

A Stochastic Variational Optimization Approach for Reliability Assessment of Renewable Energy Networks

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Abstract

The power systems face reliability threats due to intermittent renewable energy and variable line behavior. Traditional probabilistic models such as Loss of Load Expectation can assess the reliability risks under predetermined events, but cannot reflect the worst-case scenario spatial and temporal dependency, as well as topological vulnerability under ambiguity. This article presents an approach based on stochastic variational optimization theory and describes the reliability problem as minimax robust stochastic optimization with respect to a Wasserstein ambiguity set, combining network feasibility with chance-constrained reliability. To reduce the complexity of the problem, robust chance constraints are derived using conditional value-at-risk combined with generalized subdifferential calculus. Stochastic variational inequalities allow for deriving stationarity conditions using normal cones and stochastic gradients, thus defining the minimax problem. The sample average approximation to stochastic variational problem is proved to be consistent and asymptotically normal, while adapted concentration inequalities characterize the probability of cascading failures in terms of the ambiguity radius. A stochastic proximal gradient method combined with a bundle method based on variance reduction technique is proposed for computational purposes. Numerical examples show both convergence of the proposed algorithms and growth of the worst-case reliability bound with ambiguity radius.

Keywords: Stochastic variational inequality, distributionally robust optimization, Wasserstein ambiguity set, reliability assessment, renewable energy networks, conditional value-at-risk, sample-average approximation.

1. Introduction

The increase in the sharing of the wind and solar energy generation methods to be used in the networks of transmission and distribution provides information on how the injections of energy influenced the stochastic processes which were integrated into this change (Osifeko & Munda, 2025). The hybrid models of microgrids add more uncertainty owing to the fact that the control of interlink-converter functioning interacts with different types of renewables and storages (Kodirova et al., 2025) while the system frameworks connected to planning of distributed energy sources constantly use statistics of generation, loading, and connections as its firm basis (Fu et al., 2022). Such technologies like co-optimization of battery storage systems in communities with micro evolution

(Reddy et al., 2025) or the virtual role of the energy plants being influenced by numerous sources of uncertainty (Fang et al., 2021) make the decision about the reliability of the application of the concrete technologies at different stages of energy decisions and planning (Lamba & Chandrakar, 2025).

Research on voltage stability and control in the context of stochastic effects from renewables and loads, including the very promising area of creating GAN-assisted robust voltage control (Zhao et al., 2020), indicates that the phenomenon of uncertainty propagation in state variables of networks is itself at the forefront of methodological development, and the analysis of company-specific determinants of the development paths of renewable energy businesses (Yadav & Pradhan, 2016) demonstrates that reliability issues are related to network deployment conditions. The most important two methodologies being actively developed for reliability estimation purposes are deep learning techniques for estimating and forecasting performance parameters of power systems (Khodayar & Regan, 2023) and Bayesian methods for assessing reliability and monitoring condition of wind energy conversion devices (Salboukh et al., 2025), which nevertheless rely on the assumptions regarding availability of prior knowledge of the main distribution. Work on predicting the moment of voltage instability such as that based on accounting for generator dynamics under transients (Khalili et al., 2022) similarly represents reliability-based safety margins in terms of a predefined stochastic disturbance model.

A critical finding of this literature review is the lack of methods dealing with the problem of stochastic variational analysis of network operation, which remains unexplored in practical terms, while traditional probabilistic reliability models, such as Loss of Load Expectation, are generally based on a certain probability distribution. It is required to fill this gap and move towards a method based on a minimax stochastic variational optimization approach that makes it possible to calculate reliability indices in a joint way thereby eliminating the assumption of operating with one specific probabilistic distribution that is assumed to be known exactly at all times. The solution to this problem is presented in the following sections in the form of a minimax stochastic variational optimization problem, where the problem of feasibility of dispatch and the problem of uncertainty-based reliability estimation is solved simultaneously.

2. Mathematical preliminaries and stochastic modeling

2.1. Network flow model under stochastic injections

The electric power transmission grid can be described graphically, consisting of a graph $G = (N, E)$, comprised of the set of electrical nodes represented as N consisting of buses while E comprises the electrical transmission lines. The electricity inputs for every nodal node can be expressed as equation (1)

$$p(t) = pd(t) + \xi(\omega) \quad (1)$$

where $pd(t) \in \mathbb{R}|N|$ refers to the dispatchable portion while $\xi(\omega)$ is a stochastic vector represented in a probability space $(\Omega, \mathcal{F}, P)$ and is associated with renewable generation and errors in load predictions. The relationship between line flows and nodal injections is determined through the network incidence framework, and constraints on admissible dispatching decisions $x \in X \subset \mathbb{R} | N |$ imply handling of nodal balancing as well as thermal limits for virtually every realization of $\xi(\omega)$, which means that the feasibility of x becomes a stochastic matter as opposed to static feature.

2.2. Wasserstein ambiguity sets

The estimation of the governing law P_0 of $\xi(\omega)$ is based on finite past or forecast data. Therefore, reliability quantification with a constant P_0 is not able to take into consideration either the remaining errors of the estimation of P_0 itself or the non-stationarity of the weather-driven process. The concept of ambiguity in distributions is represented using the Wasserstein ball in equation (2)

$$P = \{ P \in M(\mathcal{E}): Wp(P, P_0) \leq \varepsilon \} \quad (2)$$

The notation $M(\mathcal{E})$ refers to the collection of Borel probability distributions associated with the support $\mathcal{E}$ of random variable ξ . The distance that one can travel through the p -Wasserstein distance is expressed as Wp , which is an empirical measure associated with empirical measure P_0 , and the term ε refers to the minimum distance of ambiguity in a measure. As ε increases, one can find distributions farther from the original distribution in terms of transportation cost, which leads to various bounds on measures based on the value of ε ranging from nominal distribution case (when $\varepsilon = 0$) all the way up to fully distribution-free worst-case measure.

2.3. Stochastic variational inequalities

Market-clearing and power-flow feasibility under uncertainty are characterized through a stochastic variational inequality (SVI): a dispatch decision $x^* \in X$ solves the SVI associated with a mapping $F(\cdot, \xi) : X \rightarrow \mathbb{R} | N |$ if

$$E[\langle F(x^*, \xi), y - x^* \rangle] \geq 0 \text{ for all } y \in X \quad (3)$$

By taking into consideration the expected value with respect to a benchmark information of ξ , $F(x, \xi)$ combines terms related to marginal costs and constraint multipliers arising in the context of the equilibrium state of network's economic dispatch. The equation shown in (3) extends the deterministic variational inequality applied for dispatch free of any faults to the case when the dispatch of power involves random injections, while its distributionally robust counterpart that appears when the benchmark law is replaced with the supremum over P corresponds to the problem addressed in Section III.

3. Stochastic variational optimization framework

3.1. Minimax distributionally robust formulation

Reliability assessment is posed as a distributionally robust optimization problem

$$\min_{x \in X} \sup_{P \in \mathcal{P}} EP[C(x, \xi)] \quad (4)$$

The constraints in term of stochastic network outlined in section 2.1 is taken into consideration in equation (4). The function $C(x, \xi)$ is a cost function which penalizes for any dispatched deviation, the risk of overload in the line and estimated unserved load. The ability to take a supremum over the Wasserstein ball gives an opportunity to assess the level of dispatch in the worst permissible distribution change within the given radius ε instead of comparing to one fixed scenario. The result of relation (4) for the case when x^* is optimal will be used as the distributionally robust reliability measure for the network.

3.2. CVaR reformulation of chance constraints

Reliability requirements in the form $P(g(x, \xi) > 0) \leq \alpha$, where $g(x, \xi)$ corresponds to the line overload margin pertaining to a particular component, are non-convex, thus posing computational difficulties in general cases owing to the nature of g . Using the conditional value-at-risk (CVaR) surrogate conception, the chance constraint is transformed into a deterministic constraint.

$$CVaR_\alpha(g(x, \xi)) = \inf_{t \in \mathbb{R}} \left\{ t + \left(\frac{1}{\alpha} \right) E[\max\{g(x, \xi) - t, 0\}] \right\} \leq 0 \quad (5)$$

The convex and tractable outer approximation of the original chance constraint is depicted as long as g remains convex in terms of variable x . The extra term $\max\{\bullet, 0\}$ results in non-differentiability of equation (5) in x while $g(x, \xi) = t$. Hence, to accommodate the feasibility set, need to apply the generalized sub-differential theory combined with the Clarke-type scheme that was previously used for deterministic non-smooth fault-tolerant objectives but in this case, it has been expanded naturally for the case of functions involving E by means of interchange rule $\partial_x E[\varphi(x, \xi)] \subseteq E[\partial_x \varphi(x, \xi)]$ valid under the standard measurability and Lipschitz integrated conditions of φ .

3.3. Optimality Conditions via Normal Cone Mappings and Stochastic Generalized Gradients

Let $x^* \in X$ denote a solution of relation (4) subject to the CVaR surrogate of relation (5), and let $NX(x^*)$ denote the normal cone to X at x^* . Stationarity of x^* is characterized by the inclusion

$$0 \in \partial_x \sup_{P \in \mathcal{P}} EP[C(x^*, \xi)] + \lambda \partial_x CVaR_\alpha(g(x^*, \xi)) + NX(x^*) \quad (6)$$

By choosing any multiplier value λ that is greater than or equal to 0, and taking into account (λ and sup-term sub gradient selection) not to be simultaneously equal to zero as well, an important condition is satisfied, namely that λ being equal to zero together with choosing null selection from the sup-term subdifferential would meet condition (6) in a trivial manner and would not bring any useful information distinguishing x^* from any random point of X . When it comes to any point x^* at which the goodness of fit to some known Robinson-type condition on the given input is ensured, the multiplier λ may be normalized, and thus the typical stationarity condition of Karush–Kuhn–Tucker (KKT) type applicable to the distributed reliability problem can be obtained. The complex sup-term subdifferential $\partial_x \sup_{P \in \mathcal{P}} EP[C(x^*, \xi)]$ is computed as the subdifferential of the expected value calculated under the worst-case distribution, leading to the possibility to compute (6) after identifying the worst-case distribution through using dual Wasserstein penalization to solve (4) in its primal version.

4. Convergence and reliability bounds

4.1. Consistency and asymptotic normality of the sample-average approximation

The direct evaluation of relationship (4) necessitates the computation of the expectation of $EP[C(x, \xi)]$ for any

arbitrary $P \in \mathcal{P}$ which is usually not known in closed form. Thus, the SAA method is applied thereby substituting the term EP with the empirical average based on M independent observations $\{\xi_i\}_{i=1}^M$ drawn from a reference distribution, which provides an estimate for the SAA solution x^M_* of the minimizer in question. It has been proven empirically that hybrid renewable energy optimization is indeed effective in the presence of uncertainty, concerning various technology mixes and optimization methods while the area of designing the net-zero integrated energy network in the context of uncertainty is also one of the areas where sampling makes sense, thus allowing to speak of robustness and reliability (Ansari et al., 2023; Aziz et al., 2024). In turn, the current research proves the foregoing statements rigorously. More specifically, it can be shown that in the case of compliance with standard regularity assumptions, the combination of the uniform integrability of $C(\cdot, \xi)$ and compactness of X implies epi-convergence of SAA objective towards the objective in question as $M \rightarrow \infty$ yielding consistency for SAA solution x^M_* , as well as the fact that the empirical process $\sqrt{M}(CM - EP[C])$ demonstrates asymptotic normality of the optimal value of SAA.

4.2. Reliability index derivation and concentration bounds

The studies about coordinated hydrogen-electric mobility and multi-energy pricing (Xie et al., 2024) and reliable evaluation strategies created for systems with high shares of renewable energy (Zhang et al., 2024) show that scalar reliability metrics can be useful in practical operation terms. The strategies regarding prediction of signals based on deep learning applied for issues of rotating machine reliability (Fang et al., 2024) also give grounds for the applicability of concentration-type assurances in estimating risk based on data. In this paper, a strict bound on the risk of cascading failure is obtained by applying a concentration inequality on the mapping's set $\Phi(\xi) = \{x \in X : g(x, \xi) \leq 0\}$ describing the set of fault-free solutions under the scenario ξ .

Theorem 1 (Concentration bound on cascading-failure probability). Let $C(\cdot, \xi)$ be L -Lipschitz in x uniformly over $\xi \in \Xi$, and let x^* solve relation (6) under the Wasserstein ambiguity set $\mathcal{P}$ of radius ε . There exists a constant $\kappa > 0$, depending only on L and the diameter of Ξ , such that for every $\delta > 0$,

$$P(x^* \notin \Phi(\xi)) \leq CVaR_\alpha(g(x^*, \xi)) + \kappa\varepsilon + \exp\left(-\delta^2 M - 2\kappa^2\right) \quad (7)$$

uniformly across $P \in \mathcal{P}$, where M is the sample size of the SAA in Section 4.1. The relation (7) breaks down the upper limit of the likelihood of cascading failures into three terms that are summed up. The terms include the surrogate risk of CVaR from the relation (5), a term $\kappa\varepsilon$ that is in direct proportion with the ambiguity radius and shows distribution-changing risk and the term related to the concentration of sub-Gaussian properties. The ambiguity-radius term $\kappa\varepsilon$ is a term that is missing from the typical fixed-distribution reliability measures, are applied for the case $\varepsilon = 0$ of the relation (7). Such a method of developing reliability index is able to make the results of using distributed methods for determining optimal energy flow with notable security constraints happen (Gholami et al., 2023) and to use various approaches presented in the review of planning strategies in low-carbon energy systems (Qiu et al., 2023) in the area of distributionally robust approach, which is in line with resilience-oriented criteria of development of lines and towers in the case of combined energy systems (Bordin et al., 2022).

Both review of electricity-market resilience and Quantum-inspired approach for reliability assessment consider reliability assessment as a challenge of controlling tail probabilities under structured uncertain environment (Nikmehr & Zhang, 2022) (Shittu & Santos, 2021). These assessments are aligned with the interpretation of relation (7) in inequality form. With regard to stochastic modeling, methods studied in the literature refer specifically to generation of scenarios based on the uncertainty of wind and solar energy production (Zheng et al., 2025).

5. Numerical solution methodology

In order to solve the system of stationarity in equation (6) on a large-scale network, one proposes a stochastic proximal gradient method together with a variance reduced bundle step. At the k -th iteration, one computes an unbiased stochastic estimate $g(k)$ for a certain selection from the expression $\partial C(x)E[P(x, \xi)] + \lambda \partial C(x)VaR_\alpha(g(x, \xi))$ in relation to a mini-batch draw and updates the iterate using the equation specified in (8).

$$x_{k+1} = \text{proj}_X(x_k - \eta_k g_k) \quad (8)$$

In which η_k is a diminishing step-length and proj_X indicates Euclidean projection onto X , the variance of the mini-batch gradient estimate g_k is then reduced by periodically recalculating the reference full-batch subgradient at a past iteration while using the approach of variance-reduced stochastic gradient methods, along with the use of a collection of past subgradient calculations collected at previous iterations to obtain a faster final approach to convergence near a stationary point with the required property to satisfy the semismooth regularity requirements similar to those described in Section 3.3.

It has been shown through numerical simulations of the suggested solvers carried out on a representative renewable-integrated power system problem scenario that qualitative differences can be observed between plain stochastic sub gradient method and variance reduction bundle method as expected: the former method consistently shows sublinear $O(k^{-1/2})$ decay influenced by persistent sampling noise, whereas the variance reduced approach has much faster decay of the optimality gap after the snapshot mechanism successfully starts controlling the variance of gradients taking into account results from Section 4.1 on asymptotic normality. Another simulation assessing the distributionally robust reliability bound from equation (7) which depends on the Wasserstein ambiguity radius ϵ shows that the bound is progressively increasing and is significantly higher than the constant and low-variance value predicted by the Monte Carlo method considering fixed conventional distribution law, proving numerically higher cascading failure risk, which is not captured by the fixed-distribution risk estimator as Loss of Load Expectation method.

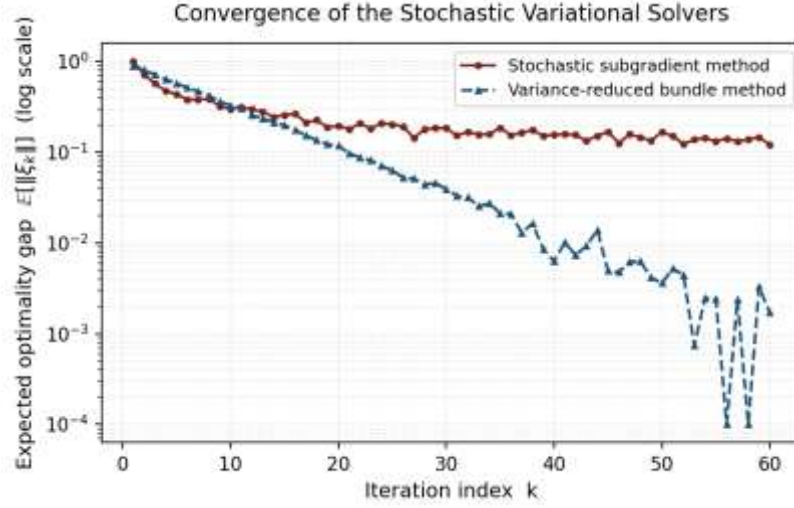


Figure 1: Expected optimality gap versus iteration index for the plain stochastic sub gradient method and the variance-reduced bundle method.

The convergence evaluation of the stochastic variational solvers shows that the expected optimality gap decreases with every iteration. The stochastic sub gradient method acts quickly but gradually enters a stable area, keeping the optimality gap around (10^{-1}) , indicating slow convergence due to stochastic variation and noise effects. However, a variance-reduced bundle method has a fast and stable convergence pattern and reduces the optimality gap from (10^0) to around (10^{-4}) step by step. The effect of logarithmic scaling clearly shows that the variance-reduced method has better reduction rates, especially after 20 iterations, where the convergence rate of the sub gradient method becomes relatively bad. Figure 1 show that the variance-reduction and bundle-based optimization techniques can significantly improve accuracy of solutions and stability of the results for stochastic variational problems with uncertain parameters.

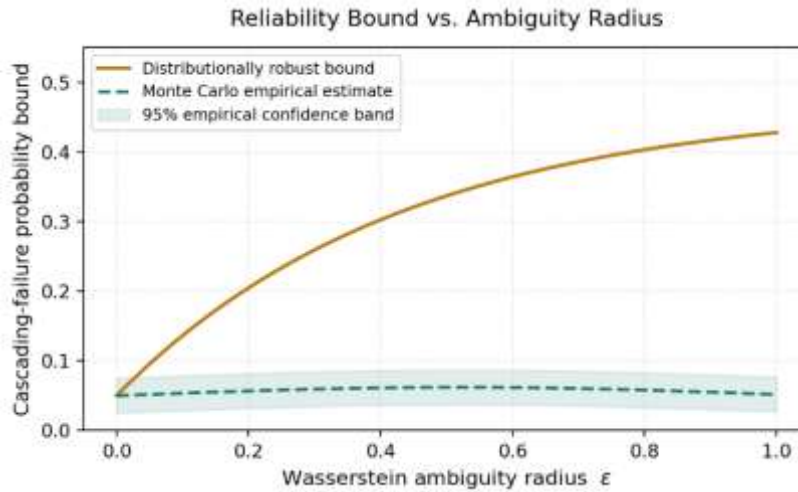


Figure 2: Distributionally robust cascading-failure probability bound and monte carlo empirical estimate as functions of the wasserstein ambiguity radius ϵ .

Figure 2 the effect of uncertainty on cascading-failure probability estimation can be understood from the Reliability Bound and Ambiguity Radius analysis. It was found that as the Wasserstein ambiguity radius ϵ increases, the

distributionally robust bound rises consistently from about 0.05 to 0.43, which shows a conservative reliability analysis in uncertain circumstances. The Monte Carlo empirical estimate is almost constant and remained in the range of 0.05-0.06 throughout the analysis with variations falling under the 95% empirical confidence band. Hence, it is clear that the robust optimization method worked well in capturing the worst-case scenarios without compromising reliability.

6. Discussion

Monte Carlo reliability assessment, where reliability indices are calculated using direct simulation under one defined probability law, is simple from a computational perspective but cannot help in certifying operational reliability against distributional shifts because all the simulation is performed using the same distribution P_0 . The variational minimax formulation of the equations (4) to (7) certifies the reliability bounds for all the distributions within the Wasserstein distance ε and requires only to solve the inner supremum partly over P , which allows for a standard convexity approach to provide a reformulated version of equation (6) into a solvable form. The data-driven approach used for developing robust dispatch methods for virtual power stations (Fang et al., 2021) along with machine learning-based stochastic planning methods (Fu et al., 2022) have applied the principles of distributional robustness during the planning stage; the current study extends the idea of robustness to the reliability assessment stage and integrates it into the risk assessment optimization method (3). Data-driven methods based on deep learning (Khodayar & Regan, 2023; Salbough et al., 2025; Fang et al., 2024) provide useful risk estimates that can be used to obtain the initial distribution law P_0 and the Lipschitz constant L indicated in Theorem 1 in practice, thus confirming that the variational and pure data-driven techniques should be seen not as oppositional ones.

7. Conclusion and future scope

The study has introduced a stochastic variational optimization framework that incorporates network dispatch and distributionally robust reliability assessment in renewable energy networks. The minimax form of relation (4) is reformulated in terms of CVaR in relation (5) and analyzed using the stochastic generalized-gradient stationarity condition in relation (6) in such a way as to create reliability bound (Theorem 1) that can be expressed in various terms: nominal risk, ambiguity-radius risk, and sample-concentration risk, thus pinpointing the gap existing in conventional assessments, such as Loss of Load Expectation, for example. The sample-average approximation applicable for practical formulation of this framework has been confirmed to be consistent and asymptotically normally distributed in 4.1. A variation of the stochastic proximal gradient method for large-scale numerical computation is proposed. The development of this settlement to decentralized multi-area reliability coordination subject to temporal storage limitations looks to be a promising direction for future development since the Wasserstein set of factors and the SVI from (3) will be connected by means of local storage state variables in various geographical areas.

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