Data-Driven Robust Decision-Making for Low-Carbon Power Systems

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Self-Introduction

Current Position

- Associate Professor, College of Electrical and Information Engineering, Hunan University (Jan 2026 – Present).

Education & Academic Experience

- Postdoctoral Fellow / Research Associate, The Chinese University of Hong Kong (Aug 2022 – Jan 2026). Supervisor: Prof. Yue Chen.
- Ph.D. in electrical engineering, Tsinghua University (2017 – 2022).
  Advisor: Prof. Qiang Lu (Academician of Chinese Academy of Sciences).
- B.E. in electrical engineering and automation & B.S. in mathematics and applied mathematics, Tsinghua University (2013 – 2017).

Research Interests

- Power system planning & operation, robust optimization, renewable energy integration, energy storage, electricity markets.

Agenda

Outline

1.1 Research Background: The Low-Carbon Transition

Global Trend

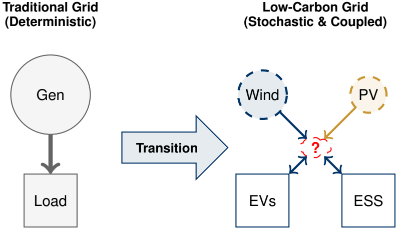
- Power systems are transitioning from centralized fossil-fuel generation to distributed low-carbon resources.

Structural Changes

- **Supply Side:** High penetration of renewable energy sources (RES) like wind and solar.
- **Demand Side:** Proliferation of electric vehicles (EVs) and flexible loads.
- **Integration:** Coupling of traffic, heat, and power networks.

The Core Dilemma

- How to ensure reliability and economic efficiency when the system is driven by weather-dependent, highly uncertain resources?



Traditional vs. Low-Carbon Power Systems

1.1 Research Background: Key Challenges

The transition introduces distinct mathematical challenges that render traditional deterministic or stochastic optimization insufficient.

Data Ambiguity

- Limited historical data.
- Ambiguous distributions.
- Result: Stochastic programming (SP) suffers from in-sample bias.

Decision-dependent uncertainty (DDU)

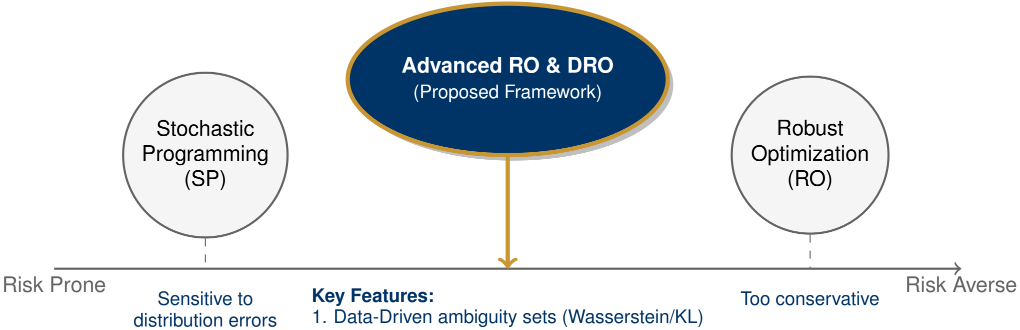
- Decisions affect uncertainty.
- Example: Grid expansion alters congestion patterns; prices affect demand.
- Result: Traditional robust optimization (RO) algorithms are suboptimal.

Computational Complexity

- Multi-timescale coupling.
- Non-convex physical laws.
- Lacks accurate predictions.
- Results: Real-time dispatch requires online or prediction-free algorithms.

1.1 Research Background: Methodological Gap

We need a framework that balances robustness (conservativeness) and economic efficiency.



Key Features:

1. Data-Driven ambiguity sets (Wasserstein/KL)
2. Decision-dependent uncertainty (DDU)
3. Integrated predict-and-optimize

1.2 Introduction: Research Framework

Theoretical Foundation

Advanced Robust Optimization (RO)

Handling decision-dependent uncertainty (DDU) & predict-and-optimize

Applied to

Applied to

Application I

Reliability-Oriented Planning

- Distributionally robust sizing
- Long-term investment
- Evaluating load-shedding/curtailment risks

Application II

Real-Time Operation & Markets

- Online algorithms
- Market mechanism design
- Flexibility aggregation

Long-term (years/decades) Time scale of decision-making **Real-time (hours/minutes)**

Outline

Traditional RO

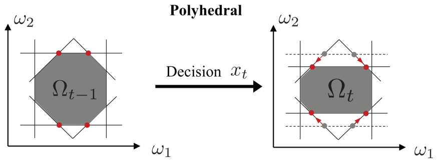
Decision-independent uncertainty (DIU)

- **Concept:** Assume that decision does not affect uncertainty.
- **Limitation:** Ignores interaction between decisions and uncertainty.

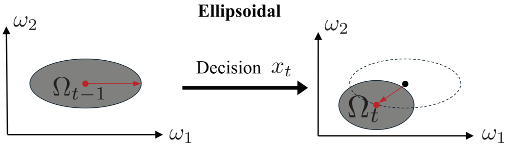
RO with DDU

Decision-dependent uncertainty (DDU)

- **Concept:** Decision may alter the uncertainty set.
- **Challenge:** Standard algorithms fail to find the optimum.



Polyhedral DDU set



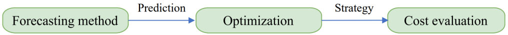
Ellipsoidal DDU set

2 Advanced RO: Predict-and-Optimize

Predict-then-Optimize

Two-stage sequential approach

- **Concept:** Train forecasting model to minimize prediction error (e.g., MSE), then plug into optimization.
- **Limitation:** Prediction accuracy does not guarantee optimal decision costs.

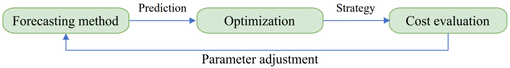


Predict-then-optimize flow

Predict-and-Optimize

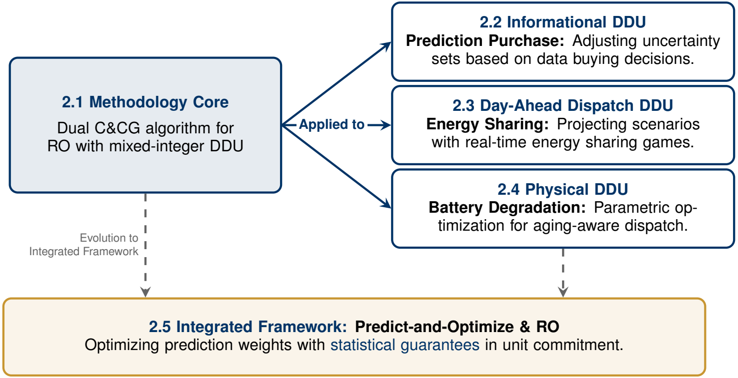
Integrated approach

- **Concept:** Integrate optimization layer directly into the training loop.
- **Innovation:** Train to minimize decision costs rather than just prediction error.



Predict-and-optimize flow

2 Advanced RO: Overview



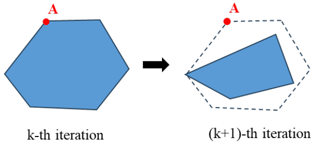
2.1 Methodology: Handling Two-Stage RO with DDU

Challenge

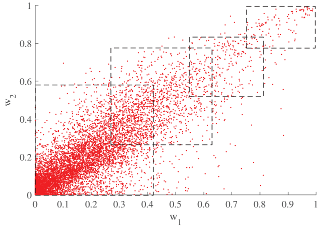
- When DDU presents, the uncertainty set $\mathcal{U}(x)$ changes with decision x.
- A worst-case scenario u^* identified previously may fall outside $\mathcal{U}(x)$ when x changes.
- Standard algorithms, such as C&CG and Benders decomposition, yield suboptimal results.

Contribution

- Proposed **dual C&CG algorithm**.
- Effective for mixed-integer DDU set.
- Transforms the inner problem using duality theory to handle the DDU structure.
- Proved finite convergence and optimality.



The worst-case scenario falls outside the new uncertainty set when decision changes.



Mixed-integer DDU set.

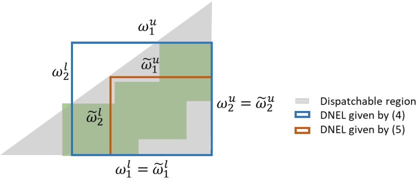
T. Tan, **R. Xie**, X. Xu, et al., "A Robust Optimization Method for Power Systems with Decision-Dependent Uncertainty," in Energy Conversion and Economics, 2024.

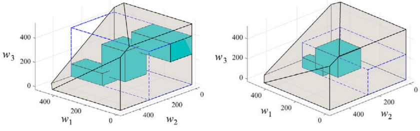
Application Case

- DNELs define the max/min power output limits for renewable generators (RGs) to ensure grid security.
- Standard models use simple boxes, which ignores correlation.
- We model RG correlations using a decision-dependent union of boxes.

Performance

- By accurately capturing correlations via DDU, the method reduces conservatism.
- The feasible operating region expands significantly.





(a) Proposed (b) Traditional

The proposed method identifies a larger safe operating region compared to the traditional conservative model.

T. Tan, **R. Xie**, X. Xu, et al., "A Robust Optimization Method for Power Systems with Decision-Dependent Uncertainty," in Energy Conversion and Economics, 2024.

2.2 Robust Dispatch with Prediction Purchase

Problem

- Operators face high uncertainty from RES/loads.
- Agents have private data but no incentive to share.

Proposed Model: Prediction Purchase

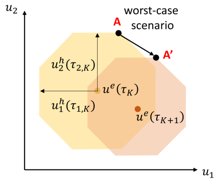
- Operator pays agents for their predictions with accuracy information.
- Operator constructs an improved uncertainty set using the predictions purchased.
- This leads to a DDU set, as it is affected by the first-stage purchase decision.

Proposed Solution: Mapping-based C&CG

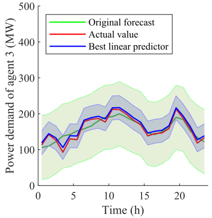
- Return the mapping constraint that tracks the worst-case vertex.

Results

- Effectively balances the cost of information vs. operational costs.
- Total cost reduced by 4% vs. no prediction purchase.



While the uncertainty set shifts, the algorithm maps the worst-case vertex.



Uncertainty set shrinks by using predictions.

R. Xie, P. Pinson, Y. Xu, et al., "Robust Generation Dispatch with Purchase of Renewable Power and Load Predictions," in IEEE Transactions on Sustainable Energy, 2024.

2.3 Robust Microgrid Dispatch with Energy Sharing & DDU

Problem

- Day-ahead connection/disconnection of renewable generators (RGs) alters the dimension and shape of the uncertainty set.
- DER owners are independent, self-interested stakeholders seeking to maximize individual profits.
- A peer-to-peer sharing mechanism is required to coordinate these prosumers to handle real-time renewable deviations.

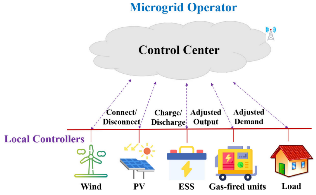
Solution: Projection-Based C&CG

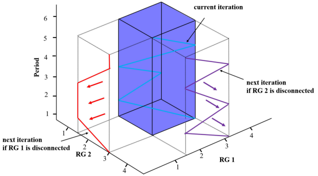
- Projects scenarios into the new set based on current decisions.
- Prosumers participate in a Generalized Nash game for real-time sharing.

Results

- Achieves centralized efficiency.
- Reduces prosumer costs by 3.0%.

Ongoing Research: Robust optimal operation of virtual power plants under decision-dependent uncertainty of price elasticity.





Projection of scenarios into the new uncertainty set.

M. Yang, **R. Xie**, Y. Zhang, et al., "Robust Microgrid Dispatch with Real-Time Energy Sharing and Endogenous Uncertainty," in IEEE Transactions on Smart Grid, 2025.

2.4 Robust Dispatch Under Battery Degradation DDU

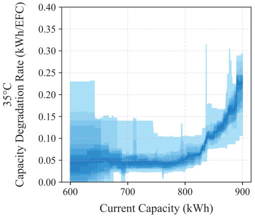
Challenge

- Charging/discharging decisions accelerate degradation; accumulated degradation then constrains future ESS flexibility.
- The probability distribution of future capacity is decision-dependent.

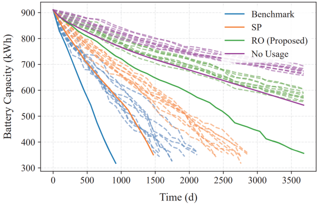
Proposed Method

- **Probabilistic Model:** XGBoost quantile regression captures temperature-dependent aging of batteries.
- **Parametric MPC:** Optimizes a trade-off between operational costs and degradation penalty terms.
- **Parameter Optimization:** Robust optimization to find the optimal degradation penalty coefficient under the worst-case degradation scenario.

Ongoing Research: Microgrid dispatch considering the DDU of energy storage system degradation



Probabilistic battery degradation model.



RO achieves the longest battery life by hedging against worst-case degradation.

R. Xie, J. Wang, J. Duan, et al., "Robust Parametric Microgrid Dispatch Under Endogenous Uncertainty of Operation- and Temperature-Dependent Battery Degradation", ECE 2025.

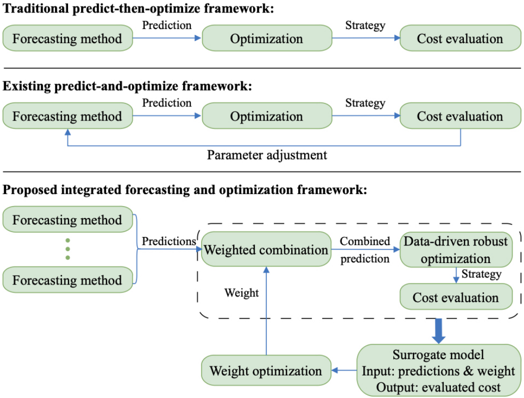
2.5 Predict-and-Optimize Robust Unit Commitment with Statistical Guarantees

Challenge

- Traditional predict-then-optimize: Minimizing prediction error is different from minimizing decision costs.
- Existing predict-and-optimize is often computationally heavy and lacks theoretical robustness.

Proposed Integrated Framework

- **Weighted Combination:** instead of tuning internal model parameters, we optimize the weights of multiple predictors to minimize decision cost.
- **Surrogate Acceleration:** An MLP neural network maps predictions & weights $\rightarrow$ decision cost, replacing the heavy optimization loop.



R. Xie, Y. Chen, and P. Pinson, "Predict-and-Optimize Robust Unit Commitment with Statistical Guarantees via Weight Combination," in IEEE Transactions on Power Systems, 2025.

2.5 Predict-and-Optimize Robust Unit Commitment with Statistical Guarantees

RO Formulation

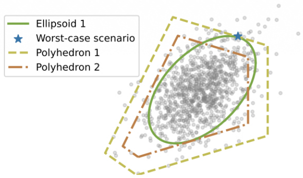
- Constructs a data-driven ellipsoidal uncertainty set.
- Reconstruction: Shrinks the set into a polyhedron based on the UC problem structure to reduce conservativeness.
- Theoretically ensure statistical guarantee by tuning the size of the uncertainty set in a data-driven way.

Results

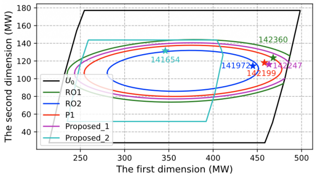
- Enhance performance and reliability compared to traditional SP and RO methods.
- Lowered the objective value by 8.30%.

Follow-up Research

- Y. Zhuang et al., "A Weighted Predict-and-Optimize Framework for Power System Operation Considering Varying Impacts of Uncertainty," in IEEE Transactions on Power Systems, early access.



Uncertainty set construction and reconstruction.



Reconstructed uncertainty set avoids high-cost scenarios.

R. Xie, Y. Chen, and P. Pinson, "Predict-and-Optimize Robust Unit Commitment with Statistical Guarantees via Weight Combination," in IEEE Transactions on Power Systems, 2025.

Outline

1. Introduction
2. Advanced Robust Optimization: Decision-Dependent Uncertainty & Predict-and-Optimize
3. Reliability-Oriented Storage and Renewables Planning via Distributionally Robust Optimization
4. Real-Time Operation and Market Mechanisms for Distributed Flexible Resources
5. Conclusion

3 Reliability-Oriented Planning: Research Background

Motivation: The Planning Dilemma

- **Context:** High penetration of renewables requires coordinating energy storage systems (ESSs) to manage volatility.
- **The Data Challenge:** Accurate probability distributions of renewable output are difficult to obtain due to limited historical data.

Methodological Gap Analysis

1. Stochastic Programming (SP)

- Assume probability distribution is known exactly.
- Results are sensitive to distributional errors from limited data.

2. Robust Optimization (RO)

- Optimize for the worst-case scenario in the uncertainty set.
- Extreme scenarios rarely happen, leading to excessive investment.

Proposed Solution: Distributionally Robust Optimization (DRO)

- **Concept:** Define an ambiguity set via KL divergence or Wasserstein metric, containing all distributions close to the empirical data.
- **Objective:** Minimize the expected cost/risk under the worst-case distribution within this set.
- **Benefit:** More reliable than SP, less conservative than RO.

3 Reliability-Oriented Planning: Overview

Specific Infrastructure

3.1 EV Charging Stations
Context: Highways
Method: KL-divergence

3.2 Remote Renewables
Context: Generation-grid coordination
Method: CVaR and curtailment function

From component to system

System Reliability & Risk

3.3 Stand-Alone Microgrids
Continuous DRO with load-shedding shortfall risk

3.4 Low-Carbon Power Systems
Bi-objective: cost vs. load-shedding risk

Integrating physical DDU

Advanced Physics

3.5 Wind & Storage Planning
DRO + DDU with wake effect coupling

Problem Context

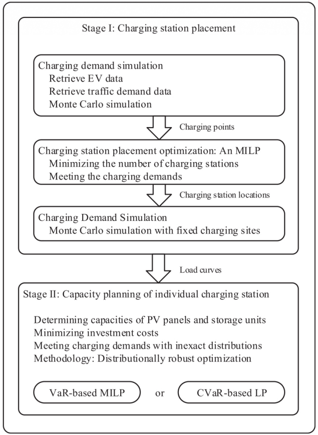
- Planning stand-alone and renewable-powered charging stations for remote highway networks.
- Challenges: Spatially correlated traffic demand and volatile solar generation.

Two-Stage Planning

- **Stage 1 (Siting):** Monte Carlo simulation captures traffic flow; MILP minimizes station count while ensuring coverage.
- **Stage 2 (Sizing):** Determining PV/storage capacity using distributionally robust optimization (DRO).
- Uses KL divergence to construct ambiguity sets for inexact distributions.

Two solution methods:

- **VaR-based MILP:** Accurate but computationally heavy.
- **CVaR-based LP:** Conservative but highly tractable.



R. Xie, W. Wei, M. E. Khodayar, et al., "Planning Fully Renewable Powered Charging Stations on Highways: A Data-Driven Robust Optimization Approach," in IEEE Transactions on Transportation Electrification, 2018.

3.2 Remote Renewable Sizing: Problem & Framework

Motivation

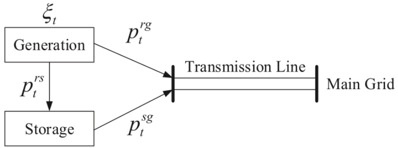
- Remote renewable plants face high grid-connection costs due to long transmission lines.
- Low utilization: Transmission capacity is often over-sized for peak generation but under-utilized on average.

Coordinated Sizing Strategy

- Deploy on-site energy storage system (ESS) to smooth output and reduce required transmission capacity.
- Minimize investment cost subject to renewable curtailment risk.

Challenge

- How to accurately model curtailment in the sizing problem under probability distribution ambiguity?



R. Xie, W. Wei, M. Ge, et al., "Coordinate sizing of energy storage and transmission line for a remote renewable power plant," in IET Renewable Power Generation, 2022.

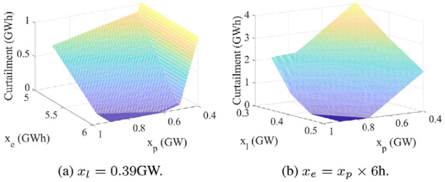
3.2 Remote Renewable Sizing: Methodological Innovation

Analytical Curtailment Function

- Treated the operation problem as a multiparametric linear program.
- **Proven Property:** The renewable curtailment is a convex and piecewise affine function of capacities and generation.
- Developed a mountain-climbing algorithm to generate the analytical expression.

Distributionally Robust Sizing

- Modeled uncertainty via Wasserstein-metric ambiguity set.
- Used CVaR to control the tail risk of curtailment under inexact distributions.
- Transformed the complex sizing problem into a tractable linear program.



Visualization of curtailment as a piecewise affine function.

Performance Comparison

Method	Cost (10^9¥)	Risk (CVaR)	Status
Proposed (DRO)	**15.32**	**-0.007**	**Safe**
Stochastic (SP)	15.17	+0.033	Risky
Robust (RO)	15.50	-0.049	Conservative

R. Xie, W. Wei, M. Ge, et al., "Coordinate sizing of energy storage and transmission line for a remote renewable power plant," in IET Renewable Power Generation, 2022.

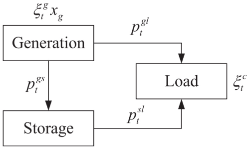
Motivation: Stand-alone microgrids require high reliability.
Methodology: Distributionally Robust Shortfall Risk

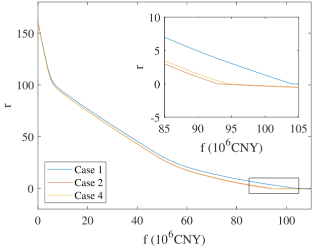
- **Ambiguity Set:** Utilized the Wasserstein metric to capture **continuous** probability distributions, overcoming limitations of discrete-only models.
- **Tractability:** Derived a conservative approximation to transform the worst-case expectation into a linear program (LP).

Theoretical Breakdown

- Validated that the Pareto frontier of investment and risk is a piecewise linear function.
- Derived analytical expressions for the Pareto set via the ϵ-constraint method.
- The proposed DRO method bridges the gap, offering a solution less conservative than RO and more reliable than SP:

$$r_{SP}(x) \leq r_{DRO}(x) \leq r_{RO}(x)$$





Pareto frontier comparison.

R. Xie, W. Wei, M. Shahidehpour, et al., "Sizing Renewable Generation and Energy Storage in Stand-Alone Microgrids Considering Distributionally Robust Shortfall Risk," in IEEE Transactions on Power Systems, 2022.

3.4 Coordinated Sizing: Problem & Methodology

The Transition Challenge:

- Retirement of fossil-fuel generators and load growth requires coordinating renewable generation (RG), transmission, and energy storage system (ESS).

Bi-Objective DRO Model

- **Objective 1:** Minimize total investment cost.
- **Objective 2:** Minimize worst-case expected operational cost in normal conditions.
- **Constraint:** Distributionally robust shortfall risk of load shedding in extreme conditions.

Methodology

- Uses Wasserstein-metric to capture inaccurate empirical distributions.
- Linearization: Use binary expansion and Big-M method to handle transmission nonlinearities.
- Lipschitz Reformulation:
  - Reformulated worst-case risk using Lipschitz constants derived via LP duality.
  - Transforms the problem into a tractable Mixed-Integer Linear Program (MILP).
- Adopts ϵ-constraint method to generate the Pareto frontier.

R. Xie, W. Wei, M. Li, et al., "Sizing capacities of renewable generation, transmission, and energy storage for low-carbon power systems: A distributionally robust optimization approach," in Energy, 2023.

3.4 Coordinated Sizing: Mathematical Innovation

Proposed Algorithm

Algorithm 1

Input: Data of problem (20), budget range $[F^l, F^u]$, and a small positive number $\delta > 0$.

Output: Pareto solutions $x(F)$ and points $(F, c(F))$ on Pareto frontier.

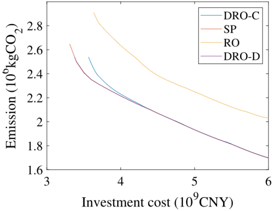
1: Initiation: Solve MILP (34) and obtain L^E from (37). $F \leftarrow F^l$.

2: Solve MILP (41) and obtain $x(F)$ with the current F; find L^N by solving (39) and (40) with fixed $x(F)$, update the optimal value of (41), and obtain $c(F)$.

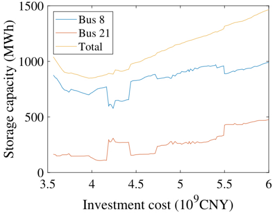
3: If $F^u - F < \delta$, terminate. Otherwise, update $F \leftarrow F + \delta$, and turn to Step 2.

Sizing Sensitivity

- To reduce daily CO_2 by 100 kg, 40 kW of renewable capacity is required.
- ESS capacity grows rapidly if thermal generation is retired aggressively.



DRO-C (proposed) sits between SP and RO.



ESS capacities increase as investment budget increases.

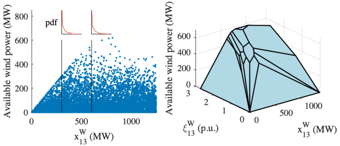
R. Xie, W. Wei, M. Li, et al., "Sizing capacities of renewable generation, transmission, and energy storage for low-carbon power systems: A distributionally robust optimization approach," in Energy, 2023.

Motivation: The Wake Effect

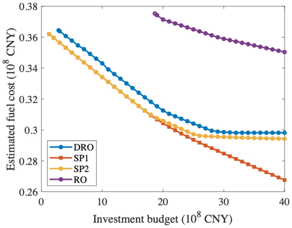
- Wake effect causes wind speed deficits and power drops for downstream turbines.
- DDU: The probability distribution of available wind power changes based on the installed capacity.

Methodology

- **Modeling:** Developed a linearized convex hull approximation of the available wind power function to handle wake nonlinearities.
- **Optimization:** Constructed a decision-dependent ambiguity set using the Wasserstein metric, where the set size scales with capacity decisions.
- **Solution:** An iterative algorithm based on minimum Lipschitz constants to transform the DDU-DRO model into a tractable linear program.



Available wind power distribution changes as capacity varies, proving endogeneity.



DRO is less conservative than RO and more robust than SP.

R. Xie, W. Wei, and Y. Chen, "Sizing Grid-Connected Wind Power Generation and Energy Storage with Wake Effect and Endogenous Uncertainty: A Distributionally Robust Method," in CSEE Journal of Power and Energy Systems, accepted.

Outline

4 Real-Time Operation & Market Mechanisms: Research Background

Context: From Planning to Real-Time Execution

- Goal: Unlock the flexibility of these resources to handle renewable volatility, minimize operational costs, and reduce carbon emissions.

Key Challenges

1. Information Uncertainty

- Real-time decisions must be made without perfect foresight of future renewable generation, prices, or arrival rates.
- Dispatch is sequential, requiring handling non-anticipativity constraints.

2. Incentive Alignment

- Distributed resources are often owned by self-interested entities maximizing their own profit.
- Market mechanisms must be designed to align individual behavior with system-level goals, e.g., decarbonization.

Methodological Innovations

- **Prediction-Free Online Control:** Utilizing Lyapunov optimization to decouple time periods and make decisions based solely on current states, avoiding forecast errors.
- **Multistage & Periodic Approaches:** Multistage robust optimization for sequential aggregation and Fourier-based periodic control for ultra-fast pulsed load coordination.
- **Market Design:** Aumann-Shapley pricing for fair carbon allocation and bilevel optimization for profit-maximizing service pricing.

4 Real-Time Operation & Market Mechanisms: Overview

Market & Incentive Mechanisms

4.1 Energy Storage Bidding
Aumann-Shapley prices
for carbon allocation

4.2 EV Sharing Pricing
Bilevel optimization for
coupled traffic-power systems

Online Control & Dispatch

4.3 Data Centers
Online Lyapunov optimization
for low-carbon management

4.4 Pulsed Loads
Periodic coordination &
Fourier-based acceleration

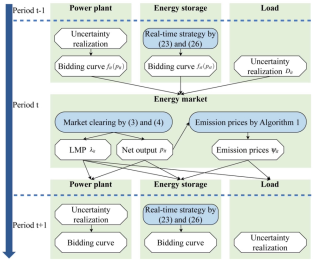
Providing economic flexibility

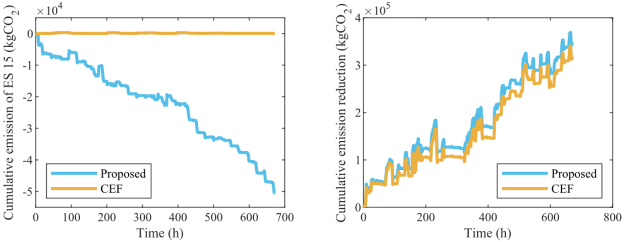
Providing physical capability

4.5 Flexibility Aggregation
Multistage RO for TSO-DSO coordination under non-anticipativity

Market Clearing Mechanism

- **Challenge:** How to incentivize ES to reduce carbon emissions via market mechanisms?
- **Aumann-Shapley Allocation:** Allocates emission responsibility to loads and ES based on their accumulated marginal contribution.
- **Parametric LP Algorithm:** A novel algorithm to calculate emission prices efficiently, outperforming numerical estimation methods.





Reduces system emissions by **9.3%** more than the carbon emission flow (CEF) method by directly incentivizing discharge during high-carbon periods.

R. Xie and Y. Chen, "Real-Time Bidding Strategy of Energy Storage in an Energy Market with Carbon Emission Allocation Based on Aumann-Shapley Prices," in IEEE Transactions on Energy Markets, Policy and Regulation, 2024.

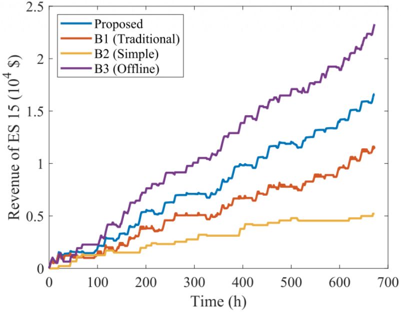
4.1 Real-Time ES Bidding with Aumann-Shapley Carbon Allocation

Real-Time Bidding Strategy

- **Improved Lyapunov Optimization:** Minimizes the exact quadratic drift-plus-penalty term rather than a linear upper bound to balance revenue and SoC stability.
- **Convex Bidding Curve:** Derives a convex bidding function (price-power curve).
- **Prediction-Free:** The derived bidding curves depend only on current observations, avoiding forecast errors.

Key Results

- **Economic Efficiency:** Achieves an about 50% higher revenue rate than the traditional Lyapunov optimization method.
- **Optimality Gap:** Achieves **70.9%** of the offline optimal revenue, which assumes perfect foresight.



Comparison of ES strategies.

R. Xie and Y. Chen, "Real-Time Bidding Strategy of Energy Storage in an Energy Market with Carbon Emission Allocation Based on Aumann-Shapley Prices," in IEEE Transactions on Energy Markets, Policy and Regulation, 2024.

Problem: Coupled Traffic-Power Systems

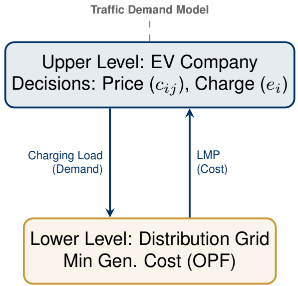
- EV sharing companies must optimize service pricing and charging schedules.
- Charging loads affect distribution locational marginal prices (LMP), creating a loop.

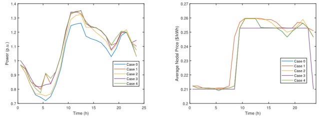
Methodology: Bilevel Optimization

- **Upper Level:** Maximize company profit.
- **Lower Level:** Distribution market clearing.

Solution Technique

1. **Polyhedral Approx:** Linearized the SOCP branch flow model.
2. **Primal-Dual:** Replaced lower level with KKT/duality conditions.
3. **Binary Expansion:** Linearized bilinear terms of price and power.
4. **Result:** A tractable mixed-integer quadratic program (MIQP).





R. Xie, W. Wei, Q. Wu, et al., "Optimal Service Pricing and Charging Scheduling of an Electric Vehicle Sharing System," in IEEE Transactions on Vehicular Technology, 2020.

4.3 Online Low-Carbon Management of Distributed Data Centers

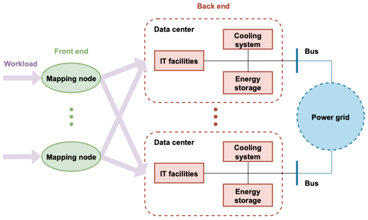
Challenges in Data Centers (DCs)

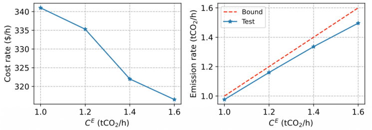
- DCs are major energy consumers, but existing online scheduling often neglects explicit carbon emission limits.
- Uncertainties: Workload arrival, ambient temperature, prices, and carbon intensity.

Methodology: Parametric Lyapunov Optimization

- Co-optimizes workload, energy, and temperature.
- **Prediction-Free:** Uses Lyapunov optimization to handle uncertainties without prior probability knowledge.
- **Parameter Optimization:** A novel linear programming (LP) method determines control parameters to minimize the optimality gap while ensuring theoretical feasibility.

Ongoing Research: Statistically-guaranteed two-stage robust resource allocation for containerized clouds under DDU.





The method effectively keeps emissions below the bound.

R. Xie, Y. Chen, and X. Weng, "Online Low-Carbon Workload, Energy, and Temperature Management of Distributed Data Centers," The 4th Energy Conversion and Economics Annual Forum (ECE Forum 2024).

Problem: The Pulse Challenge

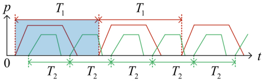
- High-energy loads consume up to 100 MJ energy in milliseconds.
- Online Requirement: Operational requirements change rapidly; strategies must be computed in seconds.

Methodology: Periodic Decomposition

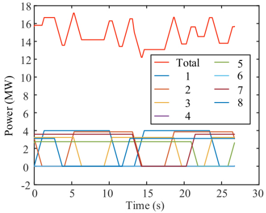
- **Periodic Framework:** Exploits the repetitive nature of pulsed loads. Optimizes a single joint charging cycle repeatedly.
- **Two-Stage Decomposition:**
  - **Step 1 (Allocation):** Maximize total utility by optimizing energy allocation.
  - **Step 2 (Time):** Minimize the cycle length to increase frequency.
- **Fourier Acceleration:** Uses Fourier series to approximate charging curves, transforming infinite-dimensional constraints into fast nonlinear programming.

Key Results

- Speed: Solves in **0.74 s**, significantly faster than PSO (54s) or MILP (timeout).
- Effectively smooths generation by coordinating charging phases.



Periodic operation framework.



Coordinated charging curves smoothing the total load.

R. Xie, Y. Chen, Z. Wang, et al., "Online Periodic Coordination of Multiple Pulsed Loads on All-Electric Ships," in IEEE Transactions on Power Systems, 2020.

R. Xie, Y. Chen, F. Li, et al., "Operationally Constrained Optimal Dispatch of Multiple Pulsed Loads in an Isolated Microgrid," 2018 IEEE Power & Energy Society General Meeting (PESGM), 2018.

Problem: Aggregation under Sequential Uncertainty

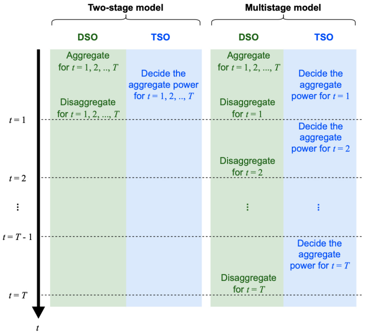
- DSOs aggregate flexibility for TSOs, but traditional two-stage models assume the TSO determines the entire future dispatch trajectory at once.
- In reality, TSO dispatch is revealed sequentially. Strategies must satisfy nonanticipativity constraints.

Proposed Multistage RO Framework

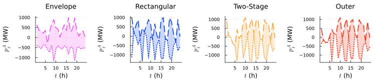
- **Multistage Model:** Captures sequential decision-making. TSO setpoint is DDU, constrained by DSO's reported range.
- **Solution Methods**
  - Rectangular Inner Approx: Uses rectangular SoC ranges to ensure feasibility; solved via iterative C&CG.
  - Envelope Inner Approx: Fast and single-stage conservative approximation.

Results

- Improves flexibility volume by up to **29.9%**.
- Reduces operation costs by up to **40.3%**.



Two-stage model vs. multistage model.



Comparison of flexibility regions.

R. Xie and Y. Chen, "Multistage Robust Optimization for Time-Decoupled Power Flexibility Aggregation with Energy Storage", arXiv:2508.14477, 2025.

Outline

1. Introduction
2. Advanced Robust Optimization: Decision-Dependent Uncertainty & Predict-and-Optimize
3. Reliability-Oriented Storage and Renewables Planning via Distributionally Robust Optimization
4. Real-Time Operation and Market Mechanisms for Distributed Flexible Resources
5. Conclusion

5. Conclusion: Summary of Contributions

Methodological Core

- **RO with DDU:**
  Dual/mapping/projection C&CG
- **Data-Driven DRO:**
  Wasserstein metric & KL divergence
- **Predict-and-Optimize:**
  Weighted predictions & statistical guarantees

Applications

Reliability-Oriented Planning
Co-planning RES/ESS/grid considering tail risks & physical DDU.

Real-Time Operation & Markets
Online Lyapunov optimization & Aumann-Shapley carbon pricing mechanisms.

Reliable & Efficient Low-Carbon Power Systems

5. Conclusion: Future Outlook

1. Data-Driven DDU

Investigate how decisions reshape uncertainty sets in complex socio-technical systems:

- Pricing effects on elastic user behavior.
- Cybersecurity risks in digitalized grids.

2. Scalability (AI+Opt)

Enhance computational efficiency for large-scale systems:

- Learning-to-Optimize: Graph neural networks (GNN) to accelerate integer programming.
- Decentralized multi-agent reinforcement learning.

3. Unified Integration

Closing the loop between planning, operation, and markets:

- Hydrogen economy: P2X coordination.
- VPPs: Aggregating massive heterogeneity under non-anticipativity.

Towards a self-adaptive, robust, and carbon-neutral energy future.

Thank You!

Q & A