

# Data-Driven Probabilistic Methods for Accounting Forecast Uncertainties in Power System Analysis and Optimization

## **Abstract:**

With ambitious government policies signaling increased renewable energy integration into the electric power grid, many operational challenges are expected to unfold. Renewable and load power forecasts are critical for power system security analysis and operation planning. However, due to the increasing penetration of renewable energy and the evolving role/nature of load demand, forecast uncertainty has become a significant issue, causing undesirable deviations from secure and cost-effective solutions. Thus, there is an increasing need to systematically accommodate forecast error uncertainty into traditional power system tools like power flow and optimal power flow (OPF). This thesis attempts to develop data-driven probabilistic methods that can effectively account for forecast uncertainties in the power system analysis and optimization tools. The proposed methods are beneficial for power system operators and electricity market players to conduct effectual risk analysis, security studies, and decision-making under forecast uncertainties.

Monte-Carlo and quasi-Monte Carlo (QMC) methods are preferred for solving probabilistic power system analysis tools, such as probabilistic power flow (PPF) and probabilistic OPF (POPF), due to their non-intrusive nature and ability to use the full deterministic model. However, the drawbacks of inconsistent accuracy, variable convergence rate, and lack of a quality measure hinder QMC's wide applicability. To this end, the first part of the thesis proposes a nonparametric QMC framework to efficiently and accurately solve PPF and POPF with non-Gaussian and dependent forecast uncertainties. The proposed framework introduces uniform experimental design (UD) sampling, which is scalable and improves the accuracy-efficiency balance of the application. Leveraging on the copula viewpoint, the proposed method directly evaluates the desired correlation matrix in standard Gaussian space, significantly reducing the computational burden. In addition, this work introduces and advocates mixture discrepancy (MD) as a robust sample quality measure, which is helpful to practitioners in identifying the best QMC sample set for solving probabilistic applications without needing any tedious simulation for comparing accuracy. The proposed UD-based QMC is validated through comprehensive case studies on the modified test systems for solving PPF and POPF. Accuracy evaluation in estimating the first four moments and approximating the full distribution of the outputs suggest that the proposed QMC framework offers accurate

probabilistic analysis compared to the existing QMC methods for a given sample size. Furthermore, both case studies substantiate MD as a first-of-its-kind sample quality measure for power system applications.

Advanced stochastic OPF formulations are recently being proposed to facilitate power system operations planning under forecast uncertainties. Most of the proposed stochastic OPF formulations require forecast errors in the form of scenarios, and the quality of the decisions made under uncertainty is sensitive to the quality of the infeed scenarios. Consequently, there is a need for accurate and efficient methods of scenario generation (SG). Most of the existing probabilistic forecasting methods are univariate and do not model the dependence structure between forecast errors. Despite the pressing need for effective multivariate SG techniques, the literature offers limited proposals in this regard. To this end, the second part of the thesis attempts to propose multivariate SG methods that benefit downstream stochastic OPF-based power system decision-making. A total of three day-ahead multivariate wind power SG methods are proposed, which vary in the method and type of dependence structure modeled. Recent literature shows that copula-based SG methods are suitable for typical operations planning routines. All the wind power SG proposals are data-driven, employ quantile regression for conditional marginal forecasts, and model the spatial/temporal dependence using state-of-the-art copula functions, enabling a modular framework of forecasting marginal distributions separately from the dependence structure. The SG proposals benefit from modular structures and can be extended to forecasting solar and load power scenarios.

The first SG proposal generates conditional joint wind power scenarios with variance reduction, conditioned on the day-ahead point forecasts. The proposed framework models the dependence among wind farms using vine copula and presents a novel analytical conditional sampling algorithm (CSA). Unlike the existing work, this CSA is inherently accurate, avoids the tedious manual conditional sample selection, and enables control over the number of conditional scenarios generated. Also, a UD-based variance reduction is integrated into the proposed CSA, which benefits the downstream OP applications with improved convergence and accuracy of the solutions. A detailed two-stage scenario evaluation procedure is carried out on a real-world dataset: univariate and multivariate quality metrics-based statistical evaluation in the first stage and a chance-constrained OPF application-based evaluation in the second stage. Results suggest that the proposed SG method significantly improves the overall quality of the forecasted wind power scenarios and provides a better cost-risk balance in the application compared to the benchmarks.

The second SG proposal models the temporal dependence among the time blocks of the forecasting horizon using regular vine copula and generates UD-based wind power scenarios. Since wind power forecast errors tend to propagate in time, generating wind power scenarios reflecting the intertemporal dependence (temporal) over the forecast horizon is paramount for downstream multi-period operations planning routines. The regular vine copula is introduced to model the temporal dependence structure of the wind power forecast error, which is shown to fit the real-world data better than the existing copula models. A modified regular vine sampling algorithm, including the UD-based sampling, is integrated into the proposed SG. A detailed multivariate scenario evaluation using multiple metrics shows that the proposed SG improves the quality of the temporal scenarios compared to the existing benchmarks. The Diebold-Mariano statistical test also verifies the significant improvement in the quality of the wind power scenarios.

The first two SG proposals majorly benefit the single-period and multi-period stochastic OPF-based applications, respectively. However, multiperiod OPF applications with multiple wind farms can benefit from accurate spatio-temporal SG methods that generate multivariate scenarios which reflect both the spatial and temporal dependence simultaneously. Consequently, the third SG proposal presents a novel conditional spatio-temporal wind power scenario generation (SG) framework using the stationary vine copula model. The proposed wind power SG is modular, scalable, facilitates efficient conditional sampling, and accurately predicts the spatio-temporal dependence structure. A case study on the real-world dataset against six state-of-the-art benchmarks verifies the efficacy of the proposed SG.

In summary, this thesis proposes data-driven probabilistic methods that effectively account for joint forecast uncertainties in power system analysis and optimization tools. These methods are designed to support power system operators and electricity market participants in their risk analyses and decision-making processes.