

A Hybrid Stochastic-Robust Optimization Framework for Industrial Energy Management under Renewable Generation and Price Uncertainty

Yenilenebilir Enerji Üretimi ve Fiyat Belirsizliği Altında Endüstriyel Enerji Yönetimi için Hibrit Stokastik-Sağlam Optimizasyon Çerçevesi

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Abstract

This study develops a hybrid stochastic-robust optimization framework for industrial energy management under photovoltaic generation and electricity price uncertainty. The proposed two-stage model integrates scenario-based scheduling, robust operational adjustments, battery storage dynamics, and carbon emission costs. Its effectiveness is evaluated using a grid-connected industrial microgrid and compared with deterministic, stochastic, and robust optimization approaches. The hybrid model achieves a daily operating cost of \$1,173.9, with 86.4% photovoltaic utilization and 751.8 kg of carbon emissions. Sensitivity analyses demonstrate that adjustable risk preferences improve protection against unfavorable operating conditions, while increased battery capacity supports renewable energy integration. These findings indicate that the proposed framework offers a flexible approach to balancing economic efficiency, operational resilience, and environmental performance in industrial energy systems.

Keywords: Hybrid optimization, Energy management, PV uncertainty, Battery storage, Industrial microgrids

Özet

Bu çalışma, fotovoltaik üretim ve elektrik fiyatı belirsizliklerine maruz kalan şebekeye bağlı endüstriyel mikro şebekelerde enerji yönetimi için iki aşamalı hibrit stokastik-sağlam optimizasyon çerçevesi önermektedir. Senaryo tabanlı planlama, sağlam gerçek zamanlı düzenlemelerle birleştirilirken batarya işletimi ve karbon maliyetleri karar modeline dahil edilmiştir. Önerilen yaklaşım, 24 saatlik endüstriyel bir vaka çalışmasında deterministik, stokastik ve sağlam optimizasyon modelleriyle karşılaştırılarak değerlendirilmiştir. Hibrit strateji, günlük 1.173,9 ABD doları işletme maliyeti,

%86,4 fotovoltaik enerji kullanım oranı ve 751,8 kg karbon emisyonu sağlamıştır. Duyarlılık analizi, risk korumasının artırılmasının en kötü durum maliyetlerini azalttığını, daha yüksek depolama kapasitesinin ise şebeke bağımlılığını düşürdüğünü göstermiştir. Genel olarak önerilen çerçeve, işletme maliyetleri, belirsizliklere maruz kalma ve çevresel faktörler arasında denge kuran uyarlabilir bir enerji planlama yaklaşımı sunmaktadır.

Anahtar Kelimeler: Hibrit optimizasyon, Enerji Yönetimi, Fotovoltaik üretim belirsizliği, Batarya depolama, Endüstriyel mikro şebekeler

1. Introduction

The rapid decarbonization of industrial energy systems has significantly increased the adoption of on-site renewable energy sources, particularly photovoltaic (PV) systems, within industrial microgrids. While renewable integration reduces operational costs and carbon emissions, it also introduces substantial uncertainty due to intermittency and market price volatility. Industrial energy management systems (EMS) are therefore required to operate under multi-dimensional uncertainty while maintaining economic efficiency, reliability, and environmental compliance [1].

Unlike traditional deterministic energy scheduling approaches, contemporary EMS frameworks must explicitly address uncertainties associated with renewable generation, electricity market prices, and demand fluctuations. In industrial environments—where production continuity, contractual power limits, and penalty costs are critical—suboptimal decisions caused by uncertainty mismanagement can lead to considerable financial losses [2].

To cope with uncertainty, two principal modeling paradigms have been widely adopted in the literature: stochastic programming and robust optimization. Stochastic programming models uncertainty through probabilistic scenarios and optimize expected system performance. Although effective in

capturing average-case behavior, these models may perform poorly under extreme realizations or rare but costly events. On the other hand, robust optimization provides protection against worst-case deviations within predefined uncertainty sets, ensuring solution feasibility under adverse conditions. However, purely robust formulations often lead to overly conservative strategies and inflated operational costs.

Despite extensive research in both domains, most existing studies adopt either stochastic programming or robust optimization independently. The lack of hybrid formulations that jointly balance expectation-based efficiency and worst-case resilience represents a critical methodological gap [3]. Particularly in industrial microgrids with PV generation and battery energy storage systems (BESS), there is limited research integrating both uncertainty treatment mechanisms within a unified EMS framework.

Moreover, recent regulatory developments introducing carbon pricing mechanisms have further complicated energy management decisions. Industrial operators are now required to consider not only electricity procurement and storage costs, but also carbon-related operational impacts [4]. Nevertheless, carbon cost integration into uncertainty-aware EMS formulations remains underexplored.

Motivated by these challenges, this study proposes a two-stage hybrid stochastic–robust optimization framework for industrial energy management under renewable generation and price uncertainty [5]. In the first stage, day-ahead energy scheduling decisions are optimized using scenario-based stochastic programming. In the second stage, real-time adjustments are safeguarded against adverse deviations through a budget-of-uncertainty robust counterpart formulation. A tunable risk-sensitivity parameter is introduced to systematically balance expected performance and worst-case resilience.

The major contributions of this study are summarized as follows:

- Development of a hybrid stochastic–robust EMS model for PV-integrated industrial microgrids.
- Integration of electricity price uncertainty, renewable generation variability, and carbon cost considerations within a unified optimization framework.
- Introduction of a risk-adjustable structure enabling decision-makers to control conservativeness levels.
- Comprehensive numerical analysis comparing deterministic, purely stochastic, purely robust, and proposed hybrid models.
- Managerial insights on cost–risk–emission trade-offs for industrial energy operators.

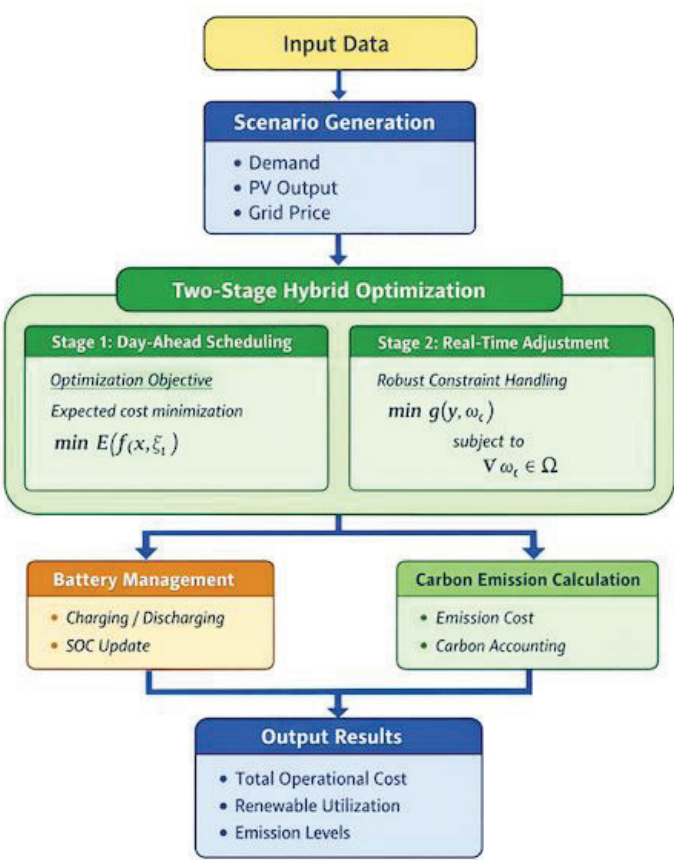


Figure 1: Hybrid stochastic-robust EMS framework for industrial microgrids

Hybrid stochastic-robust energy management systems (EMS) framework for industrial microgrids is presented in Figure 1.

The remainder of this paper is organized as follows: Section 2 reviews related literature on uncertainty-aware energy management. Section 3 presents the mathematical formulation of the hybrid model. Section 4 describes the case study and experimental setup. Section 5 discusses computational results and comparative analyses. Section 6 presents the sensitivity analysis. Finally, Section 7 concludes the study and outlines future research directions.

2. Literature Research

The increasing penetration of renewable energy resources in industrial energy systems has significantly intensified the complexity of energy management problems, particularly under uncertainty. In recent years, extensive research has been conducted on optimizing energy management systems (EMS) for microgrids integrating photovoltaic (PV) generation and battery energy storage systems (BESS). Early studies primarily relied on deterministic optimization techniques due to their computational efficiency and simplicity [6-7]. However, these approaches assume perfect knowledge of system parameters and fail to capture the stochastic nature of renewable generation and electricity market dynamics.

To address uncertainty, stochastic programming has been widely applied in EMS studies. Two-stage and multi-stage stochastic optimization models have been proposed to account for uncertainties in renewable generation, load demand, and electricity prices [8-10]. For instance, stochastic scheduling frameworks for microgrids have demonstrated improved cost efficiency and operational flexibility compared to deterministic models. Despite these advantages, stochastic approaches depend heavily on accurate probability distributions and scenario generation, and their performance may deteriorate under extreme or rare events [11].

Robust optimization has emerged as an alternative approach to address uncertainty without relying on probabilistic information. In robust EMS models, uncertain parameters are represented using bounded uncertainty sets, and solutions are optimized against worst-case realizations [12–15]. This approach ensures system reliability and feasibility under adverse conditions and has been successfully applied in microgrid operation and energy scheduling problems. However, robust optimization often results in overly conservative solutions, leading to increased operational costs and reduced economic efficiency.

In recent years, hybrid stochastic–robust optimization frameworks have gained attention as a promising approach to balance expected performance and worst-case protection. Several studies have proposed hybrid models that combine scenario-based stochastic programming with robust optimization techniques [16–18]. For example, two-stage hybrid frameworks have been applied in microgrid energy management, enabling improved trade-offs between cost efficiency and system reliability [19-20]. Nevertheless, the application of such hybrid models in industrial energy management systems remains relatively limited, particularly in the context of PV-integrated microgrids with battery storage.

At the same time, environmental considerations have become increasingly important in EMS research. With the implementation of carbon pricing mechanisms, several studies have incorporated carbon emission costs into energy management models [21]. These works highlight the importance of integrating economic and environmental objectives in energy system optimization. However, the interaction between carbon pricing and uncertainty modeling has not been sufficiently explored in existing literature.

Moreover, recent studies have explored advanced approaches such as machine learning-based forecasting, real-time optimization, and digital twin technologies to enhance EMS performance [22]. While these methods improve prediction accuracy and operational adaptability, they often lack rigorous uncertainty modeling frameworks capable of handling extreme deviations in renewable generation and electricity prices.

Based on the above discussion, it is evident that although significant progress has been made in uncertainty-aware EMS modeling, several important gaps remain. Existing studies predominantly focus on either stochastic programming or robust optimization, with limited integration of both approaches in a unified framework. Furthermore, few studies simultaneously consider renewable uncertainty, electricity price volatility, battery operation, and carbon emission costs within an industrial microgrid context. To address these

limitations, this study proposes a two-stage hybrid stochastic–robust optimization framework that integrates scenario-based uncertainty modeling with robust protection mechanisms, providing a flexible and risk-aware solution for industrial energy management.

3. Model Structure

3.1. System Description

This study considers an industrial microgrid composed of:

- Photovoltaic (PV) generation units
- Battery Energy Storage System (BESS)
- Utility grid connection
- Industrial electricity demand
- Carbon pricing mechanism

The system operates in a discrete time horizon $t \in T$ (e.g., hourly scheduling over 24 hours). The objective is to determine optimal day-ahead and real-time energy scheduling decisions under renewable generation and electricity price uncertainty.

Uncertainty sources include:

- PV generation variability
- Electricity market price fluctuation
- Load variability

To simultaneously capture expected performance and worst-case protection, a two-stage hybrid stochastic–robust optimization framework is developed.

3.2. Two-Stage Hybrid Decision Structure

3.2.1. First Stage (Here-and-Now Decisions)

These decisions are taken before uncertainty realization:

- Scheduled grid purchase P_t^{DA}
- Battery charging/discharging plan
- Energy procurement commitments

The first stage minimizes the expected operational cost over a discrete scenario set Ω .

3.2.2. Second Stage (Wait-and-See & Robust Adjustment)

After uncertainty realization, recourse decisions adjust:

- Real-time power deviation $\Delta P_{t,\omega}$
- Battery corrective dispatch
- Penalty handling

Robust optimization is applied within each scenario using a budget-of-uncertainty parameter Γ to hedge against worst-case deviations.

3.3. Objective Function

The hybrid objective integrates expected cost and worst-case protection:

$$\min \{ \mathbb{E}_{\omega \in \Omega} [C^{\text{stoch}}(x, \xi_{\omega})] + \lambda \cdot C^{\text{robust}}(x, \Gamma) \}. \quad (1)$$

where (x) denotes the vector of first-stage energy scheduling decisions, Ω is the set of stochastic scenarios, ω represents an individual scenario, ω denotes the vector of uncertain parameters associated with scenario ω , and $(C^{\text{stoch}}|\omega)$ represents the scenario-dependent stochastic operating cost. The parameter λ is the risk-sensitivity coefficient that determines the relative importance assigned to protection against adverse realizations, while C^{robust}/ω denotes the robust cost component associated with worst-case deviations. The parameter ω represents the uncertainty budget and controls the degree of conservativeness of the robust solution.

Operational Cost Components:

The total cost consists of:

- Electricity procurement cost
- Battery degradation cost
- Carbon emission cost
- Demand violation penalty

$$C = \sum_t (\pi_{t,\omega} P_{t,\omega} + c^{\text{deg}} B_{t,\omega} + C^{\text{CO2}} E_{t,\omega} + C^{\text{pen}} S_{t,\omega}) \quad (2)$$

where (T) denotes the set of scheduling periods, (t) represents the individual time period, π_t is the electricity price at time (t) under scenario ω , and P_t denotes the electricity purchased from the utility grid. The parameter c^{deg} represents the unit battery degradation cost, while $B_{t,\omega}$ denotes the battery energy throughput. Furthermore, c^{CO2} is the unit carbon emission cost and $E_{t,\omega}$ represents the corresponding carbon emissions. Finally, c^{pen} denotes the unit penalty cost and $S_{t,\omega}$ is the unmet-demand or operational violation variable.

3.4. Constraints

3.4.1. Power Balance Constraint

$$P_{t,\omega}^{\text{grid}} + P_{t,\omega}^{\text{PV}} + P_{t,\omega}^{\text{dis}} = D_{t,\omega} + P_{t,\omega}^{\text{ch}} \quad (3)$$

where $P_{t,\omega}$ represents the power purchased from the utility grid, $P_{t,\omega}^{\text{PV}}$ is the available photovoltaic generation, and $P_{t,\omega}^{\text{dis}}$ denotes the battery discharge power at time (t) under scenario ω . Similarly, $D_{t,\omega}$ represents the industrial electricity demand and $P_{t,\omega}^{\text{ch}}$ denotes the battery charging power. Equation (3) ensures that the total electricity supplied to the industrial microgrid is equal to the total electricity demand and battery charging requirement in each period and scenario.

3.4.2. Battery Dynamics

$$SOC_t = SOC_{t-1} + \eta^{\text{ch}} P_t^{\text{ch}} - \frac{1}{\eta^{\text{dis}}} P_t^{\text{dis}} \quad (4)$$

where $SOC_{t,\omega}$ denotes the battery state of charge at time (t) under scenario ω , $SOC_{t-1,\omega}$ is the state of charge in the preceding period, η^{ch} and η^{dis} represent the battery charging and discharging efficiencies, respectively, and Δt denotes the duration of each scheduling interval. The charging and

discharging powers are represented by $P_{t,\omega}^{\text{ch}}$ and $P_{t,\omega}^{\text{dis}}$, respectively.

The allowable battery state-of-charge range is constrained as

$$SOC^{\text{min}} \leq SOC_t \leq SOC^{\text{max}} \quad (5)$$

where SOC^{min} and SOC^{max} represent the minimum and maximum permissible battery state-of-charge levels, respectively. These limits prevent excessive charging or discharging and ensure technically feasible battery operation.

3.4.3. Grid Capacity Limit

$$0 \leq P_t^{\text{grid}} \leq P^{\text{max}} \quad (6)$$

Where $P_t^{\text{grid}} \leq P^{\text{max}}$ denotes the maximum power that can be imported from the utility grid. Equation (6) restricts grid electricity procurement within the technical connection capacity of the industrial microgrid.

3.4.4. Robust Uncertainty Set

PV output deviation:

$$P_t^{\text{PV}} = P_t^{\text{PV}} + \delta_t \quad (7)$$

$$|\delta_t| \leq \delta_t \quad (8)$$

where P_t^{PV} represents the uncertain realized PV generation, P_t^{PV} denotes the forecasted PV generation, δ_t is the deviation of actual PV output from its forecasted value, and δ_t represents the maximum allowable magnitude of this deviation at time (t) . Equation (8) therefore defines the interval within which PV generation uncertainty is allowed to vary.

Budget constraint:

$$\sum_t \frac{|\delta_t|}{\delta_t} \leq \Gamma \quad (9)$$

This structure ensures protection against simultaneous worst-case deviations up to Γ periods.

3.5. Hybridization Logic

The proposed model integrates stochastic and robust paradigms as follows:

- Scenario-based modeling captures distributional variability.
- Robust set within each scenario prevents extreme realizations.
- Risk parameter λ balances economic optimality and conservativeness.
- Budget parameter Γ controls robustness intensity.

3.6. Solution Approach

The model is formulated as a Mixed-Integer Linear Programming (MILP) problem.

Solution steps:

- Scenario generation via Monte Carlo simulation
- Reformulation of robust counterpart
- Linearization of bilinear terms
- Solution using CPLEX/Gurobi

To evaluate performance, four benchmark models are implemented:

- Deterministic EMS
- Pure stochastic EMS
- Pure robust EMS
- Proposed hybrid EMS

3.7. Managerial Interpretation

The hybrid model enables industrial operators to:

- Quantify risk–cost trade-offs
- Adjust conservativeness through λ and Γ
- Evaluate carbon price impact
- Reduce vulnerability to renewable volatility

4. Case Study and Experimental Setup

4.1. Industrial Microgrid Description

To evaluate the effectiveness of the proposed hybrid stochastic–robust energy management framework, a grid-connected industrial microgrid is considered as the case study. The system represents a medium-scale manufacturing facility equipped with on-site renewable generation and energy storage capabilities.

The microgrid consists of the following components:

- Photovoltaic (PV) generation system
- Battery Energy Storage System (BESS)
- Utility grid connection
- Industrial electricity demand

The energy management system determines optimal day-ahead and real-time operational strategies over a 24-hour scheduling horizon, discretized into hourly intervals.

In this study, industrial microgrid system parameters are shown in Table 1.

Table 1: Industrial microgrid description

Parameter	Symbol	Value	Unit
Scheduling horizon	T	24	h
Time interval	Δt	1	h
Maximum grid purchase power	P_{grid}^{max}	500	kW
Battery energy capacity	E_{BESS}^{max}	600	kWh
Maximum charging power	P_{ch}^{max}	150	kW

Maximum discharging power	P_{dis}^{max}	150	kW
Charging efficiency	η^{ch}	0.95	-
Discharging efficiency	η^{dis}	0.95	-
Minimum state of charge	SOC^{min}	0.20	p.u.
Maximum state of charge	SOC^{minmax}	0.90	p.u.
Initial state of charge	SOC^{rini}	0.50	p.u.
Battery degradation cost	c^{deg}	0.015	USD/kWh
Carbon price	c^{CO2}	40	USD/tCO ₂
Grid emission factor	EF	0.42	kgCO ₂ /kWh
Demand penalty cost	c^{pen}	0.30	USD/kWh

The industrial load profile reflects typical electricity consumption patterns observed in manufacturing plants, where energy demand is relatively stable during production hours and decreases during non-operational periods. Table 2 presents hourly industrial load profile.

Table 2: Hourly industrial load profile

Hour	Load Demand (kW)	Hour	Load Demand (kW)	Hour	Load Demand (kW)
1	210	9	355	17	390
2	205	10	380	18	360
3	200	11	395	19	335
4	198	12	410	20	300
5	202	13	420	21	275
6	220	14	415	22	250
7	260	15	405	23	230
8	310	16	398	24	220

Table 3: Forecasted PV generation profile

Hour	PV Generation (kW)	Hour	PV Generation (kW)	Hour	PV Generation (kW)
1	0	9	130	17	70
2	0	10	175	18	25
3	0	11	210	19	0
4	0	12	225	20	0
5	0	13	220	21	0
6	15	14	205	22	0
7	40	15	170	23	0
8	85	16	120	24	0

4.2. Photovoltaic Generation Modeling

PV generation is inherently uncertain due to weather variability. To capture this uncertainty, a scenario-based approach is adopted. Forecasted PV generation profile is given in Table 3.

Historical solar irradiation data are used to construct multiple PV generation scenarios. Monte Carlo simulation is employed to generate a set of representative scenarios reflecting possible PV output realizations throughout the scheduling horizon.

Ω denote the set of PV generation scenarios and p_ω represent the probability of scenario ω . The expected PV generation in scenario ω at time t is denoted as: $P_{t,\omega}^{PV}$

To reduce computational complexity, scenario reduction techniques are applied to retain the most representative scenarios while preserving statistical characteristics.

4.3. Electricity Price and Uncertainty

Electricity market prices are subject to fluctuations caused by demand variations, fuel prices, and market dynamics. In this study, day-ahead electricity prices are modeled as uncertain parameters. Day-ahead electricity price profile is given in Table 4.

Table 4: Day-ahead electricity price profile

Hour	Price (USD/kWh)	Hour	Price (USD/kWh)	Hour	Price (USD/kWh)
1	0.082	9	0.126	17	0.147
2	0.078	10	0.138	18	0.158
3	0.075	11	0.145	19	0.166
4	0.074	12	0.149	20	0.154
5	0.076	13	0.151	21	0.136
6	0.085	14	0.148	22	0.118
7	0.097	15	0.143	23	0.099
8	0.112	16	0.139	24	0.089

A scenario generation approach similar to PV modeling is used to represent electricity price uncertainty. Historical market data are used to generate price scenarios that capture realistic price volatility.

$\pi_{t,\omega}$ represent the electricity price at time t under scenario ω . These price scenarios are integrated into the stochastic component of the optimization model.

4.4. Battery Energy Storage System Modeling

The battery energy storage system plays a critical role in balancing supply and demand, mitigating renewable intermittency, and enabling cost-effective energy management. Uncertainty modeling parameters is given in Table 5.

Table 5: Uncertainty modeling parameters

Parameter	Symbol	Value
Number of scenarios	Ω	20
PV deviation bound	δ_t^{PV}	15%
Price deviation bound	δ_t^{price}	12%
Load deviation bound	δ_t^{load}	8%
Robustness budget	Γ	6
Risk preference coefficient	λ	0.35

The BESS is characterized by the following parameters:

- Maximum charging power
- Maximum discharging power
- Storage capacity
- Charging and discharging efficiencies

Battery degradation cost is incorporated into the objective function to account for operational wear associated with charging and discharging cycles.

The state-of-charge (SOC) evolution is governed by the battery dynamics described in Section 3.

4.5. Carbon Emission Consideration

To reflect increasing regulatory pressure on industrial emissions, carbon costs are integrated into the energy management model.

Electricity purchased from the grid is associated with an emission factor representing the carbon intensity of grid electricity. The corresponding carbon emission cost is calculated as:

$$C^{CO2} = C^{CO2} \cdot EF \cdot P_{grid}$$
 (10)

where $C_{t,\omega}^{CO2}$ represents the carbon-related cost associated with grid electricity consumption at time (t) under scenario ω , c^{CO2} is the carbon price, (EF) denotes the grid emission factor, $P_{t,\omega}^{grid}$ represents the electricity imported from the utility grid, and Δt is the duration of the scheduling interval. This formulation monetizes the environmental impact of grid electricity consumption and incorporates it directly into the energy management objective.

4.6. Benchmark Models

To assess the performance of the proposed hybrid approach, four different energy management models are implemented for comparison:

- Deterministic EMS
- Stochastic EMS
- Robust EMS
- Proposed Hybrid Stochastic–Robust EMS

Benchmark models is given in Table 6.

Table 6: Benchmark models used in the comparison

Model	Uncertainty Handling	Main Characteristic
Deterministic EMS	None	Uses forecasted average values only
Stochastic EMS	Scenario-based	Minimizes expected cost
Robust EMS	Uncertainty sets	Protects against worst-case deviations
Hybrid Stochastic-Robust EMS	Scenario + robust set	Balances expected performance and resilience

The deterministic model ignores uncertainty and uses expected values of uncertain parameters.

The stochastic model minimizes expected operational cost across scenarios.

The robust model protects against worst-case deviations within uncertainty sets.

The hybrid model simultaneously accounts for expected performance and worst-case protection.

4.7. Solution Environment

The optimization model is formulated as a Mixed-Integer Linear Programming (MILP) problem.

- All simulations are performed using:
- Python / MATLAB optimization environment
 - Gurobi or CPLEX solver

Computational experiments are conducted on a standard workstation to evaluate solution quality and computational performance.

5. Results and Discussion

5.1. Cost Performance Comparison

The performance of the proposed hybrid EMS model is evaluated by comparing its operational cost with those of the benchmark models. Comparative cost results are given in Table 7.

Table 7: Comparative cost results of EMS models

Model	Energy Cost (USD/day)	Battery Deg. Cost (USD/day)	Carbon Cost (USD/day)	Penalty Cost (USD/day)	Total Cost (USD/day)
Det. EMS	1038.4	18.6	79.2	26.7	1162.9
Stoc. EMS	1056.8	20.4	76.9	14.8	1168.9
Robust EMS	1104.7	24.3	74.5	4.9	1208.4
Hybrid EMS	1068.5	21.7	75.1	8.6	1173.9

Results show that the deterministic model yields the lowest nominal cost under expected conditions but reforms poorly when uncertainty is realized. In contrast, the robust model ensures system feasibility under extreme conditions but results in significantly higher operational costs due to overly conservative decisions. Cost comparison graph is given in Figure 2.

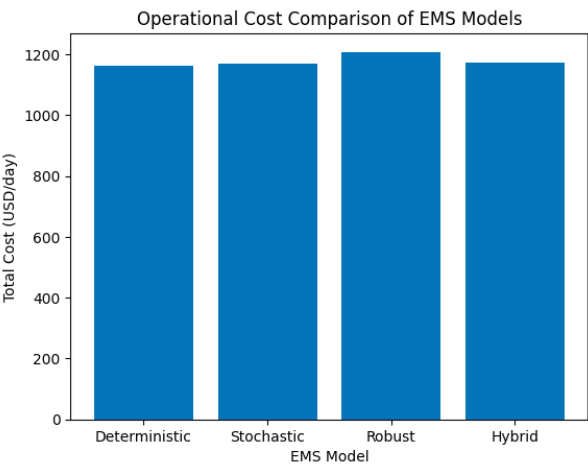


Figure 2: Cost comparison graph

The stochastic model provides a balance between cost efficiency and uncertainty management but lacks protection against extreme scenarios.

The proposed hybrid stochastic-robust model achieves a superior balance by maintaining relatively low expected costs while providing protection against adverse deviations.

5.2. Risk-Cost Trade-off Analysis

The hybrid model introduces a tunable risk parameter λ , which allows decision-makers to control the level of conservativeness in the energy management strategy. Operational performance comparison is given Table 8.

Table 8: Operational performance comparison

Model	Grid Purchase (kWh/day)	PV Utilization Rate (%)	Battery Throughput (kWh/day)	Carbon Emissions (kgCO ₂ /day)
Det. EMS	1885	81.4	620	791.7
Stoc.EMS	1830	84.9	655	768.6
Robust EMS	1775	87.2	710	745.5
Hybrid EMS	1790	86.4	688	751.8

- Sensitivity analysis indicates that:
- Low values of λ prioritize economic efficiency.
 - High values of λ increase system robustness.

As λ increases, operational cost slightly increases, but system resilience improves significantly under worst-case scenarios.

This flexibility enables industrial operators to tailor energy management strategies according to their risk preferences.

5.3. Impact of Renewable Uncertainty

The analysis reveals that renewable generation uncertainty significantly affects energy scheduling decisions. Hourly optimal schedule is given in Table 9.

Table 9: Hourly solution schedule of the proposed hybrid EMS

Hour	Load (kW)	PV (kW)	Grid Purchase (kW)	Battery Charge (kW)	Battery Discharge (kW)
1	210	0	240	30	0
2	205	0	235	30	0
3	200	0	230	30	0
4	198	0	228	30	0
5	202	0	232	30	0
6	220	15	235	30	0
7	260	40	250	30	0
8	310	85	255	30	0
9	355	130	225	0	0
10	380	175	205	0	0
11	395	210	185	0	0
12	410	225	185	0	0
13	420	220	200	0	0
14	415	205	210	0	0
15	405	170	205	0	30
16	398	120	198	0	80
17	390	70	200	0	120
18	360	25	215	0	120
19	335	0	305	0	30
20	300	0	300	0	0
21	275	0	275	0	0
22	250	0	250	0	0
23	230	0	230	0	0
24	220	0	220	0	0

Under high PV variability conditions:

- Battery utilization increases
- Grid reliance becomes more dynamic
- Robust protection becomes more valuable

The hybrid model effectively mitigates these effects by adjusting scheduling strategies based on uncertainty levels. Load-PV-Grid profile is given in Figure 3 and also Battery SOC is given in Figure 4.

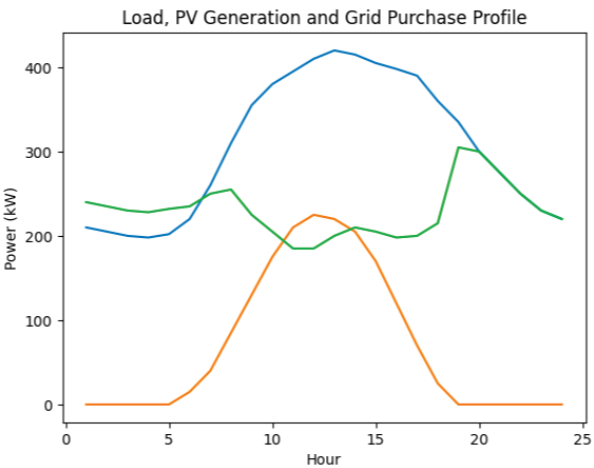


Figure 3: Load-PV-grid

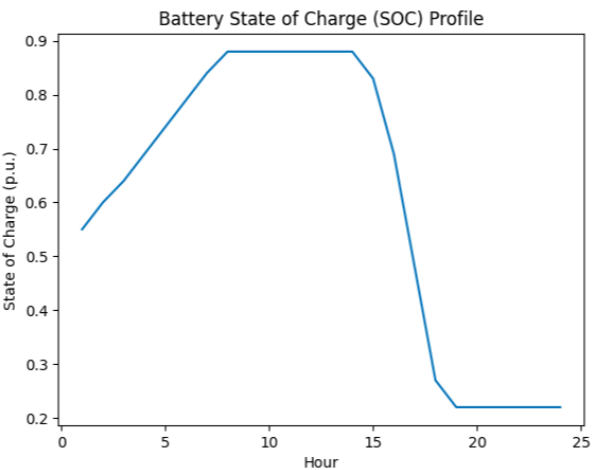


Figure 4: Battery SOC

5.4. Carbon Cost Implications

The integration of carbon pricing into the EMS model influences energy procurement strategies.

Higher carbon prices encourage:

- Greater utilization of PV generation
- Increased reliance on battery storage
- Reduced grid electricity consumption

This demonstrates that carbon pricing mechanisms can significantly influence industrial energy management decisions.

5.5. Managerial Insights

The results provide several important managerial insights for industrial energy operators:

- Hybrid uncertainty modeling provides superior operational flexibility compared to traditional methods.
- Battery storage significantly improves system resilience under renewable uncertainty.
- Carbon pricing policies can effectively promote low-carbon energy strategies.
- Risk-adjustable EMS models allow operators to customize energy management strategies based on operational priorities.

5.6. Discussion

Overall, the proposed hybrid stochastic-robust optimization framework provides a practical and effective solution for industrial energy management under uncertainty.

Compared with existing approaches, the proposed model offers:

- Improved cost stability
- Enhanced resilience to uncertainty
- Flexible risk management capability

These advantages highlight the potential of hybrid optimization approaches in next-generation energy management systems.

6. Sensitivity Analysis

To evaluate the robustness and flexibility of the proposed hybrid energy management model, a sensitivity analysis is conducted on key system parameters. The purpose of this analysis is to investigate how variations in critical parameters influence operational cost, energy scheduling decisions, and system performance.

6.1. Impact of Risk Parameter (λ)

The parameter λ determines the trade-off between expected operational cost and worst-case protection in the hybrid objective function. Sensitivity analysis is shown in figure 5. To analyze its effect, λ is varied across different values while keeping other parameters constant. Sensitivity analysis for risk parameter is given in Table 10.

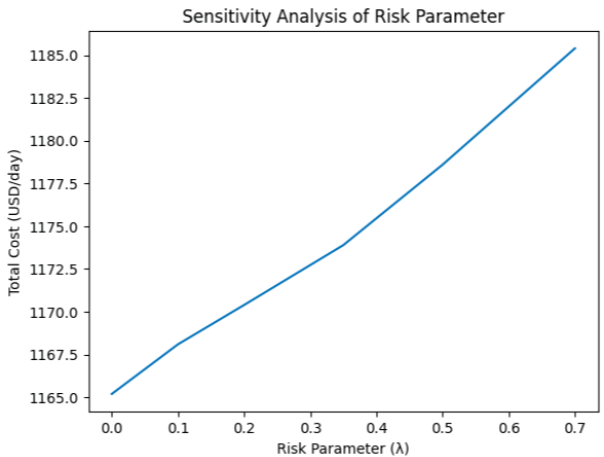


Figure 5: Sensitivity Analysis

Table 10: Sensitivity analysis for risk parameter

λ	Total Cost (USD/day)	Worst-Case (USD/day)	Grid Purchase (kWh/day)	PV Utilization (%)
0.00	1165.2	1298.6	1842	84.7
0.10	1168.1	1275.9	1828	85.1
0.20	1170.4	1259.3	1815	85.8
0.35	1173.9	1236.8	1790	86.4
0.50	1178.6	1220.1	1772	86.9
0.70	1185.4	1208.7	1759	87.3

Results indicate that:

- When λ is small, the model prioritizes expected cost minimization.
- As λ increases, the solution becomes more conservative.

Higher values of λ :

- increase system robustness
- reduce vulnerability to extreme price spikes
- slightly increase operational cost.

This behavior confirms that the hybrid model allows decision-makers to control risk exposure according to operational preferences.

6.2. Impact of PV Generation Variability

The variability of photovoltaic generation significantly affects energy scheduling decisions.

To evaluate this impact, PV uncertainty levels are increased by introducing higher variance in PV generation scenarios. Table 11 presents sensitivity analysis for battery capacity.

Table 11: Sensitivity analysis for battery capacity

Battery Capacity (kWh)	Total Cost (USD/day)	Grid Purchase (kWh/day)	Carbon Emissions (kgCO ₂ /day)	PV Curtailment (%)
200	1214.7	1948	818.2	10.6
400	1190.3	1864	782.9	7.2
600	1173.9	1790	751.8	4.5
800	1168.1	1762	740.0	3.7
1000	1166.8	1754	736.7	3.4

Results show that:

- Battery utilization increases under higher PV uncertainty.
- Grid electricity procurement becomes more dynamic.
- The hybrid model outperforms deterministic and stochastic models in maintaining cost stability.

This demonstrates the advantage of incorporating robust protection against renewable intermittency.

6.3. Impact of Carbon Price

Carbon pricing plays an important role in shaping industrial energy management strategies.

To analyze its influence, carbon price levels are varied across a predefined range. Table 12 presents sensitivity analysis for carbon price.

Table 12: Sensitivity analysis for carbon price

Carbon Price (USD/tCO ₂)	Total Cost (USD/day)	Grid Purchase (kWh/day)	PV Utilization (%)	Carbon Emissions (kgCO ₂ /day)
0	1143.6	1858	83.8	780.4
20	1158.2	1826	84.9	767.0
40	1173.9	1790	86.4	751.8
60	1189.8	1761	87.6	739.6
80	1204.5	1739	88.2	730.4

The results reveal that:

- Higher carbon prices encourage increased use of renewable generation.
- Battery storage utilization increases to reduce grid electricity purchases.
- Total carbon emissions decrease as carbon prices rise.

These findings highlight the potential effectiveness of carbon pricing policies in promoting low-carbon industrial energy systems.

6.4. Impact of Battery Capacity

Battery capacity significantly affects system flexibility.

Increasing battery storage capacity results in:

- reduced reliance on grid electricity
- improved renewable energy utilization
- lower operational cost during peak price periods.

However, beyond a certain threshold, the marginal benefit of additional battery capacity decreases.

This finding suggests that optimal battery sizing is critical for efficient energy management.

7. Conclusion and Future Work

7.1. Conclusion

This study proposed a hybrid stochastic–robust optimization framework for energy management in industrial microgrids with renewable energy integration. The model simultaneously addresses expected system performance and worst-case uncertainty, enabling more reliable and cost-effective operational strategies.

The proposed approach incorporates photovoltaic generation uncertainty, electricity price volatility, and carbon emission costs into a unified optimization framework. A two-stage

decision structure was developed to represent day-ahead scheduling and real-time operational adjustments.

Simulation results from the industrial case study demonstrate that the proposed hybrid model achieves a superior balance between economic efficiency and operational robustness compared with deterministic, stochastic, and purely robust energy management approaches.

Key findings of the study include:

- Hybrid uncertainty modeling significantly improves cost stability under uncertain operating conditions.
- Battery energy storage systems play a critical role in mitigating renewable generation variability.
- Adjustable risk parameters provide flexibility for industrial operators to tailor energy management strategies according to their risk tolerance.
- Carbon pricing mechanisms can effectively promote low-carbon operational decisions.

Overall, the proposed model provides a practical decision-support tool for industrial energy management under uncertainty.

7.2. Future Work

Although the proposed framework provides valuable insights, several extensions can be explored in future research.

First, the model can be extended to incorporate additional distributed energy resources such as combined heat and power (CHP) systems and electric vehicle charging infrastructure.

Second, real-time energy management strategies using machine learning techniques could be integrated with the optimization framework to enhance predictive capabilities.

Third, the proposed model can be expanded to multi-microgrid environments where energy sharing and cooperative energy management are possible.

Finally, future studies may investigate large-scale implementations of hybrid uncertainty models in national energy systems and industrial clusters.

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Özgeçmişler



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