Review

Not peer-reviewed version

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Posted Date: 21 November 2025

doi: 10.20944/preprints202511.1649.v1

Keywords: chance-constrained programming; machine learning; power system optimization

 doi:10.20944/preprints202511.1649.v1

Article

A Review on Machine Learning Applications in Chance-Constrained Power System Optimization

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Abstract

The growing integration of renewable energy sources increases uncertainty in power systems, exposing the limits of deterministic and chance-constrained optimization. Although chance constraints balance risk and efficiency, their adoption is restricted by computational complexity, conservatism, and distributional assumptions. Machine learning offers promising solutions for addressing chance-constrained programming challenges. This paper reviews machine learning-enhanced approaches in power systems, classifying methods into uncertainty modeling, constraint reduction, surrogate modeling, and reformulation strategies. Key challenges of generalization, data quality, and interpretability are discussed, along with opportunities such as reinforcement learning, physics-informed learning, federated learning, and digital twin integration.

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1. Introduction

The increasing penetration of renewable energy sources in power systems introduces operational uncertainties that challenge traditional deterministic optimization approaches. Wind and solar power variability, coupled with evolving load patterns and distributed energy resource integration, necessitate uncertainty management techniques to maintain system reliability and economic efficiency [1].

Beyond traditional deterministic approaches, a wide range of methods have been developed to address uncertainties in power system optimization. Stochastic programming explicitly incorporates probabilistic models of uncertain variables, often through scenario-based formulations, to capture variability in renewable generation and load [2]. Robust optimization, on the other hand, safeguards against worst-case realizations within uncertainty sets, ensuring guaranteed feasibility at the expense of potential conservatism [3]. More recent approaches, such as distributionally robust optimization, provide a balance by accounting for ambiguity in probability distributions while avoiding overly pessimistic assumptions [4]. These frameworks collectively form the foundation of uncertainty-aware optimization techniques in power systems and set the stage for chance-constrained formulations.

Chance-constrained optimization (CCO) has emerged as a principled mathematical framework for handling uncertainties in power system operations. It ensures that operational constraints are satisfied with predetermined probability levels [5]. Unlike robust optimization approaches that prepare for worst-case scenarios, chance constraints enable system operators to balance reliability requirements against economic objectives. They achieve this by allowing controlled levels of constraint violation risk. This flexibility helps avoid overly conservative and costly solutions in power systems.

However, traditional CCO face challenges that limit their practical implementation. Individual chance constraints (ICCs) are computationally tractable. However, they fail to provide adequate system-wide reliability guarantees when multiple correlated constraints exist across time periods or system components. Joint chance constraints (JCCs) ensure simultaneous satisfaction of multiple constraints with specified confidence levels, offering superior reliability assurance. However, they generally suffer from computational intractability due to their inherent nonlinear and NP-hard nature

 doi:10.20944/preprints202511.1649.v1

[6]. Classical approaches such as Boole's inequality rely on conservative approximations that fail to capture the complex dependencies of renewable generation [7].

Beyond the power systems domain, chance-constrained optimization has been widely applied in areas such as supply chain management [8,9], transportation systems [10], wireless communications [11], aerospace engineering [12], structural optimization [13], water resources management [14], healthcare and pharmaceutical systems [15], and more recently, data-driven optimization frameworks [16]. These applications highlight the versatility of CCO as a general framework for decision-making under uncertainty. They demonstrate CCO's ability to balance reliability and cost-effectiveness across diverse domains.

Machine learning (ML) techniques have emerged as transformative tools to address these fundamental limitations by leveraging data and advanced statistical learning methods. Recent research demonstrates that ML can enhance CCO for power systems through four primary mechanisms: (i) intelligent uncertainty modeling that captures complex probabilistic dependencies without restrictive parametric assumptions [7,17], (ii) surrogate modeling approaches that accelerate computationally expensive power flow evaluations and optimization processes [18], (iii) constraint reduction techniques that identify and eliminate inactive constraints to reduce problem dimensionality [19], and (iv) adaptive reformulation methods that convert intractable JCCs into computationally manageable forms while preserving solution quality [20,21].

This paper reviews ML applications in CCO for power systems, with an emphasis on methodological innovations that improve scalability, solution quality, and implementation. It also analyzes performance across applications and highlights key directions for future research. The review provides a structured understanding of how ML can enhance uncertainty management in power systems.

2. Background and Fundamentals

2.1. Chance-Constrained Optimization Framework

Chance constraints provide a mathematical framework for handling uncertainty in power system operations by allowing constraints to be violated with controlled probability levels [22]. Given uncertain parameters $\boldsymbol{\xi} \in \mathbb{R}^n$ following some probability distribution $\mathbb{P}$—either known or approximately estimated as in distributionally robust optimization [3]— a general chance constraint is formulated as:

$$\mathbb{P}[\boldsymbol{g}(\boldsymbol{x},\boldsymbol{\xi}) \leq \boldsymbol{0}] \geq 1-\alpha \tag{1}$$

where $\boldsymbol{x}$ represents decision variables, $\boldsymbol{g}(\cdot)$ denotes constraint functions, and $\alpha \in [0,1]$ is the predetermined risk level. Two primary formulations exist in power system applications.

Individual chance constraints (ICCs) apply probability requirements to each constraint separately:

$$\mathbb{P}[g_i(\boldsymbol{x},\boldsymbol{\xi}) \leq 0] \geq 1-\alpha_i, \quad \forall i \in \mathcal{I} \tag{2}$$

where $\mathcal{I}$ represents the set of constraints. ICCs are computationally tractable. However, they provide inadequate reliability guarantees for correlated constraints, particularly in multi-period scheduling where overall system reliability degrades exponentially with the number of time intervals [23].

Joint chance constraints (JCCs) ensure simultaneous satisfaction of multiple constraints with a confidence level:

$$\mathbb{P}[\boldsymbol{g}(\boldsymbol{x},\boldsymbol{\xi}) \leq \boldsymbol{0}] \geq 1-\alpha \tag{3}$$

where $g(\cdot)$ includes all $g_i(\cdot)$. JCCs provide system-wide reliability but suffer from computational intractability due to their nonconvex and NP-hard nature [6,24].

2.2. Traditional Solution Approaches and Limitations

Classical methods for solving chance-constrained problems use several approaches, each with its limitations.

 doi:10.20944/preprints202511.1649.v1

Scenario-based methods approximate the underlying probability distribution using a finite set of scenarios $\{\boldsymbol{\xi}^{(1)}, \ldots, \boldsymbol{\xi}^{(N)}\}$ and reformulate chance constraints as:

$$\frac{1}{N}\sum_{k=1}^{N}\mathbf{1}\left(\bigcap_{j=1}^{m}\left\{g_j(\boldsymbol{x}, \boldsymbol{\xi}^{(k)}) \leq 0\right\}\right) \geq 1-\alpha \tag{4}$$

where $\mathbf{1}[\cdot]$ is the indicator function. This approach can handle arbitrary distributions. However, it requires large sample sizes for statistical significance and introduces numerous binary variables, resulting in a prohibitive computational burden for real-time applications [25,26].

Conservative reformulations using Boole's inequality decompose JCCs into ICCs with adjusted risk levels:

$$\mathbb{P}[g_i(\boldsymbol{x}, \boldsymbol{\xi}) \leq 0] \geq 1 - \frac{\alpha}{|\mathcal{I}|}, \quad \forall i \in \mathcal{I} \tag{5}$$

This approach ensures computational tractability but produces overly conservative solutions, particularly when constraints are weakly correlated or when many constraints are inactive [19].

Second-order cone (SOC) relaxations offer a tractable framework to handle chance constraints. For Gaussian uncertainties, they allow exact reformulations, where the probabilistic constraint becomes a convex SOC constraint [27]. In non-Gaussian settings, conservative SOC approximations can be derived using Chebyshev inequalities or distributionally robust methods that rely only on moment information [4]. These approaches preserve convexity and polynomial-time solvability but may introduce conservatism depending on distributional assumptions and approximation quality [28]. Overall, SOC relaxations balance solution accuracy and computational tractability, making them attractive for large-scale power systems where scenario-based methods are infeasible and traditional conservative approaches are too restrictive [29].

2.3. Machine Learning Integration Motivation

The limitations of traditional approaches motivate the integration of ML techniques to enhance CCO for power systems through four key mechanisms:

Data-driven uncertainty modeling leverages historical operational data to construct nonparametric probability models without restrictive distributional assumptions [5,17]. Techniques such as kernel density estimation, Bayesian nonparametric methods, and deep generative models can capture complex dependencies in renewable generation patterns.

Surrogate modeling replaces computationally expensive power flow evaluations and optimization procedures with fast ML approximations [18]. Neural networks, polynomial chaos expansions, and Gaussian processes enable rapid uncertainty propagation and constraint evaluation.

Intelligent constraint management uses classification and clustering techniques to identify inactive constraints, reduce problem dimensionality, and improve computational efficiency [19]. Support vector machines and ensemble methods can predict binding constraints and eliminate redundant constraints from optimization formulations.

Adaptive reformulation uses learning algorithms to convert intractable JCCs into computationally manageable forms while preserving solution quality [20,21]. Reinforcement learning and online optimization methods can adaptively adjust conservatism levels based on operational feedback.

These ML enhancements address fundamental scalability and conservatism issues. They also enable real-time implementation of sophisticated uncertainty management strategies that were previously deemed computationally prohibitive.

3. Taxonomy of ML-Assisted Chance-Constrained Methods

This section presents a comprehensive taxonomy of ML techniques applied to CCO for power systems, organized into four primary categories based on their functional role in enhancing computational efficiency and solution quality.

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3.1. Learning-Based Uncertainty Modeling

Traditional chance-constrained approaches rely on restrictive parametric assumptions or empirical distributions that fail to capture complex dependencies in renewable generation. ML-based uncertainty modeling addresses these limitations through sophisticated data-driven approaches.

3.1.1. Nonparametric Probability Modeling

Kernel density estimation (KDE) has emerged as a key nonparametric technique for modeling renewable and load uncertainty in power systems. It achieves this without relying on restrictive distributional assumptions. Wu et al. [30] demonstrated that multivariate KDE enables the formulation of nonparametric JCCs over renewable resources and reserves. They further incorporated ϕ-divergence to adjust risk levels for estimation errors. Building on this, Ciftci et al. [31] applied KDE to microgrid energy management, reformulating chance constraints through quantile functions to preserve tractability while avoiding Gaussian assumptions. Their method combines KDE-based density estimation with ϕ-divergence tolerance, enabling robust scheduling under distributional ambiguity. Case studies demonstrate that this approach achieves comparable costs to idealized parametric methods while enhancing robustness against short-term variability.

Bayesian nonparametric methods, such as Dirichlet process Gaussian mixture models, enhance flexibility in CCO by inferring mixture complexity from wind data. They also enable tractable formulations through mixed-integer second-order cone programming [32]. Chance-constrained extreme learning machines embed chance constraints within model training and use a difference-of-convex surrogate. This approach generates sharper and more reliable nonparametric prediction intervals for wind power than both parametric and nonparametric benchmarks [33].

3.1.2. Deep Generative Models

Deep learning methods have been increasingly applied to capture nonlinear dependencies in renewable uncertainty modeling. They surpass the representational limits of traditional statistical approaches. Ning and You [34] introduced f-divergence-based generative adversarial networks to learn continuous reference distributions for distributionally robust CCO. Their approach captures spatial-temporal correlations in wind generation without assuming parametric forms and achieves considerable cost reductions while maintaining feasibility. Aguilar et al. [35] integrated empirical cumulative distribution function-based chance constraints with gated recurrent unit networks for time-series forecasting in virtual power plant operations. This integration enhances resilience to component failures.

3.2. Constraint Reduction and Management

Intelligent constraint management techniques leverage ML to identify inactive constraints, reduce problem dimensionality, and eliminate computational redundancies inherent in large-scale power system formulations.

3.2.1. Statistical Learning for Constraint Classification

Support vector machine-based methods have been explored for reducing conservatism and improving tractability in CCO. Baker and Bernstein [19,36] employed support vector classification to identify inactive constraints in AC optimal power flow, eliminating those with zero violation probability. They then reformulated JCCs into tighter ICCs through Monte Carlo-based probability estimation. Extending this idea, Chen et al. [37] applied One-class support vector clustering to construct polyhedral uncertainty sets that capture renewable variability more effectively than traditional box or convex hull models. Their approach demonstrated cost reduction and improved renewable utilization for HVAC load scheduling while preserving computational efficiency.

3.2.2. Transmission Constraint Screening

ML-assisted constraint screening has emerged as a powerful tool for improving the scalability of unit commitment under extreme conditions. Mohammadi et al. [38] applied ensemble bagged tree classifiers to predict binding transmission constraints during hurricanes with probabilistic line outages. This approach enabled the removal of non-binding constraints, achieving a reduction in solution time while maintaining accuracy. Zhang [39] introduced a two-step approach that integrates power flow maximization with statistical filtering to identify minimal dominating constraint sets for security-constrained unit commitment. This method is validated using MISO data, showing a reduction in problem size without compromising feasibility or reliability.

3.2.3. Dimensionality Reduction Techniques

Kernel compression methods address the computational burden of high-dimensional JCCs. Wu et al. [40] introduced kernel density estimation compression that reduces the number of constraints and special ordered set variables while preserving accuracy. Combined with ML-aided dimensionality reduction for inactive network constraints, the approach achieved significant solution time reductions while maintaining constraint satisfaction rates above 95%.

3.3. Surrogate Modeling and Acceleration

Surrogate models replace computationally expensive power flow evaluations and optimization procedures with fast ML approximations, enabling real-time implementation of sophisticated CCO.

3.3.1. Power Flow Approximation

Neural network-based surrogates have shown strong potential in accelerating power flow and optimization tasks. Chen et al. [41] introduced deep quantile regression models using dual multi-layer perceptrons—one for predicting violation quantiles via pinball loss and another for estimating losses via mean squared error. They reformulated these models as mixed-integer linear constraints using Big-M methods to replicate JCC-OPF without explicit network topology, yielding speedups of three to four orders of magnitude. Khayambashi et al. [42] proposed enhanced multi-fidelity graph neural networks, which integrate low-fidelity DC and high-fidelity AC power flow simulations. They invoke exact AC solvers selectively near critical boundaries to balance efficiency and reliability.

3.3.2. Uncertainty Propagation Surrogates

PCE provides an efficient surrogate framework for propagating uncertainty through nonlinear power system equations. Xu et al. [43] applied PCE-based surrogates for AC power flow analysis, achieving negligible computational cost. They also reduced conservativeness via hybrid adaptive screening of statistically active constraints. Extensions such as adaptive PCE (APCE) and dimensionally decomposed APCE (DD-APCE) further enhance tractability. Wu et al. [44] combined APCE with neural network voltage stability surrogates to construct stable orthonormal polynomial bases under correlated uncertainties. DD-APCE further mitigates dimensionality challenges by restricting interaction orders. Dong et al. [45] developed data-driven sparse PCE, which constructs polynomial bases from data using Bayesian compressive sensing. This approach offers computational efficiency comparable to Monte Carlo while providing improved flexibility in balancing risk and cost in integrated energy systems.

3.3.3. Optimization Acceleration

Learning-to-optimize frameworks have been proposed to overcome the computational burden of mixed-integer programming in stochastic scheduling and dispatch problems. In [46], a neural surrogate model is developed for joint chance-constrained power dispatch in virtual power plants. It employs polyhedral reformulation and explainable AI modules to deliver iteration-free near-optimal solutions with constraint satisfaction. Similarly, Liang et al. [47] accelerated unit commitment by combining clustering and gradient boosting models to predict unit statuses. They then reformulated the problem as linear programming and achieved computational gains. Expanding on outage scheduling, Dalal

 doi:10.20944/preprints202511.1649.v1

et al. [48,49] proposed a data-driven surrogate framework using nearest-neighbor classifiers and Bayesian sampling techniques to reduce simulation complexity. Their approach improved cost and reliability compared to heuristics. Chia et al. [50] introduced a deep learning framework for stochastic unit commitment with transportable energy storage. This technique predicts binary unit decisions and provides solver assistance, reducing computation time with minimal optimality loss.

3.4. Reformulation and Linearization Techniques

Advanced reformulation methods convert intractable JCCs into computationally manageable forms while preserving solution quality through intelligent mathematical transformations.

3.4.1. Data-Driven Constraint Reformulation

Sample average approximation combined with Gaussian process regression (GPR) has been proposed to address data scarcity in uncertainty modeling. Qin et al. [17] integrated GPR to generate additional scenarios for mixed-integer programming under limited samples. They also employed big-M coefficient tightening and constraint reduction to reduce problem size, outperforming scenario-based, robust, and distributionally robust methods. Building on Gaussian process surrogates, Lei et al. [51] developed a two-stage GP-based reformulation for energy and reserve scheduling under wind curtailment. Their approach captures truncated and impulse-shaped distributions through moment-based approximation and error compensation. The results present violation guarantees and achieved lower reserve costs. Xu et al. [43] introduced quantile-based reformulations that tighten bounds without Gaussian assumptions. This approach offers more accurate probability assessments for arbitrary distributions and enhances the tractability of CCO.

3.4.2. Advanced Linearization Strategies

Computationally efficient linearization has been introduced to address the dual challenges of noncontinuous kernel functions and multilinear terms in data-driven JCCs. Wu and Kargarian [52] developed a uniform kernel linearization framework using special ordered sets and convex envelope approximations, reformulated as a single-level mixed-integer linear program via Karush–Kuhn–Tucker conditions. Their approach outperforms recursive McCormick relaxations by reducing solution times while preserving confidence levels and full constraint satisfaction.

3.4.3. Distributionally Robust Reformulations

Kernel-based distributionally robust approaches make a balance between computational tractability and solution robustness. Wu et al. [40,53] proposed optimized Bonferroni approximation with linearization that reformulates kernel-based distributionally robust JCCs as linearized ICCs. This technique, combined with kernel density estimation compression and ML-aided dimensionality reduction, provides scalable solutions for high-dimensional renewable uncertainty. It also maintains acceptable solution quality.

4. Challenges and Future Research Directions

Despite significant advances in ML-enhanced CCO for power systems, several fundamental challenges remain unresolved. At the same time, emerging opportunities present promising avenues for continued research.

4.1. Current Limitations and Open Challenges

4.1.1. Generalization and Robustness Issues

ML-based approaches have demonstrated strong potential in power system optimization; however, they face significant generalization challenges under varying operating conditions, system topologies, and uncertainty patterns. Supervised learning models for constraint screening [38] and unit commitment prediction [47] often require retraining when system parameters evolve. Neural network surrogates for power flow approximation [41] may also lose accuracy under unseen or extreme scenarios. Furthermore, data-driven uncertainty modeling techniques, such as kernel density estimation and its adaptive variants [30,31], assume that historical data remains representative of future conditions. This premise is vulnerable to disruption from climate change, policy shifts, or technological transformations that alter renewable generation characteristics.

4.1.2. Data Requirements and Quality

A key limitation of ML-enhanced methods in power system optimization is the reliance on high-quality historical data, which is often scarce or incomplete. Bayesian nonparametric models [32] require large datasets to capture complex dependencies. Deep learning approaches [34] also require substantial training data for the development of generative models. In practice, operators often lack sufficient data for rare events such as hurricanes [38] or extreme renewable fluctuations. This limitation leads to reliance on synthetic data that may fail to reflect true dependencies. Additionally, challenges arise from data preprocessing and feature engineering, as approaches like sparse polynomial chaos expansion [45] depend on careful selection of basis functions and coefficient estimation. These tasks require specialized expertise that is not always available in operational settings.

4.1.3. Interpretability and Trust

The black-box nature of many ML approaches limits their adoption in safety-critical power system applications, where transparency and interpretability are essential. Although some frameworks incorporate explainable AI modules [46], most neural network-based surrogates remain opaque. This lack of transparency prevents operators from fully validating model decisions, raising concerns about regulatory compliance. These challenges are further compounded by the probabilistic nature of chance constraints, as operators must clearly understand how uncertainty realizations translate into violation probabilities. This issue is particularly critical for JCCs, where conventional intuition often fails to provide adequate guidance.

4.2. Emerging Research Opportunities

4.2.1. Online and Adaptive Learning

Real-time adaptation offers a promising pathway to enhancing the practicality of ML-enhanced CCO. Jiménez et al. [54] demonstrated the effectiveness of Q-learning for dynamically adjusting conservativeness parameters in unit commitment, resulting in cost reductions through closed-loop optimization. Extending such adaptive strategies to uncertainty model updating and constraint screening could further enhance robustness. Online and incremental learning techniques would also enable the continuous refinement of uncertainty models and neural surrogates in response to new data, thereby mitigating distribution shifts without requiring full retraining.

4.2.2. Reinforcement Learning Integration

Deep reinforcement learning offers advanced tools for making sequential decisions under uncertainty. Wu et al. [55] introduced Bayesian advantage policy optimization for stochastic dynamic optimal power flow, achieving lower costs and fewer violations than traditional methods. Extending this method to tasks such as constraint screening, uncertainty set construction, and surrogate model selection could enable the development of comprehensive adaptive frameworks. Multi-agent reinforcement learning also holds promise for coordinating distributed energy resources to satisfy local chance constraints and ensure system-wide reliability.

4.2.3. Physics-Informed Machine Learning

Integrating physical constraints and domain knowledge into ML models offers a pathway to improve generalization, reduce data requirements, and enhance interpretability. Physics-informed neural networks that embed Kirchhoff's laws and generator dynamics can strengthen power flow surrogates under unseen operating conditions. Hybrid approaches that couple first-principles equations with data-driven uncertainty modeling promise superior accuracy and reliability compared to

 doi:10.20944/preprints202511.1649.v1

purely data-driven or physics-based methods. They also ensure model components retain meaningful physical interpretations.

4.2.4. Federated and Distributed Learning

Privacy-preserving distributed optimization provides a promising direction for collaborative learning and scalable decision-making in interconnected power systems. Federated learning enables operators to jointly develop uncertainty models and constraint screening methods without exposing sensitive data. Distributed CCO frameworks decompose large problems across regional boundaries, ensuring computational efficiency and preserving probabilistic guarantees for system-wide reliability.

4.2.5. Advanced Uncertainty Quantification

Conformal prediction offers a distribution-free approach to uncertainty quantification. It provides probabilistic guarantees that can improve the reliability of neural network surrogates for power flow and constraint screening without relying on distributional assumptions. Bayesian neural networks and ensemble methods enable explicit treatment of epistemic uncertainty. This distinction from aleatory variability supports more informed risk management in CCO.

4.2.6. Digital Twin Integration

Real-time digital twins augmented with ML-enhanced CCO offer a pathway for continuous model validation and adaptation using live system measurements. By integrating offline training with online implementation, digital twin frameworks can detect and correct model degradation. Advanced metering infrastructure and phasor measurement units provide high-frequency data streams that enable ongoing updates and mitigate concerns related to distribution shift and generalization.

4.2.7. Emerging Applications

Emerging applications such as electric vehicle charging coordination, renewable-rich microgrids, and sector-coupled power-to-X systems highlight the growing need for ML-enhanced joint CCO. ML can capture complex spatio-temporal uncertainties in driving and charging patterns. This capability supports reliable market participation of distributed resources in microgrids and virtual power plants. It can also manage uncertainties in hydrogen production and integrated energy operations. This enables more resilient and efficient decision-making across diverse energy domains.

5. Conclusion

This paper reviewed ML applications in CCO for power systems. It emphasized their role in overcoming computational complexity, scalability, and conservatism through approaches such as uncertainty modeling, constraint management, surrogate modeling, and reformulation. While these techniques improve solution quality and efficiency, challenges persist in generalization, data dependence, and interpretability. Future opportunities include adaptive and physics-informed learning, reinforcement and federated learning, advanced uncertainty quantification, and digital twin-based adaptation to enable resilient and efficient power systems under uncertainty.

References

1. Morales, J.M.; Conejo, A.J.; Madsen, H.; Pinson, P.; Zugno, M. *Integrating renewables in electricity markets: operational problems*; Vol. 205, Springer Science & Business Media, 2013.
2. Birge, J.; Louveaux, F. *Introduction to Stochastic Programming*; Springer Science & Business Media, 2011.
3. Ben-Tal, A.; El Ghaoui, L.; Nemirovski, A. *Robust Optimization*; Princeton University Press, 2009.
4. Delage, E.; Ye, Y. Distributionally robust optimization under moment uncertainty with application to data-driven problems. *Operations research* **2010**, *58*, 595–612.
5. Geng, X.; Xie, L. Data-driven decision making in power systems with probabilistic guarantees: Theory and applications of chance-constrained optimization. *Annual Reviews in Control* **2019**, *47*, 341–363. https://doi.org/https://doi.org/10.1016/j.arcontrol.2019.05.005.

 doi:10.20944/preprints202511.1649.v1

6. Pena-Ordieres, A.; Molzahn, D.K.; Roald, L.A.; Wächter, A. DC optimal power flow with joint chance constraints. *IEEE Transactions on Power Systems* **2020**, *36*, 147–158.
7. Yang, L.; Xu, Y.; Sun, H.; Wu, W. Tractable convex approximations for distributionally robust joint chance-constrained optimal power flow under uncertainty. *IEEE Transactions on Power Systems* **2022**, *37*, 1927–1941.
8. Pishvaee, M.S.; Rabbani, M.; Torabi, S.A. A robust optimization approach to closed-loop supply chain network design under uncertainty. *Applied Mathematical Modelling* **2011**, *35*, 637–649.
9. Tsiakis, P.; Papageorgiou, L.G. Optimal production allocation and distribution supply chain networks. *International Journal of Production Economics* **2008**, *111*, 468–483.
10. Ghosal, S.; Wiesemann, W. The distributionally robust chance-constrained vehicle routing problem. *Operations Research* **2020**, *68*, 716–732.
11. Liu, Y.F.; Chang, T.H.; Hong, M.; Wu, Z.; So, A.M.C.; Jorswieck, E.A.; Yu, W. A survey of recent advances in optimization methods for wireless communications. *IEEE Journal on Selected Areas in Communications* **2024**.
12. Ng, H.K. Strategic planning with unscented optimal guidance for urban air mobility. In Proceedings of the AIAA Aviation 2020 Forum. AIAA, 2020, p. 2914.
13. De, S. A novel worst case approach for robust optimization of large scale structures. *Journal of Mechanical Science and Technology* **2018**, *32*, 4219–4230.
14. Van Ackooij, W.; Zorgati, R. A review of stochastic programming methods for optimization of process systems under uncertainty. *Frontiers in Chemical Engineering* **2020**, *2*, 622241.
15. Colvin, M.; Maravelias, C.T. A stochastic programming approach for clinical trial planning in new drug development. *Computers & Chemical Engineering* **2008**, *32*, 2626–2642.
16. Alcántara, A.; Ruiz, C. On data-driven chance constraint learning for mixed-integer optimization problems. *Applied Mathematical Modelling* **2023**, *121*, 445–462. https://doi.org/10.1016/j.apm.2023.04.032.
17. Qin, J.C.; Jiang, R.; Mo, H.; Dong, D. A Data-Driven Mixed Integer Programming Approach for Joint Chance-Constrained Optimal Power Flow Under Uncertainty. *International Journal of Machine Learning and Cybernetics* **2025**, *16*, 1111–1127.
18. Mohammadi, S. Surrogate modeling for solving OPF: A review. *Sustainability* **2024**, *16*, 9851.
19. Baker, K.; Bernstein, A. Joint Chance Constraints in AC Optimal Power Flow: Improving Bounds Through Learning. *IEEE Transactions on Smart Grid* **2019**, *10*, 6376–6385.
20. Yi, T.; Dey, S.; Maldonado, D.A.; Mehrotra, S.; Subramanyam, A. Chance-constrained DC optimal power flow using constraint-informed statistical estimation. *arXiv preprint arXiv:2508.21687* **2025**.
21. Li, M.; Mohammadi, J. Learning to optimize joint chance-constrained power dispatch problems. *CSEE Journal of Power and Energy Systems* **2024**. Early Access.
22. Charnes, A.; Cooper, W.W. Chance-constrained programming. *Management Science* **1959**, *6*, 73–79.
23. Prékopa, A. *Stochastic Programming*; Springer, 1995.
24. Nemirovski, A.; Shapiro, A. Convex approximations of chance constrained programs. *SIAM Journal on Optimization* **2006**, *17*, 969–996.
25. Calafiore, G.C.; Campi, M.C. The scenario approach to robust control design. *IEEE Transactions on Automatic Control* **2006**, *51*, 742–753.
26. Bienstock, D.; Chertkov, M.; Harnett, S. Chance-constrained optimal power flow: Risk-aware network control under uncertainty. *Siam Review* **2014**, *56*, 461–495.
27. Ben-Tal, A.; Nemirovski, A. *Lectures on modern convex optimization: analysis, algorithms, and engineering applications*; SIAM, 2001.
28. Nemirovski, A.; Shapiro, A. Convex approximations of chance constrained programs. *SIAM Journal on Optimization* **2006**, *17*, 969–996.
29. Baker, K.; Toomey, B. Efficient relaxations for joint chance constrained AC optimal power flow. *Electric Power Systems Research* **2017**, *148*, 230–236.
30. Wu, C.; Kargarian, A.; Jeon, H.W. Data-Driven Nonparametric Joint Chance Constraints for Economic Dispatch with Renewable Generation. *IEEE Transactions on Industry Applications* **2021**, *57*, 6537–6546.
31. Ciftci, O.; Mehrtash, M.; Kargarian, A. Data-driven nonparametric chance-constrained optimization for microgrid energy management. *IEEE Transactions on Industrial Informatics* **2019**, *16*, 2447–2457.
32. Wang, J.; Wang, C.; Liang, Y.; Bi, T.; Shafie-khah, M.; Catalão, J.P.S. Data-Driven Chance-Constrained Optimal Gas-Power Flow Calculation: A Bayesian Nonparametric Approach. *IEEE Transactions on Power Systems* **2021**, *36*, 4683–4697.
33. Wan, C.; Zhao, C.; Song, Y. Chance Constrained Extreme Learning Machine for Nonparametric Prediction Intervals of Wind Power Generation. *IEEE Transactions on Power Systems* **2020**, *35*, 3869–3882.

34. Ning, C.; You, F. Deep Learning Based Distributionally Robust Joint Chance Constrained Economic Dispatch Under Wind Power Uncertainty. *IEEE Transactions on Power Systems* **2022**, *37*, 191–203.
35. Aguilar, J.; Bordons, C.; Arce, A. Chance Constraints and Machine Learning integration for uncertainty management in Virtual Power Plants operating in simultaneous energy markets. *International Journal of Electrical Power and Energy Systems* **2021**, *133*.
36. Baker, K.; Bernstein, A. Joint Chance Constraints Reduction Through Learning in Active Distribution Networks. In Proceedings of the Proc. IEEE GlobalSIP, Anaheim, CA, USA, 2018; pp. 922–926.
37. Chen, G.; Zhang, H.; Hui, H.; Song, Y. Scheduling HVAC loads to promote renewable generation integration with a learning-based joint chance-constrained approach. *CSEE Journal of Power and Energy Systems* **2022**.
38. Mohammadi, F.; Sahraei-Ardakani, M.; Trakas, D.N.; Hatziargyriou, N.D. Machine Learning Assisted Stochastic Unit Commitment During Hurricanes With Predictable Line Outages. *IEEE Transactions on Power Systems* **2021**, *36*, 5131–5142.
39. Zhang, S. An Analytical Methodology To Security Constraints Management In Power System Operation. PhD thesis, Cleveland State University, 2022. ETD Archive. 1348. https://engagedscholarship.csuohio.edu/etdarchive/1348.
40. Wu, C.; Hasan, F.; Kargarian, A. Scalable nonparametric joint chance-constrained unit commitment with renewable uncertainty. *Electric Power Systems Research* **2025**, *245*, 111573.
41. Chen, G.; Zhang, H.; Hui, H.; Song, Y. Deep-Quantile-Regression-Based Surrogate Model for Joint Chance-Constrained Optimal Power Flow With Renewable Generation. *IEEE Transactions on Sustainable Energy* **2023**, *14*, 657–672.
42. Khayambashi, K.; Hasnat, M.A.; Alemazkoor, N. Hybrid Chance-Constrained Optimal Power Flow under Load and Renewable Generation Uncertainty Using Enhanced Multi-Fidelity Graph Neural Networks. *Journal of Machine Learning for Modeling and Computing* **2024**, *5*, 53–76.
43. Xu, Y.; Mili, L.; Korkali, M.; Chen, X.; Valinejad, J.; Peng, L. A Surrogate-Enhanced Scheme in Decision Making under Uncertainty in Power Systems. In Proceedings of the 2021 IEEE Power & Energy Society General Meeting (PESGM), Washington, D.C., USA, 2021; pp. 1–5.
44. Wu, Y.; Wu, Z.; Xu, Y.; Long, H.; Gu, W.; Zheng, S.; Zhao, J. Computationally Enhanced Approach for Chance-Constrained OPF Considering Voltage Stability. *IEEE Transactions on Power Systems* **2024**, *39*, 6998–7011.
45. Dong, B.; Li, P.; Yu, H.; Ji, H.; Song, G.; Li, J.; Zhao, J.; Wang, C. Chance-constrained optimal dispatch of integrated energy systems based on data-driven sparse polynomial chaos expansion. *Sustainable Energy Technologies and Assessments* **2023**, *60*, 103546.
46. Li, M.; Mohammadi, J. Learning to optimize joint chance-constrained power dispatch problems. *CSEE Journal of Power and Energy Systems* **2025**.
47. Liang, J.; Jiang, W.; Lu, C.; Wu, C. Joint Chance-Constrained Unit Commitment: Statistically Feasible Robust Optimization With Learning-to-Optimize Acceleration. *IEEE Transactions on Power Systems* **2024**, *39*, 6508–6520.
48. Dalal, G.; Gilboa, E.; Mannor, S.; Wehenkel, L. Unit Commitment Using Nearest Neighbor as a Short-Term Proxy. In Proceedings of the 2018 Power Systems Computation Conference (PSCC), Dublin, Ireland, 2018; pp. 1–7.
49. Dalal, G.; Gilboa, E.; Mannor, S.; Wehenkel, L. Chance-Constrained Outage Scheduling Using a Machine Learning Proxy. *IEEE Transactions on Power Systems* **2019**, *34*, 2528–2540.
50. Chia, J.S.; Tan, W.S.; Ding, Z.Y.; Wu, Y.K. Deep Learning Based Hybrid Assisted Stochastic Unit Commitment with Transportable Energy Storage. In Proceedings of the IEEE IAS Annual Meeting, 2024.
51. Lei, X.; Yang, Z.; Zhao, J.; Yu, J. Data-driven assisted chance-constrained energy and reserve scheduling with wind curtailment. *Applied Energy* **2022**, *321*, 119291.
52. Wu, C.; Kargarian, A. Computationally Efficient Data-Driven Joint Chance Constraints for Power Systems Scheduling. *IEEE Transactions on Power Systems* **2023**, *38*, 2858–2866.
53. Wu, C.; Mohammadi, A.; Mehrtash, M.; Kargarian, A. Non-parametric joint chance constraints for economic dispatch problem with solar generation. In Proceedings of the 2019 IEEE Texas Power and Energy Conference (TPEC). IEEE, 2019, pp. 1–6.
54. Jiménez, D.; Angulo, A.; Street, A.; Mancilla-David, F. A closed-loop data-driven optimization framework for the unit commitment problem: A Q-learning approach under real-time operation. *Applied Energy* **2023**, *330*, 120348.

55. Wu, Y.; Ye, Y.; Hu, J.; Zhao, P.; Liu, L.; Strbac, G.; Kang, C. Chance-Constrained MDP Formulation and Bayesian Advantage Policy Optimization for Stochastic Dynamic Optimal Power Flow. *IEEE Transactions on Power Systems* **2024**, *39*, 6788–6793.