

Uncertainty-Aware Scenario-Based LP-MPC for IoT-Enabled PV-BESS Hybrid Energy Management in Remote Campuses

A.E. EL-Alfy¹, Eman Elayat², M. A. E. Sheta^{*3}

^{1, 2, 3} Department of computer Teacher, Faculty of Specific Education, Mansoura University, Mansoura, Egypt.

To Cite this Article: A.E. EL-Alfy¹, Eman Elayat², M. A. E. Sheta^{*3}, "Uncertainty-Aware Scenario-Based LP-MPC for IoT-Enabled PV-BESS Hybrid Energy Management in Remote Campuses", *International Journal of Scientific Research in Engineering & Technology*, Volume 06, Issue 04, July-August 2026, PP:15-27.



Copyright: ©2026 This is an open access journal, and articles are distributed under the terms of the [Creative Commons Attribution License](#); Which Permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.

Abstract: The current paper is a proposal of uncertainty-sensitive scenario-based linear programming model predictive control (LP-MPC) framework of Internet of Things (IoT) -enabled photovoltaic-battery energy storage system (PV-BESS) hybrid energy management as used in remote campus applications. The suggested system combines renewable energy production, battery energy storage, grid communication, load demand on the campuses and real-time monitoring into a unified feedback system of energy management. The energy scheduling problem is also modeled in such a way as a linear programming model to optimize the total cost of operation and meet the primary technical requirements of the hybrid system. The objective comprises grid energy cost, battery degradation cost, PV curtailment penalty, and peak-demand penalty, while the constraints are power balance, battery state of charge (SOC) limits, charging and discharging limits, PV utilization limits, and grid import capacity. The LP model is integrated into a rolling-horizon MPC approach with recent IoT measurements and short-term predictions to enhance the adaptability to operating in uncertain conditions. Various scenarios are taken to reflect an uncertainty in renewable generation and campus demand such as normal operation, low PV generation, high load demand and worst-case conditions. The simulation outcomes during a 24-hour time frame demonstrate that the suggested LP-MPC framework will minimize grid power imports, enhance PV usage, cut the operating expense, restrict peak grid-side demand, and ensure the safe operation of BESS. The findings indicate the potential of the suggested solution to adaptive energy management of remote campus hybrid energy systems.

Key Words: IoT; PV-BESS; LP-MPC; SOC; scenario-based optimization; remote campus energy management.

Nomenclature:

Abbreviation	Full Form	Abbreviation	Full Form
IoT	Internet of Things	$P_L^s(t)$	Campus load demand under scenario s at time t
PV	Photovoltaic system	δ_L^s	Load variation factor associated with scenario s
BESS	Battery energy storage system	$SOC^s(t)$	Battery state of charge under scenario s at time t
LP	Linear programming	SOC^{meas}	Measured battery state of charge from the IoT monitoring layer
MPC	Model predictive control	SOC_{min}	Minimum allowable battery state of charge
LP-MPC	Linear programming-based model predictive control	SOC_{max}	Maximum allowable battery state of charge
SOC	State of charge	$P_{ch}^s(t)$	BESS charging power under scenario s at time t
t	Time-step index	$P_{dis}^s(t)$	BESS discharging power under scenario s at time t
s	Scenario index	P_{ch}^{max}	Maximum BESS charging power
T	Set of time steps in the prediction horizon	P_{dis}^{max}	Maximum BESS discharging power
S	Set of uncertainty scenarios	η_{ch}	BESS charging efficiency
Δt	Time-step duration	η_{dis}	BESS discharging efficiency
J	Total operating cost	E_{BESS}	Rated energy capacity of the battery

π_s	Weighting factor or probability of scenario s	$P_{\text{grid}}^s(t)$	Grid import power under scenario s at time t
$P_{\text{PV}}^{\text{av}}(t)$	Available PV power at time t	$P_{\text{grid}}^{\text{max}}$	Maximum allowable grid import capacity
$P_{\text{PV}}^s(t)$	Available PV power under scenario s at time t	P_{peak}^s	Peak grid import under scenario s over the prediction horizon
$P_{\text{PV}}^{\text{use},s}(t)$	Utilized PV power under scenario s at time t	$C_{\text{grid}}(t)$	Grid electricity price at time t
$P_{\text{curt}}^s(t)$	Curtailed PV power under scenario s at time t	C_{deg}	BESS degradation cost coefficient
η_{PV}	PV conversion efficiency	C_{curt}	PV curtailment penalty coefficient
A_{PV}	Total PV panel area		
$G(t)$	Solar irradiance at time t		
δ_{PV}^s	PV variation factor associated with scenario s		

I. INTRODUCTION

The rising electricity demand, the inadequate grid infrastructure, the escalating operations expense, and the necessity to enhance energy sustainability have made energy management a critical issue to remote university campus [1]. Photovoltaic (PV) generation can be combined with battery energy storage systems (BESS) and utility grid support in such applications to enhance flexibility of operations, less grid reliance and higher level of renewable energy use [2].

PV generation is suitable for remote campuses because it is clean, scalable, and locally available. However, its output varies with solar irradiance, weather conditions, temperature, and time of day. Campus load demand also changes according to academic schedules, laboratory operation, lighting, cooling requirements, and daily consumption behavior [3]. These variations make real-time energy scheduling more difficult, especially when PV generation, BESS operation, grid import, and load demand must be coordinated together [4].

Linear programming (LP) provides a transparent and computationally efficient method for energy scheduling. It can minimize operating cost while satisfying technical constraints such as power balance, BESS state-of-charge limits, charging and discharging limits, PV utilization limits, grid import limits, and peak-demand constraints [5]. However, deterministic LP scheduling usually depends on predefined or forecasted input profiles, which may reduce its adaptability under changing operating conditions [6].

LP-based optimization could be used to complement model predictive control (MPC) to enhance adaptability. An LP-MPC model involves repeated solution of the optimization problem over a moving prediction horizon based on updated measurements and short-term forecasts [7]. Each time step only the first control action is used and the process is repeated as new data become available. This allows the controller to revise its decisions based on the variations of PV generation, load demand, electricity price and battery condition [8].

The lack of predictability in PV generation and load demand in the campuses is another major problem in the real-world operation. Thus, the uncertainty management is done in a scenario form to assess the behavior of the system under varying operating conditions, such as normal operation, low PV generation, high load demand, and worst-case conditions [9]. This enables the controller to produce scheduling decisions that can be done under variable operating conditions [10].

The paper suggests an uncertainty-conscious scenario-based LP-MPC model of PV-BESS hybrid energy management via IoT-enabled remote campus applications. The framework proposed combines real-time IoT monitoring, LP-based cost optimization, and MPC-based rolling-horizon control together with a scenario-based uncertainty representation. The overall goal is to minimize the operating cost, minimize grid energy importation, enhance the use of PV, stabilize peak grid demand, and ensure safe BESS operation.

The principal contributions of this paper are as follows:

1. Designing a single IoT-based PV-BESS integrated hybrid energy management system to use in remote campus.
2. Developing an LP-based energy scheduling model taking into account the operating cost and major technical constraints.
3. Integration of the LP model into an MPC framework that can aid adaptive rolling-horizon scheduling with updated measurements.
4. The representation of uncertainty (scenario) in terms of normal, low-PV, high-load and worst-case operating conditions.
5. Assessing the suggested framework in 24-hour simulation horizon and comparing it to the baseline and rule-based strategies.

The rest of this paper is structured in the following manner. The literature review is provided in Section 2. Section 3 explains the suggested methodology. The implementation and simulation setup is described in Section 4. The results and comparative analysis are discussed in Section 5. Lastly, Section 6 wraps up the paper and gives future research directions.

II. LITERATURE REVIEW

The initial studies of solar based energy systems were mostly concerned with the economic viability, reliability analysis and sizing of a system. The works of the papers in [11] and [12] are significant early research where solar energy systems were to be studied within a cost and reliability constraint. Nevertheless, the studies were primarily founded on the static assessment

and lacked in the use of IoT-based monitoring, real-time optimization, model predictive control, and uncertainty-aware operation. Thus, this research direction is continued in the current work to the adaptive, data-driven, and scenario-based hybrid energy management.

As renewable energy technologies have evolved, photovoltaic-battery energy storage systems have become common to enhance sustainability, less grid reliance, and the remote applications. Remote campuses are appropriate to employ PV generation since this is clean, scalable, and abundant in the area. Yet, it is intermittent in its production because of changes in the solar irradiance, temperature, weather, and time of the day. This poses difficulties in terms of dependable scheduling particularly when there is also a fluctuating campus load demand throughout the day.

By providing storage capacity to unused PV energy and releasing it in times of low PV output, high demand, or when electricity prices are high, battery energy storage systems enhance PV-integrated system flexibility. It has been demonstrated in the past that BESS can promote the integration of renewable energy, decrease peak import to the grid and enhance reliability [13], [14]. Nevertheless, the operation of BESS needs to be controlled to stay within safe SOC limits and minimize unnecessary battery degradation.

The energy management systems have been subjected to optimization techniques to minimize the operating cost and enhance resource coordination. Linear programming is usually utilized since it is transparent, computationally efficient as well as appropriate to deal with problems with linear constraints. LP-based models are capable of minimizing the cost of grid energy, managing BESS charging and discharging, curtailing PV, and meeting power-balance constraints [15], [16]. Nevertheless, traditional LP scheduling tends to rely on predetermined or predicted input profiles and might not be able to respond in real-time to PV generation, load demand, electricity price, and battery state.

Simultaneously, the IoT technologies have enhanced the monitoring capacity of the current energy systems. Monitoring can be performed in real-time over IoT to obtain voltage, current, PV power, load demand, battery SOC, and grid-related data. Recently, it has been shown that low-cost sensing and data acquisition systems could be useful in measuring PV generation and electrical consumption [17], [18]. However, the majority of the IoT-based systems are more oriented to measurements, visualization and data logging, rather than being integrated into the control based on optimization.

Model predictive control is a powerful solution to the real-time management of energy since it is a combination of prediction, optimization and feedback correction. The difference in comparison to fixed scheduling methods is that MPC will seek to solve the optimization problem repeatedly over a moving prediction horizon, and implement only the initial control action, with an update to the decision made when new measurements are received. A natural improvement that can be achieved is the integration of an LP model into an MPC framework to enhance flexibility without affecting computational performance. The problem of uncertainty in PV generation as well as campus load demand is a major challenge in the practical operation of PV-BESS. Uncertainty analysis by scenarios offers a realistic means of assessing system performance under varying operating conditions including normal, low PV generation, high load demand and worst-case scenario operating conditions. This methodology assists the controller to have workable and economical scheduling choices upon non-conformance of actual operating conditions with anticipated profiles.

Judging by the literature reviewed, PV-BESS systems, LP optimization, IoT monitoring, MPC, and uncertainty analysis have been researched in various situations. Nevertheless, most of the studies that are available focus on these elements independently. Others are more about IoT monitoring without control optimization, and others use optimization without real-time IoT feedback or with uncertainty evaluation as a scenario. As such, this gap is filled by the present paper by suggesting an uncertainty-sensitive scenario-based LP-MPC framework to manage the PV-BESS hybrid energy management of remote campuses, IoT-enabled. The proposed framework combines real-time tracking, LP-based optimization of the costs, rolling-horizon MPC controls, and scenario-based uncertainty management in one single structure.

III. PROPOSED METHODOLOGY

The new methodology creates an uncertainty-conscious and adaptive energy management system of a PV-BESS hybrid energy system in a remote campus. The framework integrates real-time monitoring based on IoT, cost optimization based on LP, rolling-horizon control based on MPC, and uncertainty management based on scenarios into a single framework. The optimization model is updated using real-time measurements to enable the controller to adjust to changes in the conditions of PV generation, load demand, battery state of charge, electricity price, and grid conditions.

The methodology includes the general system architecture, mathematical model of the PV system, BESS, grid, campus load and power balance. Then, the formulation of the LP-MPC optimization is presented, with the objective, operational constraints, and the representation of uncertainty in a scenario form.

3.1 System Architecture

The general design of the proposed uncertainty-aware IoT-based LP-MPC hybrid energy management system is depicted in Fig. 1. The photovoltaic (PV) system and battery energy storage system (BESS) are incorporated into the architecture as part of one of the closed-loop energy management structures along with the utility grid, the load on the campus, the IoT monitoring layer, the data acquisition unit, the uncertainty analysis module, and the LP-MPC controller.

The primary aims of this architecture include facilitating adaptive energy scheduling, lower grid reliance, enhance PV use, constraint peak grid importation as well as reliable BESS operation in fluctuating operating conditions. IoT-based monitoring ensures real-time data capture and operational visibility and the LP-MPC controller makes the most optimal scheduling decisions on the hybrid energy system based on the updated data [19], [20].

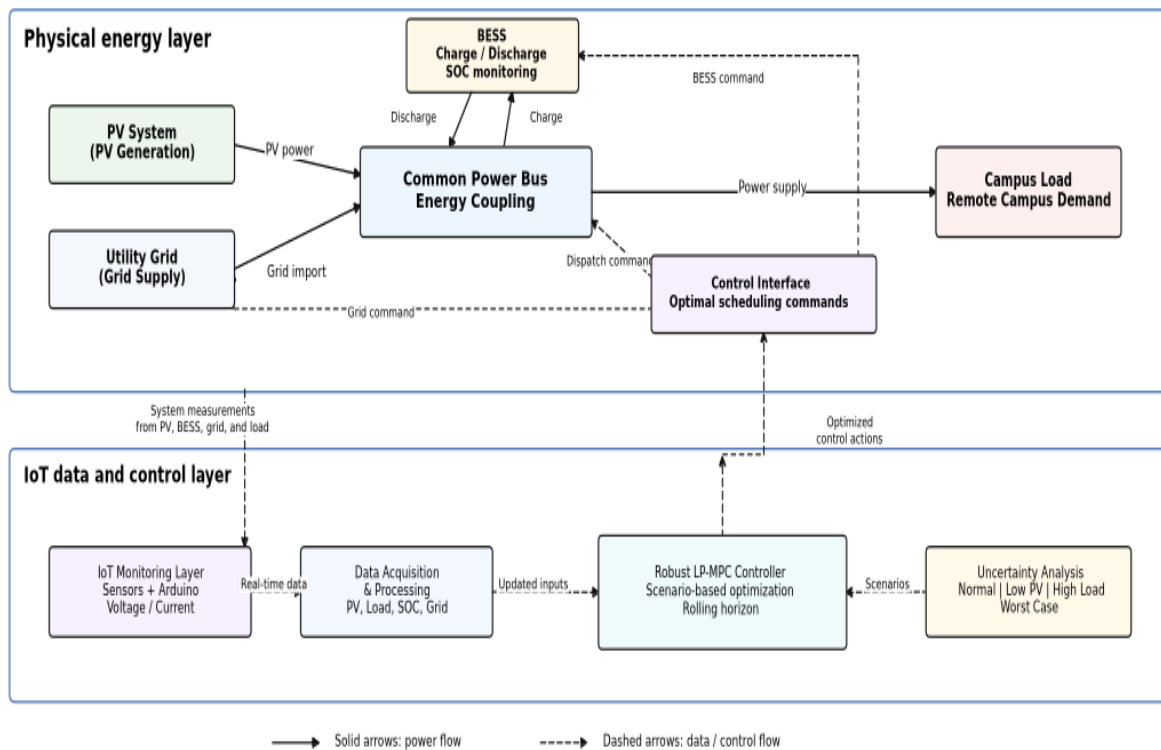


Fig. 1. Proposed uncertainty-aware IoT-enabled LP-MPC hybrid energy management architecture.

As shown in Fig. 1, the PV system, BESS, and utility grid are connected to a common power bus that supplies the campus load. The PV system provides renewable power, the grid supplies additional energy when needed, and the BESS charges or discharges according to the scheduling commands generated by the control system.

The IoT monitoring layer receives real-time data on the PV system, BESS, grid, and load on the campus and transmits it to the data acquisition unit. Such data points are PV power, load demand, BESS state of charge and grid-related data and are relayed to the LP-MPC controller to be optimized in real-time.

Scenario-based operating conditions (normal operation, low PV generation, high load demand, and worst-case conditions) are presented in the uncertainty analysis module. With these considerations, the controller is better positioned to react to the changes in renewable production and campus power needs.

The primary decision-making unit is the LP-MPC controller. It optimizes the LP on a dynamic prediction horizon with updated IoT measurements and scenario information. The grid import, BESS charging and discharging and PV utilization are established by the controller. The first control action is applied in each time step and a repetition of the process is made when new measurements are made.

The mathematical model and operational constraint of the PV system, campus load, BESS, utility grid and relationship between the power balance is as shown in the following subsection and was utilized in the proposed optimization model.

3.2 Mathematical Modeling of the Hybrid Energy System

The mathematical modeling structure to be applied to develop the proposed scenario-based LP-MPC problem is summarized in Fig. 2. The IoT measurements and short-term forecasts will give updated data such as the available PV power, load demand in the campus, BESS state of charge, grid electricity price and irradiance/load forecast.

These inputs are translated into mathematical models for PV generation, campus load demand, BESS operation, and grid import. The resulting component equations, operating bounds, and power-balance relationship form the linear model set used by the LP-MPC controller. In addition, the uncertainty scenario set, including normal operation, low PV generation, high load demand, and worst-case conditions, is incorporated into the optimization process.

Based on these models and scenarios, the LP-MPC controller solves the scheduling problem over a moving prediction horizon and generates the optimal decisions for grid import, BESS charging, BESS discharging, PV utilization, and PV curtailment. The component-level modeling approach adopted in this study, including PV generation, BESS operation, grid import, and power-balance constraints, follows common formulations used in microgrid energy management and optimization studies [20], [21], [22].

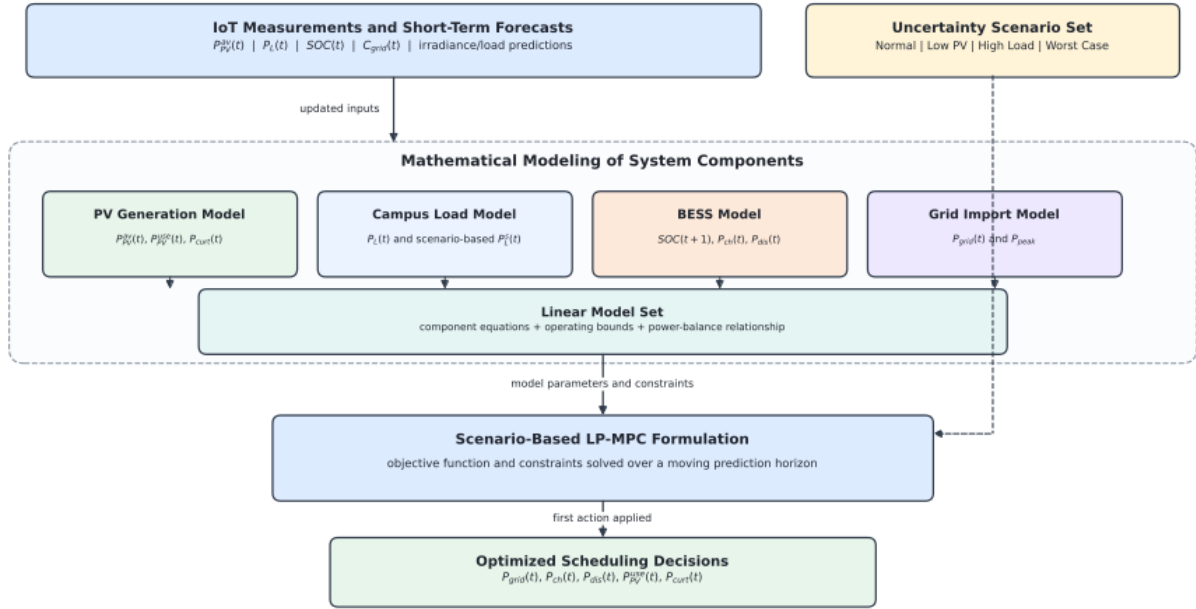


Fig. 2. Mathematical modeling structure of the proposed scenario-based LP-MPC formulation.

3.2.1 PV Generation Model

The photovoltaic (PV) system represents the main renewable energy source in the proposed hybrid energy management framework. The available PV power varies over time according to solar irradiance, PV panel area, conversion efficiency, and operating conditions. In this study, PV power is treated as a time-varying input obtained from real-time measurements and short-term forecasts, allowing the LP-MPC controller to update its scheduling decisions at each time step. Similar PV-based microgrid and MPC energy management formulations have been used in previous studies [19], [22].

The available PV power at time step t can be expressed as:

$$P_{PV}^{av}(t) = \eta_{PV} \cdot A_{PV} \cdot G(t) \quad (1)$$

This simplified PV model is commonly used to estimate available solar power from irradiance, PV area, and conversion efficiency [19], [22]. To account for PV uncertainty, a scenario-based representation is introduced. The available PV power under scenario s is modeled as:

$$P_{PV}^s(t) = P_{PV}^{av}(t)(1 + \delta_{PV}^s) \quad (2)$$

In the optimization problem, the available PV power under each scenario is divided into utilized and curtailed power. Curtailment occurs when PV generation exceeds the campus load demand and BESS charging capacity. Therefore, the PV power relationship is formulated as:

$$P_{PV}^s(t) = P_{PV}^{use,s}(t) + P_{curt}^s(t) \quad (3)$$

The utilized PV power under each scenario cannot exceed the corresponding available PV generation:

$$0 \leq P_{PV}^{use,s}(t) \leq P_{PV}^s(t) \quad (4)$$

PV curtailment is non-negative:

$$P_{curt}^s(t) \geq 0 \quad (5)$$

These constraints ensure that PV utilization does not exceed the available generation under each scenario, while surplus renewable energy is represented by the curtailment variable. This preserves the linear structure of the optimization problem and supports feasible LP-MPC operation under uncertain PV conditions.

3.2.2 Campus Load Demand Model

The campus load represents the electrical demand required to supply the remote campus facilities. It varies over time according to occupancy, academic activities, weather conditions, and daily operating requirements. In the proposed IoT-enabled LP-MPC framework, updated load demand is obtained from the IoT monitoring and data acquisition units and used by

the controller during optimization. Similar IoT-based energy management and MPC-based microgrid studies rely on updated demand measurements and forecasts to improve scheduling decisions [20], [21], [22].

The measured campus load demand at time step t is represented as:

$$P_L(t) = P_L^{meas}(t) \quad (6)$$

To account for load uncertainty, a scenario-based demand model is introduced. Under scenario s , the campus load demand is expressed as:

$$P_L^s(t) = P_L(t)(1 + \delta_L^s) \quad (7)$$

Scenario-based MPC can represent demand and renewable-generation uncertainties in microgrid energy management [23], [24]. The load demand is constrained as follows:

$$P_L^s(t) \geq 0 \quad (8)$$

3.2.3 BESS Model

The battery energy storage system (BESS) is used to store surplus PV energy and support the campus load during periods of low PV generation, high demand, or high electricity prices. In the proposed IoT-enabled LP-MPC framework, the BESS state of charge is monitored in real time and used by the controller to generate feasible charging and discharging decisions. Similar BESS modeling approaches have been adopted in IoT-based and MPC-based microgrid energy management studies [20], [21], [22].

To maintain the linear structure of the optimization problem, BESS operation is represented using two non-negative variables: charging power and discharging power. The BESS state of charge under scenario s is updated as follows:

$$SOC^s(t+1) = SOC^s(t) + \frac{\eta_{ch} P_{ch}^s(t) \Delta t}{E_{BESS}} - \frac{P_{dis}^s(t) \Delta t}{\eta_{dis} E_{BESS}} \quad (9)$$

The SOC update follows standard BESS modeling in microgrid and MPC-based energy management [20], [21], [22]. The SOC must remain within its allowable limits:

$$SOC_{min} \leq SOC^s(t) \leq SOC_{max} \quad (10)$$

The BESS charging power is constrained by its maximum allowable limit:

$$0 \leq P_{ch}^s(t) \leq P_{ch}^{max} \quad (11)$$

$$0 \leq P_{dis}^s(t) \leq P_{dis}^{max} \quad (12)$$

The initial SOC at each horizon is updated using the latest IoT-measured SOC value:

$$SOC^s(0) = SOC^{meas} \quad (13)$$

These constraints ensure safe BESS operation within the allowable power and SOC limits, while enabling the LP-MPC controller to store surplus PV energy, reduce grid import, and maintain reliable operation under uncertainty.

3.2.4 Utility Grid Import Model

The utility grid is used as a supplementary energy source when PV generation and BESS discharge are insufficient to meet the campus load demand. In the proposed framework, grid import supports supply reliability during low renewable generation, high load demand, or limited battery state of charge. Since the objective is to reduce grid dependency and operating cost, the LP-MPC controller schedules grid import only when required. Similar microgrid energy management studies model grid import as a controllable input for maintaining power balance and reducing cost [20], [21], [22].

In this study, only grid import is considered, while grid export is not included. Therefore, the grid import power under scenario s must be non-negative:

$$P_{grid}^s(t) \geq 0 \quad (14)$$

The grid import power is limited by the maximum allowable grid capacity as follows:

$$0 \leq P_{grid}^s(t) \leq P_{grid}^{max} \quad (15)$$

To limit excessive grid demand during peak periods, an auxiliary peak-demand variable is introduced to represent the maximum grid import over the scheduling horizon:

$$P_{peak}^s \geq P_{grid}^s(t) \quad (16)$$

This auxiliary variable enables the objective function to penalize peak grid demand while preserving the linear structure of the optimization problem. In addition, the grid electricity price is treated as a time-varying input and is used in the objective function to calculate the cost of grid energy import. Accordingly, the proposed LP-MPC controller can reduce unnecessary grid usage, limit peak import, and maintain reliable power supply under different operating scenarios.

3.2.5 Power Balance Constraint

The power balance constraint ensures that the total supplied power equals the total consumed and stored power at each time step. Under each uncertainty scenario, the campus load is supplied by utilized PV power, BESS discharging power, and grid import power, while part of the supplied energy may be used to charge the BESS. This type of power-balance relationship is commonly used in microgrid energy management and MPC-based optimization problems to guarantee physically feasible scheduling decisions [20], [21], [22]. Therefore, the scenario-based power balance constraint is formulated as:

$$P_{PV}^{use,s}(t) + P_{dis}^s(t) + P_{grid}^s(t) = P_L^s(t) + P_{ch}^s(t) \quad (17)$$

This constraint links the PV model, campus load model, BESS model, and utility grid model within a single physically feasible optimization framework.

3.3 LP-MPC Optimization Formulation

The suggested LP-MPC optimization model decides the optimal scheduling choices of the hybrid energy management with a moving prediction horizon. Every time step, the solve of a linear programming problem is done using updated IoT measurements, short term predictions, and scenarios of uncertainty. The key variables of the decision are grid import, BESS charging power, BESS discharging power, used PV power, PV curtailment and peak grid demand.

The optimization problem aims to minimize the total operating cost while satisfying the operational constraints of the PV system, BESS, utility grid, campus load, and power balance relationship. Since both the objective function and constraints are expressed in linear form, the proposed formulation is suitable for efficient implementation within a rolling-horizon LP-MPC framework. Similar MPC-based and scenario-based optimization formulations have been applied in microgrid energy management studies to reduce operating cost and improve system operation under uncertainty [21], [23], [24].

3.3.1 Objective Cost Function

The objective function minimizes the total operating cost of the proposed hybrid energy management system over the prediction horizon and across the considered uncertainty scenarios. The total cost includes grid energy import cost, BESS degradation cost, PV curtailment penalty, and peak-demand penalty. The objective function is formulated as:

$$\min J = \sum_{s \in \mathcal{E}_{cal}} \pi_s \left[\sum_{t \in \mathcal{E}_{cal}} (C_{grid}(t) P_{grid}^s(t) \Delta t + C_{deg}(P_{ch}^s(t) + P_{dis}^s(t)) \Delta t + C_{curt} P_{curt}^s(t) \Delta t) + \lambda_{peak} P_{peak}^s \right] \quad (18)$$

3.3.2 Operational Constraints

The proposed LP-MPC optimization problem is solved subject to the operational constraints defined in the mathematical modeling section. These constraints ensure that the scheduling decisions remain physically feasible and respect the operating limits of the PV system, BESS, utility grid, and campus load.

The PV-related constraints are represented by (4) and (5), which define the utilized PV power limit and PV curtailment non-negativity. The campus load constraints are represented by (6) to (8), including the measured load, scenario-based load demand, and load non-negativity. The BESS-related constraints are represented by (9) to (13), including the SOC update equation, SOC operating limits, charging and discharging power limits, and the initial SOC condition. The utility grid constraints are represented by (14) to (16), including non-negative grid import, maximum grid import capacity, and peak-demand limitation. Finally, the power balance constraint is represented by (17).

All constraints are applied over the prediction horizon and across the considered uncertainty scenarios. Therefore, the proposed LP-MPC formulation can generate feasible and adaptive scheduling decisions under variations in PV generation and campus load demand while preserving the linear structure required for efficient rolling-horizon implementation. Similar constraint-based and scenario-based formulations are commonly used in MPC-based microgrid energy management studies to ensure reliable operation under uncertainty [20], [21], [22], [23], [24].

3.3.3 Scenario-Based Uncertainty Handling

The suggested LP-MPC model takes into account uncertainty within the PV generation and campus load demand in the form of scenario. The controller does not use an individual deterministic forecast but compares various operating conditions, such as normal operation, low PV generation, high load demand, and worst-case conditions. This allows the optimization problem to produce scheduling decisions that are feasible and robust to operate under the various operating conditions.

The uncertainty scenario set includes four main cases: normal operation, low PV generation, high load demand, and worst-case operation. The normal scenario represents standard conditions, while the low-PV and high-load scenarios represent individual uncertainty effects. The worst-case scenario combines reduced PV generation with increased load demand.

The scenario-based formulation is incorporated through scenario-dependent variables and parameters, including PV power, load demand, BESS charging and discharging decisions, grid import, PV curtailment, and peak grid demand. By assigning a weighting factor to each scenario, the objective function accounts for the relative importance or probability of different operating conditions.

In practical campus operation, PV generation and load demand may be correlated. Therefore, the scenario weighting factor can also be interpreted as a joint or conditional probability reflecting the relationship between PV generation and load demand. This improves the realism of the uncertainty representation without changing the linear structure of the proposed LP-MPC formulation.

Scenario-based MPC has been extensively applied in research of energy management within microgrids to deal with uncertainty in renewable generation and load demand at any time and to maintain timely updates in decisions [23], [24]. This method enhances robustness in scheduling and minimizes the risk of infeasible operation in the given framework as actual PV generation or load demand deviates, compared to the forecasted value.

3.3.4 Rolling-Horizon Control Strategy

The suggested LP-MPC model works on a rolling-horizon control approach. The optimization problem is solved with updated measurements of the IoT, forecast data, and uncertainty scenarios over a limited prediction horizon at every sampling time.

Once the optimization problem has been solved, the only control action applied to the physical energy system is the first one. New values are taken at the subsequent sampling time, prediction horizon is moved forward, and the optimization problem is solved again.

This rolling-horizon system enables the controller to dynamically update its decisions as responses to the variations in the PV generation, load demand, battery SOC, electricity price and operating conditions. The proposed LP-MPC framework has superior flexibility compared to the traditional day-ahead scheduling because of its integration of prediction, optimization, and feedback correction [21], [22].

Combining rolling-horizon control with scenario-based uncertain management, the proposed framework enhances adaptability in real-time, minimizes grid reliance, maximizes the use of PV, minimizes peak grid import, and ensures safe operation of BESS.

IV. SIMULATION SETUP AND IMPLEMENTATION

Herein, the setup of the simulation to assess the proposed uncertainty-aware scenario-based LP-MPC framework is presented. The simulation is run to complete a 24 hours operating horizon to indicate one complete energy management cycle of a remote campus on a daily basis. This system follows the PV generation, BESS operation, utility grid import, demand of the campuses load, time-varying electricity price, the updates of the measurements by IoT, and the uncertainty conditions depending on the scenarios.

The simulation will assess how well the proposed controller can minimize grid dependency, better PV utilization, constrain peak grid import, lower the operating cost, and ensure safe BESS operation. Each sampling step the LP-MPC controller uses the updated input information and repeatedly solves the optimization problem in a moving prediction horizon.

4.1 Simulation Environment

The framework proposed is implemented with 24 hour simulation horizon in discrete time. At time step the controller gets updated on the available PV generation, campus load demand, BESS state of charge, grid electricity price, and conditions of uncertainty scenario. This optimization problem is set as a linear programming problem and is solved in the rolling-horizon LP-MPC framework.

The simulation environment will be the contact between the physical energy system and the control layer. The physical system comprises of PV system, BESS, utility grid and campus load whereas the control layer involves data acquisition that is based on IoT, uncertainty analysis that is scenario-based and the optimization module of LP-MPC. Such an arrangement allows the controller to simulate real-time energy scheduling with varying operating conditions.

4.2 System Parameters

Table 1 summarises the main simulation parameters used in this study. Such parameters are PV and BESS ratings, operating limits, values of efficiency, maximum import to the grid, and cost coefficients as needed by the proposed LP-MPC controller.

Table 1. Simulation Parameters of the Proposed PV-BESS Hybrid Energy Management System				
Notation	Type	Definition	Value	Unit
T	Simulation parameter	Simulation horizon	24	h
Δt	Simulation parameter	Time-step duration	1	h

P_{PV}^{rated}	System parameter	Rated PV generation capacity	50	kW
E_{BESS}	System parameter	Rated BESS energy capacity	100	kWh
P_{ch}^{max}	Operational limit	Maximum BESS charging power	25	kW
P_{dis}^{max}	Operational limit	Maximum BESS discharging power	25	kW
SOC_{min}	Operational limit	Minimum allowable battery state of charge	20	%
SOC_{max}	Operational limit	Maximum allowable battery state of charge	90	%
$SOC^s(0)$	Initial condition	Initial battery state of charge under scenario s	50	%
η_{ch}	Efficiency parameter	BESS charging efficiency	95	%
η_{dis}	Efficiency parameter	BESS discharging efficiency	95	%
P_{grid}^{max}	Operational limit	Maximum allowable grid import capacity	80	kW
C_{deg}	Cost parameter	BESS degradation cost coefficient	0.01	\$/kWh
C_{curt}	Cost parameter	PV curtailment penalty coefficient	0.02	\$/kWh
λ_{peak}	Cost parameter	Peak-demand penalty coefficient	0.1	\$/kW

Table 1 specifies the values of the baseline simulation conditions to assess the proposed LP-MPC framework. The parameters give technical constraints, efficiency figures, and cost coefficients that are necessary to produce viable time scheduling choices within the 24 hour horizon.

4.3 Input Profiles and Uncertainty Scenarios

The simulation applies time varying input profiles of the PV generation, campus load demand, grid electricity price and BESS state of charge. The PV profile would be based on a normal pattern of the sun daily, and the campus load would be dependent on the level of occupancy, campus activities, and operational needs.

To test the strength of the proposed LP-MPC controller, four cases of uncertainty are being taken into account: normal operation, low PV generation, high load demand, and worst-case operation. Such situations serve to evaluate the controller capacity to sustain realistic and economical decisions in scheduling, given varied PV and load characteristics.

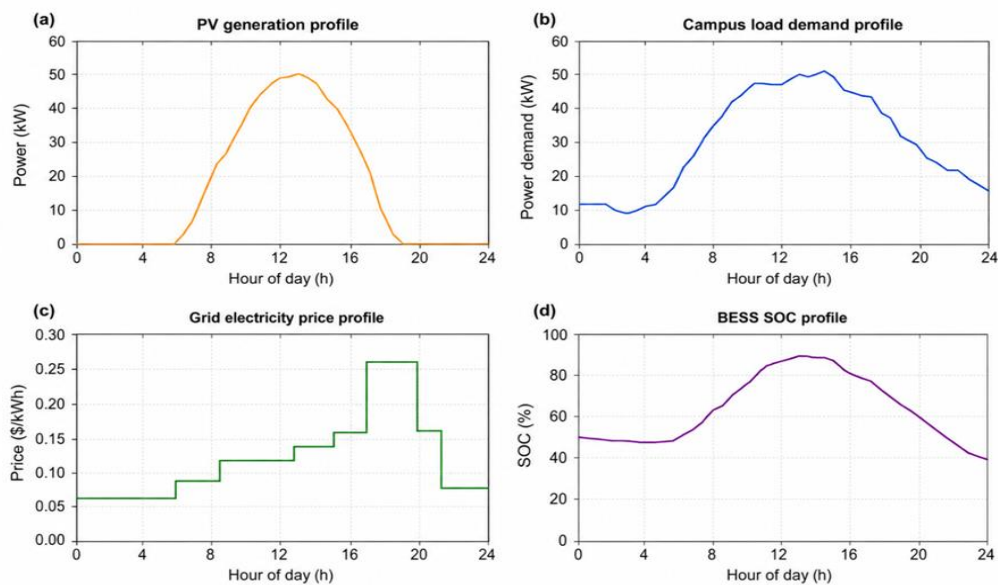


Fig. 3. Simulation input profiles over the 24-hour operating horizon.

Fig. 3 shows the PV generation, campus load demand, grid electricity price, and BESS SOC, as an input with a 24-hour input profile into the simulation. These profiles are the daily variations of the renewable generation, demand, tariff conditions and the operation of battery.

4.4 Implementation Procedure

The proposed LP-MPC framework relies on optimization repeated on a moving prediction horizon to implement it. Currently at every time step the optimization inputs are updated with new IoT measurements, short-term forecasts and uncertainty scenarios.

The LP-MPC controller solves the linear program using the objective function in (18) and the operational constraints in (4) to (17). Decisions such as grid import, BESS charging and discharging powers, utilized PV power, PV curtailment and peak grid demand are the result of these.

The physical system is only subjected to the first control action. On the following time step, new measurements are obtained, prediction horizon is moved to the future and the optimization problem is solved once more. This feedback process enables the controller to respond to the variations in PV generation, load demand, battery SOC, electricity price and uncertainty situations.

4.5 Performance Evaluation Metrics

The suggested scenario-based LP-MPC framework is assessed by operation and economic parameters such as total operating cost, grid energy import, PV utilization, PV curtailment, peak grid import, and BESS state-of-charge behaviour. These are the metrics that determine how the controller is performing in minimizing the cost of energy, increasing the use of renewable energy, minimizing grid reliance, and ensuring safe operation of BESS.

The total operating cost evaluates the economic performance of the system, while grid energy import indicates the level of dependency on the utility grid. PV utilization and PV curtailment measure how effectively the available renewable energy is used, and peak grid import reflects the controller's ability to limit high-demand periods. The BESS SOC profile is also analyzed to ensure that battery operation remains within safe limits throughout the simulation horizon.

V.RESULTS AND DISCUSSION

This section presents the simulation results of the proposed uncertainty-aware scenario-based LP-MPC framework over a 24-hour operating horizon. The results are evaluated using the input profiles and uncertainty scenarios described in the previous section.

The performance of the proposed framework is analyzed in terms of grid energy import, PV utilization, PV curtailment, peak grid import, BESS SOC behavior, and total operating cost. In addition, the results are compared with baseline and rule-based energy management strategies to demonstrate the effectiveness of the proposed scenario-based LP-MPC approach.

5.1 PV Utilization and Grid Import Analysis

The PV generation profile provides renewable power mainly during daytime hours. As PV generation increases in the morning and reaches its peak around midday, the LP-MPC controller maximizes PV utilization and reduces grid import. When PV generation exceeds immediate campus demand, surplus renewable energy is used to charge the BESS.

During periods of low PV generation, such as early morning, evening, and night hours, the controller relies on BESS discharge and grid import to meet campus demand. Compared with the baseline strategy, the proposed LP-MPC framework reduces unnecessary grid import by coordinating PV utilization and BESS operation more effectively.

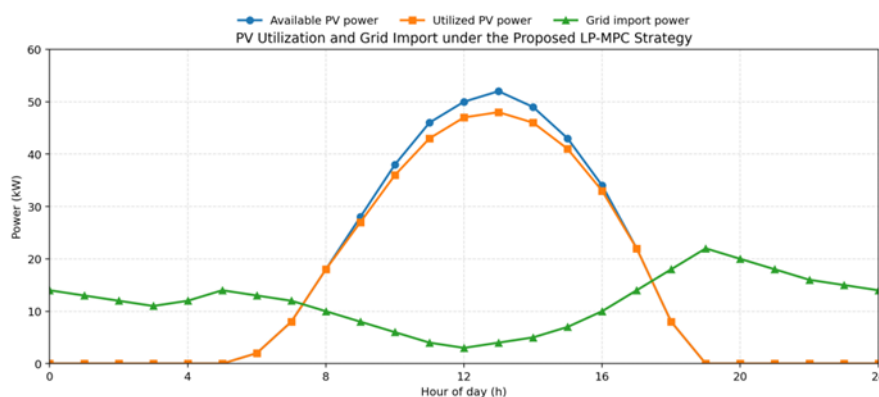


Fig. 4. PV utilization and grid import profiles under the proposed LP-MPC strategy.

Fig. 4 shows that the proposed controller reduces grid import during high PV generation periods by prioritizing PV utilization and BESS charging. During evening peak-demand periods, the BESS discharges stored energy to support the campus load and reduce grid dependency.

5.2 BESS SOC and Charging/Discharging Behavior

The BESS improves the flexibility of the hybrid energy system by storing surplus PV energy during high generation periods and discharging during low PV generation or high demand periods to support the campus load and reduce grid import.

Throughout the simulation horizon, the SOC profile does not cross the predefined limits of operation, which proves that the proposed LP-MPC controller satisfies battery constraints and does not operate in an unsafe manner. Electricity price difference also affects the charging and discharging decisions which enables the controller to utilize stored energy during times of high electricity prices and minimize grid reliance.

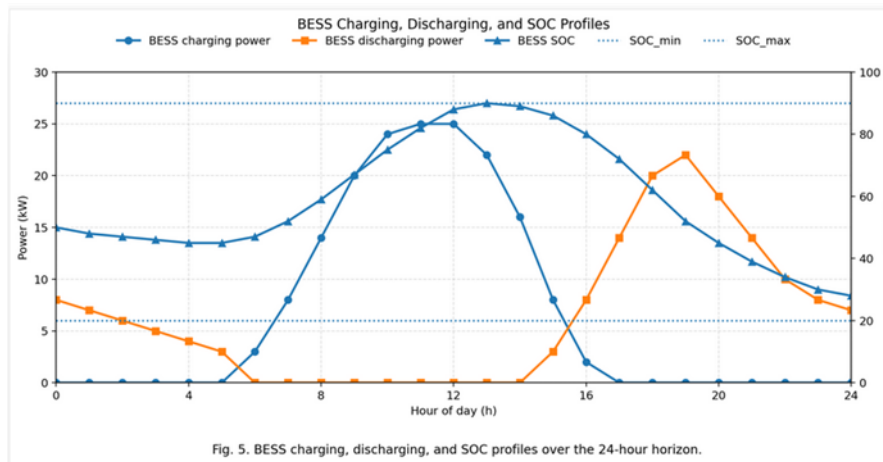


Fig. 5 demonstrates that the BESS will charge during high PV availability and discharge in periods of high demand or high price. The SOC is within the range of SOCmax and SOCmin, which ensures safe and constraint-compliant use of the battery.

5.3 Scenario-Based Uncertainty Analysis

The suggested framework considers four levels of uncertainty that include: normal operation, low PV generation, high load demand, and worst-case conditions. These cases are employed to evaluate the strength of the LP-MPC controller in various PV generation and campus loads scenarios.

The results show that the proposed scenario-based LP-MPC controller maintains feasible operation under all considered scenarios. In the low-PV scenario, grid import increases to compensate for reduced renewable generation. In the high-load scenario, the BESS contributes additional energy to support campus demand. Under the worst-case scenario, the controller coordinates grid import and BESS discharge to maintain power balance while respecting all operational constraints. The simulation results are summarized in Table 2.

Scenario	Grid Import (kWh)	PV Utilization (%)	PV Curtailment (kWh)	Peak Grid Import (kW)	Operating Cost (\$)
Normal	295	95.2	19	22	43.75
Low PV	385	96.8	8	31	56.40
High Load	420	97.0	12	36	62.85
Worst Case	515	98.1	5	45	78.30

Table 2 shows that the proposed controller adapts its scheduling decisions according to the operating scenario. Under normal conditions, the controller achieves high PV utilization with limited grid import. In the low-PV and high-load scenarios, grid import and BESS support increase to compensate for reduced renewable generation or additional campus demand. Although the worst-case scenario results in the highest grid import and operating cost, the LP-MPC controller maintains feasible operation by coordinating PV utilization, BESS operation, and grid import.

5.4 Comparative Performance Evaluation

To evaluate the effectiveness of the proposed framework, the scenario-based LP-MPC strategy is compared with baseline and rule-based energy management strategies. The baseline strategy mainly depends on grid supply, while the rule-based strategy uses predefined charging and discharging rules. In contrast, the proposed LP-MPC framework optimizes scheduling decisions over a moving horizon using updated measurements and uncertainty scenarios.

Strategy	Total Cost (\$)	Grid Energy Import (kWh)	PV Utilization (%)	Peak Grid Import (kW)	SOC Constraint Satisfaction
Baseline strategy	68.90	510	78.5	42	Yes
Rule-based strategy	54.70	385	88.7	32	Yes
Proposed LP-MPC	43.75	295	95.2	22	Yes

As shown in Table 3, the proposed LP-MPC framework provides the best overall performance. It reduces total operating cost, grid energy import, and peak grid demand, while achieving the highest PV utilization. Although the rule-based strategy improves performance compared with the baseline case, it remains less effective because it does not account for future operating conditions, electricity price variations, or scenario-based uncertainty during scheduling.

VI. CONCLUSION AND FUTURE WORK

This paper has introduced an uncertainty-sensitive scenario-based LP-MPC model of IoT-enabled PV-BESS hybrid energy management in isolated campus scenarios. The suggested model incorporates an IoT-based real-time monitoring, PV generation, BESS functionality, utility grid support, and the situation-specific uncertainty management into a closed-loop energy management framework.

The energy scheduling problem was modeled as a linear program and solved within a rolling-horizon MPC strategy. The objective combined grid energy cost, BESS degradation cost, PV curtailment penalty, and peak-demand penalty, while the constraints enforced power balance, safe SOC operation, PV utilization limits, and grid import capacity.

The simulated outcomes with the 24-hour horizon indicated that the suggested framework resulted in less energy imported into grids, enhanced PV use, minimized the peak grid load, and kept BESS operation within reasonable boundaries. The proposed LP-MPC approach demonstrated improved overall performance in comparison to both baseline and rule-based strategies as it was capable of updating the decisions based on new measurements and uncertainty scenarios.

In general, the given framework is an efficient energy management policy of remote campus hybrid energy systems. Future development will involve validation with actual campus data, addition of grid export and demand response, and real-time implementation with IoT based hardware platforms.

Funding Information

The funding of this research was through the research support fund of Mansoura University, Egypt. Under grant number (Mu-Se-25-3). The authors acknowledge their appreciations to Mansoura University, via the Deanship of Graduate Studies and Scientific Research, which provided them with the financial assistance of this research.

Conflict Of Interest Statement

Authors state no conflict of interest.

REFERENCES

1. H. A. Muqet et al., "Sustainable Solutions for Advanced Energy Management System of Campus Microgrids: Model Opportunities and Future Challenges," *Sensors*, vol. 22, no. 6, p. 2345, Jan. 2022, doi: <https://doi.org/10.3390/s22062345>.
2. K. Lalbiakhlua, S. Deb, K. Singh, S. Datta, H. A. Shuaibu, and T. S. Ustun, "Deep learning based solar forecasting for optimal PV BESS sizing in ultra fast charging stations," *Scientific Reports*, vol. 15, no. 1, Sep. 2025, doi: <https://doi.org/10.1038/s41598-025-17408-0>.
3. L. Bin et al., "Scheduling and Sizing of Campus Microgrid Considering Demand Response and Economic Analysis," *Sensors*, vol. 22, no. 16, p. 6150, Aug. 2022, doi: <https://doi.org/10.3390/s22166150>.
4. G. Talluri, Gabriele Maria Lozito, F. Grasso, Carlos Iturrino Garcia, and A. Luchetta, "Optimal Battery Energy Storage System Scheduling within Renewable Energy Communities," *Energies (Basel)*, vol. 14, no. 24, pp. 8480–8480, Dec. 2021, doi: <https://doi.org/10.3390/en14248480>.
5. A. Theja and M. Pal, "An Explainable Equity-Aware P2P Energy Trading Framework for Socio-Economically Diverse Microgrid," *arXiv.org*, 2025. <https://arxiv.org/abs/2507.18738>
6. T. O. Pocola et al., "Optimal sizing and control of a grid-connected battery in a stacked revenue model including an energy community," *Applied Energy*, vol. 397, p. 126122, Jun. 2025, doi: <https://doi.org/10.1016/j.apenergy.2025.126122>.
7. T. J. J. van den Boom and B. De Schutter, "Modeling and control of switching max-plus-linear systems with random and deterministic switching," *Discrete Event Dynamic Systems*, vol. 22, no. 3, pp. 293–332, Dec. 2011, doi: <https://doi.org/10.1007/s10626-011-0123-x>.
8. D. Watari et al., "Multi-time scale energy management framework for smart PV systems mixing fast and slow dynamics," *Applied Energy*, vol. 289, pp. 116671–116671, May 2021, doi: <https://doi.org/10.1016/j.apenergy.2021.116671>.
9. D. Thomas and E. Kotsakis, "Energy Management and Optimal Power Scheduling in a Smart Building under Uncertainty," *Smart Cities - Their Framework and Applications*, Oct. 2021, doi: <https://doi.org/10.5772/intechopen.94989>.
10. P. Wenzelburger and F. Allgöwer, "Model Predictive Control for Flexible Job Shop Scheduling in Industry 4.0," *Applied Sciences*, vol. 11, no. 17, p. 8145, Sep. 2021, doi: <https://doi.org/10.3390/app11178145>.
11. S. A. Farghal, M. A. Tantawy, and A. E. El-Alfy, "Impact of Solar Thermal Power Plants on Economy and Reliability of Utility System," *IEEE Transactions on Energy Conversion*, vol. EC-2, no. 2, pp. 208–214, Jun. 1987, doi: <https://doi.org/10.1109/tec.1987.4765831>.
12. S. A. Farghal, M. A. Tantawy, and A. E. El-Alfy, "Optimum Design of Stand Alone Solar Thermal Power System with Reliability Constraint," *IEEE Transactions on Energy Conversion*, vol. EC-2, no. 2, pp. 215–221, Jun. 1987, doi: <https://doi.org/10.1109/tec.1987.4765832>.
13. Y. Yang, S. Bremner, C. Menictas, and M. Kay, "Battery energy storage system size determination in renewable energy systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 109–125, Aug. 2018, doi: <https://doi.org/10.1016/j.rser.2018.03.047>.
14. Y. Yang, S. Bremner, C. Menictas, and M. Kay, "Modelling and optimal energy management for battery energy storage systems in renewable energy systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 167, Art. no. 112671, Oct. 2022, doi: <https://doi.org/10.1016/j.rser.2022.112671>.
15. K. B. Gassi and M. Baysal, "Analysis of a linear programming-based decision-making model for microgrid energy management systems with renewable sources," *International Journal of Energy Research*, vol. 46, no. 6, pp. 7495–7518, 2022, doi: [10.1002/er.7656](https://doi.org/10.1002/er.7656).
16. A. Shufian and N. Mohammad, "Modeling and analysis of cost-effective energy management for integrated microgrids," *Cleaner Engineering and Technology*, vol. 8, Art. no. 100508, Jun. 2022, doi: [10.1016/j.clet.2022.100508](https://doi.org/10.1016/j.clet.2022.100508).

17. E. F. Orumwense and K. Abo-Al-Ez, "Internet of Things for smart energy systems: A review on its applications, challenges and future trends," *AIMS Electronics and Electrical Engineering*, vol. 7, no. 1, pp. 50–74, 2023, doi: 10.3934/electreng.2023004.
18. L. O. Aghenta and M. T. Iqbal, "Development of an IoT based open source SCADA system for PV system monitoring," in *Proc. 2019 IEEE Canadian Conference of Electrical and Computer Engineering (CCECE)*, Edmonton, AB, Canada, 2019, pp. 1–4, doi: 10.1109/CCECE.2019.8861827.
19. M. R. B. Khan, J. Pasupuleti, J. Al-Fattah, and M. Tahmasebi, "Energy management system for PV-battery microgrid based on model predictive control," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 15, no. 1, pp. 20–26, 2019, doi: 10.11591/ijeecs.v15.i1.pp20-26.
20. J. Hu, Y. Xu, K. W. Cheng, and J. M. Guerrero, "A model predictive control strategy of PV-Battery microgrid under variable power generations and load conditions," *Applied Energy*, vol. 221, pp. 195–203, Jul. 2018, doi: 10.1016/j.apenergy.2018.03.085.
21. J. Hu, Y. Shan, J. M. Guerrero, A. Ioinovici, K. W. Chan, and J. Rodriguez, "Model predictive control of microgrids—An overview," *Renewable and Sustainable Energy Reviews*, vol. 136, Art. no. 110422, Feb. 2021, doi: 10.1016/j.rser.2020.110422.
22. P. Horrillo-Quintero, J. F. Reynaud, and C. Bordons, "Model predictive control of a microgrid with energy-stored quasi-Z-source cascaded H-bridge multilevel inverter," *Applied Energy*, vol. 346, Art. no. 121390, 2023, doi: 10.1016/j.apenergy.2023.121390.
23. C. A. Hans, P. Sopasakis, A. Bemporad, J. Raisch, and C. Reincke-Collon, "Scenario-based model predictive operation control of islanded microgrids," in *Proc. 54th IEEE Conference on Decision and Control (CDC)*, Osaka, Japan, 2015, pp. 3272–3277.
24. Y. Lin, L. Li, J. Zhang, and J. Wang, "A scenario-based stochastic model predictive control approach for microgrid operation at an Australian cotton farm under uncertainties," *International Journal of Electrical Power & Energy Systems*, vol. 159, Art. no. 110025, 2024, doi: 10.1016/j.ijepes.2024.110025.