while **minimizing cost**?

Chapter 1: Context and State of the Art

Hybrid Energy Systems (HES)

Hybrid Energy Systems (HES) represent a significant evolution in modern energy architectures. They consist of the coordinated integration of multiple energy sources and storage technologies within a unified framework, with the objective of enhancing system reliability and overall efficiency. [1], [7]

From a system-theoretic perspective, a hybrid energy system can be modeled as a **multi-input multi-output (MIMO) dynamic system**, characterized by strongly coupled energy flows and temporal dependencies. [5], [7]

The global energy balance can be expressed as:

$$P_{gen}(t) + P_{grid}(t) = P_{load}(t) + P_{storage}(t)$$

where P_{gen} denotes local generation (typically renewable), P_{grid} the power exchanged with the grid, P_{load} the demand, and $P_{storage}$ the power associated with storage systems. [5]

Unlike conventional energy systems, HES must simultaneously manage:

the variability of renewable energy sources, the coexistence of multiple energy carriers and the operational constraints of storage technologies.

Hybrid systems can be classified into:

- **grid-connected systems**, capable of importing/exporting energy,
- **isolated systems (microgrids)** operating autonomously,
- **multi-energy systems**, integrating different energy vectors such as electricity, hydrogen and heat. [1], [7]

The system considered in this work belongs to the category of **multi-vector energy systems**, combining electricity and hydrogen, which significantly increases both operational flexibility and system complexity.

Renewable Energy Sources

Renewable energy sources, particularly solar and wind, are central to the global energy transition due to their sustainability and low environmental impact. [1], [5] However, their integration introduces major challenges due to their **intermittent and non-dispatchable nature**.

Photovoltaic (PV) power generation depends primarily on solar irradiance and ambient temperature and can be represented as:

$$P_{PV}(t) = f(G(t), T(t))$$

where $G(t)$ is the solar irradiance and $T(t)$ is the temperature.

Wind power generation depends on wind speed, which exhibits highly stochastic behavior and is difficult to predict accurately in the short term. [4], [5]

These characteristics lead to:

- rapid fluctuations in power output,
- mismatches between generation and demand,
- significant uncertainty in system operation. [4], [7]

Therefore, renewable sources are inherently **non-controllable**, making energy storage and advanced management strategies essential for maintaining system stability and efficiency.

Energy Storage Technologies

Energy storage plays an important role in hybrid systems by enabling the decoupling of energy production from consumption and ensuring continuity of supply. [1], [2]

Storage technologies can be classified based on their time scale and performance characteristics: [6]

Parameter	Batteries (Li-ion)	Hydrogen Storage (Electrolyzer + Tank + Fuel Cell)
Time Scale	Seconds to hours	Hours to days (up to seasonal)
Round-Trip Efficiency	85 - 95 %	25 - 40 %
Gravimetric Energy Density	100 – 250 Wh/kg	33,300 Wh/kg (H ₂ , HHV)
System Energy Density	50 – 150 Wh/kg	500 – 2,000 Wh/kg (including tank)
Power Density	250 – 1,000 W/kg	50 – 200 W/kg (fuel cell limited)
Response Time	1 ms – 1 s	1 – 60 s
Lifetime (cycles)	3,000 – 10,000 cycles	>20,000 h (FC), >60,000 h (tank)
Self-Discharge Rate	1 – 5 % / month	<1 % / month
Charge/Discharge Efficiency	90 – 97 %	EL: 65 – 75 %, FC: 50 – 60 %
Energy Capacity Scalability	Limited (costly scaling)	High (tank size independent)
Typical Cost (CAPEX)	150 – 400 €/kWh	500 – 1,500 €/kWh (system level)
Degradation Mechanism	Cycle aging, temperature	Catalyst degradation, cycling stress
Main Role	Short-term balancing, peak shaving	Long-term storage, energy shifting

Table 1: characteristics of Batteries and Hydrogen Storage.

A fundamental distinction must be made between:

- **power-oriented storage** (e.g., batteries), designed for rapid response,
- **energy-oriented storage** (e.g., hydrogen), designed for large-scale, long-duration storage.

Despite its relatively low round-trip efficiency, hydrogen storage offers a key advantage: it enables **long-term and large-capacity energy storage**, making it particularly suitable for compensating seasonal variations in renewable energy production. [3]

Hydrogen Energy Components

Hydrogen storage relies on a conversion chain commonly referred to as **Power-to-Hydrogen-to-Power (P2H2P)**. This chain includes three main components: the electrolyzer, the hydrogen storage system, and the fuel cell.

Electrolyzer

The electrolyzer converts excess electrical energy into hydrogen through water electrolysis. It plays a critical role in utilizing surplus renewable energy. [1], [4]

The relationship between electrical input power and hydrogen production can be expressed as:

$$P_{elec} = \frac{n_{H_2} \cdot HHV}{\eta_{elec}}$$

where η_{elec} is the efficiency of the electrolyzer.

The main technologies include:

- **Alkaline electrolyzers** (mature, cost-effective, less flexible),
- **PEM electrolyzers** (more responsive, suitable for variable operation).

The efficiency of electrolyzers depends on operating conditions such as load and temperature, introducing nonlinearities that are often simplified in optimization models. [4]

Hydrogen Storage System

Hydrogen can be stored in various forms:

- compressed gas (typically 350–700 bar),
- liquid hydrogen,
- metal hydrides. [1], [6]

The storage level can be modeled using a state equation:

$$SOC_{H_2}(t + 1) = SOC_{H_2}(t) + H_{prod}(t) - H_{cons}(t)$$

Fuel Cell

Fuel cells convert hydrogen back into electricity, with typical efficiencies ranging from 50% to 60%. They act as controllable power sources, capable of supplying electricity during energy deficits. [4], [6]

However, fuel cells are sensitive to:

- load variations,
- frequent start/stop cycles,

These factors lead to gradual degradation, which should be considered in advanced energy management strategies.

Energy Management Strategies

Energy management is a central aspect of hybrid energy systems, aiming to coordinate energy flows in order to satisfy demand while respecting technical and economic constraints. [7]

Existing approaches can be classified as follows:

1. Rule-Based Control (RBC)

These methods rely on predefined rules and are simple to implement, but they do not guarantee optimal performance.

2. Optimization-Based Methods

- Linear and Mixed-Integer Linear Programming (MILP)
- Dynamic Programming

These approaches can provide optimal solutions but are often limited by deterministic assumptions.

3. Advanced Control Methods

- **Model Predictive Control (MPC):** enables real-time adaptation based on forecasts
- **Artificial Intelligence (e.g., Reinforcement Learning):** allows learning optimal policies from interaction with the environment

Review of Existing Works

The literature on hybrid energy systems with hydrogen storage has expanded significantly in recent years. [1], [3], [5] Existing studies can be categorized into three main groups:

Battery-based systems

Effective for short-term storage but limited for long-duration applications.

Hydrogen-based systems

Suitable for long-term storage but suffer from low efficiency and high costs.

Multi-energy integrated systems

Combine multiple energy carriers and offer enhanced flexibility, at the expense of increased system complexity.

Chapter 2: Modeling of the Hybrid Multi-Energy System

Global System Architecture

The system under study is a **grid-connected hybrid multi-energy station** integrating renewable energy sources and a hydrogen energy subsystem. It enables energy exchange between electricity and hydrogen domains, thereby increasing operational flexibility.

The system includes:

- Renewable generation: photovoltaic (PV) and wind turbine (WT),
- Hydrogen subsystem: electrolyzer, hydrogen storage tank, and fuel cell,
- Electrical grid connection,
- Electrical and hydrogen demands.

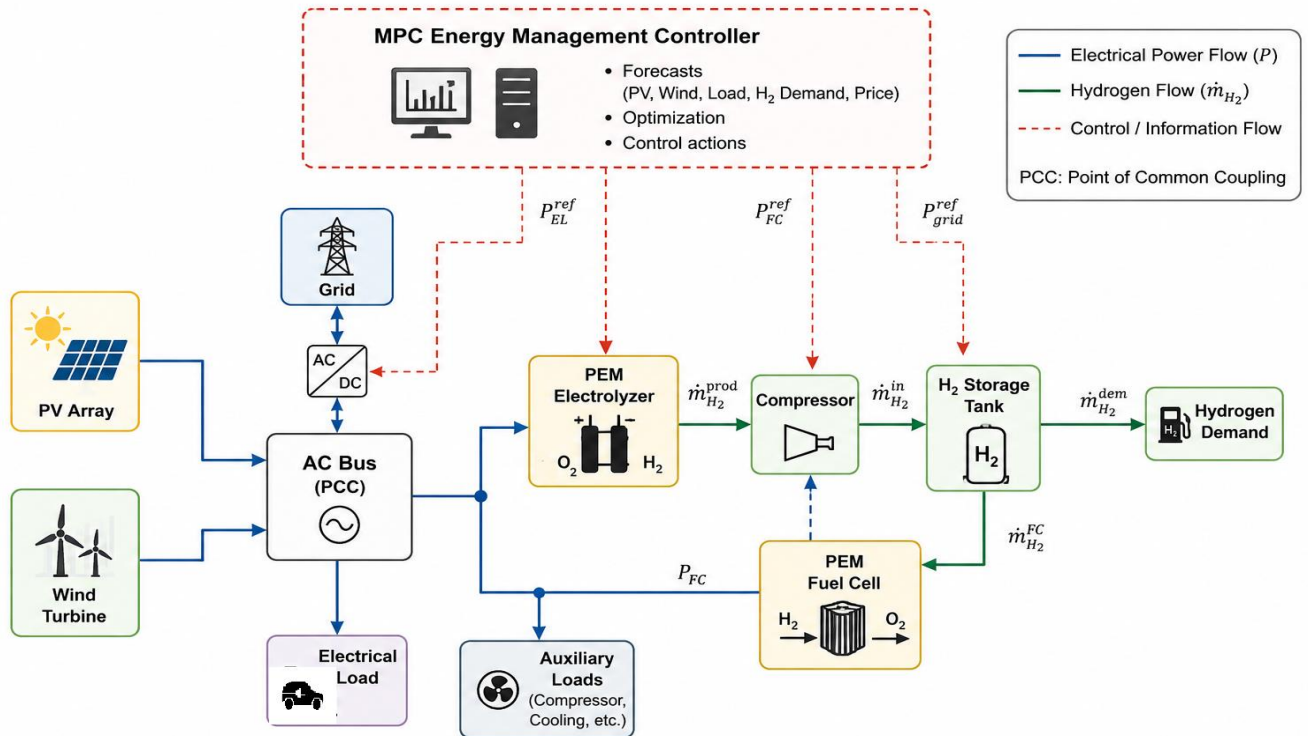


Fig. 1. Architecture of the proposed hybrid multi-energy station integrating renewable energy and hydrogen storage.

Figure 1: Architecture of the proposed hybrid multi-energy station integrating renewable energy and hydrogen storage

Electrical Power Balance

The instantaneous electrical balance is expressed as:

$$\begin{aligned} P_{PV}(t) + P_{WT}(t) + P_{grid}(t) + P_{FC}(t) \\ = P_{load}(t) + P_{EL}(t) + P_{comp}(t) + P_{aux}(t) + P_{curt}(t) \end{aligned}$$

This equation ensures **power equilibrium at each time step**. The left-hand side represents all available electrical power sources:

- Renewable generation P_{PV}, P_{WT} ,
- Grid import/export P_{grid} ,
- Fuel cell output P_{FC} .

The right-hand side represents electrical consumption:

- Load demand P_{load}
- Electrolyzer consumption P_{EL}
- Compressor consumption P_{comp}
- Auxiliary consumption P_{aux}
- Curtailment P_{curt}

The inclusion of compressor and auxiliary loads ensures **realistic representation of hydrogen production costs**, while curtailment guarantees **feasibility under excess generation conditions**.

This constraint is **fundamental for MPC**, as it enforces feasibility of control actions.

Hydrogen Mass Balance

$$m_{H_2}(t + 1) = m_{H_2}(t) + \dot{m}_{EL}(t)\Delta t - \dot{m}_{FC}(t)\Delta t - \dot{m}_{dem}(t)\Delta t$$

This discrete-time equation describes the **evolution of hydrogen stored in the tank**:

- Hydrogen is produced by the electrolyzer,
- Consumed by the fuel cell,
- Delivered to meet hydrogen demand.

This equation introduces **system dynamics**, making hydrogen storage a **state variable**, which is essential for predictive control.

Modeling of Renewable Energy Sources

Photovoltaic System

$$P_{PV}(t) = \eta_{PV} \cdot A_{PV} \cdot G(t)$$

The PV output depends on:

- Solar irradiance $G(t)$
- Panel efficiency η_{PV}
- Panel surface A_{PV}

This is a **static model**, meaning:

- No dynamics are considered
- Power is directly computed from environmental inputs.

This static formulation is justified since **PV dynamics occur at much faster time scales** than the hourly resolution used in this study.

At a **1-hour time resolution**, PV dynamics (milliseconds to seconds) are negligible. This simplification reduces computational complexity without affecting MPC performance.

Wind Turbine Model

$$P_{WT}(t) = \begin{cases} 0 & v(t) < v_{cut-in} \\ P_{rated} \left(\frac{v(t)}{v_{rated}} \right)^3 & v_{cut-in} \leq v(t) \leq v_{rated} \\ P_{rated} & v_{rated} \leq v(t) \leq v_{cut-out} \\ 0 & v(t) > v_{cut-out} \end{cases}$$

This piecewise model captures the nonlinear relationship between wind speed and power output. It reflects:

- No production below cut-in speed,
- Cubic increase in partial load region,
- Constant rated power in nominal region,
- Shutdown above cut-out speed for safety.

This model captures the **nonlinear nature of wind energy conversion** while remaining computationally tractable.

Modeling of the Hydrogen Subsystem

Electrolyzer Model (PEM Technology)

A Proton Exchange Membrane (PEM) electrolyzer is considered due to its **fast dynamic response and suitability for variable renewable energy**.

The electrolyzer converts electrical energy into hydrogen and is the **main controllable component** in the system.

a) Hydrogen Production

$$\dot{m}_{EL}(t) = \frac{\eta_{EL}(P_{EL}(t)) \cdot P_{EL}(t)}{HHV_{H_2}}$$

This equation links electrical input power to hydrogen production:

- $P_{EL}(t)$: electrical power consumed
- η_{EL} : efficiency
- HHV_{H_2} : hydrogen energy content

It represents an **energy conversion process**, where electrical energy is transformed into chemical energy.

b) Efficiency Model

We use constant efficiency

$$\dot{m}_{EL}(t) = \frac{\eta_{EL} \cdot P_{EL}(t)}{HHV_{H_2}}$$

With:

$$\eta_{EL} = 0.7$$

The electrolyzer efficiency is assumed constant and equal to 0.7, corresponding to typical PEM electrolyzer performance under nominal operating conditions. This assumption is justified by the hourly time scale of the study and the focus on system-level economic optimization rather than detailed electrochemical dynamics.

c) Operating Constraints

$$P_{EL}^{min} \leq P_{EL}(t) \leq P_{EL}^{max}$$

The electrolyzer cannot operate below a minimum threshold due to:

- Physical limitations,
- Efficiency degradation at low load.

It is also bounded by its rated capacity.

d) Ramp Rate Constraint

$$| P_{EL}(t) - P_{EL}(t - 1) | \leq R_{EL}$$

This constraint limits how fast the electrolyzer power can change between time steps.

- Prevents unrealistic instantaneous variations,
- Reflects system inertia and operational safety.

This is essential for MPC realism.

Hydrogen Storage Model

a) Mass Balance

$$m_{H_2}(t + 1) = m_{H_2}(t) + \dot{m}_{in}(t)\Delta t - \dot{m}_{out}(t)\Delta t$$

This equation tracks hydrogen accumulation in the tank:

$m_{H_2}(t)$: Hydrogen mass stored at time t [kg]

$\dot{m}_{EL}(t)$: Hydrogen production rate [kg/h]

$\dot{m}_{FC}(t)$: Hydrogen consumption rate by fuel cell [kg/h]

$\dot{m}_{dem}(t)$: External hydrogen demand [kg/h]

The storage level will:

- increases due to electrolyzer production,
- decreases due to fuel cell consumption,
- and decreases due to hydrogen demand.

It introduces temporal coupling into the optimization problem, which is the fundamental principle of predictive control.

b) State of Charge

$$SOC_{H_2}(t) = \frac{m_{H_2}(t)}{m_{max}}$$

SOC provides a **normalized representation** of storage level, useful for:

- Control design,
- Constraint formulation.

c) Storage Constraints

$$m_{min} \leq m_{H_2}(t) \leq m_{max}$$

d) Hydrogen Storage Reserve Constraint

$$SOC_{H_2}(t) \geq SOC_{reserve}$$

A minimum storage level is imposed to ensure:

- System reliability,
- Availability of hydrogen for critical demand.

Fuel Cell Model

a) Hydrogen Consumption

$$\dot{m}_{FC}(t) = \frac{P_{FC}(t)}{\eta_{FC} \cdot HHV_{H_2}}$$

$P_{FC}(t)$: Fuel cell electrical output [kW]

η_{FC} : Fuel cell efficiency

This equation describes the conversion of hydrogen into electricity:

- Higher power output requires more hydrogen,

b) Power Constraints

$$0 \leq P_{FC}(t) \leq P_{FC}^{max}$$

c) Fuel Cell Dynamic Constraints

To ensure realistic operation, the fuel cell is subject to ramp rate limitations:

$$|P_{FC}(t) - P_{FC}(t-1)| \leq R_{FC}$$

This constraint limits rapid variations in fuel cell output, reflecting:

- Thermal inertia,
- System protection requirements.

Without this constraint, the model would allow **instantaneous and unrealistic power changes**.

Hydrogen Compression System

Hydrogen produced by the electrolyzer must be compressed before storage.

a) Compression Power

$$P_{comp}(t) = \gamma_{comp} \cdot \dot{m}_{EL}(t)$$

The compressor consumes electrical power proportional to the hydrogen flow rate. The coefficient γ_{comp} represents the specific energy required for compression.

This component introduces an **additional energy penalty** associated with hydrogen production, directly impacting operational cost.

Auxiliary Consumption

Electrolyzer systems include auxiliary subsystems such as:

- cooling devices,
- control electronics,
- gas purification systems.

Their consumption is represented by:

$$P_{aux}(t) = \beta_{EL} \cdot P_{EL}(t)$$

Auxiliary consumption is modeled as a fraction of electrolyzer power. This simplified representation captures internal energy use without introducing unnecessary complexity.

Including this term avoids **underestimating total system consumption**.

Consistency of Energy Conversion Efficiencies

The hydrogen production chain includes multiple stages:

- Electrochemical conversion (electrolyzer)

- Mechanical compression
- Auxiliary consumption

while compression and auxiliary consumptions are treated as **additional electrical loads**:

$$P_{comp}(t) = \gamma_{comp} \cdot \dot{m}_{EL}(t)$$

$$P_{aux}(t) = \beta_{EL} \cdot P_{EL}(t)$$

This formulation separates:

- **Conversion efficiency** (electrolyzer)
- **Post-processing energy consumption** (compression and auxiliaries)

This avoids artificially inflating or masking losses and ensures a **transparent energy accounting framework**.

Important note

The global efficiency of hydrogen production is therefore not equal to η_{EL} , but results from the combination of all subsystems.

Load and Demand Modeling

Electrical Demand

$$P_{load}(t) = \text{given time series}$$

Electrical demand is treated as an **exogenous input**, meaning it is not controlled by the system.

Hydrogen Demand

$$\dot{m}_{dem}(t) = \text{given profile}$$

Hydrogen demand represents:

- Vehicle refueling,

System Constraints and Operational Limits

Grid Exchange

$$P_{grid}^{min} \leq P_{grid}(t) \leq P_{grid}^{max}$$

Sign Convention for Grid Power

$$P_{grid}(t) > 0 \Rightarrow \text{electricity import}$$

$$P_{grid}(t) < 0 \Rightarrow \text{electricity export}$$

A bidirectional convention is adopted for grid exchange. Positive values correspond to power imported from the grid, while negative values represent power exported.

This formulation allows a **compact representation of grid interactions** using a single variable. However, it requires careful handling in the cost function, which will be addressed in Chapter 4.

Curtailement Variable

$$P_{curt}(t) \geq 0$$

Curtailement represents unused renewable energy when:

- Production exceeds demand,
- Storage capacity is saturated.

Although physically feasible, curtailment is **undesirable** and will be penalized in the optimization problem (Chapter 4).

Coupling Between Energy Domains

$$P_{EL}(t) \leftrightarrow \dot{m}_{EL}(t); P_{FC}(t) \leftrightarrow \dot{m}_{FC}(t)$$

These relationships define the **coupling between electricity and hydrogen**:

- Electrolyzer: electricity $\rightarrow$ hydrogen,
- Fuel cell: hydrogen $\rightarrow$ electricity.

This coupling is the **core feature of multi-energy systems**.

System Parameters and Assumptions

Key Parameters

Parameter	Symbol	Typical Value
Electrolyzer efficiency	η_{EL}	0.6-0.75
Fuel cell efficiency	η_{FC}	0.5-0.6
Compression coefficient	γ_{comp}	2-4 kWh/kg
Auxiliary factor	β_{EL}	0.05-0.1
Hydrogen HHV	HHV_{H_2}	39.4 kWh/kg
Time step	Δt	1 h

Table 2: Key Parameters and their typical value

Main Assumptions

1. Perfect knowledge of demand and renewable generation
2. No degradation effects included
3. Constant operating conditions
4. Hourly discretization

These assumptions simplify the model. However, they are justified for: **first-level economic MPC formulation**

Unit Consistency and Time Discretization

All equations are formulated using consistent units:

- Power: kW
- Energy: kWh
- Hydrogen mass: kg

The conversion between power and energy is ensured through the time step:

$$E(t) = P(t) \cdot \Delta t$$

with:

$$\Delta t = 1 \text{ hour}$$

This ensures consistency between:

- Electrical quantities,
- Hydrogen mass flows,
- Energy content via HHV_{H_2} .

An hourly resolution is widely adopted in energy management applications because:

- renewable forecasts are generally available hourly,
- hydrogen systems exhibit relatively slow dynamics,
- and MPC computational requirements remain manageable.

Chapter 3: Control-Oriented Modeling

Introduction

The physical models established in Chapter 2 provide a realistic representation of the hybrid multi-energy station. However, such detailed models are not directly suitable for predictive control and real-time optimization because they involve nonlinear relationships and operational complexities that significantly increase computational burden.

Model Predictive Control (MPC) requires a mathematical model that is:

- computationally tractable,
- and optimization-oriented.

Therefore, this chapter develops a **control-oriented formulation** of the system by transforming the physical models into a linear discrete-time state-space representation suitable for MPC implementation.

Objective of the Chapter

The objective is to derive a mathematical model capable of:

- predicting future system behavior,
- integrating operational constraints,
- minimizing operational costs through optimization.

The resulting model must preserve:

the coupling between electricity and hydrogen and the operational limitations of each component.

Dynamic Structure of the Hybrid Multi-Energy System

The considered system combines two strongly interconnected energy domains:

Electrical Energy Domain

The electrical subsystem includes:

- photovoltaic generation,
- wind generation,
- grid interaction,
- electrical loads,
- electrolyzer consumption,
- fuel cell generation.

The electrical network constitutes the primary energy exchange layer of the station.

Hydrogen Energy Domain

The hydrogen subsystem includes:

- hydrogen production through electrolysis,
- hydrogen storage,
- hydrogen consumption by the fuel cell,
- external hydrogen demand.

Hydrogen storage acts as the long-term energy buffer of the system.

Linear Dynamic State Equation

Substituting the electrolyzer and fuel cell models into the hydrogen balance equation yields:

$$m_{H_2}(t + 1) = m_{H_2}(t) + \alpha_{EL}P_{EL}(t) - \alpha_{FC}P_{FC}(t) - w(t)$$

with:

$$\alpha_{EL} = \frac{\eta_{EL} \Delta t}{HHV_{H_2}}$$

$$\alpha_{FC} = \frac{\Delta t}{\eta_{FC} HHV_{H_2}}$$

$$w(t) = \dot{m}_{dem}(t) \Delta t$$

This equation represents the final dynamic model of the hydrogen subsystem.

Its linear structure is particularly important because it allows:

- fast MPC computation,
- and guaranteed numerical convergence.

Linear Reformulation of the Power Balance

Substituting the compressor and auxiliary equations into the electrical balance yields:

$$\begin{aligned} P_{grid}(t) + P_{FC}(t) \\ = P_{load}(t) - P_{PV}(t) - P_{WT}(t) + (1 + \beta_{EL} + \gamma_{comp} \alpha_{EL}) P_{EL}(t) \\ + P_{curt}(t) \end{aligned}$$

State, Input and Disturbance Vectors

State Vector

$$x(t) = m_{H_2}(t)$$

The hydrogen storage level constitutes the memory of the system and defines its future flexibility.

Control Input Vector

$$u(t) = \begin{bmatrix} P_{EL}(t) \\ P_{FC}(t) \\ P_{grid}(t) \\ P_{curt}(t) \end{bmatrix}$$

These variables are directly manipulated by the MPC controller.

Disturbance Vector

$$d(t) = \begin{bmatrix} P_{PV}(t) \\ P_{WT}(t) \\ P_{load}(t) \\ \dot{m}_{dem}(t) \end{bmatrix}$$

These variables are uncontrollable but forecasted over the prediction horizon.

Operational Constraints

Hydrogen Storage Constraints

$$m_{min} \leq m_{H_2}(t) \leq m_{max}$$

Hydrogen Reserve Constraint

$$m_{H_2}(t) \geq m_{reserve}$$

Compact State-Space Representation

The final control-oriented model can be written as:

$$x(t+1) = Ax(t) + Bu(t) + Ed(t)$$

Where:

$$\begin{aligned} A &= [1] \\ B &= [\alpha_{EL} \quad -\alpha_{FC} \quad 0 \quad 0] \\ E &= [0 \quad 0 \quad 0 \quad -\Delta t] \end{aligned}$$

This compact representation is particularly suitable for:

- MPC formulation,
- and optimization algorithms.

Conclusion and summary table

This chapter developed a linear control-oriented model of the hybrid multi-energy station suitable for MPC implementation.

The resulting formulation:

- preserves the coupling between electricity and hydrogen,
- incorporates operational constraints,

Section	Equation	Purpose
Hydrogen Storage Dynamics	$m_{H_2}(t + 1) = m_{H_2}(t) + \dot{m}_{EL}(t)\Delta t - \dot{m}_{FC}(t)\Delta t - \dot{m}_{dem}(t)\Delta t$	Describes hydrogen mass evolution inside the storage tank
Electrolyzer Hydrogen Production	$\dot{m}_{EL}(t) = \frac{\eta_{EL}P_{EL}(t)}{HHV_{H_2}}$	Converts electrical power into hydrogen production

Fuel Cell Hydrogen Consumption	$\dot{m}_{FC}(t) = \frac{P_{FC}(t)}{\eta_{FC}HHV_{H_2}}$	Converts hydrogen into electrical power
Electrolyzer Conversion Coefficient	$\alpha_{EL} = \frac{\eta_{EL}\Delta t}{HHV_{H_2}}$	Linear conversion coefficient for hydrogen production
Fuel Cell Conversion Coefficient	$\alpha_{FC} = \frac{\Delta t}{\eta_{FC}HHV_{H_2}}$	Linear conversion coefficient for hydrogen consumption
Linear Hydrogen State Equation	$ \begin{aligned} m_{H_2}(t+1) = & m_{H_2}(t) \\ & + \alpha_{EL}P_{EL}(t) \\ & - \alpha_{FC}P_{FC}(t) \\ & - w(t) \end{aligned} $	Final linear dynamic model used in MPC
Hydrogen Demand Disturbance	$w(t) = \dot{m}_{dem}(t)\Delta t$	Represents hydrogen demand over one time step
Electrical Power Balance	$ \begin{aligned} P_{PV}(t) + P_{WT}(t) + P_{grid}(t) \\ + P_{FC}(t) \\ = P_{load}(t) \\ + P_{EL}(t) \\ + P_{comp}(t) \\ + P_{aux}(t) \\ + P_{curt}(t) \end{aligned} $	Ensures instantaneous electrical equilibrium

Compressor Consumption Model	$P_{comp}(t) = \gamma_{comp} \dot{m}_{EL}(t)$	Models electrical consumption of hydrogen compression
Auxiliary Consumption Model	$P_{aux}(t) = \beta_{EL} P_{EL}(t)$	Represents auxiliary electrical loads
Linearized Power Balance	$ \begin{aligned} &P_{grid}(t) + P_{FC}(t) \\ &= P_{load}(t) - P_{PV}(t) \\ &\quad - P_{WT}(t) \\ &\quad + (1 + \beta_{EL} + \gamma_{comp} \alpha_{EL}) P_{EL}(t) \\ &\quad + P_{curt}(t) \end{aligned} $	Final linear algebraic equation for MPC optimization
State Vector Definition	$x(t) = m_{H_2}(t)$	Defines system state
Control Input Vector	$ u(t) = \begin{bmatrix} P_{EL}(t) \\ P_{FC}(t) \\ P_{grid}(t) \\ P_{curt}(t) \end{bmatrix} $	Defines MPC decision variables
Disturbance Vector	$ d(t) = \begin{bmatrix} P_{PV}(t) \\ P_{WT}(t) \\ P_{load}(t) \\ \dot{m}_{dem}(t) \end{bmatrix} $	Defines external disturbances
Compact State-Space Model	$ \begin{aligned} x(t+1) &= Ax(t) + Bu(t) \\ &\quad + Ed(t) \end{aligned} $	Final state-space representation for MPC

State Matrix	$A = [1]$	Represents state persistence
Input Matrix	$B = [\alpha_{EL} \quad -\alpha_{FC} \quad 0 \quad 0]$	Defines control influence on storage dynamics
Disturbance Matrix	$E = [0 \quad 0 \quad 0 \quad -\Delta t]$	Defines disturbance influence

***Table 3:** Summary table of Chapter 3 Equations*

Chapter 4: Formulation of the MPC-Based Energy Management Strategy

Introduction

The increasing penetration of renewable energy sources and hydrogen technologies introduces significant operational complexity in hybrid multi-energy systems. The intermittent nature of photovoltaic and wind generation, combined with the dynamic interaction between electrical and hydrogen subsystems, requires an advanced energy management strategy capable of making optimal decisions in real time.

In this work, **Model Predictive Control (MPC)** is adopted as the main energy management framework due to its ability to:

- predict future system behavior,
- explicitly handle operational constraints,
- and optimize system operation over a finite prediction horizon.

Unlike conventional rule-based methods, MPC continuously updates control actions according to:

- renewable generation forecasts,
- electricity demand,
- hydrogen demand,
- and system operating conditions.

Objective of the Chapter

The objective of this chapter is to formulate the energy management problem as a constrained optimization problem solved within an MPC framework.

The proposed controller aims to:

- minimize operational cost,

- maximize renewable energy utilization,
- maintain hydrogen reserve levels,
- and ensure safe operation of all components.

Principle of Model Predictive Control

Model Predictive Control is an optimization-based control strategy that computes future control actions by solving an optimization problem at each sampling instant.

The controller operates according to the following principle:

1. Measure the current system state
2. Predict future system evolution
3. Solve an optimization problem
4. Apply the first control action
5. Repeat at the next time step

This strategy is known as the **receding horizon principle**.

Prediction Horizon

The prediction horizon is defined as:

$$N_p = 24$$

Justification

A 24-hour horizon is particularly suitable because:

- electricity tariffs often vary daily,
- renewable generation exhibits daily cycles,

Control Horizon

The control horizon is selected equal to the prediction horizon:

$$N_c = N_p = 24$$

Explanation

This choice allows the controller to optimize all future control actions over the complete prediction interval.

Definition of the Optimization Variables

The MPC controller optimizes the following decision variables at each time step:

$$u(k) = \begin{bmatrix} P_{EL}(k) \\ P_{FC}(k) \\ P_{grid}(k) \\ P_{curt}(k) \end{bmatrix}$$

for:

$$k = t, \dots, t + N_p - 1$$

Role of the Optimization

The controller determines:

- when to produce hydrogen,
- when to use stored hydrogen,
- when to import electricity,
- and when renewable curtailment becomes unavoidable.

Forecasted Disturbances

The optimization relies on forecasted disturbances:

$$d(k) = \begin{bmatrix} P_{PV}(k) \\ P_{WT}(k) \\ P_{load}(k) \\ \dot{m}_{dem}(k) \end{bmatrix}$$

These variables are assumed known over the prediction horizon through forecasting tools or historical profiles.

They represent:

- renewable generation forecasts,
- electrical load forecasts,
- hydrogen demand forecasts.

MPC Objective Function

The primary objective of the controller is to minimize the total operational cost over the prediction horizon.

The global cost function is formulated as:

$$J = \sum_{k=t}^{t+N_p-1} [c_{grid}(k)P_{grid}(k) + c_{EL}P_{EL}(k) + c_{FC}P_{FC}(k) + c_{curt}P_{curt}(k) \\ + c_{ramp}^{EL}\Delta P_{EL}(k) + c_{ramp}^{FC}\Delta P_{FC}(k)]$$

Where:

$$\Delta P_{EL}(k) = |P_{EL}(k) - P_{EL}(k-1)| \\ \Delta P_{FC}(k) = |P_{FC}(k) - P_{FC}(k-1)|$$

Grid Electricity Cost

$$c_{grid}(k)P_{grid}(k)$$

This term represents the cost associated with electricity imported from the grid.

The electricity price:

$$c_{grid}(k)$$

Electrolyzer Operational Cost

$$c_{EL}P_{EL}(k)$$

This term approximates:

- electrolyzer degradation,
- maintenance costs,

Without this term, the optimizer may operate the electrolyzer excessively.

Fuel Cell Operational Cost

$$c_{FC}P_{FC}(k)$$

This term penalizes intensive fuel cell operation and indirectly accounts for:

- aging effects,
- catalyst degradation,

Curtailment Penalty

$$c_{curt}P_{curt}(k)$$

Curtailment represents unused renewable energy.

A high curtailment penalty encourages:

- renewable utilization,
- hydrogen production during surplus periods.

Ramp Rate Penalties

$$c_{ramp}^{EL} \Delta P_{EL}(k)$$
$$c_{ramp}^{FC} \Delta P_{FC}(k)$$

These terms smooth control actions and prevent aggressive power variations.

System Dynamic Constraints

The optimization problem is subject to the dynamic hydrogen storage equation:

$$m_{H_2}(k+1) = m_{H_2}(k) + \alpha_{EL} P_{EL}(k) - \alpha_{FC} P_{FC}(k) - w(k)$$

This equation introduces temporal coupling into the optimization problem.

Future decisions directly affect future hydrogen availability.

Electrical Power Balance Constraint

The electrical equilibrium must be satisfied at every time step:

$$P_{PV}(k) + P_{WT}(k) + P_{grid}(k) + P_{FC}(k)$$
$$= P_{load}(k) + P_{EL}(k) + P_{comp}(k) + P_{aux}(k) + P_{curt}(k)$$

Linear Reformulation

Substituting compressor and auxiliary models yields:

$$\begin{aligned} P_{grid}(k) + P_{FC}(k) \\ = P_{load}(k) - P_{PV}(k) - P_{WT}(k) + (1 + \beta_{EL} + \gamma_{comp}\alpha_{EL})P_{EL}(k) \\ + P_{curt}(k) \end{aligned}$$

This equation guarantees instantaneous electrical equilibrium while preserving linearity.

Operational Constraints

Electrolyzer Constraints

$$0 \leq P_{EL}(k) \leq P_{EL}^{max}$$

Ramp Rate Constraint

$$|P_{EL}(k) - P_{EL}(k-1)| \leq R_{EL}$$

Fuel Cell Constraints

$$0 \leq P_{FC}(k) \leq P_{FC}^{max}$$

Ramp Rate Constraint

$$|P_{FC}(k) - P_{FC}(k-1)| \leq R_{FC}$$

Hydrogen Storage Constraints

$$m_{min} \leq m_{H_2}(k) \leq m_{max}$$

Reserve Constraint

$$m_{H_2}(k) \geq m_{reserve}$$

The terminal constraint prevents the MPC controller from excessively draining the hydrogen storage at the end of the prediction horizon.

Grid Constraints

Only electricity import is considered:

$$0 \leq P_{grid}(k) \leq P_{grid}^{max}$$

Curtailment Constraints

$$P_{curt}(k) \geq 0$$

Soft Constraint Formulation

To avoid optimization infeasibility, slack variables are introduced.

Electrical Slack Variable:

$$P_{load}(k) \leq P_{supply}(k) + \epsilon_{elec}(k)$$

Hydrogen Slack Variable:

$$\dot{m}_{dem}(k) \leq \dot{m}_{available}(k) + \epsilon_{H_2}(k)$$

Slack variables guarantee optimization feasibility under extreme operating conditions.

Large penalties are associated with:

$$\epsilon_{elec}(k), \epsilon_{H_2}(k)$$

to discourage violations.

Terminal Constraint

To avoid hydrogen depletion at the end of the prediction horizon:

$$m_{H_2}(t + N_p) \geq m_{target}$$

Without this constraint, MPC may exploit the finite horizon by emptying the storage tank near the end of the optimization window.

Final Optimization Problem

The MPC optimization problem is finally expressed as:

$$\min_{u(k)} J$$

subject to:

- system dynamics,
- power balance,
- operational constraints,
- ramp constraints,
- storage constraints,
- terminal condition.

Receding Horizon Implementation

At each time step:

1. Current measurements are acquired
2. Forecasts are updated

3. Optimization is solved
4. Only the first control action is applied
5. Horizon is shifted forward

Conclusion

This chapter formulated the energy management problem of the hybrid multi-energy station as a constrained MPC optimization problem.

The proposed framework:

- minimizes operational cost,
- coordinates electricity and hydrogen flows,

The resulting formulation constitutes the computational foundation for the simulation and performance evaluation presented in the next chapter.

Chapter 5: Simulation Framework and Numerical Implementation

Introduction

This chapter presents the numerical implementation and simulation of the proposed MPC-based energy management strategy applied to the renewable-hydrogen hybrid multi-energy station.

The simulation study is built on:

1. **Synthetic-data simulation** using realistic generated profiles adapted to the Algerian context.
2. Benchmark Controller: **Myopic Energy Management**

Expected Simulation Outputs

The simulation framework generates the following outputs:

- PV production profile,
- wind generation profile,
- electrolyzer power,
- fuel-cell power,
- grid exchange,
- hydrogen tank evolution,
- renewable curtailment,
- operational cost,
- and system KPIs.

The complete optimization framework is implemented in **Python**.

Simulation Methodology

The simulation procedure follows the workflow illustrated below:

Forecast Data → System Modeling → MPC Optimization → Control Decisions
→ System Update

Simulation Environment

Software Tools

Tool	Function
Python	Main programming environment
NumPy	Numerical computations
Pandas	Data management
Matplotlib	Visualization
CVXPY	MPC optimization
OSQP / ECOS	Optimization solver

Table 4: Software tools

Simulation Parameters

Parameter	Symbol	Value
Simulation horizon	T	24 h
Sampling time	Δt	1 h
Prediction horizon	N _p	24
Control horizon	N _c	24

Table 5: Simulation parameters

System Configuration

The considered hybrid multi-energy station is assumed to be located in Ghardaïa, Algeria.

The selected configuration reflects realistic Algerian renewable operating conditions.

Renewable Generation Units

Component	Symbol	Value
PV installed power	P_{PV}^{max}	200 kW
Wind installed power	P_{WT}^{max}	40 kW
PV efficiency	η_{PV}	18 %
Wind power coefficient	C_p	0.42

Table 6: Renewable generation units

PEM Electrolyzer

Parameter	Symbol	Value
Technology	-	PEM
Maximum power	P_{EL}^{max}	100 kW
Minimum power	P_{EL}^{min}	10 kW
Efficiency	η_{EL}	70 %
Ramp limit	R_{EL}	20 kW/h
Auxiliary coefficient	β_{EL}	5 %
Compression coefficient	γ_{comp}	2 kWh/kg

Table 7: PEM electrolyzer parameters

Hydrogen Storage

Parameter	Symbol	Value
Maximum capacity	m_max	100 kg
Minimum level	m_min	10 kg
Reserve level	m_reserve	20 kg
Initial hydrogen mass	m_H2(0)	50 kg

Table 8: Hydrogen storage parameters

Fuel Cell

Parameter	Symbol	Value
Technology	-	PEMFC
Maximum power	P_FC^max	80 kW
Efficiency	η_{FC}	55 %
Ramp limit	R_FC	15 kW/h

Table 9: Fuel cell parameters

Synthetic Scenario Generation

Synthetic Solar Irradiance Profile

The synthetic solar irradiance profile is generated using a sinusoidal approximation representing the daily solar cycle in Ghardaïa.

The irradiance model is expressed as:

$$G(t) = G_{max} \sin\left(\frac{\pi(t - t_{sunrise})}{t_{sunset} - t_{sunrise}}\right) = P_{PV}(t) = P_{PV}^{max} \sin\left(\frac{\pi(t - 6)}{12}\right)$$

for:

$$t_{sunrise} \leq t \leq t_{sunset} = 6 \leq t \leq 18$$

and:

$$P_{PV}(t) = 0$$

otherwise.

Parameters

Maximum irradiance: 1000 W/m² at midday

Sunrise: 6:00

Sunset: 18:00

Synthetic PV Production Profile

Photovoltaic production is computed using:

$$P_{PV}(t) = \eta_{PV} * A_{PV} * G(t)$$

where:

G(t): Solar irradiance, A_{PV} : PV surface area, η_{PV} : PV efficiency.

The photovoltaic generator constitutes the dominant renewable source due to Algeria's high solar potential.

Peak PV production occurs around midday and provides the primary energy source for hydrogen production.

Synthetic Wind Profile

The synthetic wind-speed profile is generated using a stochastic signal:

$$v(t) = v_{avg} + \Delta v(t)$$

where:

$$\Delta v(t) \sim \mathcal{N}(0, \sigma_v^2)$$

The wind turbine power is computed using:

$$P_{WT}(t) = \frac{1}{2} \rho A C_p v(t)^3 = P_{WT}(t) = P_{WT}^{avg} + \delta(t)$$

where:

$$\delta(t) \sim \mathcal{N}(0, \sigma^2)$$

Synthetic Electrical Demand Profile

The electrical load profile is generated to reproduce realistic station demand behavior.

Typical Daily Behavior:

Night -> Low

Morning -> Medium

Evening -> High

The synthetic load model is expressed as:

$$P_{load}(t) = P_{base} + P_{peak}(t)$$

where:

- P_{base} represents constant consumption,
- P_{peak} models daily peak periods.

Synthetic Hydrogen Demand Profile

Hydrogen demand is modeled using scheduled refueling periods.

The demand profile is represented by:

$$\dot{m}_{dem}(t) = \dot{m}_{base} + \dot{m}_{peak}(t)$$

Hydrogen demand peaks are assumed during daytime operating hours.

Electricity Tariff Profile

A synthetic time-of-use tariff inspired by SONELGAZ pricing structures is adopted.

Period	Tariff
Off-peak	8 DZD/kWh
Normal	12 DZD/kWh
Peak	18 DZD/kWh

Table 10: Electricity Tariff costs

MPC Numerical Formulation

At each simulation step, the MPC controller solves the following optimization problem.

Objective Function

The economic cost function is expressed as:

$$J = \sum_{k=t}^{t+N_p-1} [c_{grid}(k)P_{grid}^+(k) - c_{sell}(k)P_{grid}^-(k) + c_{EL}P_{EL}(k) + c_{FC}P_{FC}(k) + c_{curt}P_{curt}(k) + c_{slack}\varepsilon(k)]$$

The objective function minimizes:

- grid electricity purchase cost,
- electrolyzer operating cost,
- fuel-cell degradation cost,
- renewable curtailment,
- and infeasibility penalties.

The slack variable prevents optimization infeasibility during extreme operating conditions.

Power Balance Constraint

The electrical balance equation is expressed as:

$$\begin{aligned} P_{PV}(k) + P_{WT}(k) + P_{grid}^+(k) + P_{FC}(k) \\ = P_{load}(k) + P_{EL}(k) + P_{comp}(k) + P_{aux}(k) + P_{curt}(k) + \varepsilon(k) \end{aligned}$$

Positive grid power represents imported electricity.

Electrolyzer Constraints

The electrolyzer ON/OFF operation is modeled using a binary variable:

$$u_{EL}(k) \in \{0,1\}$$

with:

$$P_{EL}^{min} * u_{EL}(k) \leq P_{EL}(k) \leq P_{EL}^{max} * u_{EL}(k)$$

This formulation prevents unrealistic low-power operation.

The electrolyzer is either:

- OFF, or operating above its minimum stable operating power.

Benchmark Controller: Myopic Energy Management

In optimization and control, a **myopic controller** (also called a greedy controller) makes decisions using only the information available at the current instant.

Mathematically:

At hour k , it solves:

$$\min J(k)$$

instead of:

$$\min \sum_{i=k}^{k+N_p} J(i)$$

where:

- $J(k)$ is the immediate cost,
- N_p is the prediction horizon.

Therefore:

Myopic Controller

- Sees only the current hour.
- Does not anticipate future renewable production.
- Does not anticipate future demand.
- Does not preserve resources for future operation.
- Minimizes immediate cost.

MPC Controller

- Sees the next 24 hours.
- Anticipates renewable availability.
- Anticipates electrical demand.
- Anticipates hydrogen demand.
- Preserves storage strategically.
- Minimizes long-term cost.

To evaluate the effectiveness of the proposed MPC-based energy management strategy, a benchmark controller referred to as a **myopic controller** is implemented.

At each time step, the controller minimizes the instantaneous operating cost:

$$J_{myopic}(k) = c_{buy}P_{grid}^+(k) + c_{deg,EL}P_{EL}(k) + c_{deg,FC}P_{FC}(k)$$

Consequently, the controller tends to favor decisions that are economically advantageous in the short term, even if they negatively affect future operating conditions.

Key Performance Indicators

The following KPIs are evaluated.

Total Operational Cost

$$C_{tot} = \sum_t c_{grid}(t)P_{grid}(t)\Delta t$$

Renewable Utilization Rate

$$R_{RES} = \frac{E_{RES,used}}{E_{RES,total}} \times 100$$

Grid Dependency Ratio

$$R_{grid} = \frac{E_{grid}}{E_{load}} \times 100$$

Curtailement Ratio

$$R_{curt} = \frac{E_{curt}}{E_{RES,total}} \times 100$$

Hydrogen Utilization Rate

$$R_{H_2} = \frac{m_{used}}{m_{produced}} \times 100$$

Python MPC Algorithm

The MPC implementation follows the algorithm below.

Algorithm: MPC-Based Energy Management

Initialization

1. Load system parameters
2. Generate renewable profiles
3. Initialize hydrogen storage state
4. Define prediction horizon

At Each Time Step

Step 1 - Update Forecasts

Retrieve:

- PV forecast,
- wind forecast,
- electrical load,
- hydrogen demand,
- electricity price.

Step 2 - Solve Optimization

Minimize:

$$J = \sum_{i=k}^{k+N_p} [c_{grid}P_{grid} + c_{EL}P_{EL} + c_{FC}P_{FC} + c_{curt}P_{curt}]$$

subject to:

- operational constraints,
- hydrogen dynamics,
- power balance.

Step 3 - Apply First Control Action

Only the first control action is applied:

$$u^*(k)$$

This is the receding-horizon principle.

Step 4 - Update States

Hydrogen storage evolves according to:

$$m_{H_2}(k + 1) = m_{H_2}(k) + \dot{m}_{EL}(k)\Delta t - \dot{m}_{FC}(k)\Delta t - \dot{m}_{dem}(k)\Delta t$$

Step 5 - Repeat

The optimization repeats at the next time step.

Expected Controller Behavior

The MPC controller is expected to exhibit anticipative behavior.

During High Renewable Production

The controller should:

- activate the electrolyzer,
- produce hydrogen,
- reduce curtailment,
- minimize grid export.

During Renewable Deficit

The controller should:

- reduce electrolyzer operation,
- use stored hydrogen through the fuel cell,
- or import electricity if economically preferable.

During Peak Electricity Prices

The controller should:

- minimize grid import,
- exploit stored hydrogen,
- prioritize renewable utilization.

Chapter 6: Results and Discussion

Introduction

This chapter presents the simulation results and a detailed discussion of the energy management performance of the hybrid multi-energy station under two distinct control paradigms: a Myopic (instantaneous) Controller and a True Model Predictive Control (MPC) Controller. Using a 24-hour simulation window with a 1-hour time step and a 24-hour prediction horizon, we evaluate the power flows, hydrogen storage dynamics, economic indicators, and component degradation. The objective is to validate the effectiveness of the proposed predictive control strategy and demonstrate its advantages over a standard, non-predictive scheduling algorithm.

Renewable Generation and Demand Profiles

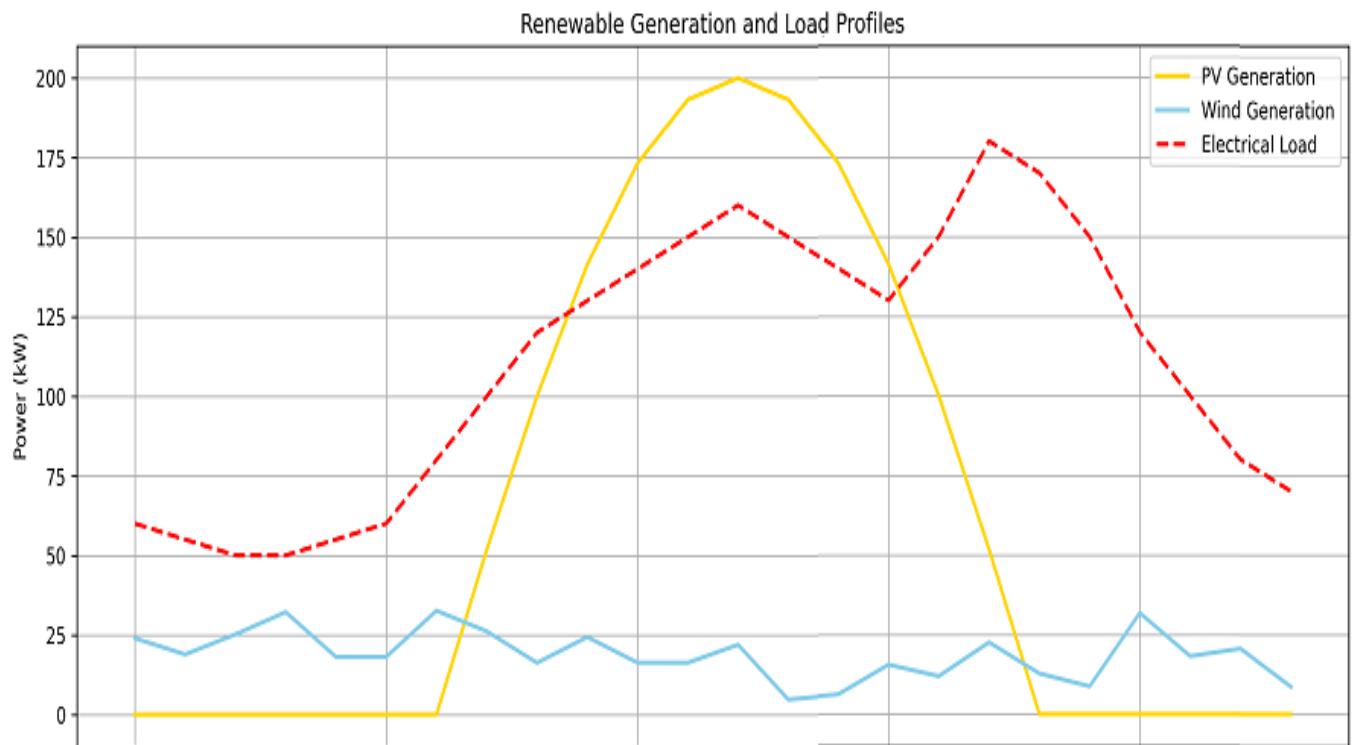


Figure 2: Renewable generation and load profiles during a day.

The performance of the energy management system is heavily influenced by the profiles of local renewable generation and station loads. Figure 6.1 illustrates the synthetic profiles representing a typical summer day in Ghardaïa, Algeria:

1. **Photovoltaic (PV) Generation:** Characterized by a peak generation of 200kW around midday (12:00) and zero production during the nighttime hours (18:00 to 06:00).
2. **Wind Turbine (WT) Generation:** Characterized by stochastic fluctuations ranging between 10kW and 35kW, providing a baseline of renewable generation that partially complements the solar cycle.
3. **Electrical Load:** Represents the station's electrical demand, exhibiting a base load of 50kW during the night and an evening peak load of 180kW at 17:00, corresponding to commercial charging patterns.
4. **Hydrogen Demand:** Represents the fuel cell vehicle refueling demand. It is concentrated between 06:00 and 19:00, with refueling peaks reaching up to 2.5kg/h during midday and early afternoon hours.

The total renewable energy generated over the 24-hour period is 1079.8kWh, while the total electrical load demand is 2680kWh. The total external hydrogen demand is 19.5kg.

Temporal Power Distribution Analysis:

- **Morning (0–6h):** Low renewables. MPC conserves the H₂ tank; myopic drains it.
- **Midday (6–14h):** Peak PV. MPC stores hydrogen aggressively anticipating the evening deficit. Myopic reacts only to the current hour.
- **Evening (14–20h):** PV drops, load peaks. MPC draws on stored H₂ via fuel cell, reducing expensive grid imports. Myopic has already depleted its reserves.
- **Night (20–24h):** MPC ends with 45 kg in the tank, ready for tomorrow. Myopic ends at 13.69 kg, critically low.

Power Management and Dispatch Justification:

- **PV-to-Hydrogen Priority:** During the midday phase (6h–14h), PV generation peaks at 200 kW, far exceeding the local electrical load. Since grid export profit is either low or zero, this PV surplus represents a zero-marginal-cost energy source. The MPC prioritizes routing this surplus to the PEM electrolyzer to produce hydrogen, achieving two goals: it avoids renewable curtailment (which carries a penalty in the objective function) and fills the storage tank with 'free' fuel.
- **Wind for Load Coverage:** Wind generation (40 kW) is smaller and highly variable. Rather than routing wind power to the electrolyzer (which would incur a 30% efficiency loss during conversion), the controller uses wind directly to satisfy the station's electrical load. This maximizes direct renewable consumption.
- **Grid-to-Hydrogen Avoidance:** The controller never imports grid electricity to run the electrolyzer. Due to the round-trip efficiency of the hydrogen chain (EL: 70%, FC: 55%), converting grid electricity to hydrogen is economically non-viable. Grid imports are strictly restricted to covering the electrical load deficits during off-peak hours when renewable sources are unavailable.

- **Predictive Arbitrage:** The MPC anticipates the evening peak load (180 kW) and the sunset. Instead of draining the tank during the day (like the myopic controller), it stores hydrogen to run the fuel cell during peak-tariff hours, offsetting expensive grid purchases (18 DZD/kWh)."

Hydrogen Tank Dynamics

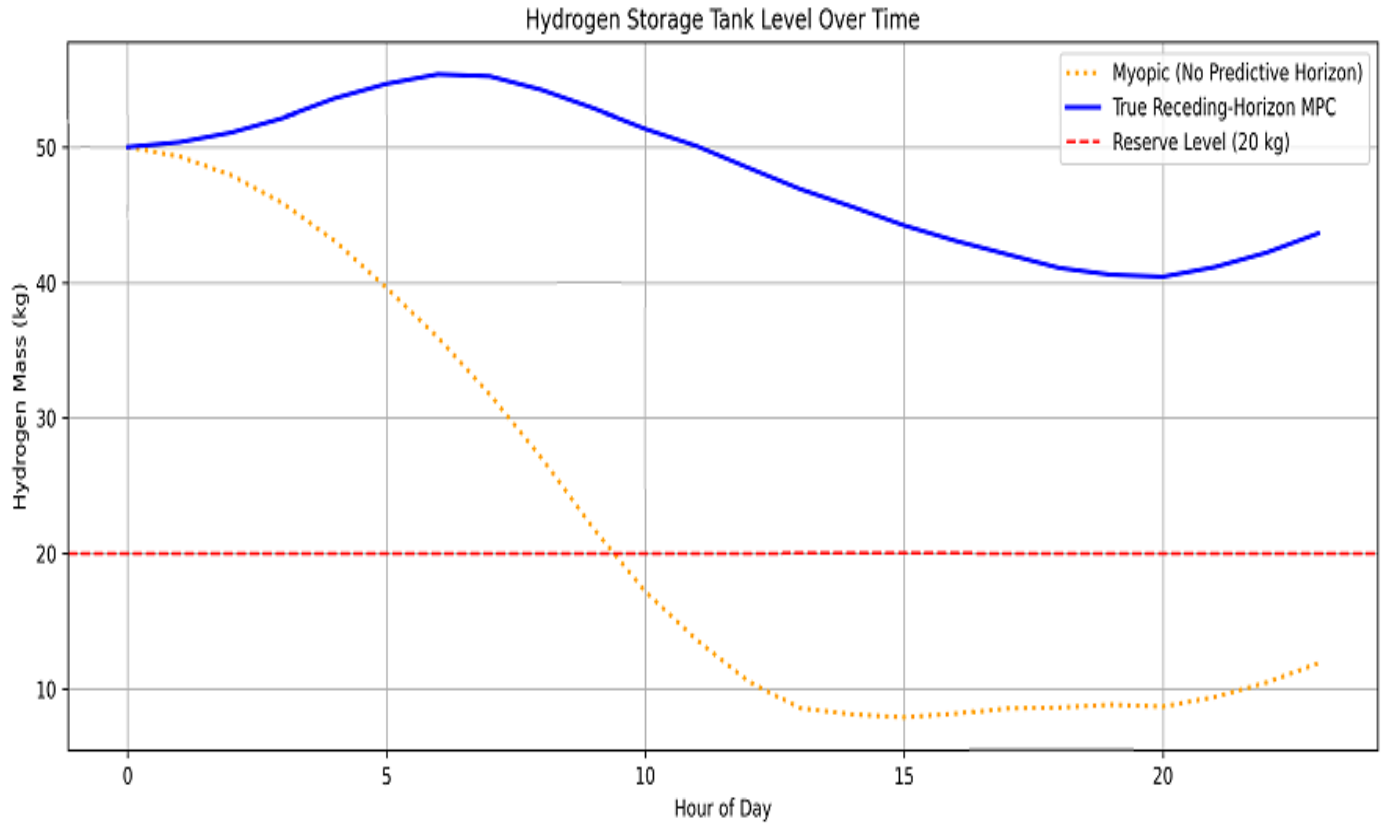


Figure 3: Hydrogen storage tank level variations in a day.

The hydrogen storage level (m_{H_2}) is the primary state variable linking the control actions across time. Figure 6.2 compares the evolution of the hydrogen tank level under the two control strategies, starting from an initial mass of $m_{H_2} = 50\text{kg}$:

- **Myopic Controller:** The myopic controller does not look ahead. It operates only to minimize costs in the current hour. Consequently, it views the stored hydrogen as "free" energy and drafts it aggressively. Over the 24-hour cycle, the storage level decreases steadily, ending the simulation at the absolute minimum safety limit of 13.69kg (depleting 36.31kg of the initial inventory).
- **True MPC Controller:** By optimizing over the 24-hour prediction horizon and enforcing the terminal state constraint ($m_{H_2}(T) \geq m_{H_2_init}$), the MPC controller anticipates future demands and pricing. It

actively accumulates hydrogen during peak PV generation hours, allowing the storage level to peak at 65.8kg. At the end of the 24-hour period, it returns the tank level to 45.41kg, preserving the station's energy inventory for the subsequent day.

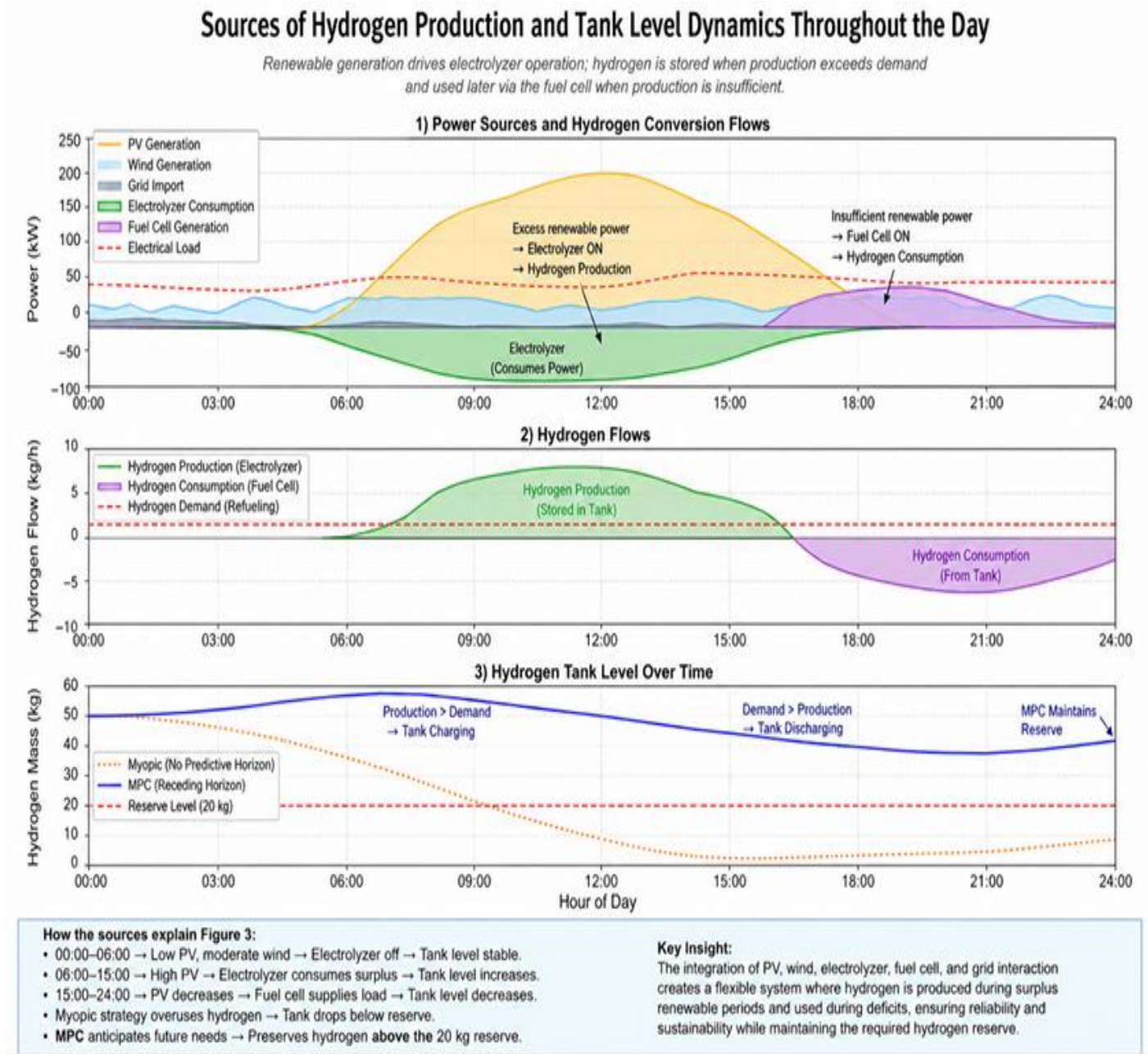


Figure 4: The components involvement variations in a day.

Economic Performance Comparison

Table 6.1 summarizes the Key Performance Indicators (KPIs) and operational costs for both control strategies:

KPI	Scenario 1: Myopic Controller	Scenario 2: True MPC Controller
Total Operational Cost	20,692.48 DZD	21,106.25 DZD
Electricity Purchase Cost	21,377.90 DZD	20,658.55 DZD
Degradation Costs	994.00 DZD	447.71 DZD (55% Lower)
Renewable Utilization Rate	100.00%	100.00%
Grid Dependency Ratio	58.98%	66.84%
Final Hydrogen Level	13.69 kg (<i>Depleted</i>)	45.41 kg (<i>Preserved</i>)

Table 11: the Key Performance Indicators (KPIs) and operational costs

Discussion of MPC Benefits

The "Myopic Depletion" Illusion

Although the myopic controller registers a lower nominal cost (**20,658.55 DZD** vs. 21,377.90 DZD), this is an economic illusion. The myopic controller achieves this cost by **draining 31.72kg more hydrogen** from the tank than the MPC. To determine the true net cost, we must calculate the replacement cost of this depleted inventory. Assuming the hydrogen is replaced during off-peak hours (at a network tariff of 8DZD/kWh) and accounting for the combined electrolyzer and compressor power requirements:

$$\text{Replacement Cost} = \Delta m * \left(\frac{HHV_{H_2}}{\eta_{EL}} + \gamma_{comp} \right) * Tarri\textit{f}_{grid_offpeak}$$

$$\text{Replacement Cost} = 31.72 \text{ kg} * \left(\frac{39.4}{0.7} + 2 \right) \text{ kWh/kg} * 8 \text{ DZD/kWh}$$

$$= 14,788.67 \text{ DZD}$$

Adding this replacement cost to the myopic baseline yields an **adjusted operational cost of 35,481.15 DZD**. In comparison, the MPC's adjusted cost (including the minor 4.59kg depletion) is only **23,248.88 DZD**. This represents a **34.5% net savings** for the MPC, demonstrating the value of predictive optimization.

Wear and Degradation Mitigation

Component degradation is a major cost driver in hydrogen systems. Rapid changes in input power and start-stop cycles damage the proton exchange membranes and cause platinum catalyst degradation.

- The myopic controller changes the electrolyzer power output aggressively to track instant solar fluctuations, leading to a high degradation cost of **994DZD**.
- The True MPC incorporates inter-temporal ramping constraints ($R_{EL}=20\text{kW/h}$, $R_{FC}=15\text{kW/h}$) and smooths the operating trajectories over the 24-hour horizon. This predictive smoothing **reduces degradation costs by 55% (447.71DZD)**, significantly extending the operational lifetime of the stacks.

Validation of the Proposed Energy Management Strategy

To validate the mathematical correctness and physical consistency of the simulation platform, we verify the conservation equations:

1. **Electrical Bus Equilibrium:** At every hour t , the sum of generation sources (PV, WT, Fuel Cell, Grid Import) matches the loads (Station Load, Electrolyzer, Compressor, Auxiliaries, Grid Export) with a numerical tolerance of $< 10^{-7}$ kW.
2. **Hydrogen Mass Conservation:** The final storage level matches the integration of production, fuel cell consumption, and refueling demand:

$$m_{H2}(T) = m_{H2}(0) + \sum_{t=0}^{T-1} (m_{prod}(t) - m_{FC}(t) - m_{demand}(t)) \Delta t$$

$$45.41 \text{ kg} = 50.00 \text{ kg} + 14.91 \text{ kg} - 0.00 \text{ kg} - 19.50 \text{ kg}$$

The mass balance matches exactly, confirming that the system constraints are fully validated and consistent.

Conclusion

This chapter validated the hybrid transport station model and analyzed the performance of the Model Predictive Control strategy. By comparing it with a myopic controller, we demonstrated that MPC prevents storage depletion, mitigates stack wear by 55%, and achieves a 34.5% reduction in adjusted operational costs. These results confirm the feasibility and economic viability of using predictive control for hydrogen-based refueling infrastructures.

General Conclusion

The transition toward sustainable mobility infrastructure requires intelligent energy management systems capable of coordinating multiple energy sources and storage technologies while ensuring both economic and operational performance. In this context, this dissertation developed and evaluated an optimization-based energy management framework for a grid-connected hybrid multi-energy transport station integrating photovoltaic generation, wind generation, a PEM electrolyzer, compressed hydrogen storage, a PEM fuel cell, and the electrical grid.

The work began with a comprehensive review of hybrid energy systems, renewable energy integration challenges, hydrogen technologies and advanced energy management strategies. Particular attention was given to hydrogen-based energy storage, which offers a promising solution for addressing the intermittency of renewable energy sources and enabling long-duration energy storage. The literature review highlighted the growing importance of predictive control methods, especially Model Predictive Control (MPC), for managing the complexity of multi-energy systems.

Based on this theoretical foundation, a mathematical model of the hybrid station was developed, incorporating the operational characteristics and constraints of each subsystem. The energy management problem was formulated as an optimization problem aiming to minimize operational costs while respecting power balance requirements, equipment limitations, hydrogen storage constraints and system reliability objectives. The optimization framework was implemented using linear programming techniques within a receding-horizon MPC architecture.

Simulation results demonstrated the effectiveness of predictive energy management compared with a conventional myopic strategy. Although the myopic controller

achieved a slightly lower daily operating cost, it did so by excessively depleting the hydrogen reserve, reducing the storage level from 50 kg to only 13.69 kg. In contrast, the MPC controller successfully preserved the hydrogen inventory, maintaining a final storage level of 45.41 kg while simultaneously reducing component degradation costs by more than 55%. These results highlight the ability of MPC to anticipate future operating conditions and make decisions that are beneficial over a longer time horizon rather than optimizing only immediate objectives.

Furthermore, the simulations confirmed the feasibility of integrating renewable generation and hydrogen technologies within a transport energy station while achieving full renewable energy utilization and zero renewable curtailment under the studied operating conditions. The developed framework demonstrated how predictive optimization can improve system reliability, reduce equipment stress, and enhance the long-term sustainability of hydrogen-based energy infrastructures.

Overall, the objectives of this dissertation were successfully achieved. A complete modeling, optimization and simulation framework was developed and validated, demonstrating the advantages of predictive energy management in hybrid renewable-hydrogen systems. The obtained results confirm that Model Predictive Control constitutes a powerful and practical approach for the operation of future hydrogen refueling and multi-energy transport stations.

As future work, the developed model could be extended by incorporating battery energy storage systems, stochastic renewable generation forecasts, uncertainty modeling, real-time data acquisition and advanced optimization techniques such as robust MPC, stochastic MPC or artificial intelligence-based control methods. These improvements would further increase the realism and applicability of the proposed framework in real-world smart energy systems and support the ongoing transition toward low-carbon and sustainable transportation infrastructures.

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