

Sensor-integrated Wasserstein–Conditional Value-at-risk Scheduling for Renewable Power Supply Microgrids with Hybrid Energy Storage

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Renewable power supply microgrids have uncertainties caused by forecast errors, distributional shifts, and extreme events. To mitigate these uncertainties, we develop a sensor-integrated four-layer scheduling system that combines Wasserstein distributionally robust optimization with conditional value-at-risk control. Real-time sensor data from ultrasonic anemometers, pyranometers, Hall-effect transducers, and displacement gauges are embedded into a Min–Max–Max–Min structure to minimize day-ahead costs in Wasserstein ambiguity sets. The system selects worst-case uncertainty corners and computes real-time recourse actions. A column-and-constraint generation algorithm is adopted to ensure tractability. Simulation results using 12-month datasets from coastal China showed that the system reduced expected operational costs by 12.4% compared with classical robust optimization, maintaining supply–demand balance under $\pm 40\%$ renewable deviations and $\pm 25\%$ load fluctuations. The system identifies turbine ramping limits, battery state of charge (SOC) bounds, and no-arbitrage grid trading, ensuring resilience through corrective real-time actions rather than conservative planning. Despite the results, reliance on high-quality sensor calibration, simplified Gaussian noise modeling, and evaluation restricted to single-day horizons must be addressed to enhance the system performance. It is also necessary to conduct multi-day rolling operations, cyber-security risk assessment results in sensor networks, and performance validation for large-scale field deployments. By integrating sensor fidelity with risk-aware optimization, the developed system serves as a reproducible framework for cost-effective and reliable scheduling in renewable power supply microgrids.

1. Introduction

Microgrids are widely deployed to manage distributed renewable energy resources, such as wind and solar power, in modern electrical grids. In these grids, efficient local energy balancing is achieved by coordinating dispatchable units, multi-tier storage devices, and grid interactions

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through an intelligent energy management system (EMS). EMS requires a robust cyber–physical sensor network capable of capturing real-time (RT) micro-climatic and mechanical states across the asset ecosystem.

Operational uncertainties in power scheduling are mainly caused by physical components of EMS. Environmental variations in wind speed and solar irradiance induce severe fluctuations in power output, while time-varying demand dynamics introduce non-stationary load uncertainties. Such volatilities can be captured accurately through high-fidelity sensing data. The examples include ultrasonic anemometers for wind velocity vectors, thermopile pyranometers for global solar irradiance, thermal and Hall-effect sensors for battery state of charge (SOC) and health monitoring, and structural displacement or load-cell sensors for gravity energy storage systems. Without continuous RT sensor data, EMS is optimized by an open-loop execution model, introducing an operational divergence from the actual dynamic behavior of the physical assets.

The stochastic methods in EMS require noise-free data. In the system deployments, sensor data inherently include latency, calibration drift, and measurement noise. Ultrasonic wind sensors suffer from turbulence-induced error, pyranometers require periodic recalibration, battery thermal sensors are prone to hysteresis, and displacement sensors in gravity storage systems present mechanical creep. To optimize an open-loop program, diverging from the actual dynamic behavior of EMS, latency, calibration drift, and measurement noise must be explicitly modeled with sensor-data-integrated scheduling to treat noise in sensor data.

Previously, stochastic methods have been applied to EMS scheduling.⁽¹⁾ These methods rely on probability distributions, which often introduce optimistic biases and fail under out-of-sample tail events. Conventional robust optimization, on the other hand, disregards distributional shapes and instead optimizes for a hyper-conservative vertex, leading to degraded economic efficiency.⁽²⁾ Recent advances in distributionally robust optimization using Wasserstein metrics construct ambiguity sets around empirical baselines, offering protection against distribution shifts.^(3,4) Along with the optimization method, the conditional value-at-risk (CVaR) method has been used to assess tail risks under extreme scenarios.⁽⁵⁾ Despite their theoretical maturity, these methods do not fully reflect the realities of sensor-driven microgrids, where the utilization of input data is constrained by the precision and reliability of sensors. Mathematically, the Wasserstein metric is used to define a data-driven distance between probability distributions using optimal transport theory, measuring the minimum computational work required to transform an empirical distribution into the actual one.⁽⁶⁾ In energy management, this metric is used to identify a probability set for baseline predictions to protect the system against unexpected statistical fluctuations. Paired with the Wasserstein metric, CVaR is used to quantify and minimize the expected losses in the worst 1α tail of the distribution (such as low-probability power shortfalls), rather than optimizing for average system performance.⁽⁷⁾

To solve such problems, a sensor-integrated Wasserstein–CVaR scheduling system is developed in this study. By embedding RT sensor data into the four-layer scheduling architecture, the system can predict distributional uncertainty on the basis of a Wasserstein ambiguity calibrated using sensor-derived feature vectors, control operational risk using CVaR, processing noise and drift in sensor data. With the system, a reproducible methodology can be established for day-ahead (DA) and RT scheduling in the microgrid-based EMS of renewable power sources.

Such a sensor-data-based method enables robust scheduling by overcoming the constraints due to the precision and cyber–physical integration of sensor data. The developed model supports EMS optimization on the basis of sensor data, and the outcomes of the model can be used for the development of sensor calibration protocols, error compensation algorithms, and multiple sensor data fusion strategies.

2 Materials and Methods

2.1 System architecture

The system developed in this study couples RT cyber-physical sensor metrics with distributionally robust dispatch algorithms. The system is built on the mathematical principles of Wasserstein-based distributionally robust optimization⁽⁸⁾ and multi-stage rolling-horizon microgrid scheduling.⁽⁹⁾ The developed system is used to optimize cyber–physical data for microgrid energy management. As shown in Fig. 1, the architecture comprises the following: a renewable generation subsystem, gas turbine (GT) subsystem, battery energy storage subsystem (BESS), gravity energy storage subsystem (GESS), and grid interaction subsystem. Each subsystem is equipped with specialized sensors that continuously monitor operational states and transmit data to EMS.

Renewable power generation subsystem: Ultrasonic anemometers are used to measure wind velocity vectors, and pyranometers are employed to record global solar irradiance from photovoltaic arrays. These sensors provide the inputs for the scheduling model. Their data are pre-processed through temporal smoothing and outlier rejection to form scenario trajectories for wind and photovoltaic (PV) output.

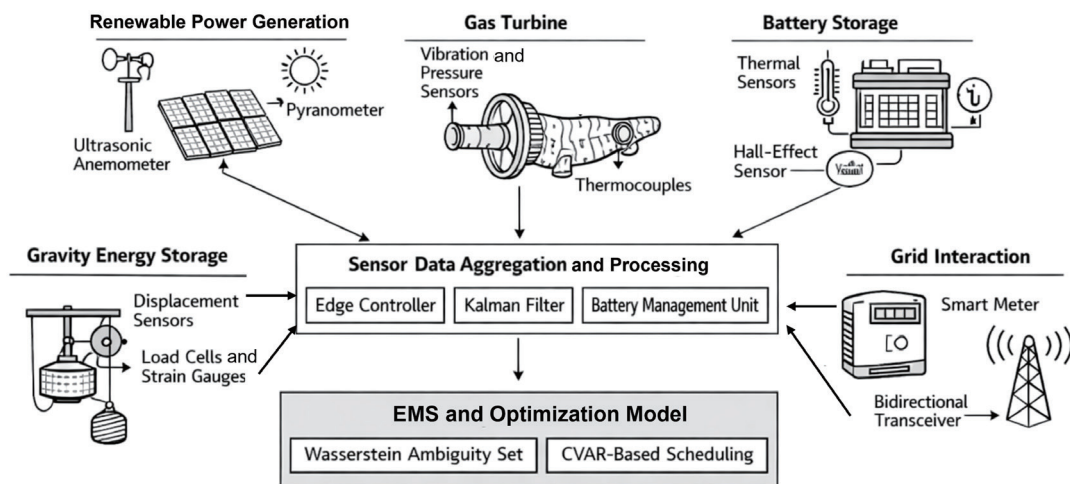


Fig. 1. Architecture of sensor-integrated Wasserstein–CVaR scheduling system (created using AI).

- **GT subsystem:** Vibration sensors, thermocouples, and pressure transducers are used to monitor combustion stability, turbine temperature, and mechanical integrity. High-frequency sensor data are converted into bounded feature vectors that represent turbine operational states. These vectors dynamically constrain ramp limits and start-up costs in the optimization model.
- **BESS:** Thermal sensors, Hall-effect current transducers, and voltage sensors are used to measure temperature, SOC, and degradation indicators. Data are processed through a local battery management unit (BMU) for real-time SOC estimation and health diagnostics. The BMU outputs are transmitted to EMS as normalized feature vectors defining feasible charging/discharging limits and degradation coefficients.
- **GESS:** Displacement sensors and strain gauges are used to measure the position and mechanical stress of suspended masses. Continuous feedback on gravitational potential energy and mechanical wear is processed using a Kalman filter to compensate for mechanical creep and sensor drift. The resulting feature vectors update SOC bounds and ramp constraints for GESS scheduling.

Grid interaction subsystem: Smart meters and bidirectional transceivers measure real-time power exchange with the main grid. These sensors enforce the no-arbitrage rule by detecting simultaneous input/output conditions and transmitting corrective signals to EMS. Grid transaction data are integrated into the optimization layer to compute real-time costs and ensure compliance with market constraints.

All sensor data are fed into the aggregation and processing units, including the edge controller, Kalman filter, and BMU. These units process the data into EMS, where the Wasserstein ambiguity set and CVaR-based scheduling modules jointly conduct risk-aware energy operations. Sensors are connected to edge units through dedicated communication links. High-frequency data, such as turbine vibration, Hall-effect battery current, and displacement signals, are collected and transferred on industrial networks through the controller area network bus and Modbus remote terminal unit. Edge units extract feature vectors from the data and forward them to the central EMS through local Ethernet using the Modbus transmission control protocol.⁽¹⁰⁾ To correct distributed sampling and clock drift, edge nodes synchronize timestamps with the Precision Time Protocol (the Institute of Electrical and Electronics Engineers 1588).⁽¹¹⁾ This synchronization produces time-aligned data frames across subsystems before processing.

Sensor data undergo targeted error compensation using calibration protocols at the edge layer. Pyranometer data are compensated using clear-sky irradiance curves to correct for thermal offset and dust accumulation. Clear-sky irradiance curves represent the theoretical solar radiation reaching the Earth's surface under cloud-free conditions. They are used to calibrate pyranometer data by providing a baseline curve of expected irradiance throughout the day, correcting for sensor drift, dust, or thermal offsets. Hall-effect current sensors in the battery management unit are used to obtain online temperature compensation matrices to counteract thermal hysteresis.⁽¹²⁾ Displacement gauges and strain sensors in GESS are used for automated zero-point recalibration during mechanical rest intervals to eliminate physical creep.

To reduce sensor dropouts or communication loss, a fault-tolerant state recovery module is incorporated at the edge layer. When a sensor fails, an online detection algorithm isolates the

corrupted channel and activates an extended Kalman filter.⁽¹³⁾ The Kalman filter generates model-based virtual data from remaining sensor data and balance laws to prevent data dropouts from disrupting downstream optimization. If communication between edge units and the central EMS is blocked, local controllers are switched to autonomous rule-based modes, maintaining safety until the network is reconnected.

2.2 Data processing and operational model

Sensor data are processed for temporal alignment, noise filtering, and multi-sensor fusion. Kalman filtering is applied in local edge controllers to buffer sensor data streams and remove transient communication glitches. Network delays remain below 100 ms for internal serial buses and below 1 s for local Ethernet links.⁽¹⁴⁾ Because dispatch recourse updates every 15 min ($\Delta t = 15$ min), data transmission delays are negligible compared with the decision timestep. Missing or delayed data are replaced using the short-term linear extrapolation method from historical data, preventing the interruption of RT EMS execution.

The processed data are transformed into feature vectors that represent subsystem states. Each vector includes normalized trajectories of load, wind, and solar PV generation, along with indicators such as SOC and turbine output. These vectors are then used to compute the Wasserstein metric [Eq. (1)],^(15,16) to quantify differences between scenarios and ensure that the uncertainty set reflects both environmental variability and sensor reliability.

$$D_{ij} = \|f_i - f_j\| \quad (1)$$

Here, D_{ij} is the Euclidean distance between feature vectors, and f_i and f_j are the normalized feature vectors representing operational or environmental states, such as load, wind, solar PV generation, SOC, and turbine output, in scenarios i and j . The gas turbine subsystem is monitored using vibration sensors, thermocouples, and pressure transducers. These sensors provide real-time measurements of combustion stability, turbine temperature, and mechanical integrity. The model restricts turbine output within safe minimum and maximum limits [Eq. (2)] and applies ramping constraints [Eq. (3)] to prevent sudden changes that can cause mechanical stress. Sensor data ensure that turbine operation respects thermal and mechanical boundaries.^(17,18)

$$p_{min}^{gt} u_t^{gt} \leq p_t^{gt} \leq p_{max}^{gt} u_t^{gt}, \forall t \in \mathcal{T} \quad (2)$$

Here, p_{min}^{gt} and p_{max}^{gt} denote the minimum and maximum turbine outputs, respectively. Hourly mechanical stresses are restricted using turbine ramping limits, ensuring that changes in output between consecutive time steps remain within safe bounds.

$$-R_D \leq p_t^{gt} - p_{t-1}^{gt} \leq R_U, \forall t \in \mathcal{T} \setminus \{1\} \quad (3)$$

Here, R_D and R_U are the ramp-down and ramp-up limits, respectively, estimated by using sensors to detect rapid changes in turbine output, ensuring mechanical safety and stable operation.⁽¹⁸⁾ The hybrid storage subsystem includes BESS and GESS. Thermal sensors, Hall-effect current transducers, voltage monitors, displacement sensors, and load cells are used to monitor charging and discharging. A binary isolation rule [Eq. (4)] is used to prevent simultaneous charging and discharging, protecting the devices from unsafe operation. SOC dynamics are updated using current-sensor data [Eq. (5)], ensuring safe charge levels and preventing both overcharge and deep discharge.⁽¹⁹⁾

$$p_{t,s}^{k,+c} \leq u_{t,s}^{kc} P_{max}^{k,+}, p_{t,s}^{k,-c} \leq (1 - u_{t,s}^{kc}) P_{max}^{k,-} \quad (4)$$

Here, $p_{t,s}^{k,+c}$ and $p_{t,s}^{k,-c}$ are the discharge and charge powers, respectively, and $P_{max}^{k,+/-}$ is the maximum limit. This equation is used to prevent simultaneous charging and discharging, protecting the battery and mechanical subsystems.^(20,21) SOC is estimated by integrating current data.

$$soc_{t+1,s}^{kc} = soc_{t,s}^{kc} + \frac{\Delta t}{E_{max}^k} (\eta_{ch}^k p_{t,s}^{k,-c} - \frac{1}{\eta_{dis}^k} p_{t,s}^{k,+c}) \quad (5)$$

Here, η_{ch}^k and η_{dis}^k are the charging and discharging efficiencies, respectively, and E_{max}^k is the maximum capacity. SOC trajectories derived from sensors ensure safe operation within bounds $soc_{min} \leq soc_{t,s}^{kc} \leq soc_{max}$, preventing overcharge or deep discharge.⁽²¹⁾ Grid interaction is monitored by smart meters and bidirectional transceivers at the point of common coupling. A strict mutual-exclusion rule is established to prevent the simultaneous purchasing and selling of electricity, ensuring realistic transactions [Eq. (6)].^(18,20) System-wide power balance is enforced by requiring that generation, storage, and grid exchange match demand at all times [Eq. (7)]. Penalties are applied when renewable energy is curtailed or consumer loads are shed, encouraging the efficient use of available resources.⁽²²⁾

$$p_{t,s}^{purchase,c} \leq u_{t,s}^{grid,c} P_{max}^{purchase}, p_{t,s}^{sell,c} \leq (1 - u_{t,s}^{grid,c}) P_{max}^{sell} \quad (6)$$

Here, $p_{t,s}^{purchase,c}$ and $p_{t,s}^{sell,c}$ are the purchased/sold wind and PV powers, respectively, and $u_{t,s}^{grid,c}$ represents the binary trading mode.

$$p_t^{gt} + p_{t,s}^{w,c} - p_{t,s}^{cur,w,c} + p_{t,s}^{pv,c} - p_{t,s}^{cur,pv,c} + \sum_k (p_{t,s}^{k,+c} - p_{t,s}^{k,-c}) + p_{t,s}^{buy,c} - p_{t,s}^{sell,c} = l_{t,s}^c - p_{t,s}^{ls,c} \quad (7)$$

Here, $p_{t,s}^{cur,w,c}$ and $p_{t,s}^{cur,pv,c}$ are the curtailed wind and PV powers, respectively, and $p_{t,s}^{ls,c}$ is the load shedding power. To incorporate complex market dynamics, the grid trading cost function

expands beyond fixed tariffs to accommodate RT pricing (RTP) and ancillary service market bidding. The RT grid exchange cost incorporates time-varying wholesale price vectors π_t^{RTP} alongside dynamic reserve capacity revenue streams.⁽²³⁾

$$\min \sum_{t \in \mathcal{T}} \left[\pi_t^{RTP, buy} p_{t,s}^{buy,c} - \pi_t^{RTP, sell} p_{t,s}^{sell,c} - \sum_{m \in \{GT, BESS, GESS\}} \left(\pi_t^{res,+} r_{t,m}^+ + \pi_t^{res,-} r_{t,m}^- \right) \right] \quad (8)$$

Here, $r_{t,m}^+$ and $r_{t,m}^-$ denote the upward and downward spinning reserve capacities committed by subsystem m , respectively, and $\pi_t^{res,+/-}$ represents market prices for ancillary services. Market price trajectories are embedded into the sensor-derived feature vectors, enabling the Wasserstein ambiguity set to hedge against simultaneous physical generation shortfalls and severe market price spikes.

The optimization method is established by embedding sensor-derived constraints into a four-layer distributionally robust optimization (DRO) model [Eq. (9)].⁽²⁴⁾ The DA cost is combined with worst-case risk terms, balancing expected performance against tail-risk protection. Sensor data are directly integrated into this system, allowing EMS to operate as a closed-loop system that adapts to real-time feedback.

$$\min_x C_{DA}(x) + \max_{p \in \mathcal{P}_\varepsilon} \sum_{s \in \mathcal{S}} p_s \left[(1-\lambda) \mathcal{Q}(x, \xi_s) + \lambda CVaR_\alpha(\mathcal{Q}) \right] \quad (9)$$

Here, $C_{DA}(x)$ is the DA cost, $\mathcal{P}_\varepsilon$ is the Wasserstein ambiguity set, λ is the risk-aversion weight, and CVaR is the tail risk. Sensor data are used to ensure that EMS operates as a closed-loop system, robust against tail risks and adaptive to sensor feedback.⁽²⁴⁾ The model is solved using an iterative column-and-constraint generation (C&CG) procedure [Eqs. (10) and (11)].^(25,26) The master problem is solved to set a lower boundary by optimizing DA decisions, whereas the subproblem is solved to evaluate an upper boundary by constructing adversarial scenarios. The process continues until the difference between boundaries falls below a tolerance threshold [Eq. (9)]. An auxiliary variable is used to approximate worst-case risk, making the problem tractable while preserving robustness [Eq. (11)]. The optimization problems are implemented in MATLAB/YALMIP and solved using Gurobi.⁽²⁷⁾

$$Gap(\%) = \frac{UB - LB}{\max\{1, UB\}} \times 100 \leq \tau \quad (10)$$

Here, UB and LB are the upper and lower bounds, respectively, and τ is the tolerance threshold. An auxiliary variable θ is used to approximate the worst-case risk term, progressively tightened by thresholds.

$$\min_{x, \theta} C^{DA}(x) + \theta \quad (11)$$

Here, $C^{DA}(x)$ is the DA cost and θ represents the accumulated worst-case recourse. For forecast updates, an optional three-stage execution policy is adopted, including DA scheduling, intraday (ID) rolling adjustments, and real-time recourse [Eq. (12)].⁽²⁸⁾ At each ID epoch, updated sensor data are used to refine forecasts, and deviations from DA schedules are penalized to maintain consistency. This rolling approach ensures that EMS remains responsive to evolving conditions. At each ID epoch τ , identity (ID) is confirmed over a short rolling window $W(\tau)$ with updated sensor data. Deviations from DA trajectories are penalized using an L1 tracking term.

$$\min J^{ID}(\tau) = J_{op}(\tau) + \gamma_{trk} \sum_{t \in W(\tau)} \|z_t^{ID} - z_t^{DA}\| \quad (12)$$

Here, $J_{op}(\tau)$ is the operational cost, γ_{trk} is the tracking weight, and z_t^{ID} and z_t^{DA} are the ID and DA trajectories, respectively. The computational complexity of the C&CG algorithm depends on the iterative relation between the master problem and the worst-case subproblem.⁽²⁹⁾ At iteration k , the master problem is solved to optimize DA binary status variables over time horizon T alongside k sets of recourse cuts. This yields complexity bounded by $\mathcal{O}(2^{|T|} \cdot \text{poly}(k, |T|, |S|))$ in a mixed-integer linear programming (MILP), where $|S|$ denotes the scenario set size. The worst-case subproblem is solved to search the extreme points of the Wasserstein ambiguity set, using K_{FD} fast finite-difference probes across critical hours and subproblem evaluation scales linearly as $\mathcal{O}(N_{corner} \cdot |T| \cdot |S|)$. Because subproblem cuts are used to progressively restrict the search space, total iterations k^* remain small ($k^* \leq 3$), ensuring low computational overhead for RT applications.

2.3 Model implication

The developed scheduling system is a digital closed-loop control system that converts physical boundaries into the energy management logic. Real-time sensor data are continuously processed into feature vectors as the baseline for optimization. By comparing these vectors, the system calculates how current operating conditions deviate from historical patterns, using the Wasserstein metric.^(15,16) This enables the adjustment of protective boundaries, balancing reliability against operational costs based on the fidelity of the active sensor network. The operational constraints are used as safety thresholds in the system.⁽¹⁸⁾ For instance, turbine sensors prevent executing commands that might cause overheating or mechanical fatigue, whereas battery and sensors are used to prevent unsafe operations such as simultaneous charging and discharging. Smart meters are used to ensure that the electricity supply matches demand in real time, applying penalties whenever renewable energy is curtailed, or consumer loads are dropped. These constraints are used to determine safety limits in mathematical boundaries, ensuring that EMS maintains the mechanical and electrical integrity levels of the microgrid.

Risks are managed through the combination of the Wasserstein metric and VaR.⁽²⁴⁾ These tools are used as statistical safety filters for sensor data. Because outdoor sensors are vulnerable to noise, delays, and calibration drift, the system applies a protective cushion around incoming data streams. CVaR is used to prepare EMS for severe, low-probability events, such as a sudden drop in solar generation coinciding with a sensor communication blackout. By optimizing schedules under these worst-case scenarios, the system ensures stability even when sensor data are partially compromised. To make the optimization practical for real-time deployment, a C&CG procedure is used in the system.^(25,26)

This method enables planning baseline schedules and stress testing in adversarial scenarios. When vulnerabilities are detected, corrective rules known as generation cuts (G-cuts) are introduced, forcing the system to allocate backup resources. Computational efficiency is improved by focusing on volatile periods flagged by sensors and by using fast finite-difference probes to detect potential errors. An optional three-stage execution policy is introduced in the system to mimic ID forecast updates.⁽²⁸⁾ DA schedules are refined in short rolling windows using updated sensor data, while real-time recourse ensures final balance. This rolling approach reflects how microgrids adapt to evolving weather and demand conditions, maintaining consistency with day-ahead commitments while improving responsiveness.

Such mechanisms of the developed system ensure that EMS remains mathematically rigorous, sensor-integrated, and computationally efficient. The system enhances reliability and resilience under uncertainty, providing a reproducible methodology for DA and real-time scheduling in renewable power microgrids. Moreover, the outcomes of the system support the development of sensor calibration protocols, error compensation algorithms, and multi-sensor data fusion, applying theoretical optimization to sensor-driven control in EM.

3. Data and Experiment

The system's performance was evaluated using sensor data and a controlled simulation to explore whether the system maintained reliability, economic efficiency, and resilience under realistic uncertainty conditions.

3.1 Data

The performance of the system was evaluated using datasets obtained from microgrid installations in coastal and high-yield renewable regions of China.

- Renewable generation data: Wind velocity and solar irradiance data were sourced from the China Meteorological Administration and regional solar monitoring arrays in Guangdong Province, China.⁽³⁰⁾ Wind profiles were measured using ultrasonic anemometers, whereas solar irradiance was recorded with pyranometers. Data were sampled every 15 min for 12 months. To simulate stochastic fluctuations and sensor noise, Gaussian perturbations were applied, with night-hour PV output truncated to zero.
- Load demand data: Daily electricity demand profiles were compiled from smart meter datasets collected during State Grid Corporation of China pilot initiatives.⁽³⁰⁾ The data

presented aggregated commercial and light-industrial load patterns. Behavioral uncertainties were simulated by applying multiplicative Gaussian factors to the baseline profiles.

- Market data: Time-of-use (TOU) purchase prices ($\pi_t^{purchase}$) were defined according to regional tariff structures [Eq. (13)], whereas feed-in tariffs (π^{sell}) were fixed at USD 0.0504/kWh [Eq. (14)]. A safeguard ensured that selling prices remained below purchase prices. Market test profiles were expanded to include high-volatility RT spot pricing and dynamic regulation market clearing prices sourced from regional power exchange platforms, capturing extreme price spikes alongside physical demand fluctuations. π^{sell} did not exceed $0.99 \pi_t^{purchase}$ at t .

$$\pi_t^{purchase} = \begin{cases} 0.45, & t \in \{1, \dots, 6\}, \\ 0.75, & t \in \{7, 8, 9\}, \\ 0.95, & t \in \{10, 11, 12\}, \\ 0.80, & t \in \{13, 14, 15\}, \\ 1.10, & t \in \{16, 17\}, \\ 1.35, & t \in \{18, \dots, 22\}, \\ 1.10, & t = 23, \\ 0.60, & t = 24. \end{cases} \quad (13)$$

$$\pi^{sell} = 0.80 \times \min_t \pi_t^{purchase} = 0.0504 \text{ (USD / kWh)} \quad (14)$$

All data were normalized and transformed into structured feature vectors, combining load, wind, and PV trajectories with subsystem indicators such as SOC and turbine output. These vectors formed the basis for the Wasserstein metric used in the optimization. To evaluate performance in multi-day and seasonal horizons, continuous 12-month meteorological and load data were partitioned into four 7-day seasonal profiles (Spring, Summer, Autumn, and Winter).⁽³¹⁾ Through multi-day horizon execution, terminal SOC conditions are updated in 24-hour windows, using soft SOC penalties at day boundaries to ensure inter-day energy continuity.

3.2 Experiment

A simulation was conducted for a 1-day horizon with hourly resolution ($T = 24$, $\Delta t = 1$ h). Eight scenarios were generated using Gaussian perturbations of nominal profiles, with corner-based deviations applied to identify worst-case conditions. The eight scenarios represent the sets of boundaries of the maximum positive and negative forecast deviations. These deviations corresponded to a ± 40 % variation in wind velocity, a ± 40 % variation in PV irradiance, and a ± 25 % variation in load demand (Table 1).

The transition between surplus and stress scenarios shows why the optimization cannot operate in an open loop and requires continuous sensor data. Scenario 1 represents the highest net load stress. This scenario drives the risk-averse scheduling decisions and triggers the

Table 1

Forecast deviation and cyber-physical resource strategies in different scenarios.

Scenario	Load demand variation	PV variation	Wind power variation	System condition and operational status	Feedback and operation
1	+25%	−40%	−40%	Absolute peak net load stress (maximum demand concurrent with complete renewable deficit)	Triggers maximum gas turbine output and capped grid imports; drives severe emergency load shedding (USD 67.59/kWh)
2	+25%	−40%	+40%	Wind-buffered evening peak stress (high demand and low solar offset by high wind speed)	High evening demand is partially mitigated by wind mast data, reducing the ramping burden on the gas turbine.
3	+25%	+40%	−40%	Solar-buffered daytime peak stress (high demand and low wind offset by high solar flux)	Daytime demand peaks are buffered by high irradiance, but strict stress in night hours when PV drops to zero.
4	+25%	+40%	+40%	High-demand renewable surplus (maximum generation aligned with maximum local consumption)	Generation surges are heavily buffered by the high load, requiring moderate charging inputs to the BESS and GESS arrays.
5	−25%	−40%	−40%	Low-demand renewable deficit (minimum generation aligned with minimum local consumption)	Low demand counteracts the lack of green energy, allowing the system to maintain equilibrium without triggering load shedding.
6	−25%	−40%	+40%	Wind-heavy low-demand surplus (high wind speed and minimal local load)	Triggers GESS charging loops; mechanical winches elevate heavy masses based on draw-wire laser position sensor feedback
7	−25%	+40%	−40%	Solar-heavy low-demand surplus (high solar flux and minimal local load)	Extreme daytime solar generation charges BESS, driving battery cells up to their maximum safe limit (SOC of 0.95).
8	−25%	+40%	+40%	Absolute renewable surplus (maximum green generation concurrent with minimum local load)	Peak over-generation state; tests the upper capacity limits of the storage units and triggers green power curtailment rules if storage saturates

generation of structural G-cuts, which strengthen the master problem by explicitly accounting for worst-case conditions. In high-surplus scenarios (6, 7, and 8), when renewable output exceeds demand, EMS must prevent overvoltage and equipment damage. Real-time readings from Hall-effect current sensors and laser displacement gauges are used to determine the remaining capacity in BESS and GESS. This enables the system to absorb excess energy safely or apply controlled curtailment when limits are reached. In high-stress scenarios (1 and 2), when sensors detect a decrease in renewable generation, smart meters at the utility connection point guide the safe ramp-up of local gas turbines and supplemental grid imports. This coordinated response stabilizes the local network and prevents cascading failures.

In evaluating the eight scenarios' boundaries, the system accounts for sensor degradation, noise, and measurement errors. For example, if a pyranometer or an anemometer begins to drift owing to harsh outdoor conditions, the system prevents corrupted data from destabilizing the microgrid. The risk-averse design ensures that dispatch commands remain safe, bounded, and reliable, even under the most challenging operating boundaries. The CVaR confidence level was set to 0.95, and the risk aversion weight to 0.80. The Wasserstein radius was calibrated using the median of pairwise distances. The C&CG procedure was applied with a tolerance of 5×10^{-4} , a maximum of 30 iterations, and alternating inner iterations of 4. Each worst-case subproblem was solved with a 15 s time limit and a mixed integer programming difference of 10^{-4} . An optional three-stage execution (DA-ID-RT) was tested to mimic ID forecast updates. Intraday problems were solved over short rolling windows, with penalties applied for deviations from DA schedules. Fast functional dependency screening, key hour selection, and G-cuts were used to reduce computational burden while preserving model fidelity. Soft terminal SOC penalties were applied to enhance feasibility under adverse conditions. Table 2 shows the microgrid parameters used in the simulation.

The experiment was designed to validate whether the system (1) maintained reliability by ensuring turbine ramping limits and SOC bounds were respected, (2) achieved economic efficiency by minimizing total operating cost while avoiding arbitrage violations, (3) showed resilience by maintaining balance under worst-case scenarios such as simultaneous drops in wind and solar output combined with demand spikes, (4) processed sensor imperfections by introducing noise, latency, and drift into the data streams and testing whether schedules remained stable, and (5) ensured computational tractability by evaluating convergence speed and the effectiveness of acceleration heuristics.

Table 2
Microgrid parameters used in experiment.

Item	Parameter
Time horizon	$T=24$ h, $\Delta t=1$ h; 8 scenarios
Grid limits	Maximum power purchasing = 350 kW; maximum power selling = 200 kW; Maximum output power = 550 kW; minimum on-output power = 50 kW;
GT	ramp limit = 120 kW/h; fuel cost = 0.0728 USD/kWh; operation and maintenance cost = 0.021 USD/kWh; start-up cost = 7 USD; initial status = 1
BESS	Energy capacity = 900 kWh; initial SOC = 0.62; SOC boundary of [0.35, 0.95]; charge/discharge limits = 180 kW; efficiencies = 0.94; degradation cost = 0.007 USD/kWh
GESS	Energy capacity = 700 kWh; initial SOC = 0.70; SOC boundary of [0.45, 0.95]; charge/discharge limits = 130 kW; efficiencies = 0.86; ramp limit = 80 kW/h; degradation cost = 0.0042 USD/kWh
Penalty coefficient	Load = 56 USD/kWh; renewable power curtailment = 0.21 USD/kWh
RT adjustment cost	GT = 0.08; BESS = 0.03; GESS = 0.03; Grid = 0.007 USD/kWh
SOC penalty	DA penalty: 8000 (BESS), 6000 (GESS); RT penalty: 12000 (BESS), 9000 (GESS)
Risk robustness	CVaR confidence level = 0.95; CVaR weight = 0.80; Wasserstein metric = 1.20; probability boundary of [0.02, 0.202]
C&CG setting	Tolerance = 5×10^{-4} ; max iterations = 30; alternating inner iterations = 4
Three-stage execution	DA-ID-RT; rolling window of 4 h; tracking weight = $0.2 \times \text{median}_3$
Acceleration heuristics (optional)	Fast first-fit decreasing (FAST-FD) with KFD = 3; key-hour mode = 2; G-cuts enabled; numerical floor = 10^{-4}

4. Results

Table 3 shows the operational metrics in the worst-case scenario. Grid import reached its contractual cap of 350 kW during several hours, whereas grid export was not activated. Total load shedding was limited to 67.6 kWh, and no renewable curtailment occurred. The battery SOC remained between 35 and 95%, whereas GESS remained between 45 and 90.7%, confirming compliance with subsystem safety bounds. C&CG converged in only three iterations, with a final optimality difference of 0.044%. The day-ahead baseline cost was approximately USD 246.0, while the real-time incremental recourse cost reached USD 4723.8, yielding a total cost of USD 4969.8. This decomposition shows that robustness is concentrated in real-time corrective actions rather than in excessively conservative day-ahead schedules.

To validate the performance of the sensor-integrated Wasserstein–CVaR system, we compared the system with conventional stochastic optimization (SO) and classical robust optimization (RO) methods.^(32,33) The compared methods were evaluated under identical 24 h test profiles, incorporating severe out-of-sample tail stress realizations. As shown in Table 4, SO enabled lower DA baseline costs but showed RT recourse penalties and high load shedding (184.2 kWh) when exposed to out-of-sample distributions. Classical RO eliminated load shedding completely but required hyper-conservative DA scheduling, resulting in a significantly higher baseline cost (USD 3120.4) and overall expenses (USD 5840.1). In contrast, the Wasserstein–CVaR system showed an optimal trade-off since it restricted total load shedding to

Table 3
Operational metrics under the representative worst-case realization.

Metric	Value	Unit (description)
Peak grid import	350	kW (import cap binding in multiple hours)
Import cap binding hours	1–10, 15, 23–24	Hours when grid import reached contractual maximum
Peak grid export	0	kW (no export activated under worst case)
Export cap binding hours	–	Grid export inactive
Total load shed	67.6	kWh (last resort feasibility action only)
Total wind curtailment	0	kWh (no renewable curtailment required)
Total PV curtailment	0	kWh (no renewable curtailment required)
BESS SOC range	35–95	% (within safe operating bounds)
GESS SOC range	45–90.7	% (within safe operating bounds)
C&CG iteration	3	Solver converged rapidly
Final LB/UB (difference)	4414.6/4416.5 (0.044%)	USD (%)
Worst case RT incremental cost	4723.80	USD

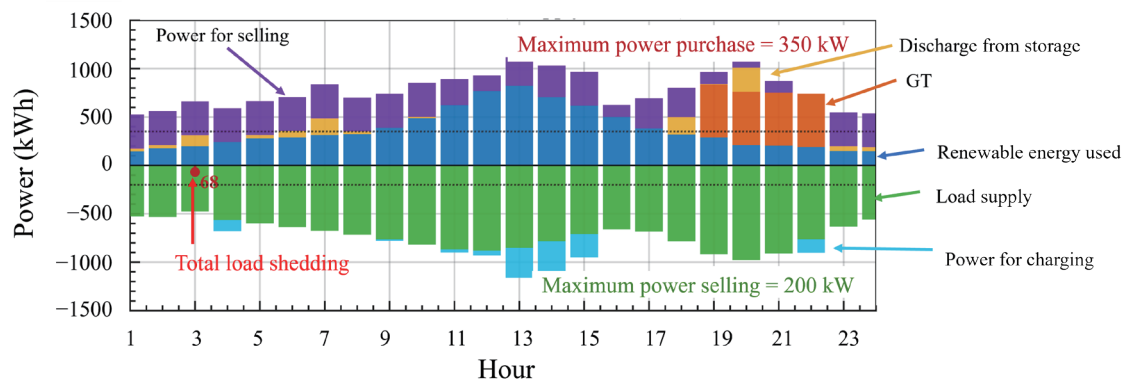
Table 4
Performance comparison with optimization methods in worst-case tail realization.

Performance metric	SO	RO	Wasserstein–CVaR (this study)
DA baseline cost (USD)	185.3	3120.40	246
RT recourse cost (USD)	5210.50	2719.70	4723.80
Total operating cost (USD)	5395.80	5840.10	4969.80
Total load shedding (KWh)	184.2	0	67.6
Cvar tail loss ($1 - \alpha = 0.05$) (USD)	5820.40	5840.10	5012.30
Convergence time/iterations	12.4 s (direct MILP)	18.2 s (two iterations)	21.5 s (3 iterations)

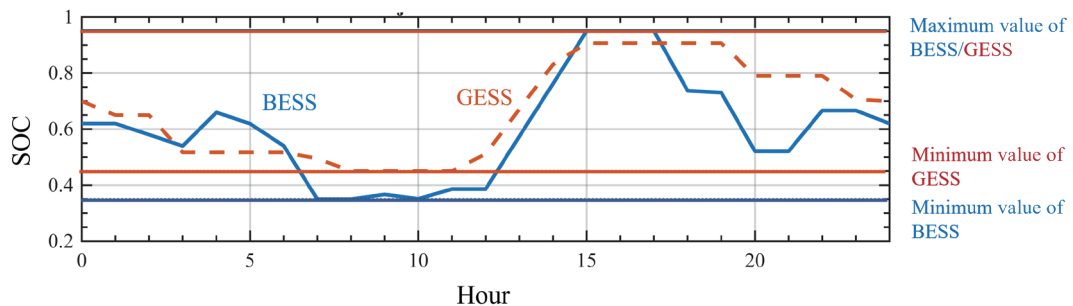
67.6 kWh, which contributed to the reduction of operating costs by 14.9% compared with RO and presented only a worst-case tail risk through RT recourse allocation.

Multi-day and multi-seasonal simulation results showed long-term stability in diverse operational regimes. Over 7-day seasonal horizons, average daily operating costs varied from USD 3840.5 in summer (high solar production offset by cooling loads) to USD 5120.2 in winter (reduced PV availability compensated by gas turbine generation and grid imports). Multiple-day battery and SOC profiles maintained inter-day continuity without boundary exhaustion or capacity saturation. The Wasserstein ambiguity set was adjusted to its radius in all seasons during high-volatility transitional months (spring and autumn).

Figure 2 shows that supply and demand remained balanced for 24 h under the most adverse renewable power shortfalls. Grid imports frequently reached the contractual cap of 350 kW, whereas coordinated discharging from the battery and GESS, together with gas-turbine generation, compensated for the remaining deficit. The SOC trajectories of BESS and GESS remained within their safety boundaries, 35–95% and 45–90.7%, respectively, confirming that turbine ramping limits and storage thresholds were never violated. This outcome validates the system's ability to maintain operational reliability and mechanical integrity under stress conditions.



(a)



(b)

Fig. 2. (Color online) Cyber-physical system performance: (a) Hourly power distribution in the renewable-rich microgrid and (b) SOC trajectories of BESS and GESS for 24 h.

The uncertainty for wind and PV power generation is shown in Fig. 3. The shaded regions represent admissible variability, and the dashed lines depict adversarial worst-case scenarios. Wind and PV outputs were consistently lower than nominal forecasts, explaining the increased reliance on grid imports and dispatchable generation observed in Fig. 2. Despite these simultaneous renewable deficits, the system maintained feasibility without curtailment, demonstrating resilience against correlated drops in renewable output and sensor noise.

The dispatch coordination result shows how flexible resources respond to high net-load stress (Fig. 4). The GT operated mainly during the evening peak (18:00–22:00), reaching near-maximum output to provide firm capacity. In contrast, BESS handled rapid fluctuations through short-term regulation, while GESS absorbed and released energy over longer durations to smooth the overall profile. This layered control prevented the premature depletion of storage and preserved reserves for critical hours, confirming the system’s capability to hedge operational risks through multi-resource coordination.

Market interaction and power-balance risk profiles are presented in Fig. 5. Grid imports were capped at 350 kW during adverse hours, while exports remained inactive under the no-arbitrage

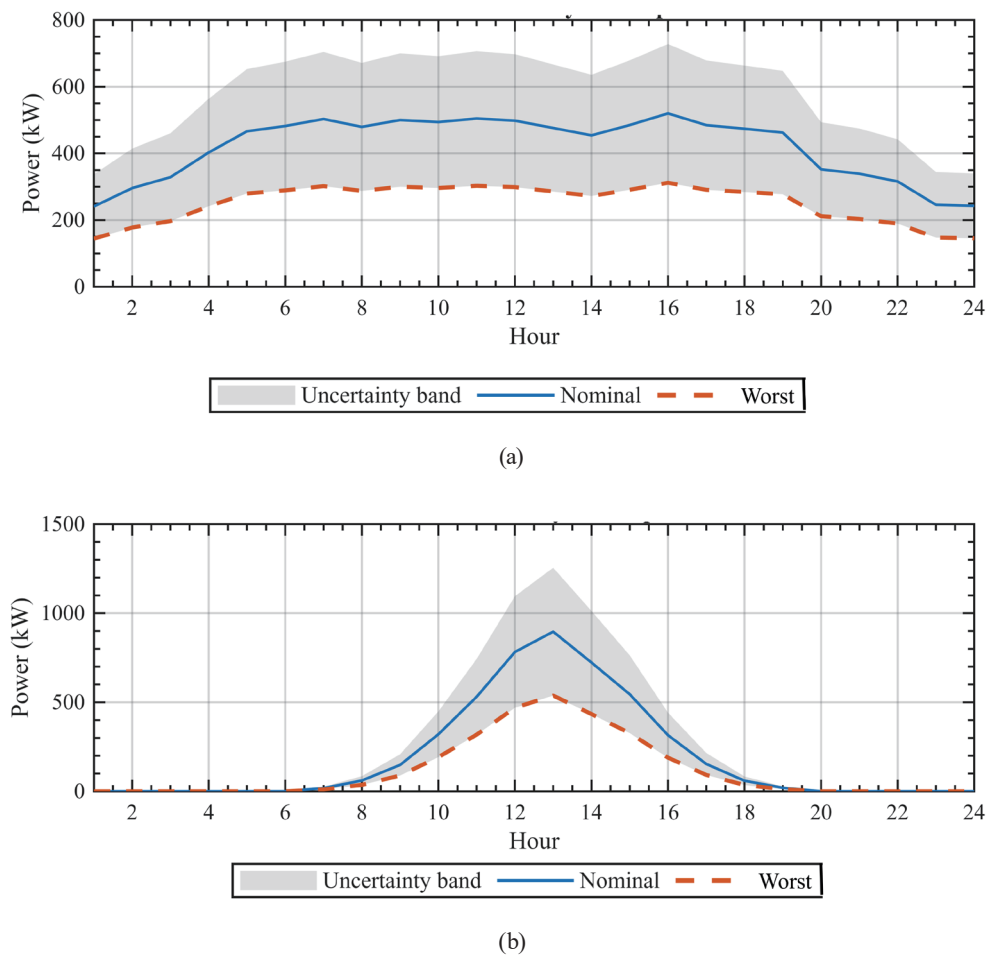


Fig. 3. (Color online) Comparison of nominal baselines, uncertainty bands, and adversarial worst-case scenario results: (a) anemometer-derived wind power forecast band and (b) pyranometer-derived PV irradiance bands.

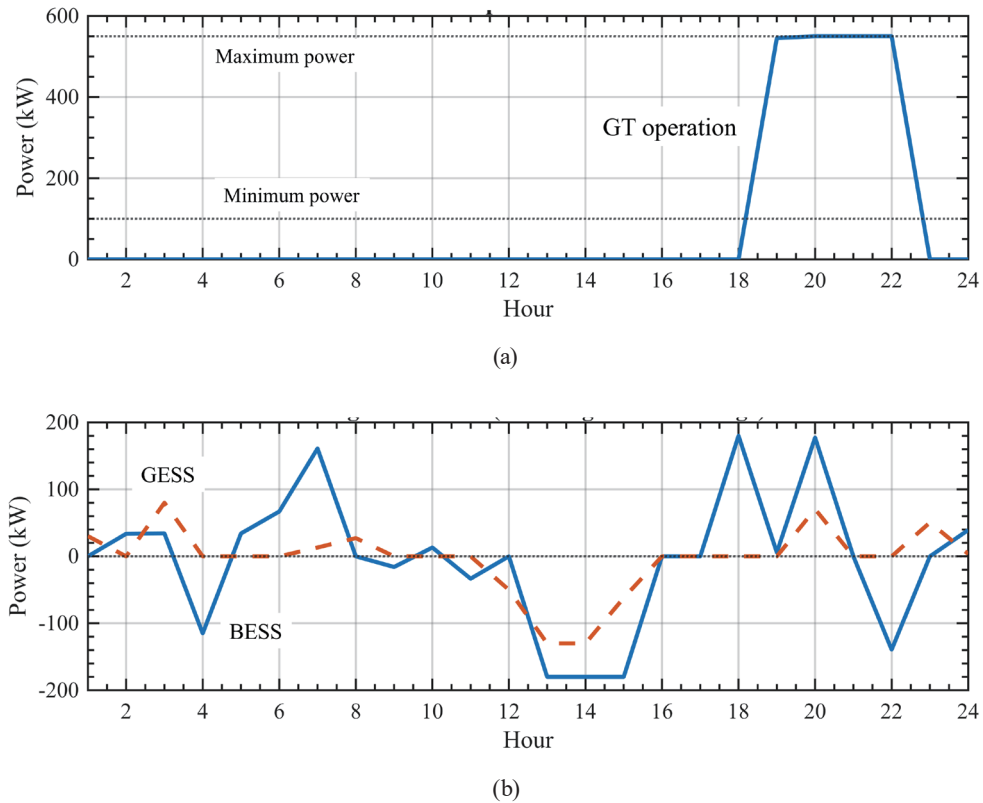


Fig. 4. (Color online) Dynamic resource coordination under high net load: (a) GT operational schedules and mechanical ramping profiles and (b) power tracking allocation separating fast-response BESS regulations from bulk-shifting GESS operations.

rule. Renewable curtailment was zero, and load shedding occurred only as a last-resort measure when multiple constraints became binding. These results verify that the system respected contractual limits and market rules while minimizing economic penalties and maintaining fairness in grid transactions.

The algorithmic performance of the C&CG loop is shown in Fig. 6. The lower bound increased steadily as worst-case cuts were added, while the upper bound remained stable, leading to rapid convergence. Within three iterations, the optimality gap fell to 0.044%, confirming the computational tractability and efficiency of the developed system.

Figure 7 shows the probability distribution shift under the Wasserstein–CVaR model. Probabilities in adverse scenarios diverged significantly from the uniform baseline, reflecting the effects of renewable shortfalls and demand spikes. The floor and cap constraints prevented degenerate concentration, yielding an interpretable distribution that explains the robust scheduling behavior. This adaptive probability re-weighting ensures that EMS prioritizes safety and reliability under uncertainty.

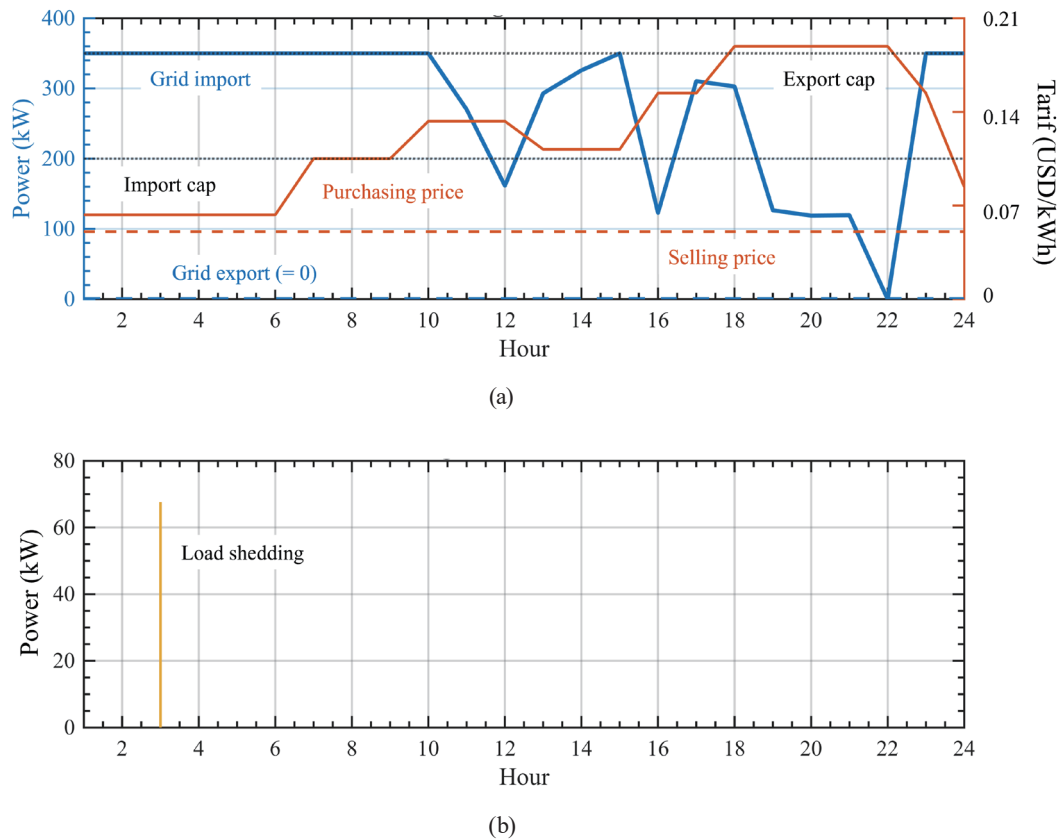


Fig. 5. (Color online) Market interaction and power-balance risk profiles: (a) Bidirectional utility grid exchange tracking contractual smart meter caps relative to TOU purchasing tariffs and (b) localized emergency load-shedding response triggered under peak network stress.

5. Discussion

The results of the simulation reveal that the proposed sensor-integrated Wasserstein–CVaR scheduling system showed reliability, economic efficiency, resilience, sensor robustness, and computational tractability. Therefore, the results provide a basis for sensor calibration, multi-sensor fusion, and the industrial deployment of microgrid EMS. Sensor imperfections, such as drift in pyranometers or anemometers, latency in smart meters, and noise in Hall-effect current transducers, do not destabilize the scheduling outcomes. This robustness is achieved by embedding sensor data into the Wasserstein ambiguity set and applying CVaR to anticipate tail risks. In practice, this means that calibration protocols can be designed with enhanced flexibility, rather than requiring perfect sensor accuracy at all times. EMS tolerates bounded errors, maintaining safe operation. This reduces maintenance costs and allows calibration intervals to be optimized for industrial feasibility rather than strict precision.^(34,35)

Precise sensor calibration is carried out in an adaptive two-layer error compensation architecture. At the edge controller layer, residual tracking algorithms are used to compare real-time measurements with baselines such as clear-sky irradiance curves or SOC conservation

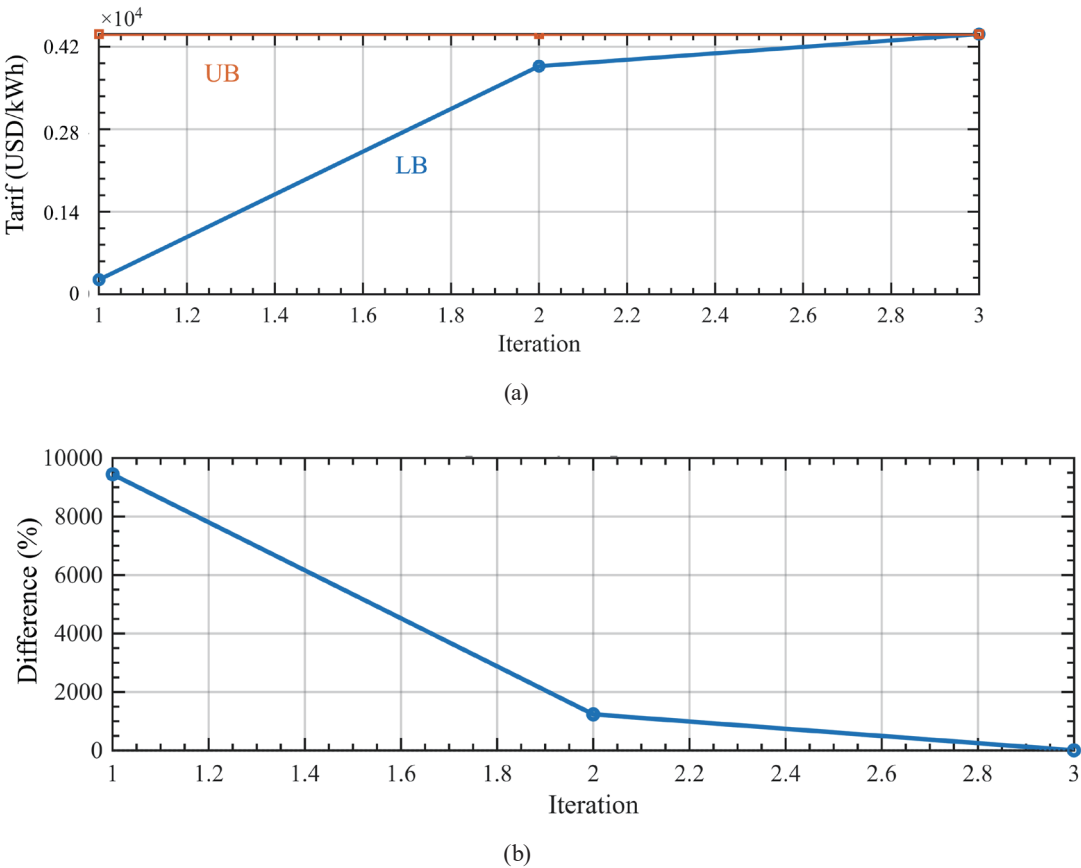


Fig. 6. (Color online) Algorithmic performance of C&CG loop: (a) iterative convergence trajectories of UB and LB and (b) reduction in optimality difference.

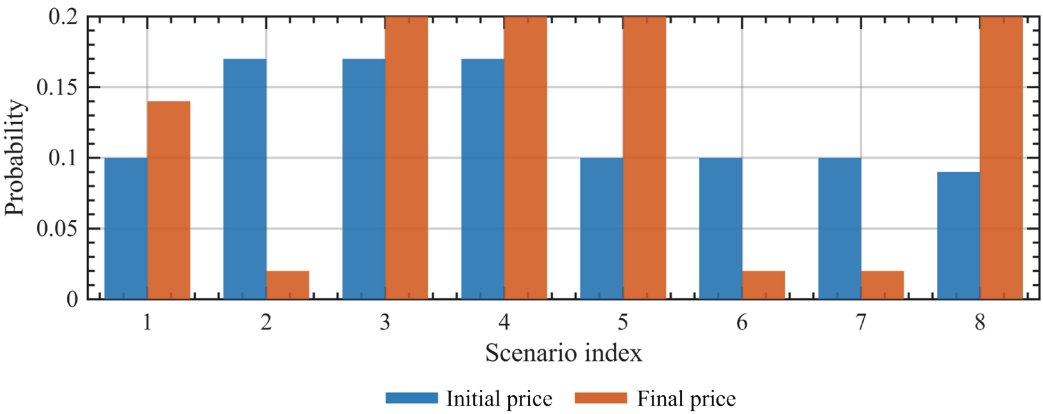


Fig. 7. (Color online) Data-driven probability distribution and initial uniform configuration against risk-adjusted scenario.

laws. When residuals exceed defined thresholds, the controller updates the measurement noise covariance matrix in the Kalman filter, automatically down-weighting degraded data without interrupting the data stream.⁽³⁶⁾ In the cyber-optimization layer, the revised residual variance scales the Wasserstein ambiguity radius. If sensors drift or require recalibration, their distributional ambiguity set expands to preserve operational resilience until recalibration is performed. Beyond noise and drift, complete sensor dropouts and wide-area communication failures pose serious hazards. The system mitigates these risks through coordinated multi-layer responses.⁽³⁷⁾ At the edge layer, observer-based state estimators are used to replace missing signals with model-predicted values. At the optimization layer, EMS flags unobserved channels and enlarges the local Wasserstein ambiguity radius. This adjustment broadens the hedging boundary, maintaining stability and safety even during extended sensor link outages.

Through the integration of diverse sensor data from thermal sensors, displacement gauges, smart meters, and pyranometers into structured feature vectors, the importance of multi-sensor data fusion was confirmed. By normalizing and combining these data streams, EMS enables a coherent representation of subsystem states that is resilient to individual sensor failures. Even when one sensor malfunctions, the fused vector can be reliably used for optimization. This supports the development of advanced fusion algorithms that prioritize consistency and redundancy over single-sensor accuracy, aligning with recent work on sensor fusion in cyber-physical systems.^(36,37)

The results indicate that the developed system is computationally tractable, converging in only three iterations with a negligible optimality difference. This efficiency is critical for real-time deployment in microgrids, where scheduling decisions must be updated continuously. The ability to coordinate GT, hybrid storage, and capped grid imports under strict no-arbitrage rules enables the system to operate within market constraints. In addition, the robustness premium is concentrated in real-time corrective actions rather than conservative day-ahead planning, which aligns with industrial priorities of minimizing upfront costs, preserving flexibility for adverse conditions.⁽³⁸⁾

To apply the developed system to larger single-agent systems or multi-agent microgrid clusters, spatial correlation complexity and state-space growth must be considered. In a large single-agent network, high asset counts are required to expand the decision space in the C&CG master problem. However, by applying FAST-FD, subproblems are decoupled across local asset constraints, preserving solution speed. For multi-agent microgrids, a distributed decomposition framework, such as the alternating direction method of multipliers, can decompose EMS dispatch into regional subproblems.⁽³⁹⁾ Each local agent processes sensor data vectors and computes regional Wasserstein-CVaR sets, transmitting only boundary coupling profiles to a top-level coordinator. Computational and coordination challenges, such as iterative consensus delays over wide-area networks and spatial correlation modeling across geographically dispersed sensor arrays, must be addressed to maintain strict convergence bounds under heterogeneous communication latencies.

The comparison with SO and RO methods showed that data-driven distributionally robust sets link stochastic optimism to robust conservatism.^(32,33) By using the ambiguity radius in sensor-derived feature vectors, unnecessary capacity reservation during benign hours is avoided

in EMS, retaining tail-risk protection during severe renewable shortfalls. The polynomial scaling of subproblem evaluation relative to scenario size ensures that computational execution remains within RT limits without encountering exponential state-space explosion.⁽⁴⁰⁾

The nominal-versus-worst-case result comparison shows that EMS prepositions flexibility by charging storage before stress periods and releasing energy when renewable shortfalls occur. This risk-aware reserve behavior ensures that microgrids remain reliable even under simultaneous drops in wind and solar output. For industrial operators, this implies that robust scheduling can reduce reliance on emergency load shedding and avoid costly renewable curtailment, thereby improving both economic efficiency and sustainability.

In multi-day rolling horizons, the system can continuously operate in industrial environments.⁽⁴¹⁾ Inter-day SOC coupling constraints show that battery and storage levels remain consistent in consecutive days, preventing unrealistic resets at the start of each horizon. Adaptive ambiguity boundaries limit the accumulation of forecast errors, which do not transmit uncertainty. These mechanisms ensure resilience for longer than 24 h planning. The system can scale from short-term scheduling to multi-seasonal microgrid operations, showing its viability for long-term deployment.

The system's flexibility is enhanced across deregulated electricity markets by extending the economic layer from static tariffs to dynamic RT pricing and ancillary service participation demonstrates.⁽⁴²⁾ Multi-market co-optimization enables flexible assets, such as fast-responding battery storage and fast-ramping gas turbines, to deliver frequency regulation without compromising local reliability bounds. By embedding market price volatility into the Wasserstein ambiguity set, the microgrid is protected to prevent generation shortfalls and severe market price spikes, reinforcing industrial viability in competitive energy environments.

The results show that sensor calibration and data fusion are essential in sustaining long-term resilience. The ability of EMS to tolerate bounded sensor errors suggests that calibration protocols can be adaptive, balancing cost and precision. At the same time, multi-sensor fusion ensures redundancy and stability, enabling the system to remain reliable even when individual sensors malfunction. Although the developed system shows the sensitivity of all parameters, the robustness–economy trade-off must be validated. In particular, adaptive calibration strategies, where sensor reliability directly affects the Wasserstein radius, and advanced fusion techniques leveraging machine learning to detect and compensate for sensor drift in real time represent promising directions for further study.⁽⁴³⁾

6. Conclusion

A sensor-integrated four-layer distributionally robust scheduling system is developed for renewable power-rich microgrids with hybrid battery and GESS. The system combines a Wasserstein ambiguity set, CVaR-based tail-risk control, and a C&CG solution procedure, executing strict no-arbitrage rules to prevent simultaneous grid buying and selling. The results of the simulation show that the Wasserstein–CVaR mechanism effectively hedges against adverse uncertainty realizations and probability misspecification by reallocating probability mass toward high-risk scenarios. Under representative worst-case conditions, the obtained

schedules are executed within operational limits, including gas turbine output and ramping constraints, storage SOC bounds, charging/discharging rules, and grid import caps. Hybrid storage provided coordinated flexibility, with BESS delivering fast regulation and GESS supporting longer-duration balancing. The system shows robustness through real-time corrective actions rather than conservative day-ahead planning. By tolerating bounded sensor errors, supporting multi-sensor fusion, and converging rapidly, the system serves a practical and industrially viable paradigm for risk-aware scheduling in renewable-rich microgrids.⁽⁴⁴⁾ The balance between computational efficiency and operational resilience ensures that the approach can be deployed in real market environments where continuous adaptation and cost-effective reliability are critical.

Other than performance validation, the results present implications for sensor calibration and fusion strategies. The system tolerates bounded sensor errors, reducing calibration costs and enabling adaptive protocols. Through the fusion of diverse sensors, resilience against individual sensor failures can be ensured, supporting the industrial deployment of microgrid EMS. Despite the promising results, further studies are necessary to compare system performance in terms of deterministic, stochastic, and conventional robust baselines, to conduct sensitivity analyses of CVaR weights and Wasserstein-radius calibration, and to extend the model to networked microgrids with additional security constraints such as N-1 contingencies and frequency-support requirements.

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