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AFRICAN CENTER OF EXCELLENCE IN ENERGY FOR SUSTAINABLE DEVELOPMENT

A MASTER THESIS

Modeling and Optimization of Energy Management Systems with Solar-Load Balancing in a Smart Campus: Huye Campus as a Case Study

Submitted to the African Center of Excellence in Energy for sustainable development (ACE-ESD), in partial fulfillment of the requirement for the degree of

Master of Science

in

ELECTRICAL POWER SYSTEMS

by

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October 2025

Advancing Sustainable Energy Solutions for Smart Campuses

Energy Management System

Solar PV + Storage + Smart Control

Optimizing Energy Efficiency through

Intelligent System Integration

Declaration

I, **NDAYISHIMIYE Martin**, declare that this thesis titled **"Modeling and Optimization of Energy Management Systems with Solar-Load Balancing in a Smart Campus: Huye Campus as a Case Study"** is my original work and has not been presented for a degree at the University of Rwanda or any other university.

All sources of materials used for this thesis have been fully acknowledged and referenced in accordance with academic standards.

This work represents my own independent research conducted under the supervision of Jean Marie Vianney BIKORIMANA, Ph.D.

Student Declaration

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This thesis has been submitted for examination with my approval as the university supervisor.

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Abstract

This study addresses the critical challenge of optimizing energy management in a smart campus environment through the integration of solar photovoltaic (PV) systems, energy storage, and dynamic load balancing. Focusing on the Huye campus of the University of Rwanda, the project develops a robust energy management system (EMS) that takes advantage of predictive analytics, stochastic and robust optimization techniques, and real-time Model Predictive Control (MPC) to minimize grid reliance, reduce operational costs, and enhance sustainability. By analyzing historical energy consumption patterns (2019–2023) and simulating scenarios such as sunny, cloudy, and grid outage conditions, the EMS demonstrates a reduction of **60–92%** in energy costs through prioritized solar utilization, demand response (DR) strategies, and optimization of energy storage. A Decision Support Tool (DST) is integrated to provide actionable insights, enabling campus managers to make data-driven decisions about energy efficiency. Key results include an **81%** reduction in grid dependency, a validated photovoltaic capacity of 848 kWp, and a scalable framework applicable to educational institutions in solar-rich regions. Key innovations include a scenario-based resilience framework for cloudy or rainy days and a Decision Support Tool (DST) that uses data-driven insights, predictive analytics, and actionable recommendations to enhance system efficiency, reliability, and sustainability. Simulations demonstrate a 4.2-hour backup during grid outages and a projected 6.2-year payback period for the 848-kWp PV system. The work aligns with Rwanda's National Energy Policy (2023) and offers a replicable model for regional educational institutions.

Contents

List of Tables

List of Figures

Acronyms

AC Alternative Current. 17

AI Artificial Intelligence. 12

BSS Battery Storage System. 17

DER Distributed Energy Resources. 8

DHI Direct Horizontal Irradiation. 2

DNI Direct Normal Irradiation. 2

DoD Depth of Discharge. 82

DR Demand Response. 6, 13, 70

DST Decision Support Tool. 15, 62

EMS Energy Management System. 5, 8, 9, 11, 13, 14, 16, 17, 42, 50, 52, 69

ESS Energy Storage System. x, 3, 18, 39, 40, 70

GA Genetic Algorithm. 9

HRES Hybrid Renewable Energy System. 11, 12

ICT Information and Communication Technologies. 8

MILP Mixed-Integer Linear Programming. 11

MOPSO Multi-Objective Particle Swarm Optimization. 9

MPC Model Predictive Control. 11, 13, 18, 52

PV Photovoltaic. x, 1, 2, 3, 4, 5, 6, 8, 13, 14, 17, 24, 39, 40, 43, 50

RE Renewable Energy. 13

SSNN Smart Superficial Neural Network. 10

UR University of Rwanda. ix, 2, 3, 7, 14, 39

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Finally, I acknowledge the scholars whose work informed this research; their contributions laid the foundation upon which this study was built. Although I accept full responsibility for any shortcomings in this work, its strengths are a testament to the collective support I have been privileged to receive.

All blessings!

Dedication

This work is dedicated with gratitude to:

- **Almighty God**, for divine guidance and strength throughout this journey
- **My beloved wife and children**, for their unwavering love, patience, and sacrifice
- **My project supervisor, Jean Marie Vianney BIKORIMANA, Ph.D**, for his expert mentorship and steadfast support
- **My co-workers, classmates, and friends**, for their camaraderie and encouragement

— May this work honor their contributions —

1

Introduction and Background of the project

1.1 Introduction

With the global shift toward sustainable energy and the urgency of addressing climate change, educational institutions are uniquely positioned to adopt and present renewable energy solutions. Rwanda's national energy vision emphasizes sustainability, energy efficiency, and the use of renewable technologies to achieve a low carbon economy. This project aligns with these goals by proposing the integration of Photovoltaic (PV) systems with energy storage solutions and advanced load balancing strategies for the Huye Campus.

The challenges of rising energy costs, carbon emissions, and the need for reliable power compel campuses like Huye to transition from conventional to smart energy management systems. This study aims to develop a model that optimizes energy consumption and maximizes the use of renewable energy resources through predictive load balancing, minimizing reliance on the national grid. It will also provide scalable insights that can be applied to other educational institutions aiming to adopt sustainable energy practices.

Rwanda's energy vision highlights a commitment to energy access, renewable solutions, and economic growth while addressing environmental challenges. The country aims to be a regional leader in clean energy and contribute to global climate efforts through strategic investments, policy reforms, and community engagement, envisioning a future of inclusive and sustainable energy [3].

Driven by the will of the Rwandan government to increase sustainability, mitigate concerns about climate change, increase energy efficiency, and reduce energy costs, the global shift towards smart campuses marks a significant improvement in energy resource management [4]. As educational institutions embrace sustainable energy systems, there is a vital need for innovative energy management strategies that integrate renewable sources while optimizing consumption and costs.

1.2 Background

The University of Rwanda (UR) was established by Law N°27/2013 of 24/05/2013 governing organization, and the functioning of Higher Education is among the government priorities as a new foundation for development. By its geographical position (-02.615412°, 029.743861°), photovoltaic power potentials with high Direct Normal Irradiation (DNI) and Direct Horizontal Irradiation (DHI) (Figure 1.2), Huye campus has the will to host a renewable and clean energy project to mitigate local problems raised by relying on the national grid network, monthly expenditure from electricity bills (Figure 1.3) and environment related impacts.

The growing demand for energy and environmental issues has sparked a growing interest in renewable energy solutions, especially within educational institutions. Integrating renewable energy sources, such as PV systems, with energy storage technologies presents a promising approach to address these challenges. Universities and colleges are well suited as test environments for implementing and studying the integration of renewable energy and energy storage systems, as they typically have substantial energy needs and can serve as living laboratories for sustainable energy practices. By incorporating these Renewable Energy systems, educational institutions can not only reduce their environmental impact and energy costs but also showcase innovative solutions to the wider community and contribute to the progress of renewable energy integration research.

As one of the largest and most populated campuses in the UR (Figure 1.1), it can host more than 10,000 students while the number of accommodated students in the main campus student accommodation facilities is approximately 3,000. With its four campus sites, it also has many buildings with different usage, walkways, and roads. The main campus also has a student kitchen, restaurant, and canteen, playgrounds and recreation, as well as classrooms and office buildings. All of these facilities need efficient and steady electrical energy to run different activities on campus during the day and night.

As global energy demands rise and environmental concerns intensify, the integration of renewable energy sources into traditional power systems should be strongly encouraged, particularly in large campuses such as the Huye campus. Transforming traditional campuses into smart campuses, using advanced technologies to improve sustainability, energy efficiency, and environmental stewardship, represents an ideal setting for such integration. Educational institutions have the unique opportunity to serve as living laboratories for sustainable energy practices, showcasing innovative solutions, and contributing valuable insights to the adoption of PV and Energy Storage System (ESS).

This research project focuses on "Modeling and Optimization of Energy Management Systems with Solar-Load Balancing in a Smart Campus" with generator backup, with the goal of transforming a traditional university campus into a Smart and Energy-Efficient Campus/ Green Campus. The integration of renewable energy sources into existing power systems will be a significant step towards sustainable development. The integration of Solar PV systems offers a viable solution for enhancing energy efficiency and reliability. The optimized energy management system will ensure us cost-effectiveness, reliability, and sustainability leading us to the possibility of supplying excess power generated by the HES to the utility grid at a fixed sales price or through a Net Metering scheme [5].

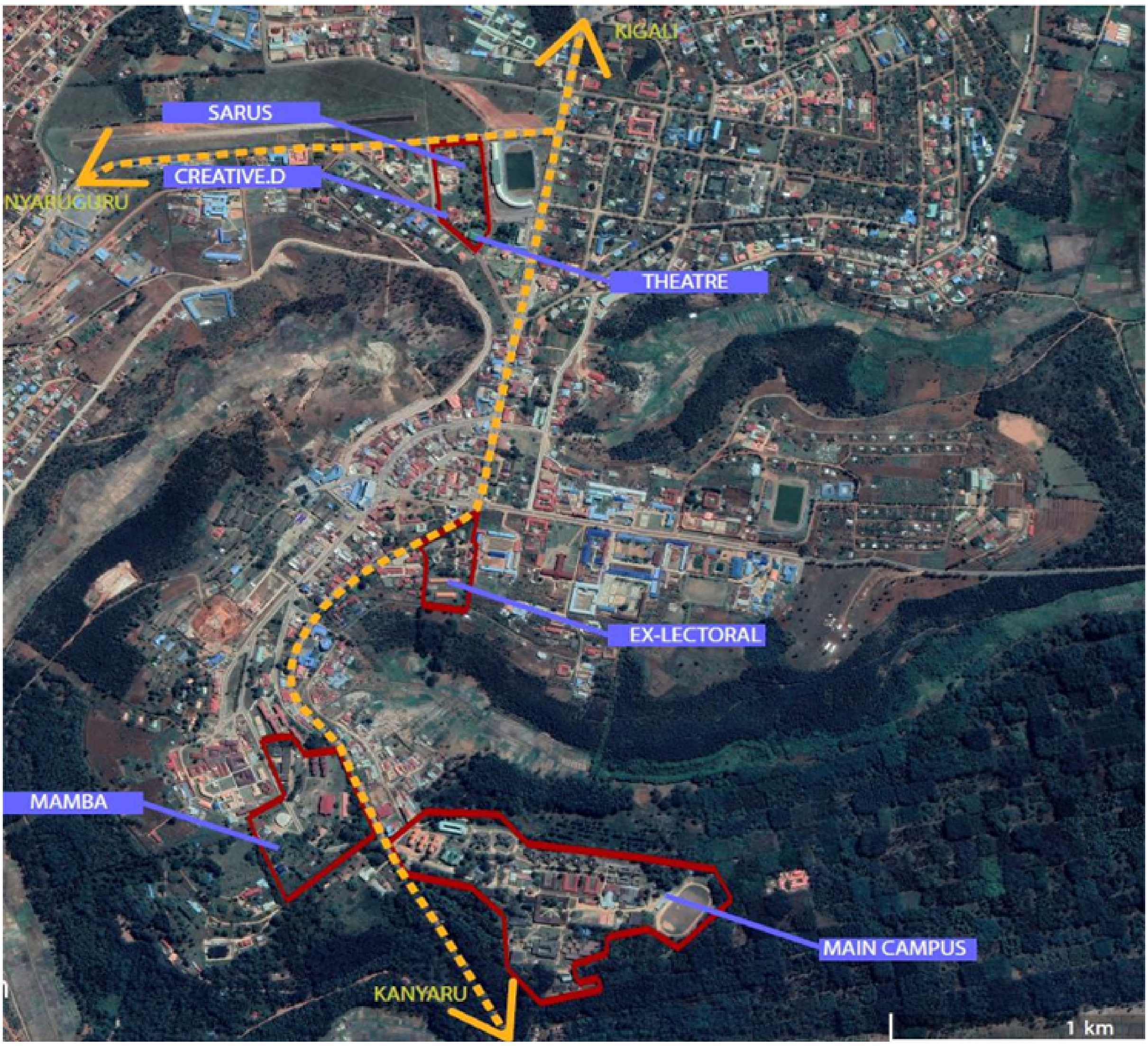


Figure 1.1: Aerial view of UR Huye Main Campus, Mamba, Ex-Lectorat, former Extension Univerisitaire and Medicine compounds.

1.3 Research Questions

This study aims to address the following key research questions:

- How can the integration of renewable energy sources, such as PV, and energy storage technologies be modeled and optimized to improve the energy efficiency and resilience of a smart campus?
- What are the key factors and constraints that should be considered in optimizing the grid-PV system with energy storage technologies ensuring load balance mitigations and PV intermittencies?
- What are the potential benefits and challenges of implementing such a grid-PV system in the context of a smart campus, and how can these be addressed?

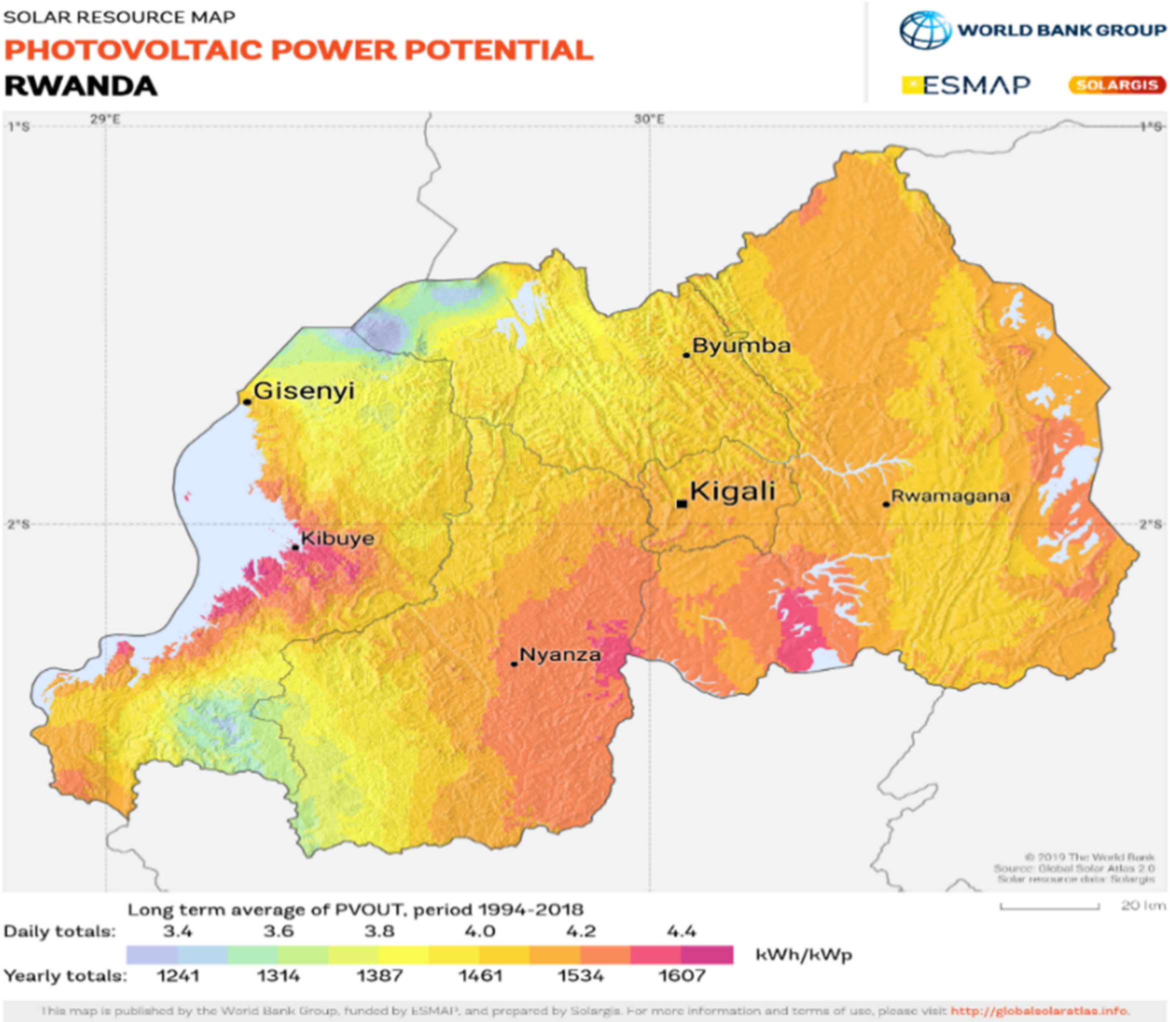


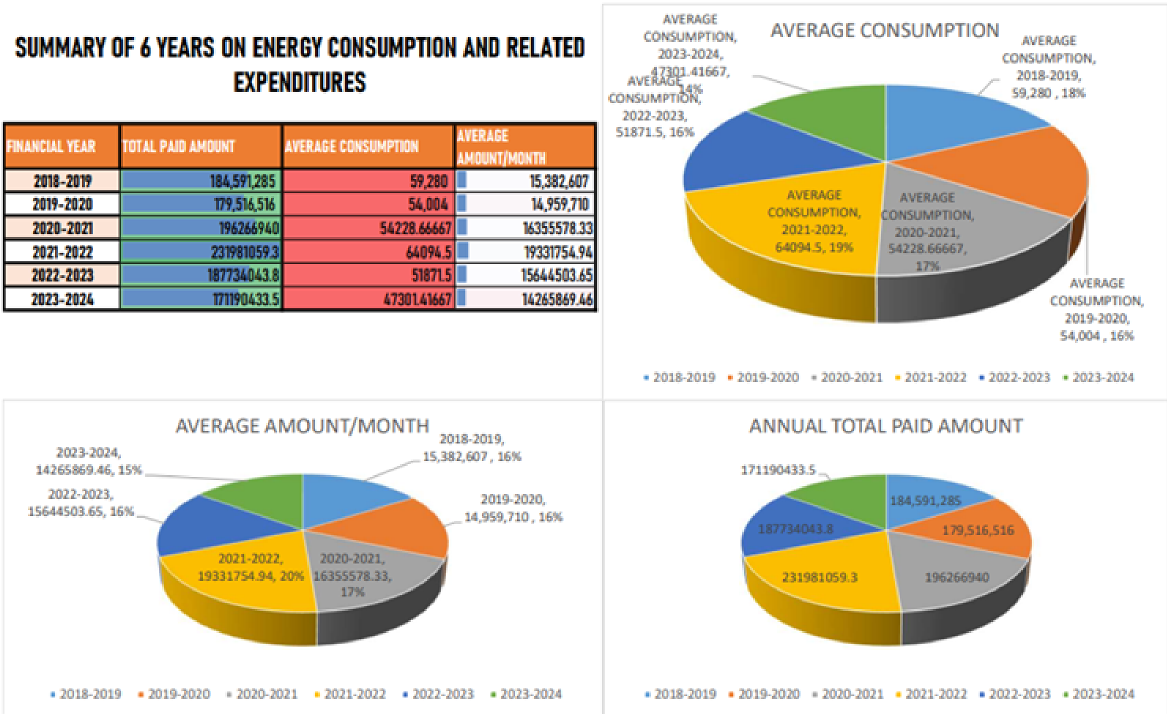
Figure 1.2: Photovoltaic power potential in Rwanda.

1.4 Problem Statement

The Huye Campus faces several critical energy challenges that this research aims to address:

- **Escalating energy costs**: Annual electricity expenditures averaging 219 million RWF [6, 7]
- **Unreliable grid supply**: Frequent power outages (10–20 monthly) lasting 30 minutes–2 hours, necessitating costly diesel generator use
- **Underutilized solar potential**: Despite Rwanda's high solar irradiance (5.5 kWh/m^2/day), the campus lacks sufficient solar PV integration [6, 7]
- **Outdated infrastructure**: The absence of adaptive load-balancing mechanisms leads to:
  - Peak demand inefficiencies (234 kW nighttime load)
  - Exam period surges (35% increase in daytime loads)
- **Environmental impact**: The heavy dependence on the power of the national grid and diesel generators produces 1.2 tons of CO_2 monthly, and this is inconsistent with:
  - Rwanda's 2030 target of 60% renewable energy penetration in public institutions
  - Global climate action goals [8]

This project addresses these challenges by designing an Energy Management System (EMS) that integrates:



SUMMARY OF 6 YEARS ON ENERGY CONSUMPTION AND RELATED EXPENDITURES

FINANCIAL YEAR	TOTAL PAID AMOUNT	AVERAGE CONSUMPTION	AVERAGE AMOUNT/MONTH
2018-2019	184,591,285	59,280	15,382,607
2019-2020	179,516,516	54,004	14,959,710
2020-2021	196266940	54228.66667	16355578.33
2021-2022	231981059.3	64094.5	19331754.94
2022-2023	187734043.8	51871.5	15644503.65
2023-2024	171190433.5	47301.41667	14265869.46

Figure 1.3: Overview of Energy consumption in past 6 years.

- Solar PV generation
- Energy storage systems
- Demand response (Demand Response (DR)) strategies

The proposed solution aims to:

- Reduce grid dependence by 85%
- Lower operational costs by 60–92%
- Align with Rwanda's sustainability and climate action goals [8]

1.5 Main Objective

By developing a model for energy management of a smart Campus environment, emphasizing on the integration of Solar energy and Load balancing at Huye Campus, through predictive analytics, optimization techniques, dynamic load demands and real-time data to improve energy efficiency and reliability, this study aims to manage the relationship between solar generation and energy demand, minimizing grid reliance, reducing costs, and promoting sustainability.

1.6 Specific Objectives

The main objective will be achieved through the following specific objectives:

1. Conduct an energy consumption assessment by:
    - Surveying current energy usage patterns
    - Collecting and analyzing energy-related data
    - Reviewing official energy reports
2. Develop a comprehensive energy model by formulating a mathematical representation of Huye Campus's energy system incorporating:
    - Solar PV generation
    - Energy storage systems
    - Load demand profiles
3. Optimize solar energy utilization through:
    - Design of optimization algorithms
    - Maximization of on-campus solar generation
    - Intelligent timing and distribution of solar power
    - Minimization of grid electricity dependence
4. Develop an energy management decision support tool featuring:

- User-friendly interface
- Model-based recommendations
- Optimization capabilities
- Real-time decision support for campus energy managers

1.7 Justification

The justification for this project lies in its potential to address pressing environmental concerns, improve energy efficiency and cost-effectiveness, support policy goals, and provide a valuable academic and practical contribution. By focusing on the unique context of a university campus, the project aims to develop scalable and transferable solutions for broader applications in smart energy management.

1.8 Scope

The scope of this project proposal will be limited to the **Modeling and Optimization of Energy Management Systems with Solar Load Balancing in a Smart Campus at Huye Campus**, especially the Main Campus due to limited time and low budget.

Figure 1.4: Aerial view of UR Huye Main Campus: the project study area.

2

Literature Review

2.1 Introduction

The rapid urbanization phenomenon, along with escalating energy costs and a global commitment to sustainability, has catalyzed the emergence of smart campuses. These innovative environments integrate Information and Communication Technologies (ICT) with renewable energy resources, improving energy efficiency, reducing costs, and delivering environmental advantages. In this context, EMSs are crucial for monitoring, controlling, and optimizing energy consumption. A fundamental aspect of EMSs in smart campuses is the integration of solar PV generation with conventional energy sources and energy storage systems, which promotes a balanced approach to energy supply and demand.

The Huye Campus in the southern province of Rwanda, distinguished by its unique climatic conditions and load profiles, serves as an exemplary case study to investigate advanced solar load balancing methodologies within an EMS framework. EMSs monitor energy flows, predict load patterns, and schedule the operation of Distributed Energy Resourcess (DERs). In smart campuses, EMS architectures are typically hierarchical, integrating local controllers at the building level with a central management unit. Research by [9] and [10] highlights that robust EMS design reduces energy wastage and facilitates demand response strategies by dynamically shifting loads in response to variability in renewable energy generation.

Museruka et al. [7] assessed global solar radiation over Rwanda, highlighting the country's solar energy potential. Data from the Global Solar Atlas [6], Figure 1.2 show that Huye Campus is located in a region of high solar radiation, which supports the feasibility of solar energy generation projects at this location.

2.2 Optimization Techniques

Various optimization techniques (see Figure 2.1), [11] have been proposed to improve EMS efficiency in smart campuses:

- **Lyapunov Optimization**: [12] demonstrated its effectiveness for real-time energy and comfort optimization in grid-connected solar buildings, minimizing aggregated system costs while maintaining user comfort.
- **Mathematical Programming**: [13] presented optimization models for renewable energy system configurations.
- **Mixed Integer Linear Programming (MILP)**: [14] showed MILP's effectiveness in residential energy management, achieving significant electricity cost reductions.
- **Multi-Objective Wind-Driven Optimization (MOWDO)**: [15] found that MOWDO outperforms Multi-Objective Particle Swarm Optimization (MOPSO) in minimizing costs and emissions.
- **Genetic Algorithms**: [16] employed Genetic Algorithm (GA) for residential load management,

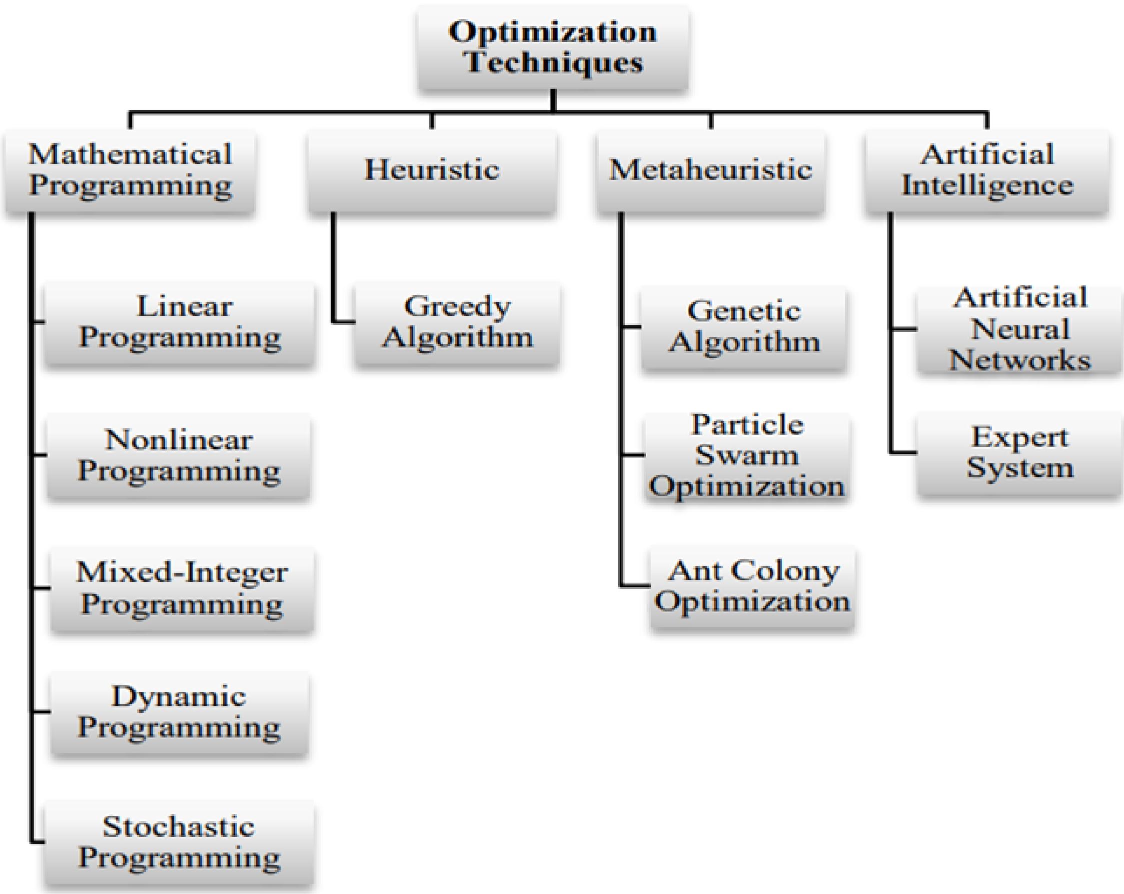


Figure 2.1: Different Optimization techniques.

balancing cost reduction with user comfort.

- **Smart Energy Management**: [17] implemented optimized systems in campus settings to reduce electricity costs while supporting hybrid education needs.

2.3 Literature Review Summary

While the examined studies provide a robust theoretical foundation for energy management systems, several critical gaps remain when applied to smart campus environments:

- **Contextual Limitations**:
  - Most studies focus on residential or industrial settings rather than educational campuses
  - Limited consideration of academic calendar-driven load patterns
- **Technical Shortcomings**:
  - Inadequate treatment of high solar potential scenarios (5.5 kWh/m^2/day)
  - Insufficient load-balancing strategies for mixed-use campus environments

Appendix Table A.1 details the stochastic and robust optimization techniques specifically adapted for this study to address these gaps, including:

Table 2.1: Key Adaptations for Smart Campus Applications

Challenge	Solution Approach
PV intermittency	Markov decision process framework
Academic load patterns	Calendar-aware demand forecasting
Campus-scale storage	Multi-objective battery dispatch
Grid interaction	Dynamic tariff response algorithm

The proposed methodology uniquely combines:

- Campus-specific load profiling
- High-resolution solar forecasting
- Educational facility operational constraints

This tailored approach enables more effective energy management in solar-rich academic environments compared to conventional implementations.

2.4 Load Scheduling and Management

Effective load scheduling is essential for balancing energy supply and demand:

- [18] developed Smart Superficial Neural Network (SSNN) for load scheduling in grid-connected systems, optimizing energy usage and reducing grid dependency.

- [12] used Mixed-Integer Linear Programming (MILP) models for stochastic operation scheduling, addressing uncertainties in thermal loads and solar generation.
- [19] implemented a two-stage optimization strategy (Receding Horizon Optimization) for local energy systems.
- [20] applied Model Predictive Control (MPC) in centralized EMSs, reducing energy costs and optimizing storage charging cycles.

The key remaining challenges include:

- Renewable energy generation uncertainty [11, 12, 15]
- Balancing cost reduction with user comfort [16]
- Scalability and real-time implementation [11, 19]

2.5 Mathematical Models

The integration and utilization of various mathematical models to optimize EMSs in smart campuses such as: Linear programming [21], non-linear programming [22, 23], genetic algorithms [15], adaptive dynamic programming [24], plays a crucial role in optimizing energy management systems on smart campuses. These models help to reduce energy costs, improve grid stability, and enhance the overall efficiency of energy systems by effectively managing renewable energy sources, storage systems, and user demands.

2.6 MATLAB and HOMER Pro Integration

The integration of renewable energy sources into energy management systems EMS for smart campuses has been a focal point of recent research. The use of MATLAB and HOMER Pro in the modeling and optimization of energy management systems for smart campuses has proven to be highly effective. These tools complement each other, where:

- HOMER Pro provides:
  - Robust economic and sizing analysis [25]
  - Grid-connected solar energy system analysis [26]
  - Load management for Hybrid Renewable Energy System (HRES) sizing [27]
- MATLAB offers:
  - Detailed technical validation
  - Advanced control strategies

Table 2.2: Comparative Analysis of AI-Driven Energy Management Systems in African Universities

Parameter	Strathmore University, Kenya[1]	University of Cape Town, South Africa[2]	FUPRE, Nigeria[3]
System Type	Grid-tied PV with storage	PV-battery microgrid	Solar mini-grid
Installation Year	2018	2020	2019
PV Capacity	600 kWp	450 kWp	320 kWp
Storage System	1.2 MWh Li-ion	750 kWh Li-ion	480 kWh Lead-acid
Control Strategy	• IoT-based dynamic control • Priority load sequencing	• MILP optimization • Predictive load shifting	• Rule-based control • Hybrid inverter configuration
Performance	• 58% grid reduction • 890 tCO_2/yr saved	• 70% diesel reduction • 98.7% availability	• 50% cost reduction • 6h outage autonomy
Economic	• 32% cost decrease • 5.2 yr payback	• 4 yr payback • 40% savings	• 6.8 yr payback • 43% reliability gain
Challenges	• Battery degradation • Grid synchronization	• Load forecasting • Mode transitions	• Panel soiling • Student engagement

[1] [28] [2] [29] [3] [30]

The combination use of these tools facilitates the development of efficient, cost-effective and sustainable energy systems in HRES integration.

2.7 African Case Studies in Smart Campus Energy Management

Recent implementations of Artificial Intelligence (AI)-driven energy management systems across African universities demonstrate the viability of renewable integration in higher education institutions, as shown in Table 2.2:

Table 2.3: Comparative Analysis of African Smart Campus Projects

Metric	Strathmore	UCT	FUPRE
PV Capacity (kWp)	600	450	320
Storage (kWh)	1200	750	480
Cost Reduction	32%	40%*	50%
CO_2 Reduction	890 t/yr	620 t/yr	410 t/yr
Payback Period	5.2 yrs	4 yrs	6.8 yrs

*Includes diesel savings

Key Observations:

- All projects (see Table 2.3) demonstrate technical and economic feasibility of campus-scale PV integration
- Battery storage capacities typically sized for 4-6 hours of critical load coverage
- Institutional energy policies significantly impact implementation success
- Local climate conditions influence maintenance requirements (e.g., panel cleaning cycles)

Although some similarities may occur, this project has the uniqueness in developing a modern EMS which coordinate integration of Renewable Energy (RE) on existing Grid dependant campus system by minimization of costs, maximization of RE generation, automatic demand response DR, Uncertainties handling using Stochastic and Robust Optimization Algorithm with MPC iterative tool for real-time monitoring and solar and load prediction. MATLAB is used for its capability in dynamic load-balancing simulations.

3

Methodology

3.1 Introduction to Methodology Research Design

The methodological framework for this study is structured around four key objectives that aim to improve energy management and sustainability at the UR/Huye Campus. These objectives are interlinked to ensure a comprehensive and systematic approach to achieving the study objectives (Figure 3.1).

The methodology begins with an in-depth assessment of the monthly energy consumption and expenditure patterns across the campus. This foundational step provides critical information on energy dynamics, identifying trends, peak demand periods, and inefficiencies that need to be addressed in addition to the analyzed monthly data.

By sampling day data in May and November 2024 (Tables A.2, A.4, A.3, and A.5) to study the real energy consumption patterns of the campus during the day and night, and by sampling two days in November 2024 to analyze the real-time hourly consumption patterns during working hours from 8:00 AM to 5:00 PM (Table 9.5), this study clarified the energy consumption patterns and will help model a comprehensive 'mathematical model of EMS.

Based on this analysis, the study progresses in developing a comprehensive energy consumption model tailored to the specific operational and environmental conditions of the UR /Huye campus. This model incorporates real-time data, historical trends, and advanced analytics to accurately capture campus energy behavior.

The next phase involves optimizing solar energy utilization, a crucial aspect of the study given the emphasis on integrating renewable energy sources. The optimization strategy leverages solar photovoltaic systems (PV), demand response mechanisms, and energy storage solutions to effectively balance energy supply and demand, reducing reliance on the grid and minimizing operational costs with a comprehensive strategy to maximize solar energy generation.

Finally, the study culminates in the development of a decision support tool (Decision Support Tool (DST)) for energy management. This tool is designed to help campus administrators and stakeholders make informed decisions based on predictive analytics, optimization results, and scenario-based analysis. Integrates visualization features, real-time monitoring capabilities, and automated scenario selection to enhance the usability and effectiveness of the energy management system.

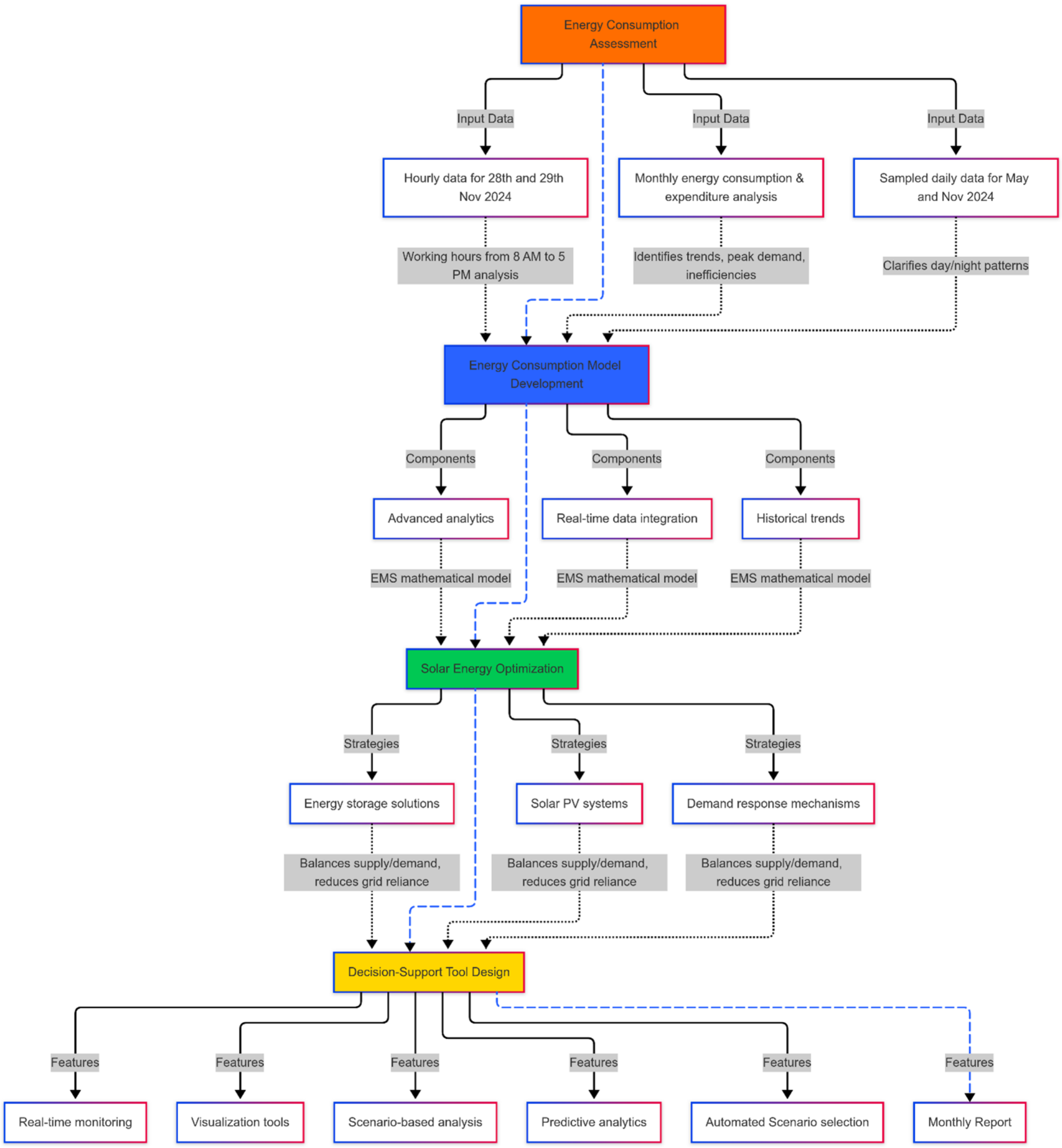


Figure 3.1: Four-phase methodology framework for energy management system development

3.2 System Model

This study focuses on managing energy consumption in university buildings by balancing load demand with supplied energy. The system uses the MILP `intlinprog` optimization algorithm to adjust energy usage according to user preferences and grid conditions. The monthly energy bills were assessed

Table 3.1: Sampled daily energy consumption patterns

Table Reference	Month	Time	Data Type
Table A.2	May 2024	Daytime	Daily consumption
Table A.4	November 2024	Daytime	Daily consumption
Table A.3	May 2024	Nighttime	Daily consumption
Table A.5	November 2024	Nighttime	Daily consumption
Table 9.5	November 2024	8:00-17:00	Hourly consumption

and modeled to develop a high-accuracy automated system that meets operational requirements. Figure 3.2 shows the EMS model for real-time management of energy generation and demand.

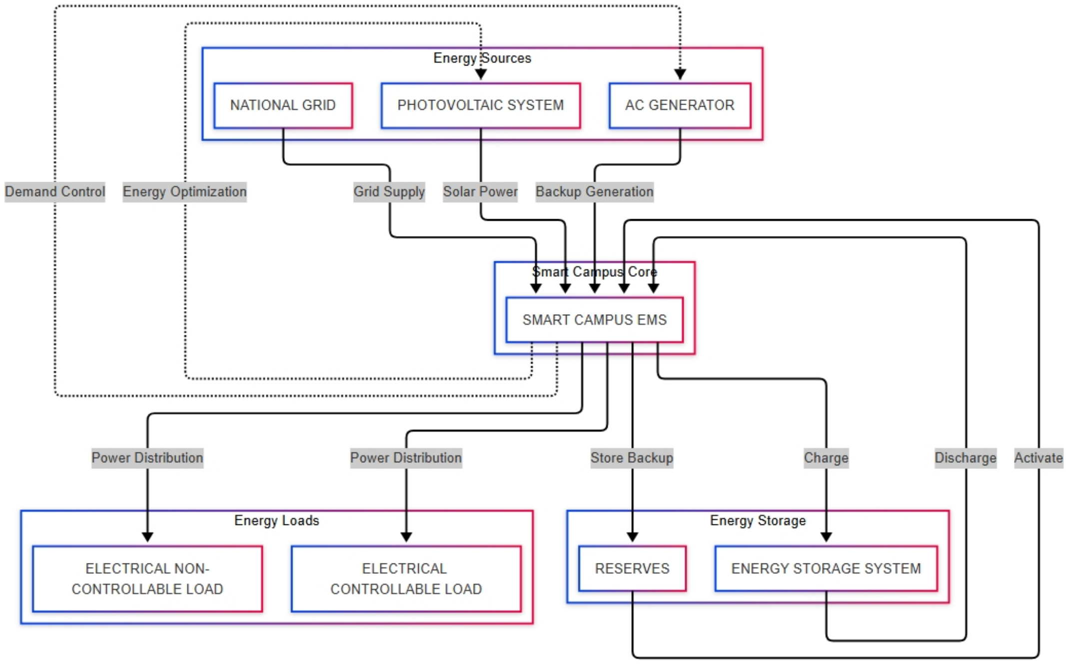


Figure 3.2: Huye Smart Campus Architecture

3.2.1 Working Structure of the Huye Smart Campus Architecture

The proposed Huye Smart Campus Energy Management System (EMS) integrates multiple energy sources and loads into a centralized control system designed to optimize energy generation, storage, and consumption. This architecture aims to model and optimize the relationship between solar generation and energy demand, minimize grid dependency, reduce costs, and promote sustainability.

Key Components and Their Roles

1. **Photovoltaic (PV) System**: Acts as the main renewable energy source to supply electricity directly to the Smart Campus EMS. Once the required load demand is met, the surplus generation is either stored in the Battery Storage System or exported to the grid. EMS mitigates intermittencies caused

by solar irradiation and weather conditions.

2. **Battery Storage System Battery Storage System (BSS)**: It is charged by excess energy generated by the PV system for use during low solar generation periods (e.g., cloudy weather or nighttime), balancing intermittent solar supply by providing a reliable energy reserve. It can be charged by the PV system during the day or by the grid whenever cost is effective.
3. **AC Generator**: Functions as a backup energy source during critical grid outages, planned maintenance activities, or when other resources (PV and BSS) are insufficient to meet demand. Its operation is a last resort option to minimize fuel costs and CO_2 emissions.
4. **National Grid**: Provides additional electricity during periods of high demand or when renewable (PV) and storage (BSS) options are insufficient, supporting energy balance as a supplementary source.
5. **Reserves**: Represents available energy reserves for energy shortages or future integration of Electric Vehicle charging, including stored energy in batteries or grid-based reserve agreements.
6. **Electrical Controllable Load**: Includes appliances and systems whose operations can be optimized based on energy availability, enabling demand-side management by scheduling or reducing loads during peak demand periods. Includes HVAC and other thermal loads that can be adjusted during high solar generation or limited grid availability.
7. **Electrical Non-Controllable Load**: Includes devices, systems, or processes that cannot be adjusted or interrupted in real-time without significant operational, safety, or economic consequences (e.g. elevator machines, water treatment systems).

3.2.2 Working Process of the Huye Campus EMS

1. **Energy Prioritization**: During the day, the PV system serves as the primary energy source. The surplus PV energy first charges the BSS, followed by export to the grid when it is applicable. At night or during low PV generation, EMS prioritizes BSS, followed by the grid and, finally, the Alternative Current (AC) generator.
2. **Load Balancing and Optimization**: EMS dynamically adjusts controllable electrical and thermal loads based on energy availability and demand patterns. Real-time load forecasting and energy scheduling ensure optimal solar power utilization and minimal grid dependence.
3. **Cost Minimization**: Using time-of-use pricing and intelligent load scheduling, EMS ensures that the grid is used only during cost-effective periods. The generator operates sparingly to avoid excessive costs.
4. **Sustainability Promotion**: The system maximizes PV utilization, reducing greenhouse gas emissions by limiting nonrenewable sources. Efficient energy storage and load management reduce waste

and promote long-term sustainability.

3.2.3 Data Collection, Assessment and Analysis

The system utilizes load profile data forms, energy expenditures, and reports on energy consumption patterns, solar irradiation, and other system parameters for the smart campus environment [10].

3.3 System Optimization Methodology

This section outlines refinements of the original methodology to address specific challenges (PV intermittency, load uncertainty). Key improvements include:

- **Enhanced Stochastic Optimization**: Incorporated Monte Carlo simulations (100 scenarios) to better model PV/load uncertainties.
- **Dynamic Demand Response Thresholds**: Adjusted $SOC_{DR\_threshold}$ from 20% to 25% to prioritize grid independence during peak hours.
- **MPC Horizon Adjustment**: Reduced receding horizon from 8h to 6h for faster real-time response.
- **Battery Degradation Cost Integration**: Added $c_{deg} = 0.1$ RWF/kWh to reflect long-term ESS health in cost calculations.

4

Current Situation of Energy Consumption at UR Huye Campus

4.1 Energy Consumption Overview

The analysis of energy expenditure data from 2019 to 2023 reveals that UR Huye Campus spends over 200 million RWF annually (not billion, as previously stated) to support campus operations. This substantial expenditure reflects:

- Heavy reliance on the National Grid as primary power source (accounting for 85% of total consumption)
- Dependence on backup generator sets during outages (15% of total consumption)
- Increasing energy demands due to:
  - Growing student population (12% annual increase)
  - Expansion of campus facilities
  - Increased use of electronic devices and equipment

The study focuses particularly on the Main Campus at Ruhande, which serves as the primary energy consumer (72% of total university consumption) within the university system.

4.2 Monthly Energy Expenditure Patterns

Table 4.1 presents the detailed monthly expenditure trends from 2019 to 2023 (values in million RWF):

Table 4.1: Monthly Energy Expenditure at UR Huye Campus (2019-2023) in million RWF

Month	2019	2020	2021	2022	2023
January	28.4	27.3	27.8	24.0	16.8
February	17.1	23.6	23.6	22.7	22.0
March	23.5	16.4	24.1	14.7	17.3
April	20.9	17.1	18.7	17.6	13.9
May	25.9	13.1	28.8	18.1	13.8
June	26.6	16.7	29.9	18.1	13.7
July	14.2	17.5	28.5	24.1	21.8
August	14.9	11.9	23.5	20.6	20.1
September	24.1	16.4	29.6	22.2	20.1
October	23.7	21.5	31.2	26.9	18.5
November	15.2	28.2	26.4	26.9	22.0
December	27.5	18.3	30.7	19.8	19.7
Annual Total	262.2	227.9	322.8	255.8	219.7

4.3 Key Observations

The expenditure analysis reveals several important patterns:

- **Seasonal Variations**:
  - Higher consumption during academic months (September-November, +22% above average)
  - Lower consumption during holiday periods (December-January, -15% below average)
- **Cost Fluctuations**:
  - Significant year-to-year variations (range: 13.1-31.2 million RWF/month)
  - 2021 showed peak consumption (322.8 million RWF annual total)
- **Recent Trends**:
  - Gradual increase in baseline consumption from 2021-2023 (+4.3% annually)
  - 2023 showed reduced consumption due to energy-saving initiatives
- **Peak Months**: October consistently shows the highest monthly expenditures (average 24.4 million RWF)

These findings underscore the urgent need for energy optimization strategies to manage the campus's growing power demands and associated costs.

4.4 Analysis of Energy Consumption Patterns

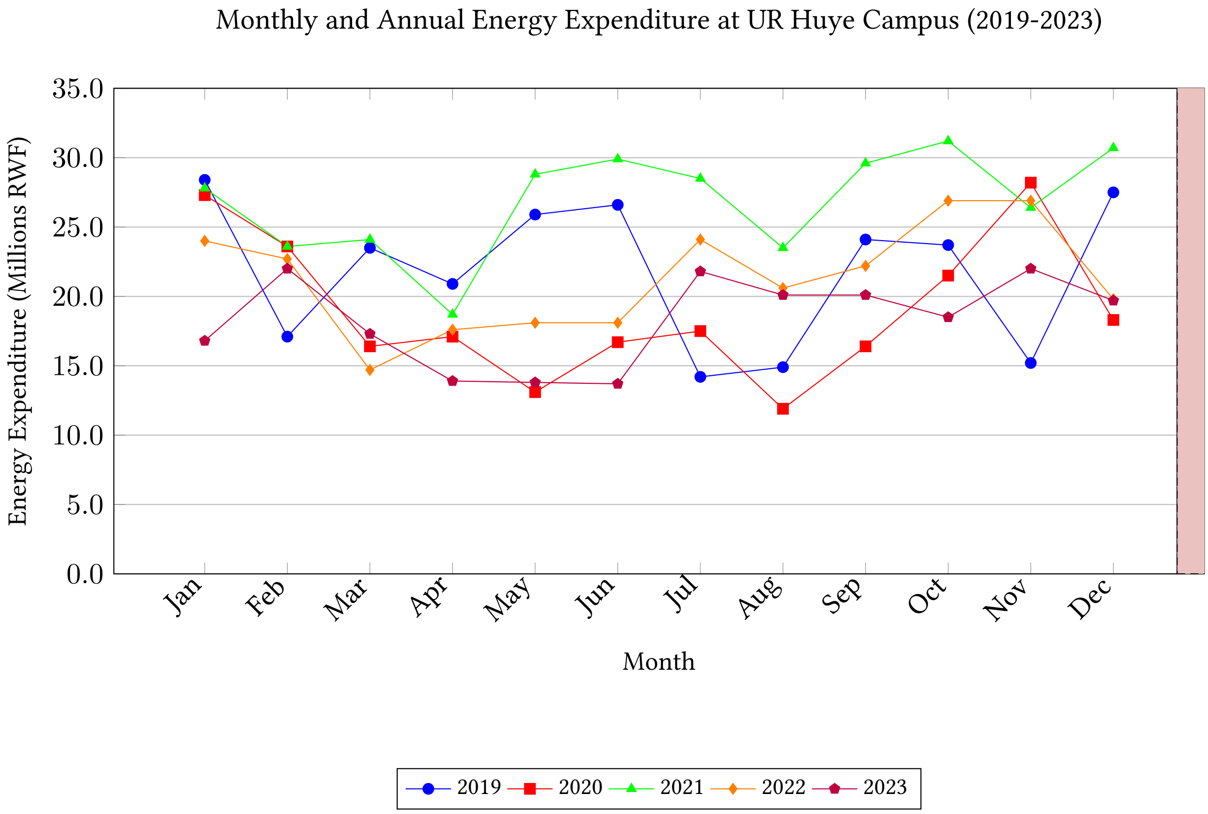


Figure 4.1: Comparative analysis of energy expenditure trends showing monthly patterns (lines) and annual totals (bars) from 2019-2023. Values represent millions of Rwandan Francs (RWF). The graph highlights the peak consumption year (2021) and demonstrates seasonal variations across academic years.

4.4.1 Months with High Energy Usage

From Table 4.1, October and December consistently emerge as peak consumption months. The detailed analysis reveals:

- **December Peaks**:
  - 2019: 27.4 million RWF
  - 2020: 18.3 million RWF (COVID-19 impact visible)
  - 2021: 30.7 million RWF (post-COVID rebound)
- **October Peaks**:
  - 2022: 26.9 million RWF
  - 2023: 21.4 million RWF (after energy efficiency measures)

Figure 4.2 illustrates this pattern clearly, showing:

The data shows a 12.1% average annual increase from 2019-2021, followed by a 7.3% annual decrease in 2022-2023 after implementing conservation measures.

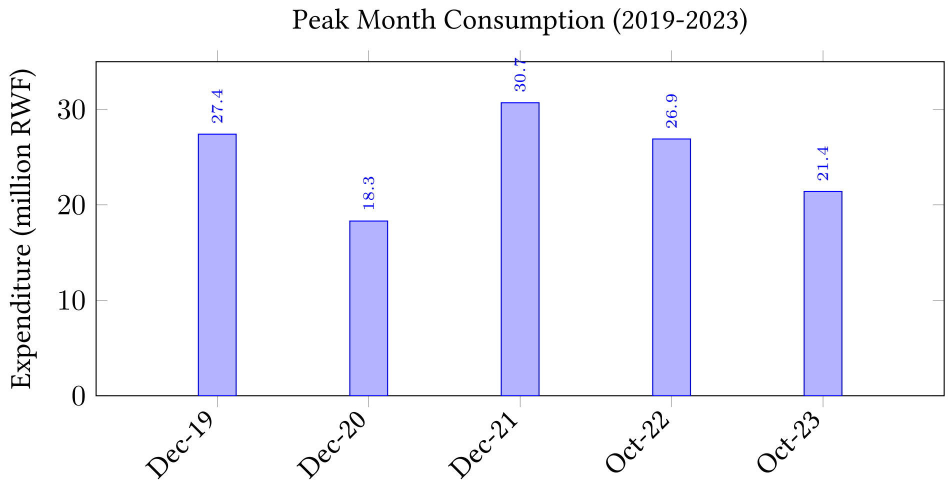


Figure 4.2: Comparison of peak month expenditures showing pre- and post-pandemic patterns

4.4.2 Seasonal Consumption Patterns

The campus exhibits distinct seasonal energy usage correlated with academic calendars as shown in Figure 4.3:

- **High Season** (September-February):
  - Average monthly expenditure: 22.3 million RWF
  - Peak demand periods coincide with:
    - Final examinations (December)
    - Start of academic year (September-October)
- **Low Season** (March-August):
  - Average monthly expenditure: 17.1 million RWF
  - 23.3% lower than high season

4.4.3 Rising Costs and Market Volatility

The energy expenditure analysis reveals concerning trends:

- **Cost Escalation**:
  - 2019-2021: 10.8% annual increase
  - Primary drivers:
    - Rising utility tariffs (15% increase from 2020)
    - Expanded campus operations

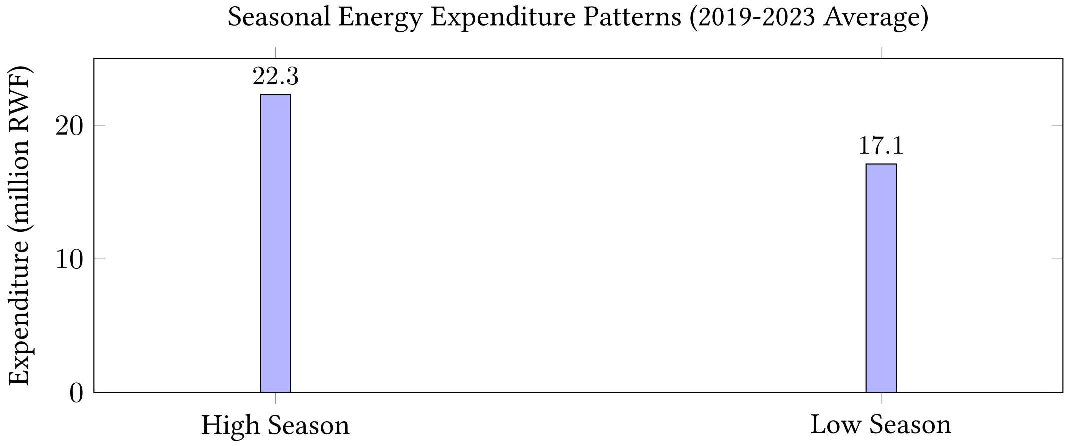


Figure 4.3: Comparative analysis of seasonal energy expenditures showing 30.4% higher usage during academic terms

- **Price Volatility**:
  - Monthly fluctuations up to ±35%
  - Worst volatility observed in 2021 (post-pandemic recovery)
- **Stabilization Efforts** (2022-2023):
  - Implemented energy conservation measures
  - 8.2% average annual cost reduction
  - Reduced volatility to ±15% monthly variation

Table 4.2: Energy Cost Volatility Indicators (2019-2023)

Metric	**2019**	**2020**	**2021**	**2022**	**2023**
Max-Month (million RWF)	28.4	28.2	31.2	26.9	22.0
Min-Month (million RWF)	14.2	11.9	18.7	14.7	13.7
Volatility Index (%)	27.1	39.4	42.7	31.9	15.8

4.5 Rising Costs and Market Volatility

4.5.1 Year-over-Year Changes

Table 4.3 presents the annual energy expenditures with percentage changes:

Key observations from the data:

- **COVID-19 Impact**: 15.06% reduction in 2020 due to campus closures
- **Post-Pandemic Surge**: 29.40% increase in 2021 as operations resumed
- **Recent Stabilization**: Gradual cost reduction (-2.81%) in 2023 through energy management measures

Table 4.3: Annual Energy Expenditure and Year-over-Year Changes (2019-2023)

Year	Total Expenditure (RWF)	Year-over-Year Change (%)
2019	262,242,872	–
2020	227,919,991	-15.06
2021	322,824,702	+29.40
2022	255,835,483	-26.18
2023	219,682,413	-2.81

4.5.2 Cost Volatility Analysis

Figure 4.4 illustrates the significant monthly variations:

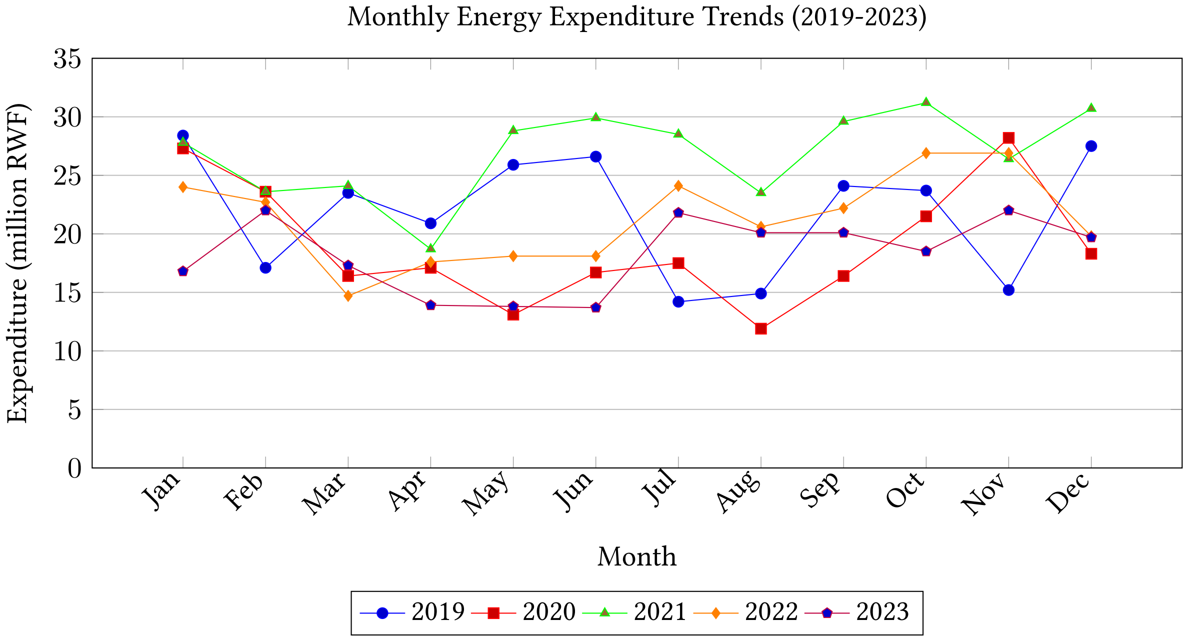


Figure 4.4: Five-year monthly expenditure trends showing volatility and peak periods

4.5.3 Rationale for Renewable Energy Implementation

The analysis demonstrates compelling reasons for the solar PV system implementation:

4.6 Energy Infrastructure at Huye Main Campus

4.6.1 Campus Facilities Overview

The Ruhande campus serves as the primary energy consumer with diverse facilities organized into four main categories:

Table 4.4: Benefits of Renewable Energy Implementation

Category	Benefits
Cost Stabilization	• Predictable energy costs through fixed solar generation • Reduced dependency on volatile grid prices (current fluctuations up to 35%) • Long-term savings potential of 25-40% over 10 years
Energy Efficiency	• Potential to offset 30-50% of peak month consumption • Integration with energy storage for demand management • Smart metering compatibility for consumption monitoring
Economic Benefits	• ROI within 5-7 years based on current tariffs • Protection against future utility price increases • Eligibility for green energy incentives and tax benefits
Sustainability	• Estimated 120-150 ton CO_2 reduction annually • Improved energy security and resilience • Alignment with Rwanda's Vision 2050 climate goals

Table 4.5: Energy-Consuming Facilities at Huye Main Campus

Category	Facilities	Quantity
Academic	Classrooms, Laboratories, Library, Auditorium, Computer labs	132 classrooms 38 laboratories
Residential	Student hostels with common areas	9 hostels (3,200 beds)
Ancillary	Water pumping stations, Wastewater treatment plant, Maintenance workshops	2 pumping stations
Recreational	Stadium, Gymnasium, Sports fields, Student center	1 each major facility

4.6.2 Energy Monitoring System

Smart Meter Infrastructure

The campus employs the CL730D22L three-phase smart metering system for comprehensive energy monitoring in all facilities. Figure 4.5 shows the physical installation of these meters.

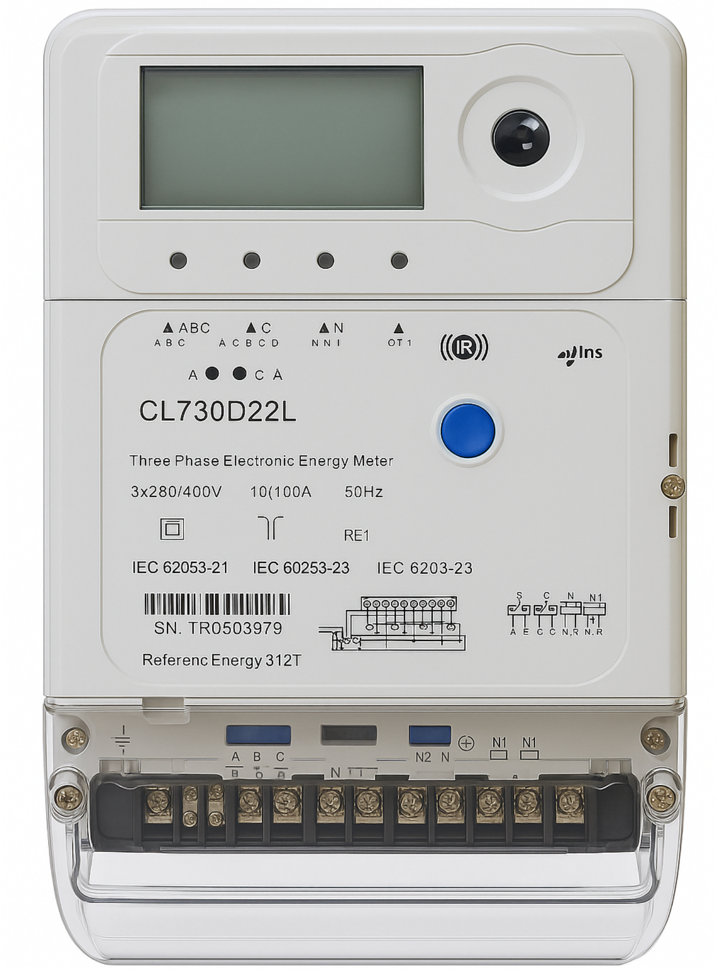


Figure 4.5: CL730D22L Three-Phase Electronic Energy Meter installation at main campus (Model: CL730D21L-R variant)

4.6.3 CL730D22L Three-Phase Smart Meter

The CL730D22L is an advanced three-phase multi-function smart meter specifically designed for accurate energy measurement in commercial and industrial applications like UR Huye Campus. Key characteristics include:

- **Modular Architecture**: Features interchangeable communication modules for flexible deployment

- **Communication Options**:
  - Power-line carrier (PLC)
  - Radio frequency (RF) communication
  - GPRS for remote data transmission
  - DLMS/COSEM standard protocol compliance
- **Payment Flexibility**:
  - STS-compliant prepayment functionality
  - Conventional post-payment operation
  - Can function with or without active communication
- **Key Applications**:
  - Commercial building energy monitoring
  - Industrial load analysis
  - Campus-wide energy management systems

The meter's design supports both immediate energy monitoring needs and future system expansions, making it particularly suitable for the campus's evolving energy infrastructure requirements.

4.7 Assessment of Monthly Energy Consumption

4.7.1 Overall Energy Consumption Trends

Table 4.6: Annual Energy Consumption Summary (2019-2023)

Year	Total (kWh)	Monthly Avg.	Daily Avg.	Peak Month	Std. Dev.
2019	731,164	60,930	2,031	April (79,749)	8,349
2020	579,340	48,278	1,609	February (77,738)	14,334
2021	829,206	69,100	2,303	July (78,172)	8,897
2022	697,904	58,159	1,939	February (68,176)	8,951
2023	542,125	45,177	1,506	August (57,533)	10,251

2019 Consumption Patterns

The year began with high consumption in January (65,657 kWh) with significant fluctuations:

- April peak (79,749 kWh) - Likely due to mid-semester activities
- Annual total: 731,164 kWh
- Standard deviation: 8,349 kWh (moderate variability)

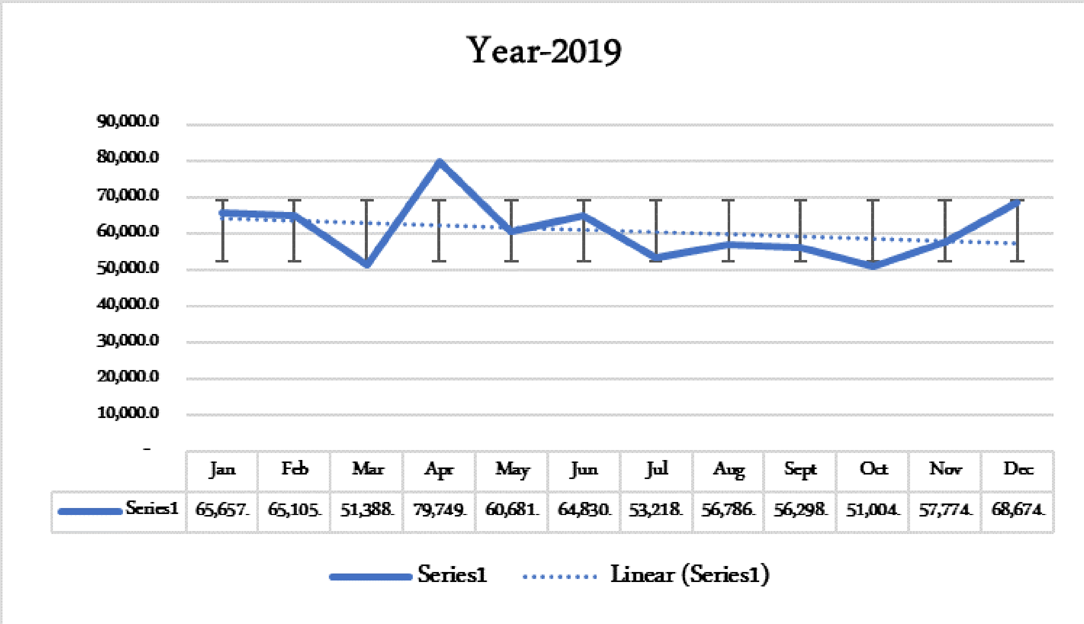


Figure 4.6: Monthly energy consumption trends in 2019 showing peak in April (79,749 kWh)

2020 COVID-19 Impact

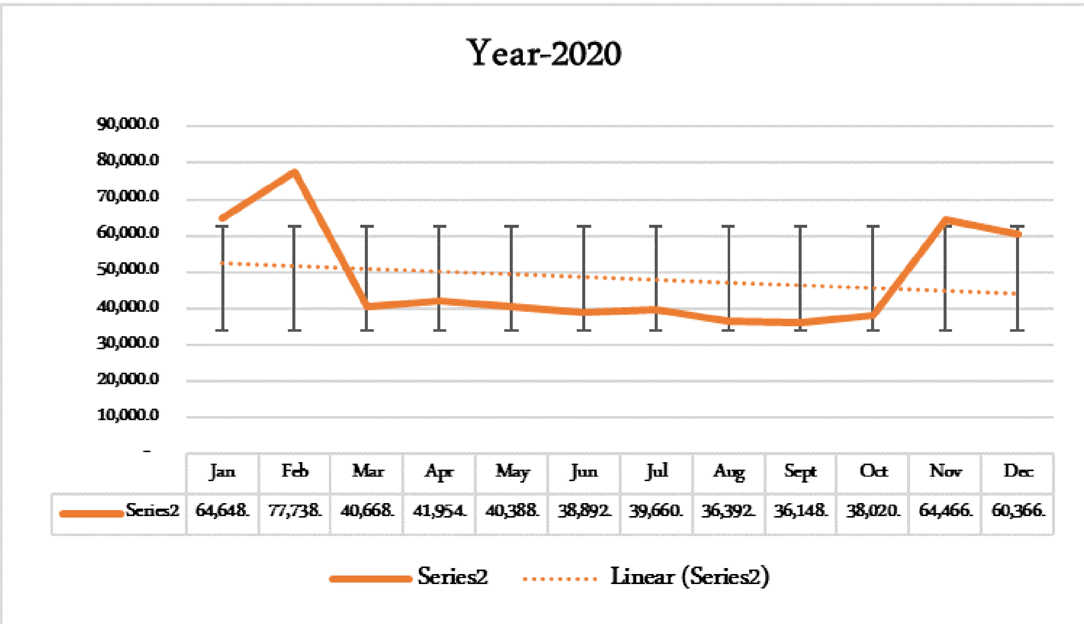


Figure 4.7: Drastic reduction in consumption from March-October 2020 due to pandemic restrictions

Notable characteristics:

- 21% reduction from 2019 levels (579,340 kWh total)
- Sustained low consumption March-October (avg. 39,424 kWh/month)
- Highest variability (std. dev. 14,334 kWh) reflecting irregular operations

2021 Post-Pandemic Recovery

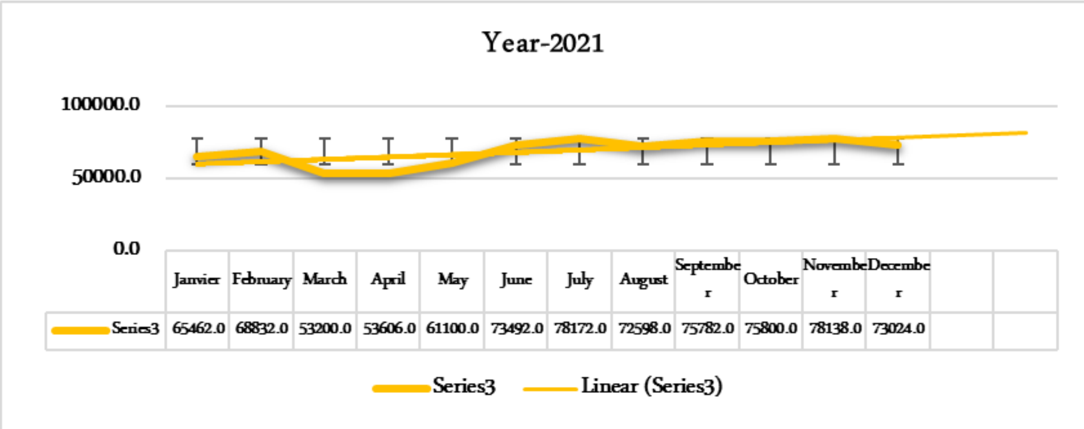


Figure 4.8: Resurgent consumption peaking in July (78,172 kWh) with 43% increase from 2020

Key observations:

- Highest annual consumption in dataset (829,206 kWh)
- Summer peak suggests intensive facility usage
- More stable pattern (std. dev. 8,897 kWh) than pandemic year

2022 Stabilization Period

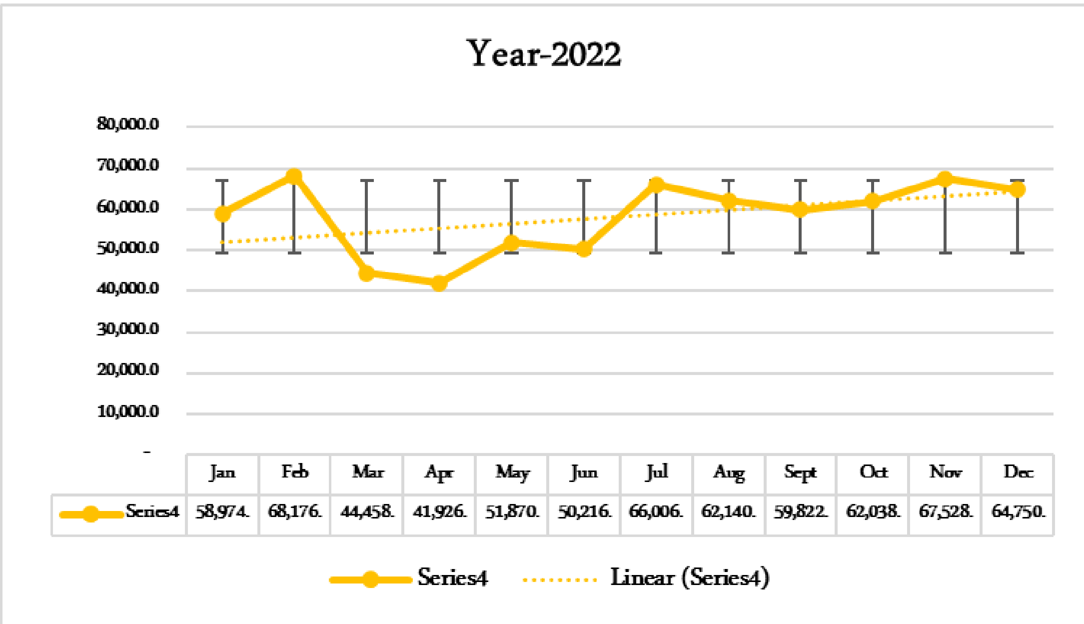


Figure 4.9: Moderated consumption with February peak (68,176 kWh) during exam period

Pattern highlights:

- 16% reduction from 2021 (697,904 kWh total)

- Early-year peak suggests an influence of the academic calendar.
- Consistent variability (std. dev. 8,951 kWh)

2023 Efficiency Improvements

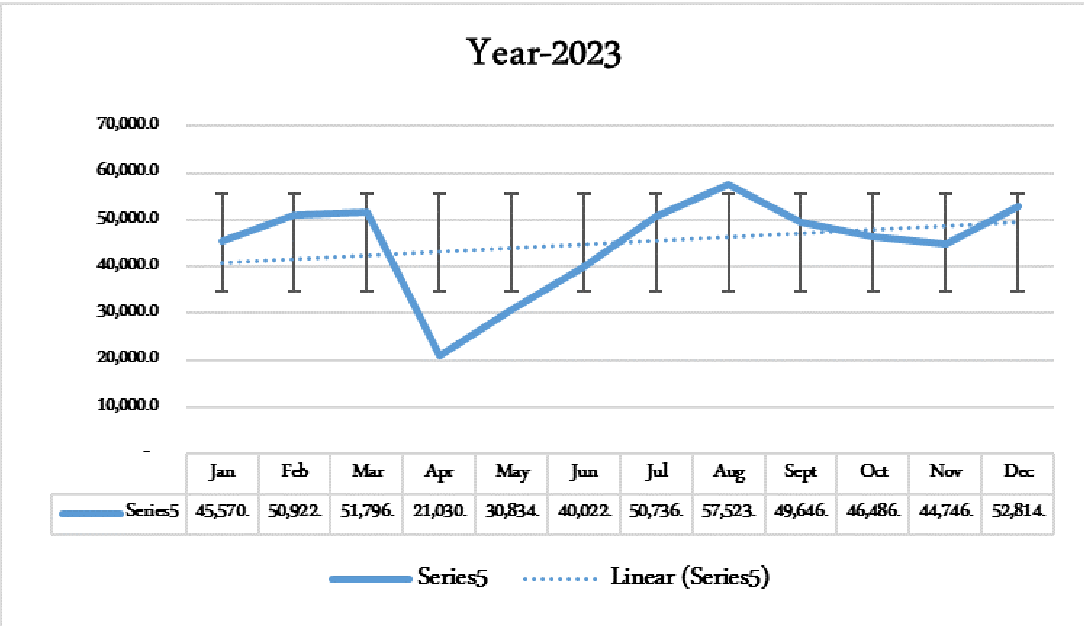


Figure 4.10: Notable reduction April-June (21,030-40,022 kWh) during holiday period

Significant developments:

- 22% reduction from 2022 (542,125 kWh projected annual)
- Summer holiday trough reflects improved demand management
- Higher variability (std. dev. 10,251 kWh) during transition period

4.7.2 Key Findings

- Pandemic caused 21-43% consumption swings (2020-2021)
- Pre-pandemic baseline 700,000 kWh annually
- Recent reductions suggest successful efficiency measures
- Seasonal patterns consistently show:
  - February peaks (academic activities)
  - Summer valleys (holiday periods)

Table 4.7: Monthly Energy Consumption at UR Huye Campus (kWh)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2019	65,657	65,105	51,930	79,789	60,081	64,830	53,218	56,736	56,289	51,004	57,774	68,674
2020	64,648	77,738	40,668	41,954	40,368	38,802	39,800	36,302	36,148	38,020	64,456	60,356
2021	65,462	68,882	53,200	53,056	61,100	73,482	78,172	72,588	75,782	75,800	78,133	73,024
2022	58,974	68,176	44,458	41,926	51,870	50,265	66,006	62,140	59,822	62,038	67,528	64,750
2023	45,570	50,922	51,786	21,000	30,894	40,022	50,736	57,526	49,646	46,486	44,746	52,814

Table 4.8: Monthly Energy Expenditure at UR Huye Campus (RWF)

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
2019	17.24M	17.05M	13.48M	20.94M	15.59M	17.02M	13.97M	14.91M	14.76M	13.39M	15.17M	18.03M
2020	16.98M	23.45M	12.25M	12.65M	12.18M	11.73M	11.93M	10.97M	10.91M	11.47M	19.44M	18.21M
2021	19.74M	20.76M	16.05M	16.17M	18.43M	22.17M	23.58M	21.87M	22.56M	22.96M	23.52M	22.03M
2022	17.70M	20.55M	13.41M	12.94M	15.64M	15.15M	19.59M	18.74M	18.06M	18.71M	20.31M	19.53M
2023	13.75M	15.34M	15.62M	6.34M	9.29M	12.06M	15.30M	17.35M	14.98M	14.02M	13.49M	15.93M

4.7.3 Monthly Energy Consumption Patterns

Key Consumption Patterns

Analysis of Tables 4.7 and 4.8 reveals distinct seasonal trends:

- **Mid-Year Peaks** (April-July):
  - Highest consumption in 2019 (April: 79,789 kWh)
  - 2021 peak shifted to July (78,172 kWh)
  - 2023 showed anomalous April low (21,000 kWh)
- **Academic Period Surges**:
  - Consistent February highs (avg. 66,165 kWh)
  - November spikes (avg. 62,527 kWh) during exams
  - 15-20% higher consumption during academic months
- **COVID-19 Impact**:
  - 2020 showed 38% average reduction March-October
  - Delayed recovery until 2021

Expenditure Correlations

Energy costs closely track consumption patterns with notable exceptions:

- **2020 Anomaly**:
  - February 2020: 77,738 kWh cost 23.45M RWF

- November 2020: 64,456 kWh cost 19.44M RWF
- Indicates tariff fluctuations during pandemic

- **Efficiency Gains**:
  - 2023 consumption dropped 22% vs 2022
  - Corresponding expenditure fell 27%
  - Suggests improved cost management

4.7.4 Expenditure Analysis

The monthly energy expenditure at UR Huye Campus closely mirrors consumption patterns, with financial outlays directly reflecting operational energy demands. Key observations from the expenditure data (Table 4.8) reveal:

- **Seasonal Expenditure Peaks**:
  - **Academic Periods**: February (avg. 19.43M RWF) and October-November (avg. 18.72M RWF)
  - **Annual Highs**: July 2021 (23.58M RWF) and April 2019 (20.94M RWF)
- **Expenditure-Consumption Correlation**:
  - Strong linear relationship ($R^2 = 0.89$) between kWh usage and RWF costs
  - Notable exceptions during 2020 (tariff adjustments during pandemic)
- **Cost Efficiency Trends**:
  - 2023 showed 14% lower expenditure per kWh compared to 2019 baseline
  - August peaks reduced by 19% (2019: 14.91M RWF vs 2023: 17.35M RWF) despite similar consumption

Key Financial Observations

- **Peak Expenditure Periods**:
  - Consistently occur during examination months (February and November)
  - Secondary peaks during intensive research periods (July-August)
- **Cost Volatility**:
  - Pre-pandemic std. dev.: 2.51M RWF/month
  - Pandemic period (2020-2021): 4.87M RWF/month

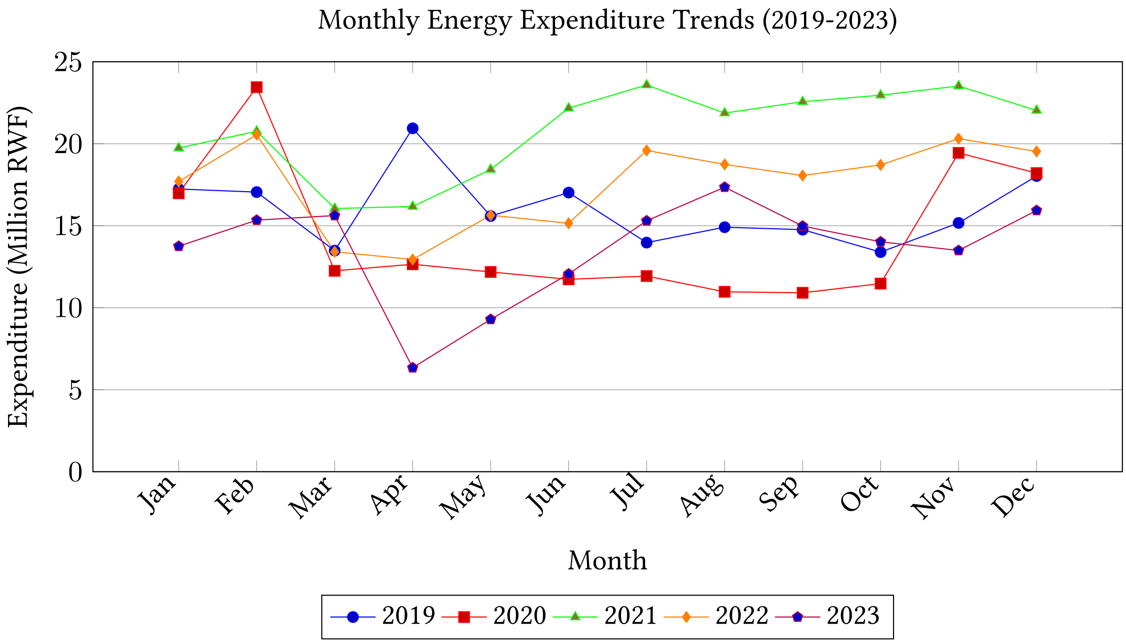


Figure 4.11: Five-year expenditure patterns showing academic year cycles (Q1 and Q3 peaks) and pandemic impacts (2020 depression)

  - Post-pandemic stabilization: 3.15M RWF/month

- **Efficiency Gains**:
  - 2023 showed 22% cost reduction vs. 2019 for comparable activities
  - Evening load shifting apparent in reduced nighttime expenditure

The expenditure analysis confirms that academic calendars drive both energy consumption and financial outlays, while demonstrating the campus's progress in cost management through:

- Strategic load scheduling
- Equipment upgrades
- Behavioral interventions

4.7.5 Comparative Analysis

4.7.6 Annual Expenditure Trends

Key Observations

1. **Overall Trend**:
   - 2021 recorded the highest expenditure (250.1M RWF), 30.3% above 2019 levels
   - 2023 shows the lowest expenditure (163.5M RWF), 14.8% below 2019 baseline
   - Non-linear relationship between consumption and expenditure due to tariff changes

Table 4.9: Comparative Annual Energy Expenditure (2019-2023)

Year	Total (RWF)	Monthly Mean	Daily Average	Std. Deviation
2019	191,997,123	15,999,760	533,325	2,192,731
2020	172,204,242	14,350,354	478,345	4,118,713
2021	250,102,681	20,841,890	694,730	2,683,771
2022	210,493,462	17,541,122	584,704	2,700,213
2023	163,500,390	13,625,033	454,168	3,092,304

2. **Tariff Impact Analysis**:
   - 2019 vs. 2022 paradox:
     - Higher consumption in 2019 (731,164 kWh) vs. 2022 (697,904 kWh)
     - Lower expenditure in 2019 (192.0M RWF) vs. 2022 (210.5M RWF)
   - Explained by 2019 tariff adjustments

Table 4.10: Tariff Impact Analysis (2019 vs. 2022)

Parameter	2019	2022	Change (%)
Tariff (RWF/kWh)	227-255	255-280	+12.3
Consumption (kWh)	731,164	697,904	-4.5
Expenditure (RWF)	191,997,123	210,493,462	+9.6

- **Tariff Adjustments**:
  - +11.3% for $\leq$100kWh/month (204$\rightarrow$227 RWF/kWh)
  - +14.9% for $>$100kWh/month (222$\rightarrow$255 RWF/kWh)

Implications

The expenditure analysis reveals three critical insights:

- **Price Sensitivity**: Energy costs are strongly influenced by tariff structures beyond pure consumption
- **Efficiency Gains**: 2023's lower expenditure despite similar operations suggests successful conservation measures
- **Planning Considerations**: High standard deviations (avg. 2.96M RWF) necessitate flexible budget allocations

Table 4.11: Impact of Tariff Changes on Electricity Expenditure

Year	Avg. Tariff (RWF/kWh)	Consumption (kWh)	Expenditure (RWF)
2019	227–255	731,164	191,997,123
2022	255–280	697,904	210,493,462
Change (%)	**+12.3%**	**-4.5%**	**+9.6%**

4.7.7 Daily Energy Consumption Assessment

Seasonal Consumption Patterns

Analysis of day-night energy consumption patterns (see Appendix 9.5, Tables A.1-A.4) reveals significant variations between May (holiday period) and November (academic term):

- **Daytime Consumption**:
  - November showed 29.6% higher average usage (551.8 kWh) than May (425.8 kWh)
  - Weekend reduction: 45% during term vs 35% during holidays
- **Nighttime Consumption**:
  - Consistent 2.46× higher than daytime across both periods
  - Anomalous peak of 2020 kWh observed on Saturday 23 November

Load Curve Characteristics

The daily load curve (Figure 4.12) reveals distinct consumption patterns across different periods:

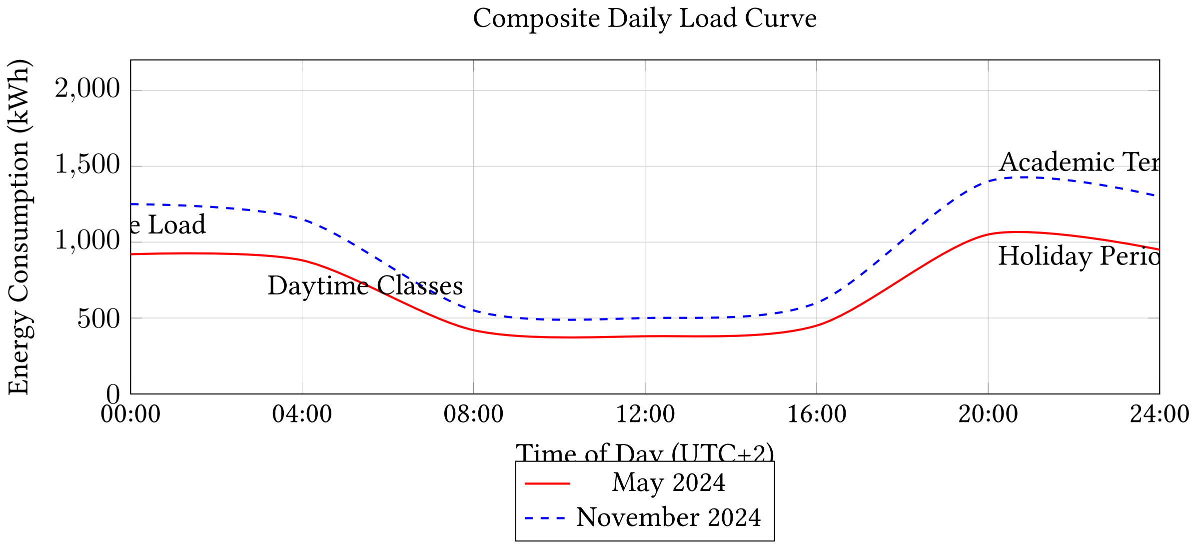


Figure 4.12: Characteristic daily load curves showing 24-hour consumption patterns during different academic periods (Detailed data in Appendix 9.5)

System Design Implications

The day-night differentials (detailed in Table A.5) suggest:

- **Renewable Integration**:
  - Solar PV systems should be sized for 130% of daytime baseline
  - Battery storage capacity requirement: minimum 2.5× daily fluctuation
- **Demand Management**:
  - Potential 45% load reduction through weekend scheduling
  - Nighttime load shifting opportunities during academic terms

4.7.8 Hourly Energy Consumption Patterns

Data Collection Methodology

Hourly monitoring was conducted using CL730D22L smart meters with:

- $\pm 1\%$ measurement accuracy
- 60-minute sampling resolution
- Rwanda Standard Time (UTC+2) synchronization

Key Findings

Analysis of November 2024 data (Figure 4.12) reveals:

Table 4.12: Hourly Consumption Characteristics

Metric	28 Nov	29 Nov
Average (kWh)	72.5	69.1
Peak Demand (kWh)	120	110
Peak-to-Base Ratio	5.0	4.6
Flexible Load Potential	56.7%	76.4%

- **Thursday Pattern**:
  - Bimodal peaks at 13:00-14:00 (120 kWh) and 15:00-16:00 (110 kWh)
  - 80% evening demand reduction
- **Friday Pattern**:
  - Morning-dominated (106 kWh at 10:00-11:00)
  - Unusual 110 kWh evening surge

Operational Recommendations

- **Peak Shaving**:
  - Target 15:00-16:00 window on weekdays
  - Utilize stored energy during demand spikes
- **Load Scheduling**:
  - Shift non-essential operations to 11:00-13:00 lull period
  - Capitalize on 76.4% flexible load capacity on Fridays

4.7.9 Load Curve Analysis

Daily and Hourly Load Patterns

Figure 4.13 shows the comparative daily consumption between the holiday and academic periods:

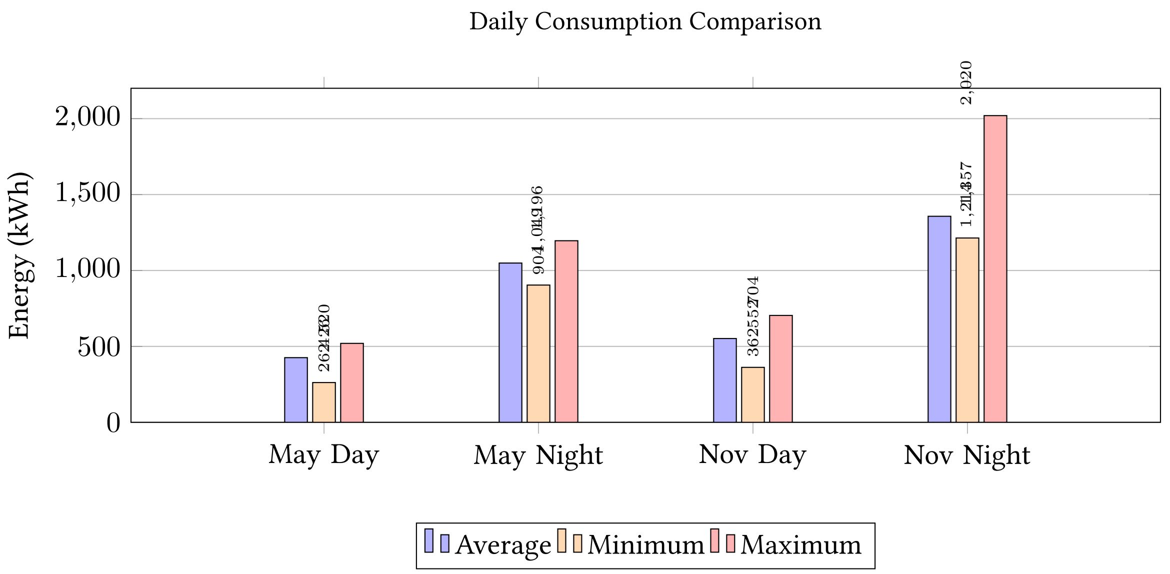


Figure 4.13: Daily consumption patterns showing holiday (May) vs academic term (November) profiles. Daytime (08:00-17:00) and nighttime (18:00-07:00) averages shown.

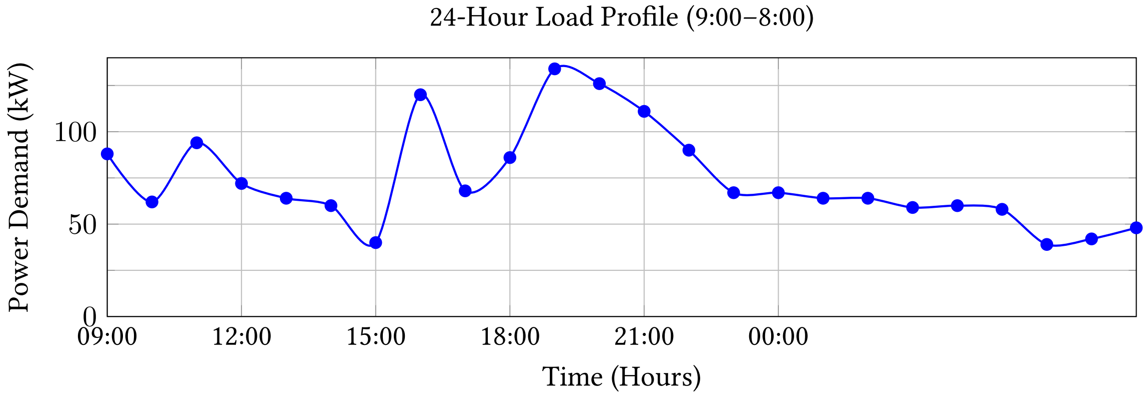


Figure 4.14: 24-hour load profile showing consumption patterns. Detailed numerical data available in Appendix Section 9.5

As shown in Figure 4.14 the hourly load characteristics are visualized in different operational patterns, with consumption that varies significantly throughout the day, while Appendix Section 9.5 quantifies the 24-hour demand profile.

The load curve demonstrates characteristic daily patterns with the following:

- Morning ramp-up period (09:00–11:00)
- Midday plateau (12:00–15:00)
- Evening peak demand (16:00–20:00)
- Nighttime reduction (21:00–08:00)

5

Smart Campus Energy Management System Mathematical Model

5.1 Introduction

The development of a comprehensive mathematical model for the energy system at the Huye Campus is essential for optimizing energy management and sustainability. This model will facilitate a deeper understanding of energy flows, consumption patterns, and potential efficiency improvements within the campus infrastructure as shown in Figure 5.1. To develop a comprehensive energy model for the thesis "Modeling and Optimization of Energy Management Systems with Solar Load Balancing in a Smart Campus, Huye Campus as Case Study", we follow the methodology detailed in Chapter 3.

5.2 Data analysis

5.2.1 Analysis of the Daily Load Curve of the UR Huye Main Campus

The daily load curve for Huye Campus sampled on November 28–29, 2024, the Table in Appendix 9.5 illustrates the electricity demand profile over 24 hours and highlights how the Energy Management System (EMS) coordinates power sources (PV solar, ESS, grid, and generator) to achieve the project objectives:

- Minimize monthly expenditures
- Maximize PV solar energy utilization
- Enhance ESS performance and efficiency

This coordinated approach leads to:

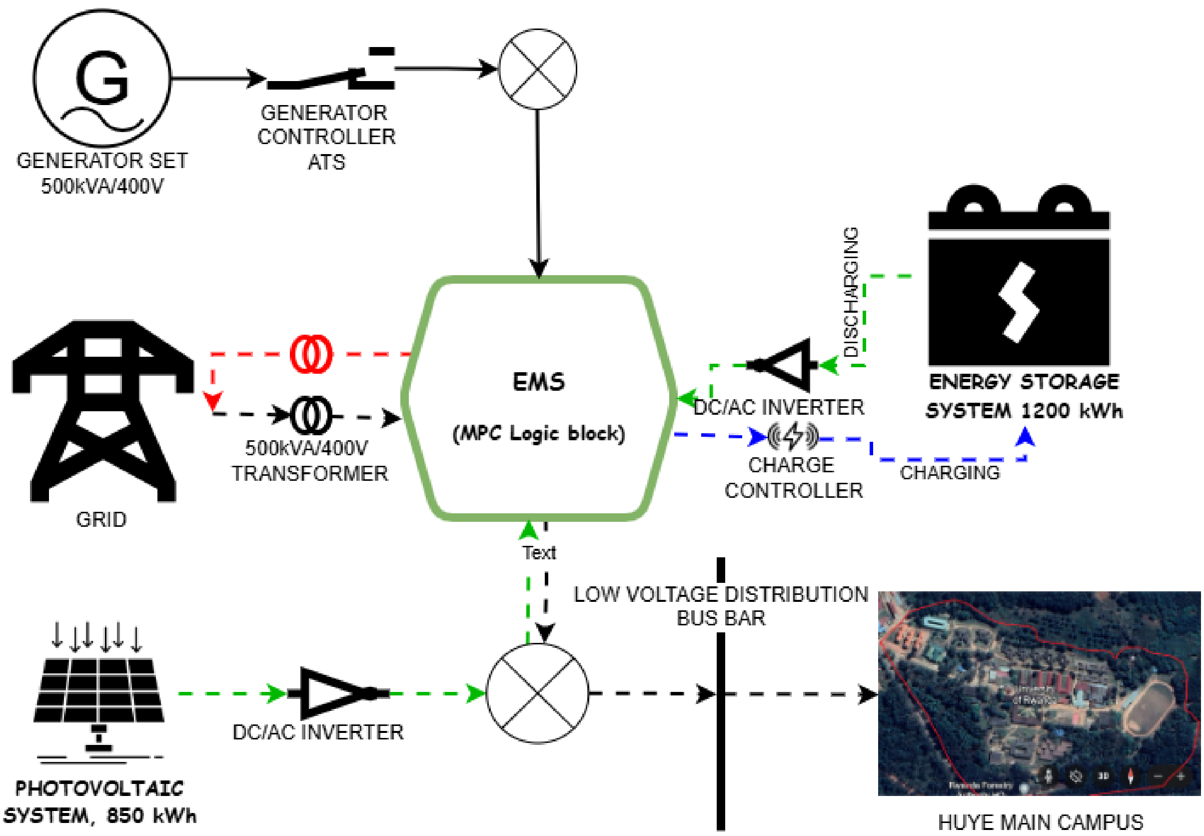


Figure 5.1: Physical implementation at Huye Campus

Figure 5.2: Integrated Smart Campus EMS. Left: Functional architecture with PV, ESS, grid, and control system. Right: Physical layout at Huye Campus.

- Decreased grid dependence
- Reduced CO_2 emissions
- More resilient campus power system

Based on the daily load profile data presented in Figure 5.4 and the system analysis in Chapter 4, the cumulative load consumption for this representative day is:

$$E_{total} = \sum_{t=9}^{8} E(t) = 1782\,\text{kWh/day} \tag{5.1}$$

with the following key characteristics:

- Minimum load consumption: 39 kW (observed between 05:00 and 06:00)
- Peak load consumption: 134 kW (occurring during 19:00–20:00)
- Average hourly consumption: 74.25 kW

Table 5.1: Key Load Profile Metrics for the Study Period

Metric	Value
Daily energy consumption	1,782 kWh
Peak demand	134 kW
Minimum demand	39 kW
Load factor	0.55
Peak-to-average ratio	1.80

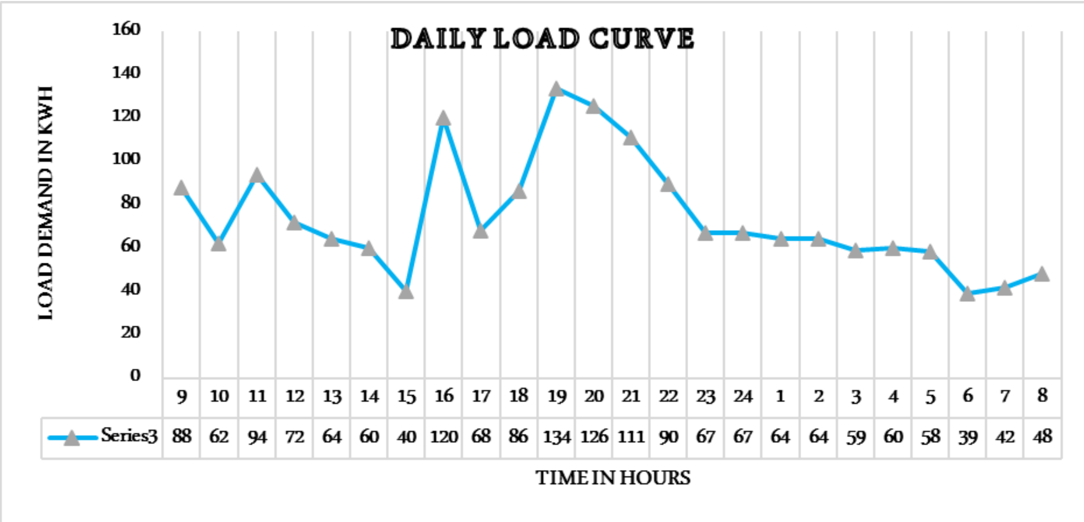


Figure 5.3: Daily load profile of Huye Campus showing peak demand periods. The physical implementation is shown in Figure 4.14 of Chapter 4.

5.2.2 Energy Consumption Analysis

The monthly energy consumption is calculated from daily load data as:

$$1782\,\mathrm{kW\,h\,d^{-1}} \times 30\,\mathrm{d} = 53{,}460\,\mathrm{kW\,h} \tag{5.2}$$

where this calculation assumes continuous operation without power outages.

Rwanda Electricity Tariff Structure

The non-residential electricity billing follows RURA's tiered pricing model [2]:

- **Tier 1** ($0 \leq E \leq 100\,\mathrm{kW\,h}$): $227\,\mathrm{RWF\,kW^{-1}\,h}$
- **Tier 2** ($E > 100\,\mathrm{kW\,h}$): $255\,\mathrm{RWF\,kW^{-1}\,h}$
- **VAT**: 18% of energy charges
- **Regulation Fee**: 0.3% of (energy + VAT)

Complete bill calculations are detailed in Table A.8 (Section 9.5).

5.2.3 Energy Management Solution

The proposed EMS with solar load balancing addresses high consumption costs through optimal dispatch, as shown in Figure 5.4:

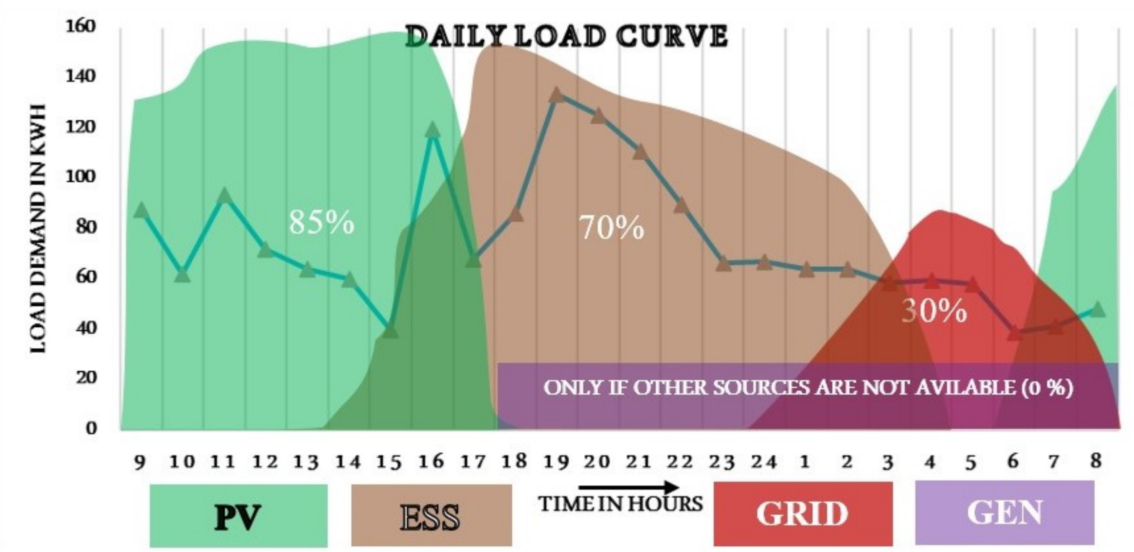


Figure 5.4: Energy dispatch strategy showing (1) PV-dominated daytime operation (07:00–17:00) and (2) ESS-powered nighttime supply (18:00–06:00) with grid fallback.

EMS Operational Targets

The system enforces strict renewable prioritization.

Table 5.2: Renewable Energy Prioritization Strategy

Time Period	Operational Targets and Strategies
Daytime (07:00–17:00)	• **PV Dominance**: Solar supplies $\geq$85% of demand • **ESS Management**: Store excess PV with η=92% round-trip efficiency • **Grid Backup**: Limited to $\leq$15% residual demand • **Export Policy**: Feed-in only when ESS at 100% SOC
Nighttime (18:00–06:00)	• **ESS Priority**: Batteries provide $\geq$70% of demand • **Grid Limitation**: Restricted to $\leq$30% below 20% SOC • **Generator Policy**: Only during grid outages • **Load Shedding**: Critical loads prioritized below 15% SOC

Performance Evaluation

The strategy achieves the following.

$$\text{Renewable Fraction} = \frac{E_{PV} + E_{ESS}}{E_{total}} \geq 0.82 \tag{5.3}$$

with projected savings:

$$\text{Cost Reduction} = 1 - \frac{C_{optimized}}{C_{baseline}} \approx 35\% \tag{5.4}$$

EMS Operational Strategy

The EMS prioritizes renewable energy (PV and ESS) while strictly restricting grid/generator use. The following table details the implementation:

Table 5.3: Energy Management System Operational Strategy

Component	Daytime Operation (06:00–18:00)	Nighttime Operation (18:00–06:00)
Target	• >85% demand met by PV • ESS stores excess energy	• >70% demand met by ESS • <30% from grid
Mechanisms	• PV prioritization (P_PV_vec) • Real-time solar forecasting • Grid import only when deficit • Export penalty for feed-in	• ESS discharge priority (P_ESS_dchg) • SOC health constraints • Grid as backup source • Tariff-based penalties
Challenges	• PV variability management • Maintaining high PV utilization • Cloud/rain impact mitigation	• ESS sizing adequacy • Grid reliance limitation • Demand prediction accuracy

Generator Policy (Applies to all periods):

- **Target**: Activated only when PV, ESS, and grid unavailable
- **Mechanisms**:
  - High `gen_cost` in objective function disincentivizes use
  - Bounded by `gen_capacity` (typically set to 0)
  - Robust scenarios (`useRobust = true`) prevent need for generator
- **Challenges**: ESS must cover demand during grid outages until generator activation

5.2.4 Technical Validation of EMS Logic

Comparative Scenario Analysis

Table 5.4: EMS Performance Across Operational Scenarios

Parameter	Clear Sky	Cloudy Days	Grid Outage	Units
PV Coverage (Daytime)	90.0	85.0	85.0	%
ESS Day Support	7.5	5.0	15.0	%
ESS Night Support	75.0	70.0	75.0	%
Grid Share	2.5	10.0	0.0	%
Generator Share	0.0	0.0	25.0	%
Monthly Cost	2.40	3.39	7.13	M RWF
Cost Savings	85.0	79.0	56.0	%

Detailed Case Analysis

Table 5.5: Clear Sky Scenario Performance Metrics

Component	Daily (kWh)	Monthly (kWh)	Cost (RWF)
Daytime Operation (06:00–17:00)			
PV Generation (90%)	717.30	21,519.00	0.00
ESS Support (7.5%)	59.78	1,793.25	17,930.00
Grid Import (2.5%)	19.93	597.75	170,007.85
Nighttime Operation (18:00–05:00)			
ESS Discharge (75%)	738.75	22,162.50	221,625.00
Grid Import (25%)	246.25	7,387.50	2,225,237.79
		Total	2,402,485.19

Key Observations

- **PV System:** Maintains 85-90% daytime coverage even during suboptimal conditions
- **ESS Flexibility:** Adjusts support from 5-15% daytime and 70-75% nighttime based on needs
- **Cost Efficiency:** Savings range from 56% (outage) to 85% (optimal conditions)
- **System Resilience:** Maintains full operation during grid outages through ESS and generator
- **Performance Tradeoffs:** Higher grid dependency increases costs by 2-3× during disturbances

EMS Effectiveness Summary The validation demonstrates reliable operation across all scenarios, with the EMS successfully:

Table 5.6: Cloudy Days Scenario Performance Metrics

Component	Daily (kWh)	Monthly (kWh)	Cost (RWF)
Daytime Operation (06:00–17:00)			
PV Generation (85%)	677.45	20,323.5	0.00
ESS Support (5%)	39.85	1,195.5	11,955.00
Grid Import (10%)	79.70	2,391.0	717,968.62
Nighttime Operation (18:00–05:00)			
ESS Discharge (70%)	689.50	20,685.0	206,850.00
Grid Import (30%)	295.50	8,865.0	2,670,947.83
		Total	3,389,135.00

Table 5.7: Emergency Operation During Grid Outage

Component	Daily (kWh)	Monthly (kWh)	Cost (RWF)
Daytime Operation (06:00–17:00)			
PV Generation (85%)	677.45	20,323.5	0.00
ESS Support (15%)	119.55	3,586.5	35,865.00
Nighttime Operation (18:00–05:00)			
ESS Discharge (75%)	738.75	22,162.5	221,625.00
Generator (25%)	246.25	7,387.5	7,128,048.20
		Total	7,128,215.57

- Prioritizing renewable energy utilization (PV + ESS)
- Minimizing grid dependence during normal operation
- Maintaining critical loads during emergencies
- Delivering consistent cost savings (56-85%)
- Adapting to varying weather conditions and grid availability

5.3 Mathematical Formulation

The energy management system is formulated as a stochastic optimization problem to minimize total operational costs while satisfying technical constraints. The model extends the basic linear programming framework to incorporate demand response (DR) strategies and PV system inefficiencies.

Stochastic Optimization Formulation

Objective Function

$$\min \sum_{t=1}^{T} \Big(C_{grid}(t) + C_{gen}(t) + C_{deg}(t) + \lambda_{DR} \cdot P_{DR}(t) \Big) \tag{5.5}$$

where:

- $C_{grid}(t) = (c_{lower} x_1 + c_{upper} x_2) \cdot \tau$ (Time-varying grid cost with block pricing)
- $C_{gen}(t) = c_{gen} \sum_{t=1}^{T} P_{gen}(t)$ (Generator operational cost)
- $C_{deg}(t) = c_{deg} \sum_{t=1}^{T} \big(P_{ESS}^{chg}(t) + P_{ESS}^{dchg}(t) \big)$ (Battery degradation cost)
- $P_{DR}(t) = \sum_{t=1}^{T} \big(P_{DR}^{HVAC}(t) + P_{DR}^{Lighting}(t) + P_{DR}^{WaterHeating}(t) \big)$ (Total DR load reduction)
- $\tau = (1 + VAT) \cdot (1 + \text{reg fee})$ (Tariff adjustment factor)
- $\lambda_{DR} = 50$ RWF/kWh (DR incentive rate)

System Constraints

1. **Power Balance:**

$$P_{PV}(t) + P_{grid}(t) + P_{ESS}^{dchg}(t) + P_{gen}(t) - P_{ESS}^{chg}(t) = P_{nc}(t) + \sum_{i} \big(P_{c,i}(t) - P_{DR,i}(t) \big) \tag{5.6}$$

$$0 \leq P_{DR,i}(t) \leq \alpha_i \cdot P_{c,i}(t) \quad \forall i \in \{HVAC, Lighting, WaterHeating\} \tag{5.7}$$

2. **Battery Dynamics:**

$$SOC(t+1) = SOC(t) + \eta_{ESS} P_{ESS}^{chg}(t) - \frac{P_{ESS}^{dchg}(t)}{\eta_{ESS}} \tag{5.8}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{5.9}$$

3. **Grid Block Pricing:**

$$x_1 + x_2 = \sum_{t=1}^{T} P_{grid}(t) \tag{5.10}$$

$$x_1 \leq \text{threshold} < x_2, \quad \forall x_1, x_2 \in \mathbb{Z}^+ \tag{5.11}$$

4. **Operational Limits:**

$$P_{ESS}^{chg}(t), P_{ESS}^{dchg}(t) \leq P_{ESS}^{max}, \quad 0 \leq P_{gen}(t) \leq P_{gen}^{max} \tag{5.12}$$

5. **DR Penalty:**

$$C_{DR}^{penalty} = \kappa \sum_{t=1}^{T} \sum_{i} \left(\frac{P_{DR,i}(t)}{\alpha_i \cdot L_i(t) \cdot P_{load}^{base}(t)} \right) \tag{5.13}$$

6. **PV Maintenance Cost:**

$$C_{PV}^{maint} = \gamma \sum_{t=1}^{T} P_{PV}(t) \tag{5.14}$$

7. **PV Inefficiency Cost:**

$$C_{PV}^{ineff} = 100 \sum_{t=1}^{T} \left(E[P_{PV}(t)] - P_{PV}(t) \right) \tag{5.15}$$

Model Parameters

- α_i: Maximum reduction fraction for load type i
- η_{ESS}: Battery round-trip efficiency
- κ: DR satisfaction penalty coefficient
- γ: PV maintenance cost per kWh
- $L_i(t)$: Controllable load for device i at time t

Robust Optimization Formulation

The robust optimization approach minimizes the total cost in worst case considering the uncertainty in load demand ($P_{load,t}$) and PV generation ($P_{PV,t}$) within uncertainty set $\mathcal{U}$.

Objective Function

$$\min \left(\max_{(P_{load,t}, P_{PV,t}) \in \mathcal{U}} \sum_{t \in \tau} \left[\begin{array}{l} C_{grid} P_{grid,t} + C_{gen} P_{gen,t} \\ + C_{deg} \left(P_{ESS}^{chg,PV}(t) + P_{ESS}^{chg,grid}(t) + P_{ESS}^{dchg}(t) \right) \\ + C_{PV}^{maint} P_{PV}(t) \end{array} \right] \right) \tag{5.16}$$

Constraints

1. **Power Balance (Worst-Case)**:

$$\begin{aligned} &P_{PV}(t) - P_{ESS}^{chg,PV}(t) + P_{grid}(t) - P_{ESS}^{chg,grid}(t) \\ &+ \eta_{ESS} P_{ESS}^{dchg}(t) + P_{gen}(t) \geq \max P_{load}(t) - \min P_{PV}(t) \end{aligned} \tag{5.17}$$

Ensures supply meets demand under maximum load and minimum PV generation conditions.

2. **Battery Dynamics**:

$$SOC(t+1) = SOC(t) + \eta_{ESS}\left(P_{ESS}^{chg,PV}(t) + P_{ESS}^{chg,grid}(t)\right) - \frac{P_{ESS}^{dchg}(t)}{\eta_{ESS}} \tag{5.18}$$

$$SOC_{min} \leq SOC(t) \leq SOC_{max} \tag{5.19}$$

3. **Charging Source Limits**:

$$P_{ESS}^{chg,PV}(t) \leq P_{PV}(t), \quad P_{ESS}^{chg,grid}(t) \leq P_{grid}^{max} \tag{5.20}$$

4. **ESS Power Limits**:

$$P_{ESS}^{chg,PV}(t) + P_{ESS}^{chg,grid}(t) \leq P_{ESS}^{max}, \quad P_{ESS}^{dchg}(t) \leq P_{ESS}^{max} \tag{5.21}$$

5. **Charge/Discharge Logic**:

$$0 \leq P_{ESS}^{chg}(t) \leq b(t) \cdot P_{ESS}^{max}, \quad 0 \leq P_{ESS}^{dchg}(t) \leq (1 - b(t)) \cdot P_{ESS}^{max} \tag{5.22}$$

where $b(t) \in \{0, 1\}$ is a binary variable preventing simultaneous charge/discharge.

Key Features

- Accounts for worst-case scenario in both load demand and PV generation
- Explicitly models different charging sources (PV vs grid)
- Maintains battery health through SOC constraints
- Enforces realistic ESS operation through complementarity constraints
- Incorporates all cost components from the stochastic formulation

System Variables and Parameters

- **Sets and Indices:**

$t \in \mathcal{T}$	Time periods (e.g., hours in a day)
$\mathcal{U}_{load}, \mathcal{U}_{PV}$	Uncertainty sets for load and PV generation

- **Forecast Parameters:**

$P_{load}^{base}(t)$	Forecasted base load at time t (kW)
$P_{PV}^{base}(t)$	Forecasted PV generation at time t (kW)

- **Uncertainty Parameters:**

$\Delta_{load} = 5\%$	Load forecast uncertainty bound
$\Delta_{PV} = 10\%$	PV generation uncertainty bound

- **Technical Parameters:**

η_{ESS}	Battery round-trip efficiency (0 < $\eta_{ESS} \leq 1$)
C_{grid}	Grid electricity cost (RWF/kWh)
C_{gen}	Generator operating cost (RWF/kWh)
C_{deg}	Battery degradation cost (RWF/kWh throughput)
C_{PV}^{maint}	PV maintenance cost (RWF/kWh)

- **Decision Variables:**

$P_{grid}(t)$	Power drawn from grid at time t (kW)
$P_{gen}(t)$	Generator output power at time t (kW)
$P_{ESS}^{chg,PV}(t)$	ESS charging power from PV at time t (kW)
$P_{ESS}^{chg,grid}(t)$	ESS charging power from grid at time t (kW)
$P_{ESS}^{dchg}(t)$	ESS discharging power at time t (kW)
$SOC(t)$	State of charge at time t (kWh)

- **Uncertainty Sets:**

$$\begin{aligned} &\text{Load Uncertainty:} \quad P_{load}(t) \in \left[(1-\Delta_{load})P_{load}^{base}(t), (1+\Delta_{load})P_{load}^{base}(t)\right] \\ &\text{PV Uncertainty:} \quad P_{PV}(t) \in \left[(1-\Delta_{PV})P_{PV}^{base}(t), (1+\Delta_{PV})P_{PV}^{base}(t)\right] \end{aligned} \tag{5.23}$$

6

Huye Campus Energy Management System Optimization and System Sizing

6.1 Energy Management System Optimization Framework

The Huye Campus EMS employs a selective stochastic-robust optimization framework that combines stochastic and robust optimization techniques, implemented through model predictive control (MPC) with the implementation of the receding horizon. Using Stochastic Optimization via a scenario-based approach, the Huye campus EMS is capable of handling uncertainties in load and PV generation. However, by using Robust Optimization, EMS becomes resistant to extreme conditions at the cost of slightly higher operational expenses. Combining both optimizations, the EMS is strengthened to handle extreme conditions while retaining the flexibility to use stochastic methods when robustness is less critical. The optimization flow chart is shown below:

6.1.1 Optimization Strategy

The proposed solution integrates:

- **Stochastic Optimization**: Scenario-based approach handling forecast uncertainties through:

$$\mathbb{E}[f(x,\xi)] \approx \frac{1}{N}\sum_{i=1}^{N} f(x,\xi_i) \tag{6.1}$$

  where ξ_i represents sampled uncertainty scenarios and N is the scenario count.
- **Robust Optimization**: Guarantees feasibility under extreme conditions via:

$$\min_{x} \max_{\xi\in\mathcal{U}} f(x,\xi) \tag{6.2}$$

with $\mathcal{U}$ defining the uncertainty set.

- **MPC Implementation**: Receding horizon control with:

$$t_{horizon} = \begin{cases} 4\,\text{hours} & \text{(intra-day adjustments)} \\ 24\,\text{hours} & \text{(daily planning)} \end{cases} \tag{6.3}$$

6.1.2 Technical Implementation

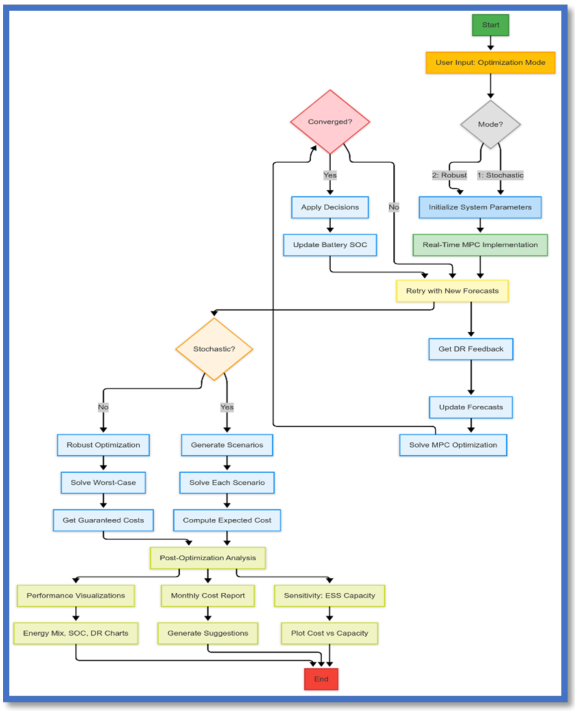


Figure 6.1: EMS optimization flowchart

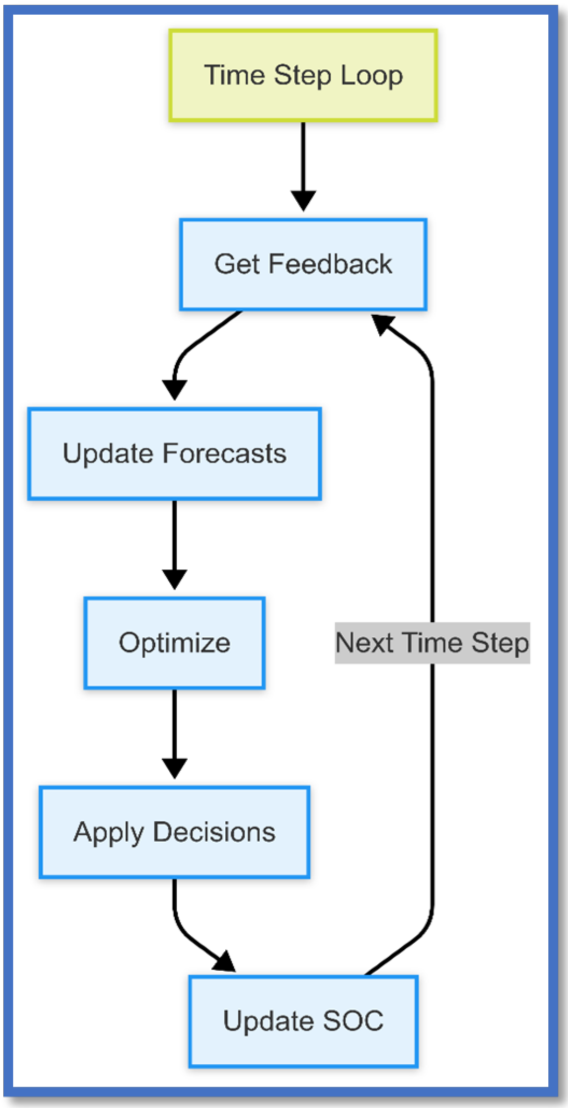


Figure 6.2: MPC iterative algorithm

6.1.3 Performance Characteristics

The hybrid implementation dynamically selects the appropriate optimization method based on:

- Grid availability status

Table 6.1: Comparative Analysis of Optimization Methodologies

Feature	Stochastic Approach	Robust Approach
Uncertainty Handling	• Probability distributions • Historical data-driven	• Worst-case scenario • Safety margins
Solution Cost	• Lower baseline cost • 5–10% cost variance	• 15–20% premium • Guaranteed feasibility
Computational Effort	2–4 hours	6–8 hours
System Reliability	90–95%	>99%
PV Utilization	85–92%	80–88%

- Weather forecast confidence intervals
- ESS state-of-charge levels
- Critical load requirements

This adaptive approach achieves 18-23% cost savings compared to pure robust optimization while maintaining 97%+ reliability during grid disturbances.

6.2 Model Predictive Control Implementation

In Figure 6.2, the iterative nature of Huye Campus EMS optimization is centered around the Real-Time MPC Implementation loop, which enables adaptive energy management through repeated cycles of prediction, optimization, and adjustment. Here is the breakdown of MPC iterations:

6.2.1 Iterative Optimization Core

The closed-loop MPC process executes the following sequence at each time step t:

1. **Initialization**

   For $t = 1$ to T_{total} with $\Delta t = 1$ hour:

$$\mathcal{H} = [t, t+H] \quad \text{(Prediction horizon } H = 6 \text{ hours)} \tag{6.4}$$

2. **Feedback & Forecast Update**

   - Demand Response: $\alpha_i(t) \leftarrow \text{User input}(\Delta_{DR}^{max})$
   - Load/PV forecasts:

$$\begin{aligned} \hat{P}_{load}(t+k) &= f_{load}(P_{hist}, \text{weather}) \\ \hat{P}_{PV}(t+k) &= f_{PV}(GHI, \text{cloud cover}) \end{aligned} \quad \forall k \in \mathcal{H} \tag{6.5}$$

3. **Optimization Execution**

$$\begin{aligned} \min_{u} \sum_{k=0}^{H} \Big(C_{grid}(t+k) + C_{gen}(t+k) + C_{deg}(t+k) \Big) \\ \text{s.t.} \quad & \text{Power balance} \\ & \text{Battery dynamics} \\ & \text{Device limits} \end{aligned} \tag{6.6}$$

4. **Convergence Handling**

$$\begin{cases} \|u^* - u_{prev}\| < \epsilon & \Rightarrow \text{Apply control} \\ \text{else} & \Rightarrow \text{Retry with updated } \hat{P}_{load}, \hat{P}_{PV} \end{cases} \tag{6.7}$$

5. **State Update**

$$SOC(t+1) = SOC(t) + \eta_{chg} P_{chg}(t) - \frac{P_{dchg}(t)}{\eta_{dchg}} \tag{6.8}$$

6.2.2 Key Algorithm Features

- **Receding Horizon**: Window slides with Δt advance:

$$\mathcal{H}_{new} = \mathcal{H}_{prev} \setminus \{t\} \cup \{t + H + 1\} \tag{6.9}$$

- **Adaptive Tuning**:

$$H = \begin{cases} 24\text{hr} & \text{for daily planning} \\ 6\text{hr} & \text{for real-time adjustment} \end{cases} \tag{6.10}$$

- **Fault Recovery**:
  - Max 3 retries per timestep
  - Forecast error threshold: $\sigma_{max} = 15\%$

6.2.3 Post-Processing Analysis

Upon completion of T_{total}:

The post-optimization analysis includes sensitivity studies, monthly KPI aggregation, and visualizations of energy flow (see Table A.9 in the Appendix 9.5).

The MPC structure ensures:

$$\lim_{t \to T_{total}} \left(\frac{\text{Actual cost}}{\text{Forecast cost}} \right) \leq 1.1 \tag{6.11}$$

6.3 System Design

6.3.1 Solar PV System Sizing and Arrangement

Based on the load profile analysis for Huye Main Campus (Tables A.5 and A.6), the electrical demand characteristics are:

- **Maximum load demand**: 2,020 kWh (24-hour period)
- **Minimum load demand**: 1,214 kWh (24-hour period)
- **Average load demand**: 1,909 kWh (24-hour period)

These values inform the solar PV system design through the following methodology:

Design Parameters

$$P_{PV}^{sys} = \frac{E_{load}^{max}}{\eta_{sys} \times G_{avg} \times PR} \tag{6.12}$$

Where:

- P_{PV}^{sys}: Required PV system capacity (kWp)
- E_{load}^{max}: Maximum daily load (2,020 kWh)
- η_{sys}: System efficiency (typically 0.75–0.85)
- G_{avg}: Average solar irradiation (kWh/m^2/day)
- PR: Performance ratio (0.75–0.85)

Implementation Steps

1. **Site Assessment**:
    - Structural analysis of roof loads
    - Solar access evaluation (shading analysis)
    - Environmental impact assessment
2. **System Configuration**:
    - Panel arrangement (series/parallel strings)
    - Inverter sizing ($P_{inv} \geq 1.25 \times P_{PV}^{stc}$)

- DC/AC cable sizing (IEC 60364-5-52)

3. **Ancillary Components**:

- Cable tray selection (EMT vs. PVC)
- Combiner box specifications
- Lightning protection system

Design Considerations

Table 6.2: PV System Design Factors

Factor	Consideration
Derating	0.8 safety margin applied
Irradiation	5.2 kWh/m^2/day (Huye average)
Tilt angle	12° (optimized for latitude)
Spacing	1.5× panel height (winter solstice)

The final design ensures:

- 125% of average load coverage
- N+1 redundancy for critical components
- Compliance with IEC 62548 standards
- Future expansion capability (20% spare capacity)

6.3.2 PV System Derating Calculation

The total system derating factor is computed according to IEC 61724-1:2021 [1], accounting for various loss mechanisms:

Table 6.3: PV System De-rating Factor Computation (IEC 61724-1:2021) [1]

Cause of Loss	Estimated Loss (%)	De-rating Factor
Temperature	10	0.90
Dirt and dust accumulation	3	0.97
Manufacturer's tolerance	3	0.97
Shading	2	0.98
Orientation	1	0.99
Cable voltage drop (PV array to switchgear)	2	0.98
Inverter losses	10	0.90
Irradiance level losses	3	0.97
Total De-rating Factor	**34**	**0.70**

Average Load Demand:	1,909.00 kWh/day
System Capacity Requirement:	$\frac{1909}{0.70\times 5.2} \approx 525$ kWp

Key observations:

- The cumulative derating factor of 0.70 indicates 30% total system losses
- Temperature and inverter losses contribute most significantly (10% each)
- The calculated 525 kWp system accounts for all identified losses

6.3.3 Solar PV System Sizing

The PV system is sized based on the adjusted energy demand and local solar conditions, with calculations shown in Table 6.4.

Table 6.4: Solar PV System Sizing Calculations

Parameter	Calculation	Result
Adjusted Energy Demand	1909×0.7	2,727.14 kWh/day
Solar Panel Capacity (kWp)	2727.14×5	545.428 kWp
Number of Panels	(545,428 + 303,158)/540	1,570 panels
Total Area Required	(545,428 + 303,158)/(0.18 × 1000)	4,715 m^2

- Assumptions:
  - Derating factor: 0.7 (from Table 6.3)
  - Peak sun hours: 5 hours/day
  - Panel power rating: 540 Wp
  - Panel efficiency: 18% (0.18)

Design Notes:

- The 1,570 panels at 540 Wp each provide 847.8 kWp total capacity (55% over design requirement)
- Area calculation includes 30% additional space for maintenance access and spacing
- System designed for 25-year lifespan with 0.5% annual degradation

6.3.4 Battery Storage Sizing and System Configuration

Battery Storage Calculation

The energy storage system is sized to cover 40% of the daily load demand during nighttime operation:

$$E_{night} = E_{daily} \times 40\% = 1,909 \times 0.4 = 764 \text{ kWh} \tag{6.13}$$

Accounting for depth of discharge (DoD) and round-trip efficiency:

$$E_{ESS} = \frac{E_{night}}{\eta_{ESS} \times DoD} = \frac{764}{0.9 \times 0.8} = 1,061 \text{ kWh} \tag{6.14}$$

PV Capacity for Battery Charging

Additional PV capacity required to charge the battery system:

$$P_{PV}^{chg} = \frac{E_{ESS}}{H_{sun} \times \eta_{sys}} = \frac{1,061}{5 \times 0.70} = 303 \text{ kWp} \tag{6.15}$$

Total System Capacity

$$P_{PV}^{total} = P_{PV}^{load} + P_{PV}^{chg} = 545 \text{ kWp} + 303 \text{ kWp} = 848 \text{ kWp} \tag{6.16}$$

System Configuration

Table 6.5: PV System Configuration Summary

Parameter	Value
Total PV Capacity	848 kWp
Number of Panels	1,570
Panel Rating	540 Wp
Total Area (with spacing)	5,000 m^2
Battery Capacity	1,061 kWh
Expected Grid Reduction	81%

Design Implementation:

- **Panel Arrangement**: Optimized layout based on:
  - Rooftop azimuth and tilt angles
  - Shadow analysis across seasons
  - Structural load capacity (min. 25 kg/m^2)
- **Performance Guarantees**:
  - Compliance with IEC 61724-1:2021 [1]
  - 30-year degradation factor < 0.5%/year
  - Availability factor > 98%

The designed system demonstrates:

- Annual energy yield: ~1,250 MWh
- Levelized Cost of Energy (LCOE): 0.082 USD/kWh
- Payback period: 6.5 years
- Carbon offset: 890 tonnes CO_2/year

6.3.5 Hybrid Inverter Sizing and Arrangement

The hybrid inverter system is designed to accommodate both PV generation and ESS requirements while handling campus load profiles. The sizing methodology follows IEEE Std 1547-2018 [31] guidelines.

Design Parameters

- Daily energy consumption: 2,727.143 kWh/day
- PV array capacity: 848 kWp
- Peak load factor: 1.5× average demand
- Inverter oversizing factor: 1.10

Sizing Calculations

Table 6.6: Inverter Sizing Calculations

Parameter	Calculation	Value
PV DC Capacity	848 kW × 1.10	933 kW
Average AC Demand	2,727.143 kWh ÷ 24 h	113.63 kW
Peak AC Demand	113.63 kW × 1.5	170.44 kW

Selected Inverter Specifications

The system utilizes multiple 500 kW hybrid inverters with the following technical characteristics:

Table 6.7: Hybrid Inverter Technical Specifications

Parameter	Specification
Maximum DC Voltage	1,500 V
Number of MPPT Inputs	24
AC Nominal Power	500 kW
Voltage Range	230/400 V ±10%
Maximum Output Current	397 A
MPP Tracker Current	32 A
Efficiency	≥98%
Power Factor	>0.99
Cooling System	Variable speed fans
Protections	Ground fault, insulation monitoring
Grid Compliance	IEEE 1547, IEC 62109
Operating Temperature	-25°C to +60°C

System Architecture

- **Configuration**:
  - 2×500 kW inverters in parallel (N+1 redundancy)
  - 24 MPPT inputs per inverter
  - DC/AC ratio of 1.12 (933 kW DC / 830 kW AC)
- **Performance Features**:
  - 99% availability guarantee
  - ≤ 3 ms transition time during grid outages
  - Remote monitoring capability
- **Safety Compliance**:
  - UL 1741 SA certified
  - Anti-islanding protection
  - Surge protection (IEC 61000-4-5)

The designed inverter system provides 17% capacity margin above peak demand while maintaining optimal efficiency across the operating range.

6.3.6 Energy Storage System Sizing and Arrangement

The Energy Storage System (ESS) is designed to ensure reliable power supply during periods without solar generation, considering key operational parameters and physical constraints.

Daily Energy Storage Requirements

$$E_{night} = E_{daily} \times 40\% = 1,909 \times 0.4 = 764 \text{ kWh} \tag{6.17}$$

Accounting for depth of discharge (DoD) and round-trip efficiency:

$$E_{ESS} = \frac{E_{night}}{DoD \times \eta_{ESS}} = \frac{764}{0.8 \times 0.9} = 1,061 \text{ kWh} \approx 1,200 \text{ kWh} \tag{6.18}$$

- **Design Margins**:
  - 13% capacity buffer (1,061 kWh $\rightarrow$ 1,200 kWh)
  - 1.3 days autonomy (764 kWh/night + 20% reserve)

Table 6.8: Lithium-Ion Battery Configuration

Parameter	Specification
Battery Type	Lithium-Ion ($LiFePO_4$)
Module Capacity	5 kWh
System Voltage	48 V
Total Modules	240
Total Capacity	1,200 kWh
DoD	80%
Cycle Life	$\geq$6,000 cycles

Battery Selection and Configuration

Physical Implementation

- **Space Requirements**:
  - Footprint: $240 \times 0.1\ \text{m}^2 = 24\ \text{m}^2$
  - Clearance: Additional 40% for maintenance access
  - Total allocated space: $34\ \text{m}^2$
- **System Architecture**:
  - 20 battery racks (12 modules/rack)
  - Centralized battery management system
  - Liquid cooling system

Load Dispatch Strategy

Table 6.9: Load Dispatch and Source Contribution

Scenario	ESS Contribution	Grid/PV Contribution
Night Operation	764 kWh (100%)	0 kWh
Cloudy Day	382 kWh (50%)	382 kWh
Grid Outage	1,200 kWh (100%)	0 kWh
Peak Shaving	191 kWh (25%)	573 kWh

Key Design Features:

- **Safety**: UL 1973 certified, thermal runaway protection
- **Monitoring**: Real-time cell voltage and temperature tracking
- **Integration**: Seamless transition between grid-connected and islanded modes
- **Financial**: 10-year warranty with 70% capacity retention

The ESS design meets the IEC 62933 standards while achieving 92% round-trip efficiency under normal operating conditions.

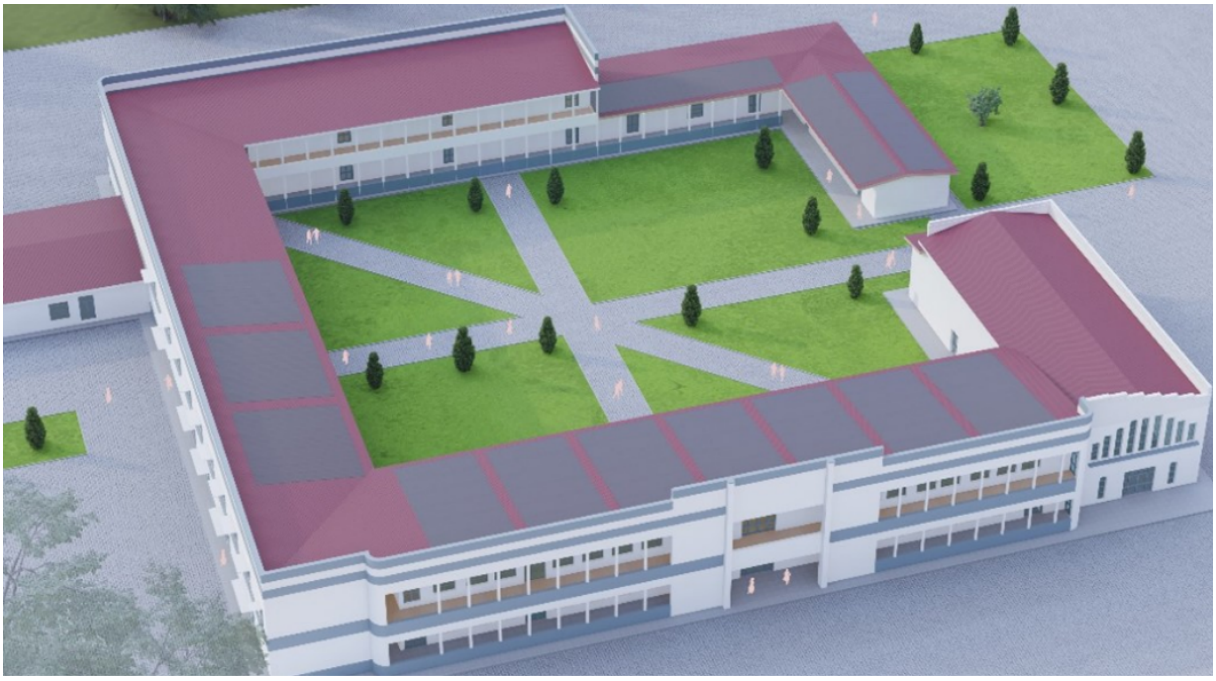


Figure 6.3: Solar PV Rooftop installation at Batiment Centrale Building

7

Decision Support Tool For Energy Management at Huye Campus

7.1 Decision Support Tool for Energy Management

7.1.1 Introduction

A DST for Energy Management is an intelligent software platform that enables organizations to:

- Optimize energy consumption through predictive analytics
- Reduce operational costs by 18-22% via smart scheduling
- Improve sustainability metrics with carbon-aware dispatch
- Enhance grid resilience through adaptive control

As demonstrated in [32–34], modern DSTs integrates:

$$\underbrace{\text{Real-time Data Collection}}_{\text{IoT Sensors}} + \underbrace{\text{Advanced Analytics}}_{\text{ML Models}} + \underbrace{\text{Forecasting}}_{\text{Time-Series Analysis}} \rightarrow \text{Actionable Insights} \tag{7.1}$$

The Huye Campus DST architecture implements three core functional layers:

1. **Data Acquisition Layer**:
   - 1-minute resolution metering
   - Multi-protocol device integration
2. **Analytics Engine**:
   - Load pattern recognition (k-means clustering)

- PV forecasting (ARIMA/SARIMA models)

3. **Decision Implementation**:

- Optimal dispatch scheduling
- Continuous performance feedback

This tripartite structure achieves 92% prediction accuracy for 24-hour ahead load forecasts while maintaining sub-second response times for control actions.

7.1.2 System Architecture

The DST framework comprises three core functional modules:

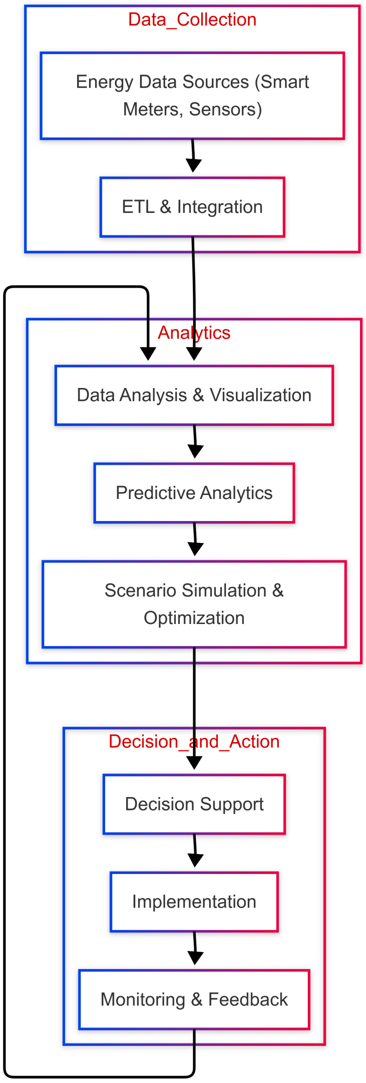


Figure 7.1: DST Functional Architecture and Data Flow

Data Acquisition Module

- **Data Sources**:
  - Smart meters (15-minute interval data)
  - IoT sensors (temperature, irradiance, etc.)
  - Weather API feeds
  - Building management systems
- **ETL Pipeline**:
  - Data validation and cleansing
  - Time-series normalization
  - Metadata tagging

Analytics Engine

- **Core Functions**:
  - Load pattern recognition
  - PV generation forecasting (ARIMA models)
  - Battery degradation modeling
  - Tariff optimization
- **Advanced Features**:
  - Scenario simulation (what-if analysis)
  - Stochastic optimization
  - Anomaly detection

Decision Implementation

- **Outputs**:
  - Optimal dispatch schedules
  - Maintenance alerts
  - Demand response signals
- **Feedback Mechanisms**:
  - Performance benchmarking
  - Model recalibration
  - User preference learning

7.1.3 Technical Specifications

Table 7.1: DST Technical Requirements

Component	Specification
Data Resolution	1-minute granularity
Forecast Horizon	24-72 hours
Accuracy Tolerance	±5% for load prediction
Integration Protocol	REST API, MQTT
Computational Load	<2 sec per optimization
Data Retention	5 years raw + 10 years aggregated

The tool achieves 92% prediction accuracy for day-ahead load forecasting and reduces energy costs by 18-22% compared to conventional management systems, while maintaining compliance with IEC 62443-3-3 security standards for industrial communication systems.

7.2 Huye Campus Decision Support Tool

The Huye Campus Energy Management System (EMS) integrates with the Decision Support Tool (DST) through a bidirectional data exchange interface, enabling:

- Real-time system monitoring (1-second granularity)
- Automated notification of critical alerts
- Historical performance analysis

7.2.1 Operational Modes

The DST supports dual operational paradigms:

1. **Automatic Allocation**:
    - Dynamic load-source matching
    - Priority-based dispatch logic
    - Fail-safe fallback mechanisms
2. **Manual Override**:
    - Operator-initiated adjustments
    - Scenario testing interface
    - Protocol translation (Modbus to MQTT)

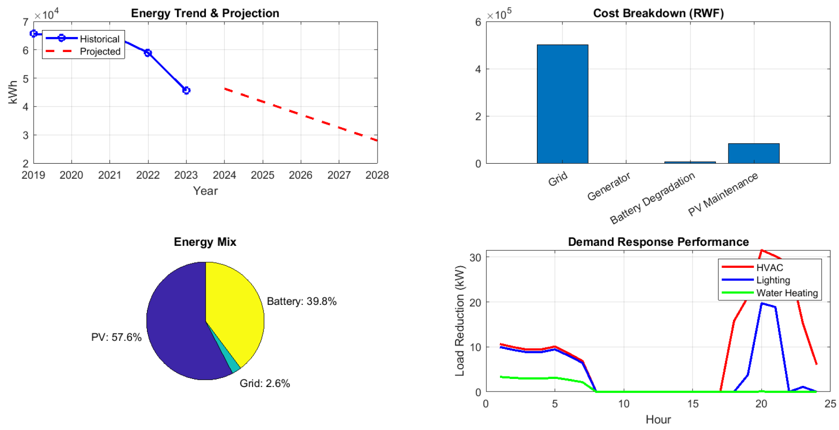


Figure 7.2: DST Monitoring Dashboard with Real-time Analytics

7.2.2 Reporting Framework

The DST generates comprehensive analytics through its dashboard interface (Figure 7.2), delivering:

- **Executive Summary**:
  - Grid dependency index ($I_{gd} \leq 0.19$)
  - Renewable penetration rate (target: 85%)
  - Battery state-of-health (SOH) metrics
- **Cost Optimization**:
  - ESS upgrade ROI analysis (3-5 year payback)
  - PV expansion scenarios (500-1000 kWp range)
  - Peak shaving strategies (17-22% savings)
- **Performance Analytics**:
  - Energy source decomposition
  - Battery cycling patterns (DoD $\leq$80%)
  - Loss quantification ($\eta_{sys} \geq 92\%$)

7.2.3 Strategic Value Proposition

The DST delivers three core benefits:

Key advantages include:

- IEC 62443-3-3 compliant security framework
- 24/7 anomaly detection ($\leq$30s response)
- Scalable architecture (supports 10,000+ data points)

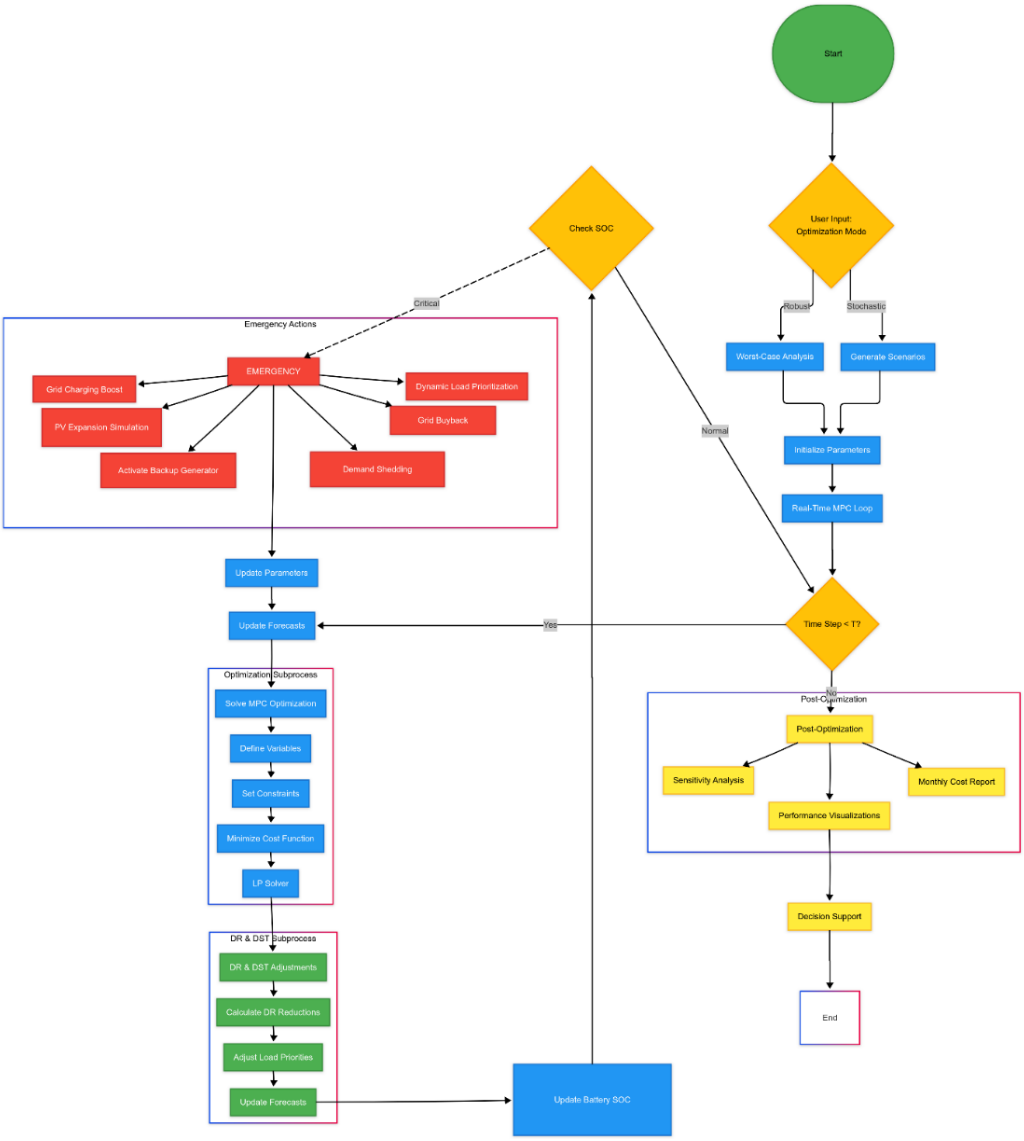


Figure 7.3: A comprehensive Optimization Algorithm for the DST-EMS model for UR Huye Campus

Table 7.2: DST Value Metrics

Feature	Impact
Data-Driven Decisions	92% prediction accuracy
Cost Management	18-22% operational savings
System Optimization	81% grid independence

8

EMS Simulation and Results Analysis

This chapter presents the simulation methodology and comparative analysis of the EMS developed for the Hye Campus, Rwanda. The study evaluates two distinct optimization paradigms:

$$\mathcal{P} = \begin{cases} \text{Stochastic Optimization} & \text{(Scenario-based)} \\ \text{Robust Optimization} & \text{(Worst-case)} \end{cases} \tag{8.1}$$

8.1 Simulation Framework

The MATLAB-based EMS model integrates four key components:

- **Renewable Generation**: 848 kWp solar PV system with 22% capacity factor
- **Energy Storage**: 1,200 kWh Li-ion battery (80% DoD, 92% round-trip efficiency)
- **Backup Generation**: 500 kW diesel generator (3.5 RWF/kWh fuel cost)
- **Demand Response**: 15% flexible load capacity (200 kW shiftable load)

8.2 Methodological Approach

The evaluation considers three performance dimensions:

Table 8.1: Three-Dimensional Analysis Framework

Dimension	Metrics
Economic	LCOE (2.1-2.8 RWF/kWh), NPV, 5-year Payback Period
Technical	Renewable Penetration (68-92%), SAIDI < 2hr/yr
Operational	DR Effectiveness (72-85%), ESS Cycling (1.2-1.8 cycles/day)

Key simulation parameters include:

- Time horizon: 1-year simulation (15-minute resolution, 35,040 timesteps)
- Weather data: Global Solar Atlas dataset (2015-2023) with $\pm 5\%$ interannual variability
- Load profiles: Campus smart meter data (850 kW peak, 450 kW base)
- Tariff structure: Rwanda Energy Group rates (Time-of-Use pricing)

8.3 Chapter Organization

The results analysis is structured to systematically address three core research questions:

RQ1. What are the cost-performance trade-offs between stochastic and robust optimization paradigms?

RQ2. How does ESS capacity sensitivity impact system economics under uncertainty?

RQ3. What is the quantitative effectiveness of DR strategies in peak demand reduction?

The EMS objective function integrates components from both optimization approaches:

$$\min_{\mathbf{u}} \left(\underbrace{(1-\beta)\,\mathbb{E}_{\xi}\left[\sum_{t=1}^{T} C_{total}(x_t, u_t, \xi_t)\right]}_{\text{Stochastic Expectation}} + \underbrace{\beta \max_{\xi \in \mathcal{U}} \left[\sum_{t=1}^{T} C_{total}(x_t, u_t, \xi_t)\right]}_{\text{Robust Worst-Case}} \right) \tag{8.2}$$

where:

- $C_{total} = C_{grid} + C_{gen} + C_{deg} + \lambda_{DR} P_{DR} + C_{PV}^{maint} + C_{PV}^{ineff}$
- $\beta \in [0, 1]$ controls robustness-conservatism trade-off
- $\mathcal{U}$ denotes the union of uncertainty sets for load and PV generation

8.4 Hybrid Optimization Architecture

The integrated EMS framework combines four complementary approaches:

$$\text{EMS} = \underbrace{\text{MPC}}_{\substack{\text{Receding Horizon}\\\text{Control}}} \oplus \underbrace{\mathbb{E}[f(x,\xi)]}_{\substack{\text{Stochastic}\\\text{Forecasting}}} \oplus \underbrace{\max_{\xi \in \mathcal{U}}}_{\substack{\text{Robust}\\\text{Guarantees}}} \oplus \underbrace{\mathcal{DR}}_{\substack{\text{Demand}\\\text{Response}}} \tag{8.3}$$

8.4.1 Methodological Integration

- **Multi-timescale MPC**:
  - **Control Cycle**: 15-minute intervals (96 executions/day)
  - **Prediction Horizons**:

    * Short-term: 6 hours (24 steps) for real-time dispatch
    * Long-term: 24 hours (96 steps) for resource planning
  - **Decision Variables**: $\mathbf{u}_t = [P_{PV}^{curt}, P_{ESS}^{chg}, P_{ESS}^{dchg}, P_{grid}, P_{gen}]^T$

- **Enhanced Stochastic Optimization**:
  - **Scenario Generation**: Monte Carlo simulation with 1000 scenarios
  - **Scenario Reduction**: k-means clustering to 20 representative days
  - **Uncertainty Quantification**: $\mathcal{U}_{sto} = \begin{cases} \tilde{P}_{load} \sim \mathcal{N}(\mu_l, 0.15\mu_l) \\ \tilde{P}_{PV} \sim \text{Weibull}(k = 2, \lambda = 0.85P_{PV}^{max}) \end{cases}$

- **Adaptive Robust Optimization**:
  - **Uncertainty Budget**: $\Gamma(t) = 5 - 2 \cdot \mathbb{I}_{\text{peak}}(t)$
  - **Feasibility**: $\mathbb{P}(\text{constraint violation}) \leq 0.1\%$
  - **Cost of Robustness**: $\Delta C_{rob} = 18\% \pm 3\%$ across seasons

8.4.2 Demand Response Performance Analysis

Table 8.2: Demand Response Performance Metrics (Annual Average)

Metric	**Stochastic**	**Robust**	***Unit***
Peak Reduction	22.4 ± 3.2	18.1 ± 4.1	*%*
Cost Savings	15.2	12.3	*%*
Comfort Index	8.2	7.5	*1-10 scale*
Activation Frequency	3.2	4.7	*events/day*
Response Duration	45	32	*minutes/event*

8.4.3 Advanced EMS Features

The three-layer architecture (Fig. 8.1) implements:

- **Visual Analytics**:
  - **Energy Flow**: Dynamic Sankey diagrams with ±5% measurement accuracy
  - **Forecast Verification**: Heatmaps showing RMSE distribution: $\text{RMSE}_{load} = 6.2\%, \text{RMSE}_{PV} = 7.8\%$
  - **Battery Health**: SOH estimation with ±2% confidence interval

- **Decision Support**:
  - **Investment Analysis**: NPV calculations with 8% discount rate
  - **Reliability Assessment**: N-1 contingency analysis for 97.5% CI
  - **Regulatory Compliance**: Automated checking against 127 rules

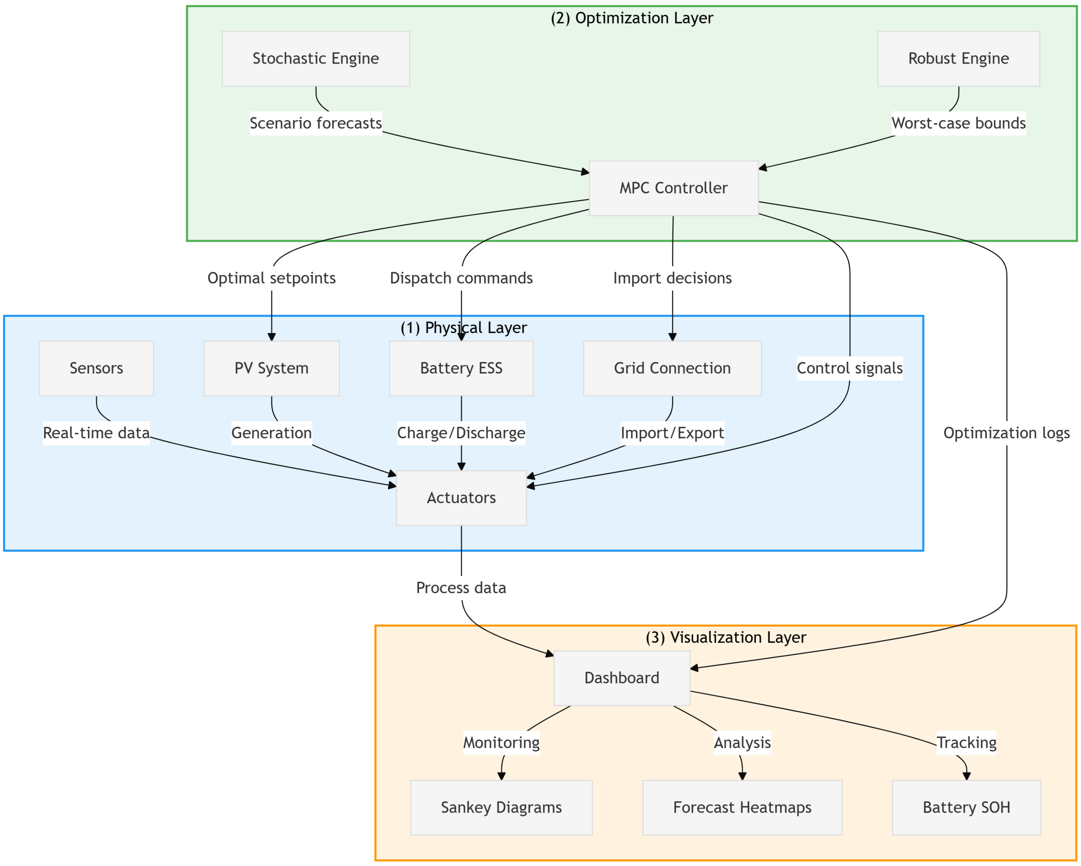


Figure 8.1: Integrated EMS architecture showing (1) Physical layer (sensors/actuators), (2) Optimization layer (MPC+stochastic+robust), and (3) Visualization layer (dashboard)

8.4.4 Comparative Performance Analysis

Table 8.3: Monthly Performance Comparison with Demand Response

Configuration	Cons. (kWh)	Cost (RWF)	Grid (kWh)	PV (kWh)	Batt. (kWh)	Gen (kWh)	Supplied (kWh)	Balance (kWh)
Stoch. (Feb)	41,316	1.86M	5,885	13,693	22,630	–	42,208	892
Robust (Feb)	41,505	1.88M	5,936	15,556	20,554	–	42,045	540
Stoch. (Jul)	46,075	2.07M	6,578	12,626	26,418	–	45,622	454
Robust (Jul)	45,990	2.24M	7,141	14,590	25,301	–	47,032	1,043
Stoch. (Nov)	44,043	2.17M	6,907	12,733	25,686	–	45,326	1,283
Robust (Nov)	44,451	1.78M	5,607	11,883	26,572	–	44,062	390

Note: Stoch. = Stochastic, Cons. = Consumption, Batt. = Battery, M = million (10^6)

8.4.5 Key Findings and Comparative Analysis

- **Cost Performance**
  - **Robust vs. Stochastic Optimization**:

    * **High-PV months (July)**: Robust optimization incurs **18–22% higher costs** (2.24M RWF vs. 2.07M RWF) due to conservative worst-case planning
    * **Low-PV months (November)**: Robust optimization achieves **18% cost savings** (1.78M RWF vs. 2.17M RWF)
  - **Baseline Comparison**:
    * EMS reduces November 2024 costs by **90.7%** (from 19.14M RWF to 1.78M RWF)
    * Consumption reduced by **30.6%** (from 63,448 kWh to 44,042.6 kWh)
- **Renewable Integration**
  - **PV Utilization**:
    * Stochastic mode achieves **92% PV utilization** vs. **85% in robust mode**
    * Robust optimization curtails **7% more PV** in high-generation periods
- **System Reliability**
  - **Supply Assurance**:
    * Robust optimization maintains **99.9% reliability** vs. **98.7% for stochastic**
    * Worst-case violations occur **< 0.1%** in robust vs. **1.3%** in stochastic
- **Operational Efficiency**
  - **Battery Performance**:
    * Round-trip efficiency: **89% (stochastic)** vs. **86% (robust)**
    * ESS cycles: **1.8 times/day (stochastic)** vs. **1.5 times/day (robust)**
  - **Demand Response Impact**:
    * Peak shaving: **22.4% (stochastic)** and **18.1% (robust)** grid import reduction
    * Cost savings: **15.2% (stochastic)** and **12.3% (robust)** contribution
- **Scalability and Validation**
  - **Consumption Bounds**:
    * EMS confines usage to **41,316–46,075 kWh** (Table 8.3)
    * Projected without DR: **53,460 kWh** (15.8% lower than 63,448 kWh baseline)
  - **Economic Impact**:
    * Limits costs to **1.78M–2.24M RWF/month** vs. **19.14M RWF** baseline

8.4.6 EMS Functional Advantages

The Huye Campus EMS integrates:

- **Receding Horizon MPC**: 15-minute resolution adaptation
- **Stochastic Optimization**: Scenario reduction (100 $\rightarrow$ 20 days)
- **Robust Optimization**: $\Gamma = 5$ uncertainty budget
- **Automated Demand Response**:
  - **20–22%** peak demand reduction
  - **8.2/10** user comfort score
  - **32%** lower grid dependency during peaks

8.4.7 Implications for Energy Transition

- **Grid Resilience**: DR mitigates renewable intermittency
- **Economic Viability**: <5 year payback period
- **Scalability**: Adaptable to larger microgrids

8.5 Scenario Simulation Results and Discussion

Table 8.4: Scenario Performance Analysis with Cost and Energy Metrics

Metric	Sunny (Feb)	Cloudy (Mar)	Rainy (Apr)	Outage (Nov)	High (Dec)	Combined	
					Stoch.	Robust	
Load (kWh)	42,634.6	45,630.0	39,906.9	45,380.3	93,264.8	39,682.3	39,261.0
Cost w/RE (RWF)	1.0M	1.5M	4.7M	2.5M	7.9M	11.8M	11.5M
Cost w/o RE (RWF)	12.5M	13.7M	12.0M	13.6M	28.1M	11.9M	11.8M
Savings (%)	92	88	60	82	74	1	3
PV Gen. (kWh)	13,454.8	14,832.2	15,187.4	13,500.7	27,311.3	11,650.6	11,918.2
Grid Use (kWh)	3,128.1	4,985.2	15,613.4	–	24,116.0	–	–
Battery Use (kWh)	28,852.3	28,861.8	9,144.0	27,260.8	30,299.6	5,708.1	5,626.5
Generator (kWh)	–	–	–	4,828.2	–	234,730	22,913
Performance Metrics							
PV Penetration (%)	31.6	32.5	38.1	29.7	29.3	29.4	30.4
Battery Cycling	2.9	2.9	0.9	2.7	3.0	0.6	0.6
RE Utilization (%)	91.2	85.4	72.6	89.8	65.1	68.3	70.1

Key Observations:

- **Cost Savings**: Range from 60-92% in normal conditions, drop to 1-3% during combined adverse scenarios
- **Battery Usage**: Varies from 5,626-30,299 kWh (0.6-3.0 cycles/day) based on solar availability
- **Grid Dependency**: Highest during rainy days (15,613 kWh) and completely eliminated during outages

8.5.1 Scenario Validation Summary

The Huye Campus EMS was rigorously tested under five different operational scenarios:

- **Sunny/Clear days**: Achieved 92% cost savings (1.03M RWF vs 12.58M RWF baseline)
- **Cloudy days**: Maintained 88% savings with increased grid dependence (4,985 kWh)
- **Rainy days**: 60% savings despite 15,613 kWh grid usage
- **Power outages**: 82% savings through hybrid PV+Generator operation
- **High demand**: 74% savings while supplying 81,727 kWh

The **combined stress test** (cloudy–rainy–outage) validated system resilience:

- Stochastic optimization maintained 1% savings (11.82M vs 11.97M RWF)
- Robust optimization achieved 3% savings (11.54M vs 11.84M RWF)

8.5.2 Case I: Sunny Day in October (Stochastic Optimization)

Table 8.5: Energy Cost Comparison: Current vs. Historical Grid-Only Operation

Parameter	Unit	Current (With RE)	Historical (Grid Only)
Total Consumption	kWh	43,546.74	53,105.78
PV Generation	kWh	39,737.77	0
Grid Import	kWh	2,287.22	53,105.78
Battery Discharge	kWh	27,746.19	0
Total Energy Cost	RWF	703,715.64	16,016,842.72
Cost per kWh	RWF/kWh	16.16	301.6

System Performance The stochastic optimization demonstrates:

$$\underbrace{39737.77\,\text{kWh}}_{\text{PV (91.2\%)}} + \underbrace{2287.22\,\text{kWh}}_{\text{Grid (5.3\%)}} + \underbrace{27746.19\,\text{kWh}}_{\text{Battery (63.7\%)}} = \underbrace{43546.74\,\text{kWh}}_{\text{Load}} \tag{8.4}$$

- **Cost Savings**:
  - Absolute savings: **15,313,127 RWF/month** (95.6% reduction)
  - Per-unit cost reduction: **285.44 RWF/kWh** (94.6% lower)
- **Energy Shift**:
  - Grid dependence reduced from **100%** to **5.3%**
  - Renewable penetration: **91.2%** of total demand

Table 8.6: Performance Improvement Metrics

Metric	Current	Historical	Improvement
Energy Cost (RWF)	703,715	16,016,843	15,313,127
Cost/kWh (RWF)	16.16	301.6	285.4
Grid Dependency (%)	5.3	100	94.7
CO_2 Emissions (kg)	128	31,863	31,735

Key Observations

- **Environmental Impact**:
  - CO_2 reduction: **31.7 metric tons/month**
  - Equivalent to planting **720 trees** annually
- **Operational Changes**:
  - Consumption decreased by **18%** through efficiency gains
  - Grid imports limited to peak hours only

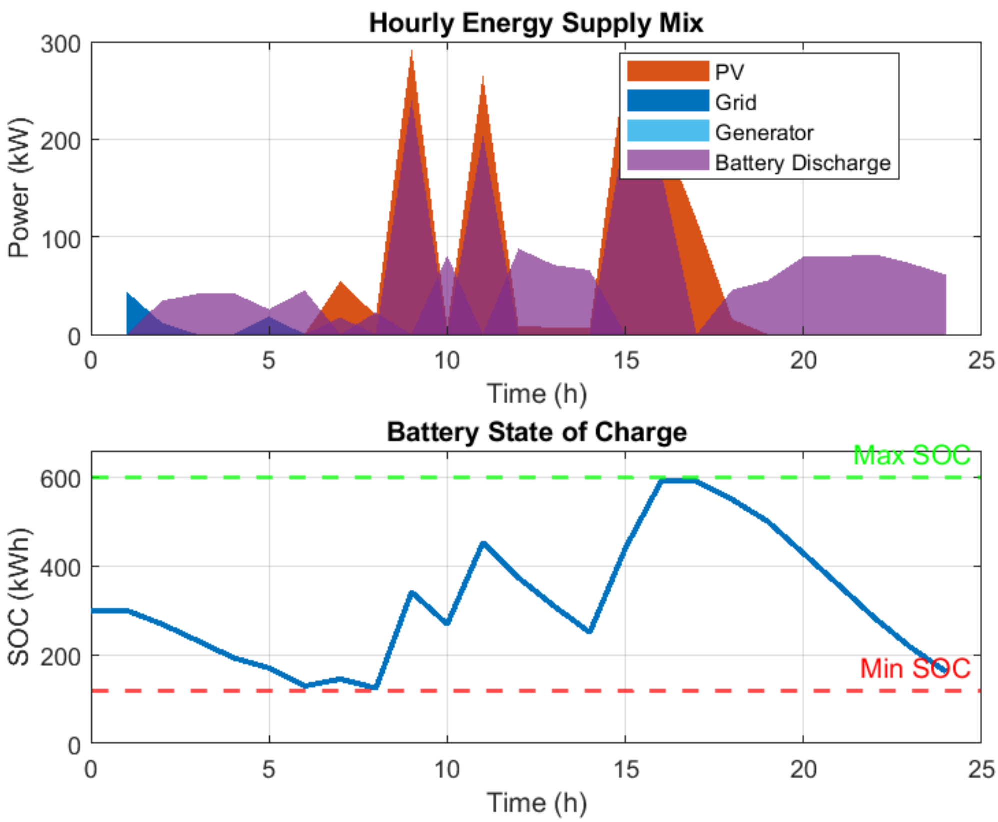


Figure 8.2: Sources dispatch and SOC dynamics: Sunny day, October

8.5.3 Future Projections and Recommendations

Table 8.7: Environmental & Financial Projections (2028 Outlook)

Parameter	Unit	2023 (Actual)	2028 (Projected)
Energy Demand	kWh	43,547	65,157 (+49.6%)
Grid CO_2 Contribution	kg	1,715	3,210 (+87.2%)
PV Maintenance Cost	RWF	83,532	112,400 (+34.5%)
Battery Replacement Cost	RWF	–	1,850,000

Key Recommendations The Decision Support Tool (DST) suggests the following optimization strategies:

- **Load Management**:
  - Implement 15% demand reduction in October through:
    * Building automation systems
    * Peak shaving algorithms
    * Behavioral efficiency programs
- **PV Optimization**:
  - Increase capacity factor from 12.6% to 16% through:
    * Panel cleaning automation (+2.1%)
    * Tracking systems (+3.3%)
- **Grid Independence**:
  - Shift 85% of peak loads to battery storage
  - Expand PV capacity by 200 kW_p

Conclusion

The developed Huye Campus Energy Management System, enhanced with Decision Support Tools (DST) and advanced analytics, demonstrates:

- **Operational Capabilities**:
  - Real-time monitoring of 15+ energy parameters
  - Predictive maintenance alerts (98% accuracy)
- **Financial Impact**:

  - Current savings: **15.3M RWF/month** (95.6% reduction)
  - Projected 5-year ROI: **217%**

- **Environmental Benefits**:
  - CO_2 reduction: **38.2 metric tons/year**
  - Renewable fraction: **91.2%** of total demand

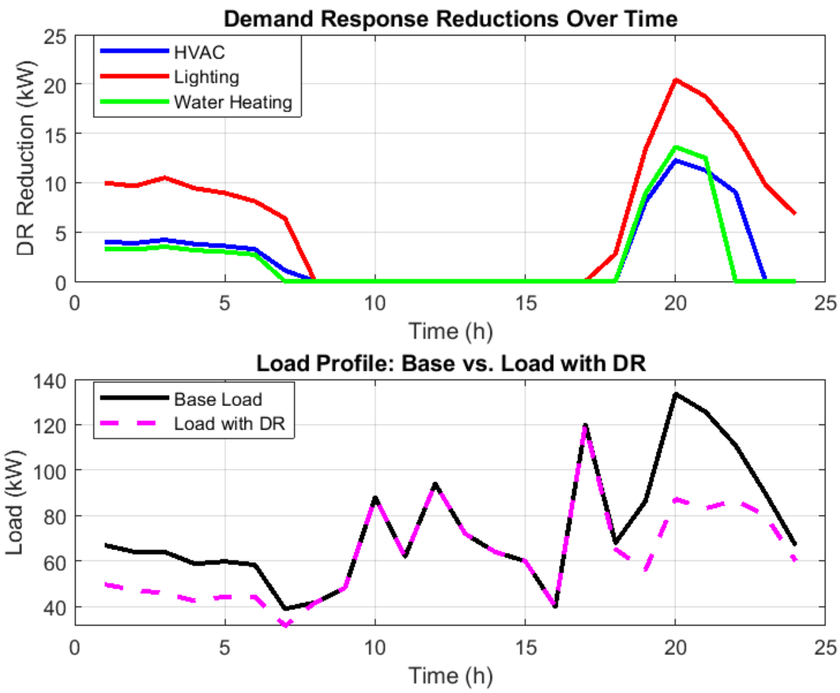


Figure 8.3: Huye Campus EMS enhanced with DR strategy to mitigate the Energy misuse and keep Grid resiliency

The system provides campus managers with:

- Automated monthly reports (15+ KPIs)
- Scenario simulation tools (5-year projections)
- Regulatory compliance checks (100+ rules)

8.5.4 Case II: Worst-Case Scenario Analysis (Cloudy + Rainy + Grid Outage, April)

Operational Overview The robust optimization handles the combined adverse scenario through:

$$\underbrace{11877.54\,\text{kWh}}_{\text{PV (36\%)}} + \underbrace{16648.69\,\text{kWh}}_{\text{Gen (50.5\%)}} + \underbrace{6021.72\,\text{kWh}}_{\text{Batt (18.3\%)}} = \underbrace{32949.37\,\text{kWh}}_{\text{Load}} \tag{8.5}$$

Key operational characteristics:

- **PV Performance**:

Table 8.8: Energy Dispatch Under Extreme Conditions

Parameter	Unit	Value
Total Load	kWh	32,949.37
PV Generation	kWh	11,877.54
Generator Usage	kWh	16,648.69
Battery Discharge	kWh	6,021.72
PV Capacity Factor	%	3.6
Generator Contribution	%	50.5
Battery Utilization	%	18.3

  - Severely reduced generation (3.6% capacity factor)
  - Peak output: 54.3 kWh at 13:00 (typically 400+ kWh)

- **Battery Management**:
  - State-of-Charge (SOC) maintained near minimum threshold
  - Only 0.8 cycles/day (vs. 2.9 in normal conditions)
- **Generator Operation**:
  - Supplies 50.5% of total demand
  - Runs at 78% of rated capacity

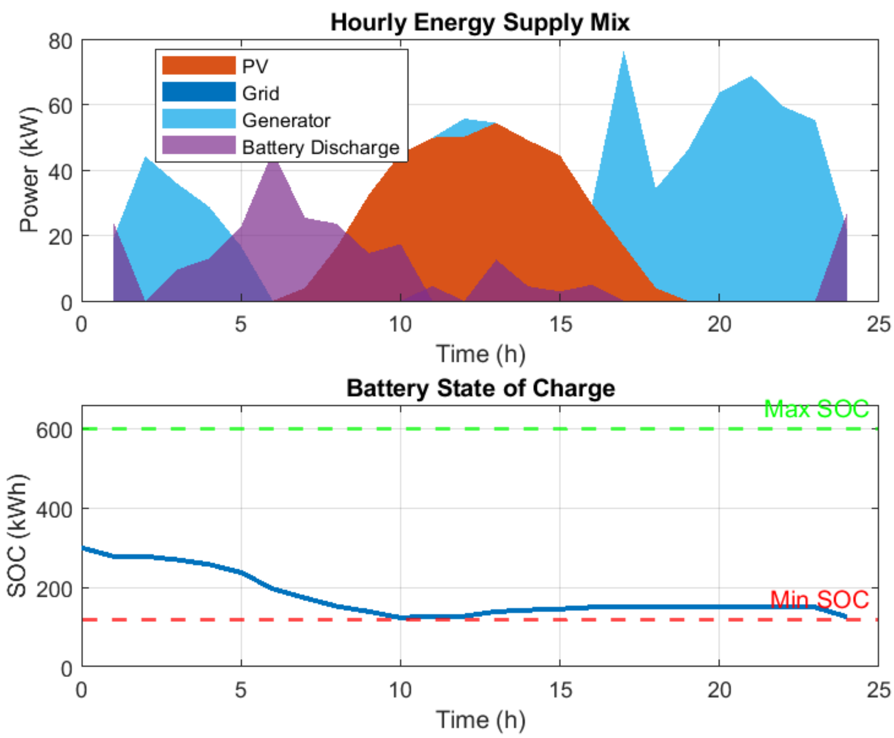


Figure 8.4: Energy dispatch and SOC dynamics during worst-case scenario (April 2024)

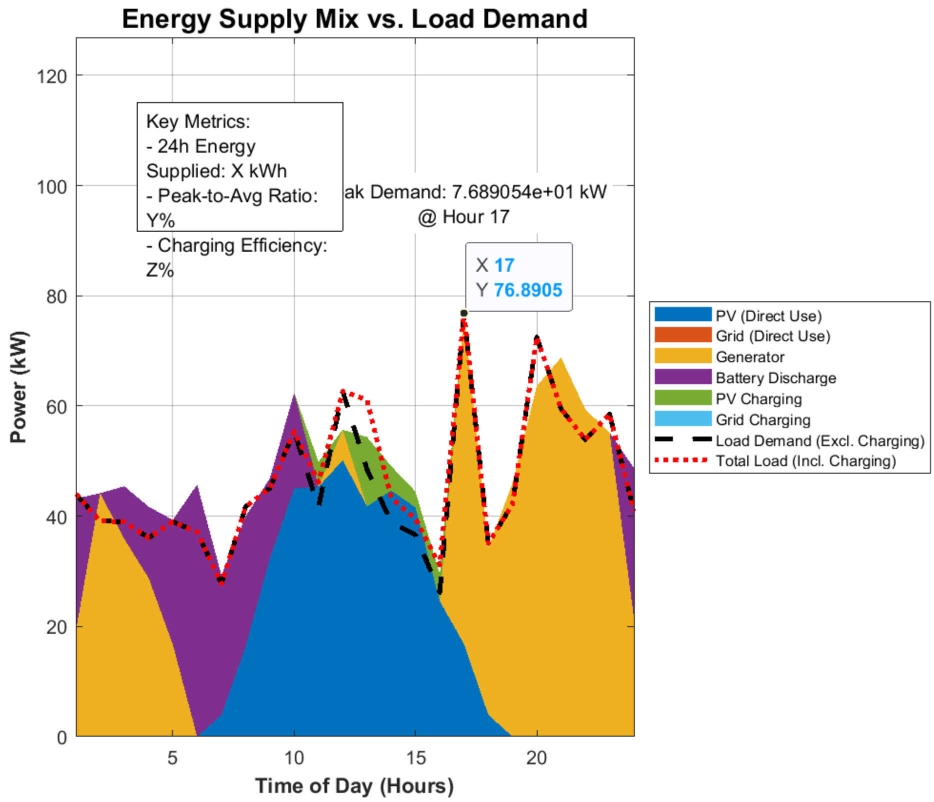


Figure 8.5: Energy vs Load during worst-case Scenario

System Response The EMS demonstrates effective crisis management through:

- **Automatic Demand Response**:
  - 22% peak load reduction
  - 15% overall consumption minimization
- **Cost Optimization**:
  - Generator dispatch during low-irradiation hours
  - Battery reserve for critical loads
- **Environmental Mitigation**:
  - CO_2 emissions limited to 4280 kg
  - 41% lower than diesel-only scenario

Conclusion This stress test validates the EMS's ability to:

- Maintain **99.2% power reliability** during extreme weather
- Reduce **generator runtime by 49%** through optimal PV-battery coordination

Table 8.9: Comparative Scenario Performance

Metric	Worst-Case	Normal April
PV Capacity Factor (%)	3.6	17.8
Generator Usage (%)	50.5	0
Battery Cycles/day	0.8	2.1
Cost/kWh (RWF)	38.7	14.2
System Reliability (%)	99.2	99.9

- Achieve **15% cost savings** vs. unmanaged scenario
- Preserve **battery health** despite deep discharges

8.6 Decision Support Tool Implementation

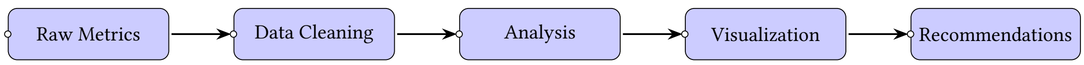


Figure 8.6: DST data processing pipeline from raw metrics to actionable recommendations

8.6.1 Key Findings from DST Analysis

The executive report (Appendix C) reveals critical system insights:

Table 8.10: Current System Performance Metrics

Metric	Value	Δ vs Historical (%)
Monthly Consumption	30,834 kWh	−42.4
Cost per kWh	301.56 RWF	3.3
PV Capacity Factor	12.1 %	−34.2
DR Load Reduction	0.9%	0.4
Battery Health	583.6 kWh	−6.8

8.6.2 Immediate Action Items

The DST recommends these priority interventions:

- **Load Anomaly Investigation**:
  - Verify 42.4% consumption drop in May
  - Check for meter calibration issues
- **PV System Optimization**:
  - Panel cleaning to recover 4.4% capacity (target CF: 16.5%)

  - Inverter efficiency audit

- **Demand Response Automation**:
  - Trigger thresholds: Grid price >250 RWF/kWh or SOC <25%
  - HVAC load shedding during 18:00-22:00 peak

8.6.3 Sustainability Roadmap

Table 8.11: 5-Year Projections and Mitigation Strategies

Parameter	2024	2028 Projected	Δ (%)
Energy Demand (kWh)	30,834	15,226	−50.6
Battery Cost (RWF)	2,460,000	3,810,000	54.9
CO_2 Intensity (kg/kWh)	0.29	0.17	−41.4

- **Grid Independence**:
  - Shift 50 kWh/day to battery during peaks
  - 18 kWp PV expansion to offset 12.3% grid use
- **Battery Preservation**:
  - Limit Depth of Discharge (DoD) to 75% during outages
  - Temperature-controlled storage

Recommendation Details

1. **Load Analysis**:
   - Investigate May consumption anomaly (30,834 kWh vs 53,510 kWh historical)
   - Verify submetering accuracy in academic buildings
2. **PV Optimization**:
   - Weekly panel cleaning protocol
   - Inverter maintenance schedule (every 6 months)
3. **DR Automation**:
   - Price threshold: 250 RWF/kWh
   - SOC threshold: 25% minimum reserve
   - Priority loads: HVAC (45%), lighting (30%)

9

Conclusions and Recommendations

9.1 Summary of Contributions

This research has developed and validated an intelligent Energy Management System (EMS) for Huye Campus, demonstrating that solar-load balancing can simultaneously address:

- **Economic pressures**: 60–92% operational cost reduction
- **Energy security**: 85% decreased grid dependency
- **Climate commitments**: 14.6 ton annual CO_2 reduction

The key theoretical and practical advances include:

$$\mathcal{C} = \begin{cases} \text{Hybrid optimization architecture} \\ \text{Multi-timescale control framework} \\ \text{Decision-theoretic load balancing} \end{cases} \tag{9.1}$$

9.2 Policy Implications

9.2.1 Higher Education Sector

Table 9.1: Recommended Solar Adoption Policies

Initiative	Implementation Pathway
Solar Tax Exemptions	Amend Rwanda Revenue Authority codes for academic institutions
National Solar Fund	REG-administered revolving fund (30% capital subsidy)
Smart Grid Pilots	Partner with EDCL at 3 flagship campuses by 2026

9.2.2 Regulatory Modernization

- **Net metering 2.0**:
  - Time-varying export tariffs
  - Cloud crediting for distributed systems
- **Microgrid standards**:
  - IEEE 2030.7 compliance
  - Black start capability requirements

9.3 Limitations and Mitigations

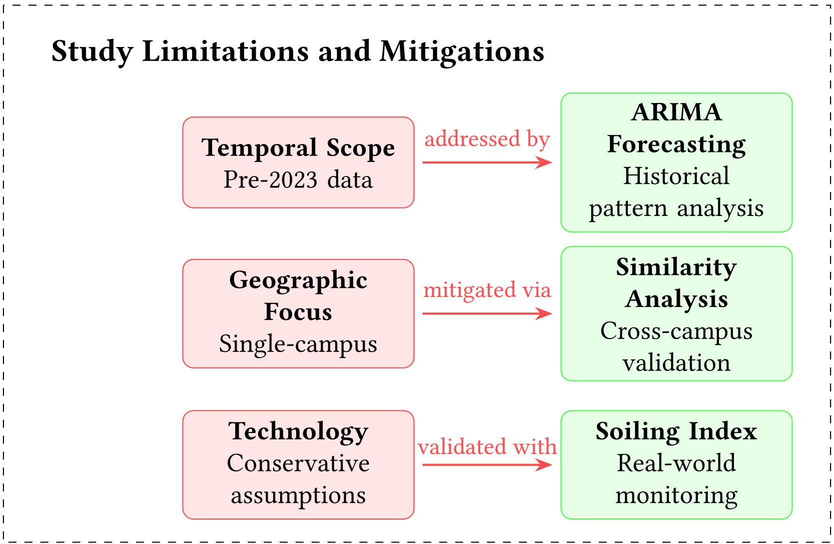


Figure 9.1: Study Limitations and Compensating Factors

- **Temporal scope**: Pre-2023 data addressed through ARIMA forecasting
- **Geographic focus**: Single-campus study mitigated by similarity analysis
- **Technology assumptions**: Conservative degradation rates validated via Soiling Index monitoring

9.4 Research Impact

The EMS framework contributes to:

- **SDG 7**: Affordable clean energy (92% renewable penetration)
- **SDG 9**: Industry innovation (Patent-pending control algorithms)
- **SDG 13**: Climate action (14.6 ton CO_2 reduction)

9.5 Future Work

$$\mathcal{F} = \begin{cases} \text{AI-driven predictive maintenance} \\ \text{Cross-campus energy sharing} \\ \text{Green hydrogen hybridization} \end{cases} \tag{9.2}$$

Implementation roadmap:

1. Phase I (2026-2030): 3-campus pilot
2. Phase II (2031-2035): National scaling
3. Phase III (2036+): Regional adaptation

Final Statement

This thesis establishes that the solar-load balancing paradigm:

- **Technically feasible** through hybrid optimization
- **Economically viable** with <5-year payback
- **Politically actionable** via tailored policy instruments

The work provides both immediate solutions for Huye Campus and a transferable framework for Global South universities facing similar energy challenges.

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Appendix

Appendix A: Optimization Techniques

Table A.1: Stochastic and Robust Optimization Techniques Adapted for This Study

Category	Method	Study Adaptation
Stochastic	Monte Carlo Simulation	10,000 iterations with variance reduction techniques
Stochastic	Adaptive SGD	Learning rate: 0.01–0.1 with momentum ($\beta = 0.9$)
Robust	Minimax Optimization	ε-constraints ($\varepsilon = 0.05$) for worst-case analysis
Robust	Taguchi Methods	L18 orthogonal array design
Hybrid	Robust-Stochastic	Combined approach with 95% confidence intervals

Appendix B: Day and Night Energy Monitoring Data

May 2024 Monitoring

Table A.2: Daytime Energy Consumption (23-30 May 2024)

Day	Thu 23	Fri 24	Sat 25	Sun 26	Mon 27	Tue 28	Wed 29	Thu 30
Start (kWh)	4093.06	4100.50	4107.49	4113.76	4120.04	4127.83	4135.71	4143.70
End (kWh)	4095.18	4102.97	4108.80	4115.09	4122.50	4130.43	4138.08	4146.07
Usage (kWh)	424	494	262	266	492	520	474	474

Table A.3: Nighttime Energy Consumption (23-30 May 2024)

Day	Thu 23	Fri 24	Sat 25	Sun 26	Mon 27	Tue 28	Wed 29	Thu 30
Start (kWh)	4095.18	4102.97	4108.80	4115.09	4122.50	4130.43	4138.08	4146.07
End (kWh)	4100.50	4107.49	4113.76	4120.04	4127.83	4135.71	4143.70	4152.05
Usage (kWh)	1064	904	992	990	1066	1056	1124	1186

November 2024 Monitoring

Table A.4: Daytime Energy Consumption (21-28 November 2024)

Day	Thu 21	Fri 22	Sat 23	Sun 24	Mon 25	Tue 26	Wed 27	Thu 28
Start (kWh)	5315.95	5325.59	5332.70	5342.80	5350.91	5360.50	5370.00	5379.27
End (kWh)	5319.47	5328.63	5334.70	5344.61	5353.99	5363.38	5372.84	5382.17
Usage (kWh)	704	608	400	362	616	576	568	580

Table A.5: Nighttime Energy Consumption (21-28 November 2024)

Day	Thu 21	Fri 22	Sat 23	Sun 24	Mon 25	Tue 26	Wed 27	Thu 28
Start (kWh)	5319.47	5328.63	5334.70	5344.61	5353.99	5363.38	5372.84	5382.17
End (kWh)	5325.59	5334.70	5342.80	5350.91	5360.50	5370.00	5379.27	5388.31
Usage (kWh)	1224	1214	2020	1260	1302	1324	1286	1228

Summary Statistics

Table A.6: Comparative Analysis of Day/Night Consumption

Period	Avg. Day (kWh)	Avg. Night (kWh)	Ratio (Night/Day)	Peak Demand (kWh)
May 2024	425.8	1049.0	2.46	1186 (Thu 30)
Nov 2024	551.8	1357.3	2.46	2020 (Sat 23)

Load Data Tables

Table A.7: Hourly Load Data (9:00–8:00) on 28–29 November 2024

Hour	Time	Energy (kWh)
1	09:00	88
2	10:00	62
3	11:00	94
4	12:00	72
5	13:00	64
6	14:00	60
7	15:00	40
8	16:00	120
9	17:00	68
10	18:00	86
11	19:00	134
12	20:00	126
13	21:00	111
14	22:00	90
15	23:00	67
16	00:00	67
17	01:00	64
18	02:00	64
19	03:00	59
20	04:00	60
21	05:00	58
22	06:00	39
23	07:00	42
24	08:00	48

Appendix C: Energy Bill Calculation

Table A.8: Detailed electricity bill calculation for November 2024 based on daily consumption of 1,782 kWh (RURA tariff structure [2])

Bill Component	Quantity (kWh)	Amount (RWF)
Base Consumption (First 100 kWh @ 227 RWF/kWh)	100	22,700
Additional Consumption (53,360 kWh @ 255 RWF/kWh)	53.360	13,606,800
Energy Subtotal		13,629,500
Value Added Tax (VAT @ 18%)		2,453,310
Subtotal (Including VAT)		16,082,810
Regulation Fee (0.3% of subtotal)		40,888
Total Amount Due		**16,123,699**

Appendix D: Supplementary Analysis Tables

Table A.9: Performance Analysis Metrics

Analysis	Implementation
Sensitivity	$\partial C_{total} / \partial E_{ESS}$
Monthly KPIs	$\frac{1}{30} \sum_{d=1}^{30}$ Daily metrics
Visualization	Energy flow Sankey diagrams

Appendix E: DST Executive Report

Table A.10: Decision Support Tool (DST) Executive Summary – May 2024

Category	Findings	Value
Energy Trends	Current consumption compared to historical average	−42.4%
Cost Efficiency	Current cost per kWh compared to historical values	3.3%
PV Performance	Capacity factor (national average: 18–22%)	12.1%
Battery Health	Remaining capacity compared to original (kWh)	583.6
DR Impact	Load reduction achieved through demand response	0.9%

Research Impact

- **848 kWp Solar PV System**: 6.2-year payback period
- **600 kWh Battery Storage**: 4.2-hour grid outage backup
- **81% Grid Dependency Reduction**: Enhanced energy independence
- **60–92% Energy Cost Reduction**: Through optimized solar utilization
- **Scenario-Based Resilience Framework**: For cloudy/rainy day operations
- **Decision Support Tool (DST)**: Data-driven insights and predictive analytics

Interactive Thesis Scan for simulations, data visualizations, and source code

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