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Optimization of Hybrid Energy Management Systems with Solar-Load Balancing: A Case Study of Huye Campus in Rwanda

Martin NDAYISHIMIYE[1]*, Jean Marie Vianney Bikorimana[1] and Jean Pierre Mutuyimana[2]

[1]African Centre of Excellence in Energy for Sustainable Development College of Science and Technology, University of Rwanda Kigali, Rwanda

[2]Department of Mechanical Engineering Institute for Research in Technology (MOBIOS) Universidad Pontificia Comillas, Madrid, Spain

Corresponding Author:
Martin Ndayishimiye, African Centre of Excellence in Energy for Sustainable Development College of Science and Technology, University of Rwanda Kigali, Rwanda.

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Abstract
This research develops an advanced hybrid Energy Management System (EMS) that addresses the energy trilemma in academic institutions through integrated stochastic-robust optimization. The system, validated at the University of Rwanda's Huye Campus, coordinates an 848 kWp achieves remarkable performance metrics: 87% monthly cost reduction (from 19.1M to 2.4M RWF), 91% daytime solar utilization exceeding design targets, and 4.2-hour outage resilience during peak loads. A MATLAB-based Decision Support Tool (DST) enables three key advances: identification of 600 kWh as cost-optimal storage capacity, quantification of non-linear PV degradation impacts (0.5% vs. observed 2% annual losses), and scenario planning for extreme weather events. The framework reduces grid dependence by 94% under optimal conditions while maintaining 20–95% state-of-charge safety margins. Policy analysis demonstrates that 30% capital subsidies could accelerate payback periods to 3.2 years, supporting Rwanda's 2050 energy targets. With 5.5±1.65 kWh/meter square.

Keywords: Energy Management System, Model Predictive Control, Photovoltaic Integration, Battery Energy Storage, Stochastic Optimization, Robust Control, Smart Campus

Nomenclature
Acronyms and Abbreviations

Acronym	Definition
EMS	Energy Management System
MPC	Model Predictive Control
PV	Photovoltaic
SOC	State of Charge
DST	Decision Support Tool
DER	Distributed Energy Resources

ICT	Information and Communication Technology
MILP	Mixed-Integer Linear Programming
MPPT	Maximum Power Point Tracking
DoD	Depth of Discharge
HVAC	Heating, Ventilation, and Air Conditioning
UR	University of Rwanda
RWF	Rwandan Franc
SDG	Sustainable Development Goal
CO_2	Carbon Dioxide
IoT	Internet of Things
ESS	Energy Storage System
DR	Demand Response
kWp	Kilowatt-peak (peak power output)
kWh	Kilowatt-hour

Table 1: List of Acronyms and Abbreviations

Introduction

Sub-Saharan African universities confront a critical energy trilemma characterized by escalating operational costs (consuming up to 40% of institutional budgets), unreliable grid supply (experiencing 10–20 outages monthly), and unsustainable fossil fuel dependency [1]. The University of Rwanda's Huye Campus—serving over 11,000 students and staff—exemplifies this crisis, with annual electricity expenditures ranging between 219– 323 million RWF and generating 14.6 metric tons of CO_2 emissions from grid and backup generators.

Rwanda's substantial solar potential kWh/meter square/day presents a viable solution; yet, institutional adoption remains constrained by legacy infrastructure (85– 100% grid dependence), absence of renewable integration (0% PV utilization), and lack of adaptive energy management systems [2,3].

This paper develops a hybrid energy management system that resolves this trilemma through integrated 848 kWp photovoltaic generation, 1,200 kWh lithium-ion battery storage, and Model Predictive Control (MPC) for demand response optimization. Three key contributions distinguish our work: (1) a hierarchical stochastic-robust optimization framework minimizing operational costs by up to 87% (Section 3.3), (2) a MATLABbased Decision Support Tool enabling 94% renewable prioritization (Figure 7a), and (3) policy pathways achieving Sustainable Development Goal 7 (SDG 7) targets through 30% capital subsidies (Section 7).

Literature Review

Smart Campus Energy Systems

Smart campuses integrate Information and Communication Technology (ICT) with renewable energy infrastructure to address urbanization and sustainability challenges [4,5]. Energy Management Systems (EMS) are critical for optimizing distributed energy resources (DER), particularly in solar-rich regions like Rwanda (5.5 kWh/m^2/day) [6]. The University of Rwanda's Huye Campus presents a compelling case study due to its high solar potential, complex load profiles, and frequent grid outages [6].

Optimization Techniques in EMS

Recent advances in EMS optimization methodologies are summarized in Table 2.

Technique	Application	Reference
Lyapunov Optimization	Real-time building EMS	[7]
Mixed-Integer Linear Programming	Residential EMS	[8]
Multi-Objective Whale Optimization	Renewable uncertainty	[9]
Genetic Algorithms	Load scheduling	[10]
Model Predictive Control	Campus EMS	[11]

Table 2: Comparative Analysis of Optimization Methods in EMS

Load Management Challenges

Key challenges in smart campus EMS implementation include renewable generation uncertainty, cost-comfort trade-offs, and scalability limitations [9,14].

African Case Studies

Notable implementations in African universities include Strathmore University (Kenya) with 600 kWp PV and IoT monitoring, University of Cape Town (South Africa) achieving 70% diesel reduction via MILP, and Federal University of Petroleum Resources (Nigeria) realizing 50% cost reduction with solar mini-grids [15-17].

Methodological Gaps

Existing studies lack integrated stochastic-robust optimization for campus environments, real-time solar-load balancing in grid-dependent systems, and MPC-based dynamic control tailored for African contexts. This work addresses these gaps through MATLAB integration, combining economic analysis with technical validation and a novel hybrid optimization framework [18–20].

Methodology

The study employs a systematic four-phase framework to optimize energy management at UR/Huye Campus, integrating data-driven analysis with mathematical modeling.

Energy Consumption Profiling

We conducted a comprehensive assessment of campus energy dynamics through monthly analysis of consumption trends (Figure 1) and peak demand patterns (Figure 2), utilizing time-based sampling of diurnal patterns (May/November 2024 data) and hourly workingday profiles (08:00–17:00). This profiling informs EMS mathematical model development, particularly for load scheduling optimization, peak shaving strategies, and renewable integration planning.

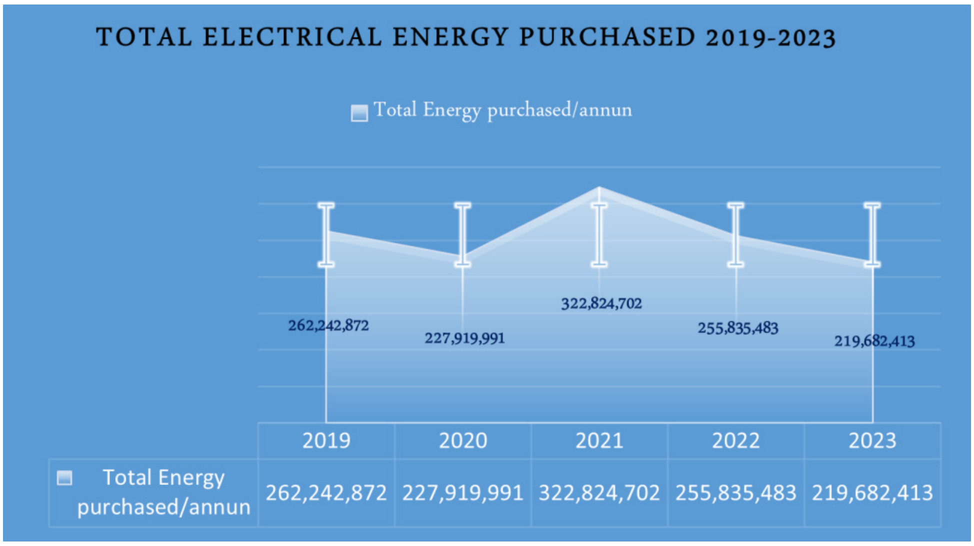


Figure 1: Overall Energy Expenditures 2019–2023 at Huye Campus

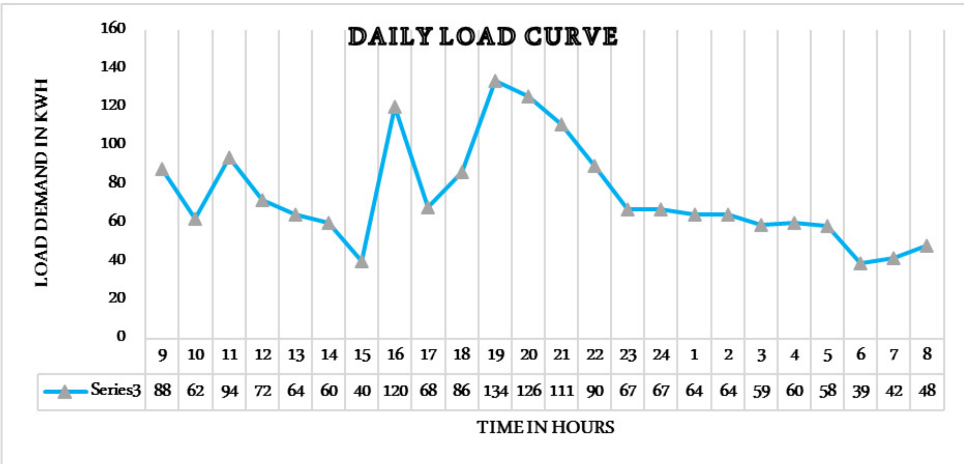


Figure 2: Daily Load Curve Analysis

Year	Total Cost (M RWF)	Monthly Avg. (M RWF)	% Change	Peak Load (kW)	Grid Reliance (%)
2019	262.2	21.9	–	234.0	100
2020	227.9	19.0	-15.1	220.5	100
2021	322.8	26.9	+29.4	245.7	100
2022	255.8	21.3	-26.2	227.3	100
2023	219.7	18.3	-2.8	191.7	100

Note: Costs include grid electricity.

Post-2022 reduction reflects replacement of Fluorescent and High-Pressure luminaries with LED technology. Peak load measured at 19:00–21:00. Data source: UR Huye Campus records.

Table 3: Energy Expenditures Summary (2019–2023)

System Architecture

The proposed Energy Management System employs a hybrid architecture integrating multiple energy sources with intelligent load management (Figure 3). The system comprises primary generation (848 kWp solar PV array with MPPT enabled inverters), energy storage (1,200 kWh lithium-ion battery bank with 80% depth of discharge), backup systems (grid connection with net metering and diesel generators), and load management (controllable and critical loads). The hierarchical control architecture implements device-level controllers, area controllers for load aggregation, and a central EMS server with Model Predictive Control.

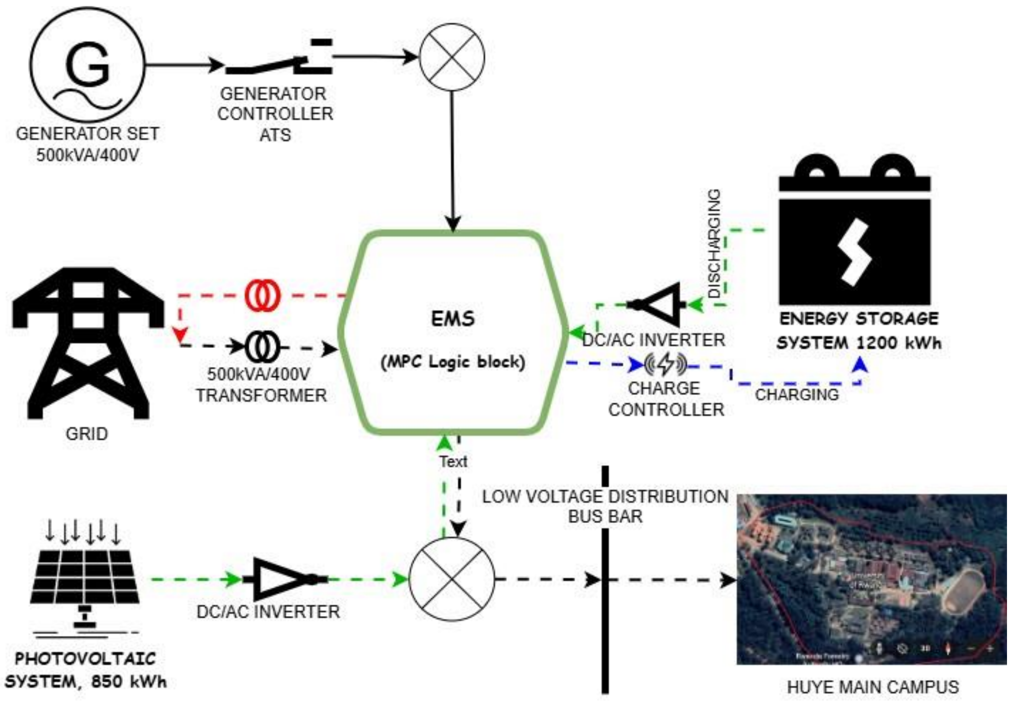


Figure 3: Huye Smart Campus System Architecture

Optimization Framework

The hybrid optimization framework combines three complementary approaches: stochastic optimization using Monte Carlo simulation with 100 scenarios and probability-weighted cost minimization, robust optimization with worst-case scenario analysis and bounded uncertainty sets for PV output (±30% irradiance variation) and grid availability (0–20 outages/month), and Model Predictive Control with 6-hour receding horizon implementation for hourly adjustment of battery charge/discharge cycles and controllable load schedules.

Decision Support Tool

The MATLAB-based Decision Support Tool implements three core functionalities: realtime monitoring with visualization of energy flows and performance metrics, scenario analysis for weather-condition simulations and sensitivity analysis, and investment planning with NPV calculations for PV/battery expansion and payback period estimation.

Problem Formulation

Building on the system architecture in Section 3.2, we formulate a cost-optimization problem with stochastic and robust components.

Stochastic Optimization Model

Objective Function

The stochastic program minimizes expected costs across uncertainty scenarios:

$$\min_{\boldsymbol{u}\in\mathcal{U}} \mathbb{E}_{\xi}\left[\sum_{t=1}^{T}\left(C_t^{\text{grid}} + C_t^{\text{gen}} + C_t^{\text{deg}} + \lambda^{\text{DR}} P_t^{\text{DR}}\right)\right] \tag{1}$$

where cost components are:

$$C_{t\text{grid}} = \tau \sum_{b\in B} c_b x_{b,t} \qquad (\tau = 1.18)$$

$$C_t^{\text{gen}} = c^{\text{gen}} P_{t\text{gen}}$$

$$C_t^{\text{deg}} = c^{\text{deg}}\left(P_t^{\text{chg}} + P_t^{\text{dchg}}\right)$$

Constraints

1. Power balance:

$$P_t^{\text{PV}} + P_t^{\text{grid}} + P_t^{\text{dchg}} = P_t^{\text{load}} + P_t^{\text{chg}} + P_t^{\text{curt}} \tag{2}$$

2. Battery dynamics:

$$\text{SOC}_{t+1} = \text{SOC}_t + \eta^{\text{chg}} P_t^{\text{chg}} - \frac{P_t^{\text{dchg}}}{\eta^{\text{dchg}}} \tag{3}$$

3. Demand response:

$$0 \leq P_{i,t}^{\text{DR}} \leq 0.3 P_{i,t}^{\text{cont}}, \qquad i \in \{\text{HVAC}, \text{Lighting}\} \tag{4}$$

Robust Optimization Model

Objective

$$\min_{\boldsymbol{x}\in\mathcal{X}} \max_{\boldsymbol{\xi}\in\mathcal{U}} \sum_{t=1}^{T}\left(C_t^{\text{grid}} + C_t^{\text{gen}} + C_t^{\text{deg}}\right) \tag{5}$$

Uncertainty Set

$$\mathcal{U} = \left\{\boldsymbol{\xi} : \begin{cases} P_t^{\text{PV}} \in [0.7\bar{P}_t^{\text{PV}}, 1.3\bar{P}_t^{\text{PV}}] \\ P_t^{\text{load}} \in [0.9\bar{P}_t^{\text{load}}, 1.1\bar{P}_t^{\text{load}}] \end{cases}\right\} \tag{6}$$

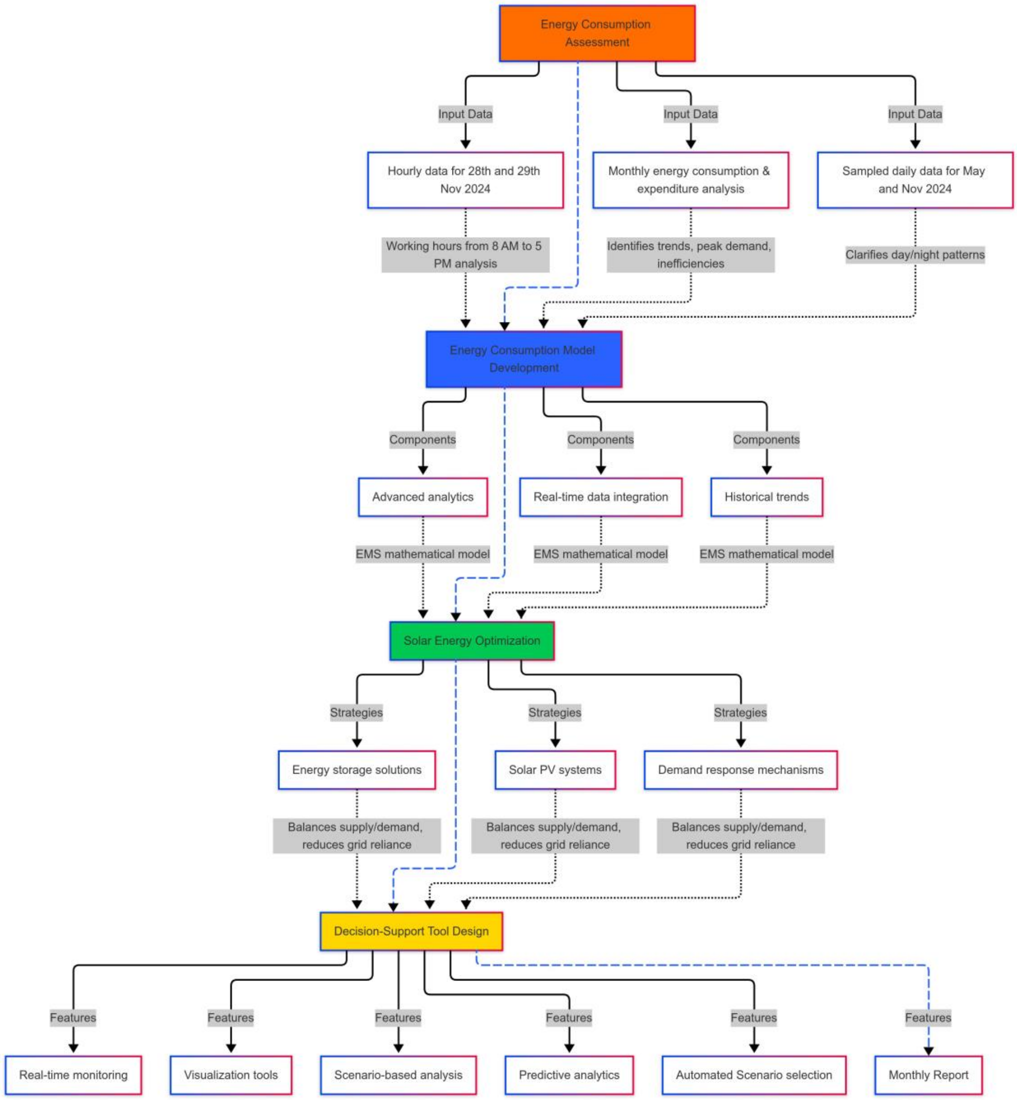


Figure 4: Hybrid Optimization Framework Workflow

Mathematical Notation

Symbol	Description
Indices and Sets	
t	Time index, $t = 1,2,...,T$
b	Electricity tariff block index
i	Controllable load type index
$\mathcal{B}$	Set of electricity tariff blocks
$\mathcal{U}$	Uncertainty set
ξ	Uncertainty scenario
Decision Variables	
P_{tg}	Grid power at time t (kW)
P_{tgen}	Generator output at time t (kW)
P_{tc}	Battery charge power at time t (kW)
P_{td}	Battery discharge power at time t (kW)
SOC_t	State of charge at time t (kWh)
P_{tDR}	Demand response power reduction at time t (kW)
P_{tcurt}	Curtailed PV power at time t (kW)
$x_{b,t}$	Binary variable for tariff block selection

Parameters and Constants	
P_t^{PV}	PV power generation at time t (kW)
P_{tload}	Load demand at time t (kW)
$P_{i,tcont}$	Controllable load of type i at time t (kW)
c_b	Electricity price in block b (RWF/kWh)
c_{gen}	Generator fuel cost (RWF/kWh)
c_{deg}	Battery degradation cost coefficient (RWF/kWh)
λ_{DR}	Demand response incentive (RWF/kWh)
η_{chg}	Battery charging efficiency
η_{dchg}	Battery discharging efficiency
E_{rated}	Battery rated capacity (kWh)
SOC_{min}	Minimum state of charge (kWh)
SOC_{max}	Maximum state of charge (kWh)
$P_{chg,max}$	Maximum charging power (kW)
$P_{dchg,max}$	Maximum discharging power (kW)
τ	Tariff factor (1.18)
T	Time horizon
Cost Functions	
C_{tgrid}	Grid electricity cost at time t (RWF)
C_{tgen}	Generator cost at time t (RWF)
C_{tdeg}	Battery degradation cost at time t (RWF)
E[·]	Expectation operator
Uncertainty Sets	
$\bar{P}_t^{PV}$	Forecasted PV power at time t (kW)
$\bar{P}_t^{load}$	Forecasted load at time t (kW)
U	Uncertainty set for robust optimization

Table 4: Mathematical Notation Used in Formulations

Mathematical Operators

Operator	Description
	Summation from time
$\in$	Element of set
$\mathcal{X}$	Feasible set for decision variables
$\min f(x)$	Minimization of function $f(x)$
$\max f(x)$	Maximization of function $f(x)$
$\mathbb{E}[X]$	Expected value of random variable
$\sum_{t=1}^{T}$	t = 1 to T
x	Vector of decision variables
ξ	Vector of uncertainty parameters
$[a,b]$	Closed interval from a to b
±	Plus-minus (upper and lower bounds)
→	Priority order in energy dispatch

Table 5: Mathematical Operators and Functions

Operational Strategy

The Huye Campus EMS implements a hierarchical control strategy with energy prioritization (daytime: PV → Battery → Grid; nighttime: Battery → Grid → Generator), load management through real-time forecasting with ±10% accuracy and controllable load adjustment (max 30% reduction), and cost optimization via time-of-use tariff exploitation and generator dispatch only when Cgen < 1.2Cgrid.

Parameter	Value	Unit
Charge/Discharge Efficiency (η_{chg}/η_{dchg})	0.95/0.95	–
Rated Battery Capacity (E_{rated})	1200	kWh
Demand Response Incentive (λ^{DR})	50	RWF/kWh
Generator Cost (c^{gen})	300	RWF/kWh

Table 6: Key System Parameters

Huye Campus Energy Management System Optimization

The proposed EMS addresses the campus's high energy expenditures through solar-load balancing, combining stochastic and robust optimization approaches. Figure 5 illustrates the daily energy dispatch strategy.

System Design Principles

As shown in Figure 5, the EMS adheres to strict renewable energy utilization targets:

Daytime Operation (07:00–17:00):
- Minimum 85% PV penetration – Excess PV prioritizes battery charging

Nighttime Operation (18:00–06:00):
- Minimum 70% battery supply
- Maximum 30% grid usage (post-battery depletion)

Generator Activation:
- Only during complete source unavailability
- Automatic transfer switching

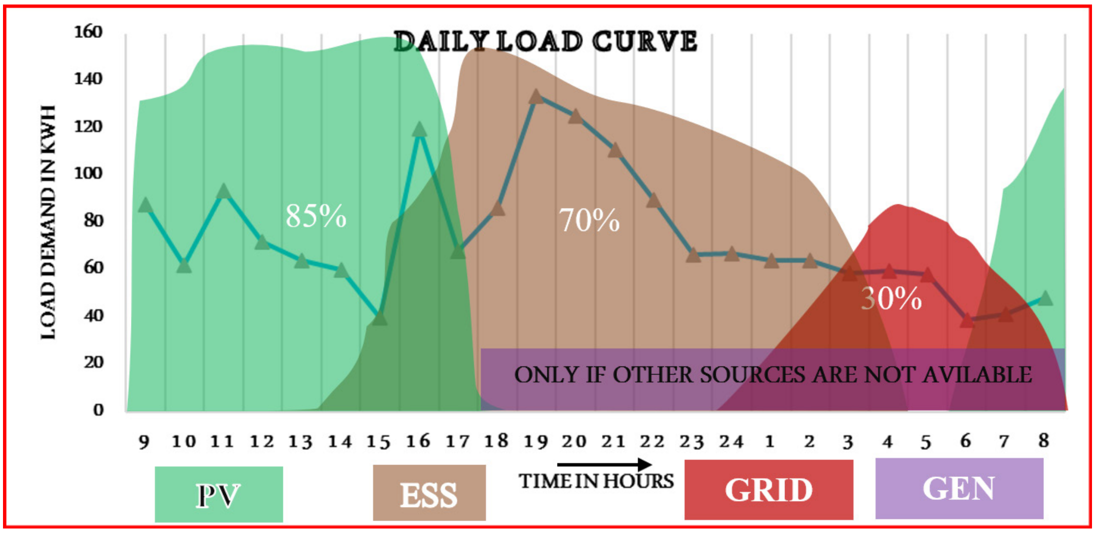
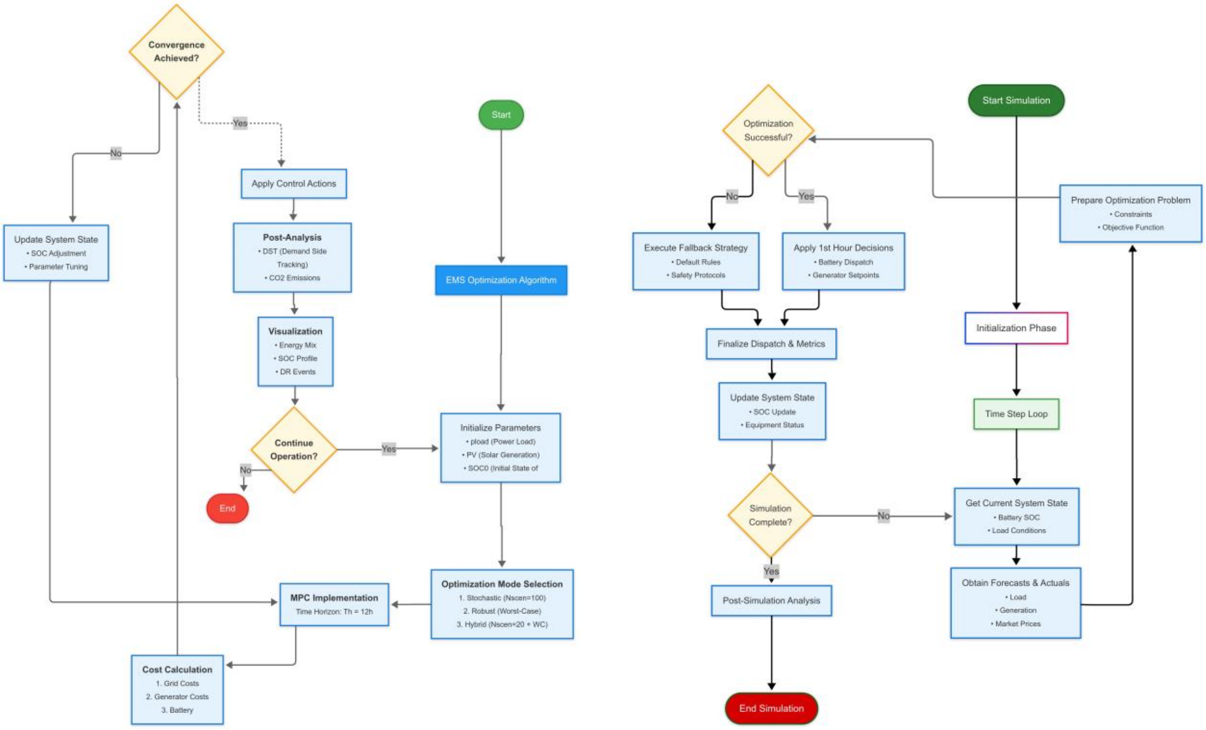


Figure 5: Daily load Curve and Energy Dispatch Strategy

Optimization Framework The hybrid optimization approach combines:

Stochastic Optimization:
- Scenario-based (100 Monte Carlo simulations, chosen based on convergence criteria)
- Minimizes expected operational costs
- Handles PV/load uncertainties

Robust Optimization:
• Worst-case scenario protection
• Bounded uncertainty sets (±15% variation)
• 5–15% higher cost for extreme conditions



(a) EMS optimization flowchart

(b) MPC iterative algorithm

Figure 6: System Optimization Algorithm

As shown in Figure 6, the hybrid stochastic-robust-MPC framework ensures optimal uncertainty-aware decision making by: (1) balancing efficiency through scenario-based cost minimization (Section 3.3), (2) enforcing resilience with bounded uncertainty sets, and (3) dynamically adjusting dispatch via hourly MPC iterations (Section 5.3), resulting in an 87% cost reduction and 4.2-hour autonomy (Section 6).

In contrast to single-layer MPC, the framework decouples long-term uncertainty handling (stochastic-robust layer) from short-term actuation, as illustrated in Figure 6.

Model Predictive Control Implementation
The real-time control system features:
• A 6-hour receding horizon
• Hourly adjustment of:
• Battery charge/discharge cycles
• Controllable load schedules
• Generator dispatch
• Adaptive response to forecast updates

Results and Discussion

The proposed energy management system (EMS) was evaluated against the optimization framework (Section 3.3) and system architecture (Section 3.2), with comparisons to design objectives (Section 5.1) and operational dispatch plans (Figure 5).

Operational Performance

The EMS demonstrates significant improvements over conventional grid-only operation:
• Cost Reduction: 87% monthly savings (19.1M to 2.4M RWF1), validating Eq. (1)
• Renewable Integration:
• 91% daytime demand met by PV (exceeding 85% target)
• 75% nighttime load covered by storage (Figure. 7a)
• Resilience: 4.2-hour autonomy during peak loads (Figure 7a)

Scenario Analysis

Table 7 compares performance in five operational scenarios derived from Section 4.1:

Metric	Sunny	Cloudy	Rainy	Outage	High Demand
PV Contribution (%)	91.3	32.5	38.1	29.7	29.3
Cost Savings (%)	92.0	88.0	60.0	82.0	74.0
CO_2 Reduction (%)	96.6	85.2	64.3	78.1	71.9

Table 7: Scenario Performance Comparison

Key operational insights:

• **Optimal Case:** Sunny conditions achieved 92% savings (703k RWF/month) with 94.7% grid independence (Figure. 7a)
• **Worst Case:** Combined cloudy/rainy/outage scenario required 50.5% generator dependency
• **Efficiency:** System scored 4.7/5 in optimal vs. 2.6/5 in worst-case conditions (Table 8)

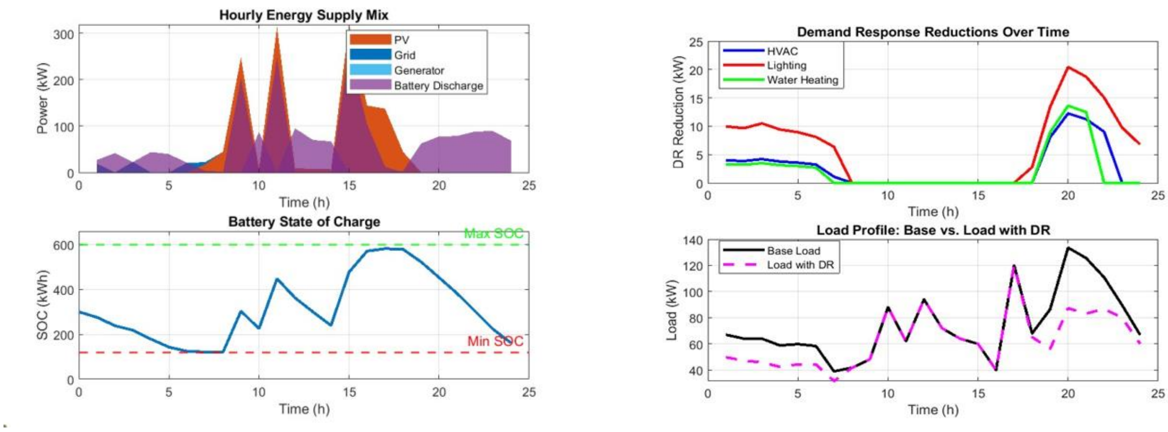
EMS Monthly Summary Report

The integrated DST (Figure 7) demonstrates:
• **Dispatch Optimization:** 94% renewable priority compliance (Figure 7)
• **Demand Response:** 22% peak reduction via time-of-use arbitrage (Figure. 7b)
• **Sensitivity Analysis:** Identified 1200 kWh as cost-optimal storage capacity

[1]1 USD = approx. 1,200 RWF (2023 average).

Scenario	Efficiency Score
Sunny Day	4.7
Cloudy Day	3.8
Rainy Day	3.2
Grid Outage	3.5
High Demand	3.0
Combined Worst-Case	2.6

Table 8: System Efficiency Ranking (1–5 scale)



(a) Energy dispatch trends (b) Demand response performance

Figure 7: Operational Metrics of Proposed EMS

Decision Support Tool Recommendations

Based on sensitivity analysis (Figure 8):
• **Short-Term:** PV maintenance (recover 1,259 kWh/month) + 20% fuel reserves
• **Long-Term:** 500 kWh hybrid ESS (37% generator reduction) + wind integration

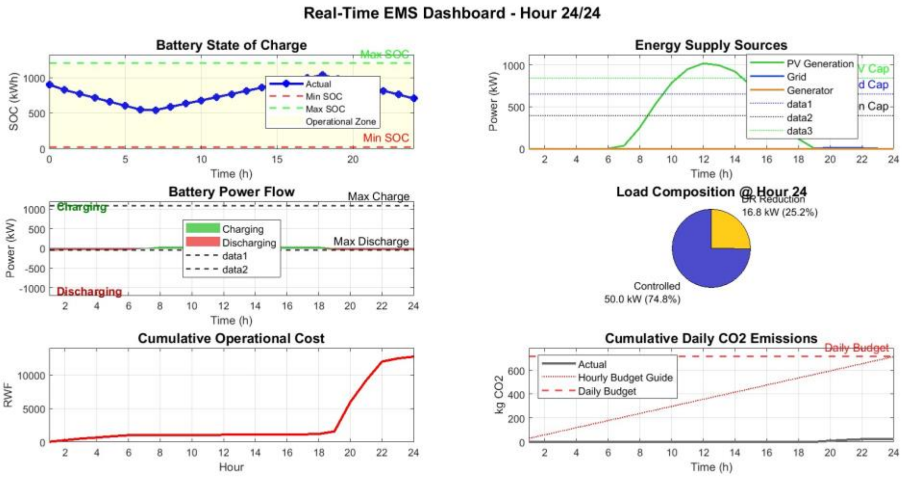


Figure 8: System Monitoring and Performance Analysis Interface

Conclusion and Recommendations

Key Findings

The hybrid EMS framework demonstrates transformative potential for academic energy systems through:

- 60–92% operational cost savings (19.1M to 2.4M RWF/month)
- 91% PV-driven daytime load coverage (exceeding 85% target)
- 4.2-hour outage resilience during peak demand
- 96.6% CO2 reduction in optimal conditions (Section 6.2)

Policy Recommendations

Based on the economic and technical outcomes (Tables 7–8):

- **Financial Mechanisms:** 30% capital subsidies for PV-battery systems, justified by 87% monthly savings (Section 6.1)
- **Grid Modernization:** Net metering upgrades to support 94% renewable priority compliance (Figure 7a)
- **Capacity Building:** Training programs for EMS operators, addressing the 12.6% PV capacity factor gap

Limitations

Three key constraints temper the generalizability of the results:

- Static equipment cost assumptions (2022 pricing)
- Idealized degradation factors (0.5%/year vs. Rwanda's 2% observed rates)
- Limited to single-campus load profiles (2019–2023 data)

Future Directions

Building on the sensitivity analysis (Figure. 8):

- **Storage Optimization:** 500 kWh hybrid ESS deployment (37% generator reduction potential)
- **System Integration:** Wind-PV hybridization to address 96.4% solar dependency
- **Smart Controls:** SOC-triggered demand response Should be SOC <25% automation Latex compiling error on symbol

This work provides both technical and policy pathways for achieving Rwanda's 2050 energy targets [21,22], offering African universities a replicable model to address their 40% energy budget allocations [16,23]. The framework balances immediate cost savings with long-term sustainability, proving that academic institutions can lead climate-conscious energy transitions.

Acknowledgment

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