

DATA-DRIVEN PROBABILISTIC METHODS FOR ACCOUNTING FORECAST UNCERTAINTIES IN POWER SYSTEM ANALYSIS AND OPTIMIZATION

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INDIAN INSTITUTE OF TECHNOLOGY DELHI
AUGUST 2023**

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ACCOUNTING FORECAST UNCERTAINTIES IN
POWER SYSTEM ANALYSIS AND OPTIMIZATION**

by

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Submitted

in fulfillment of the requirements of the degree of
Doctor of Philosophy

to the



INDIAN INSTITUTE OF TECHNOLOGY DELHI

AUGUST 2023

Certificate

This is to certify that the dissertation entitled '**Data-Driven Probabilistic Methods for Accounting Forecast Uncertainties in Power System Analysis and Optimization**', being submitted by **Mr. Attoti Bharath Krishna** for the award of the degree of **Doctor of Philosophy** is a record of bonafide research work carried out by him in the Department of Electrical Engineering at Indian Institute of Technology Delhi, New Delhi.

Mr. Attoti Bharath Krishna has worked under my supervision and has fulfilled the requirements for the submission of this dissertation, which to my knowledge has reached the requisite standard. The results obtained here have not been submitted to any other University or Institute for the award of any degree.

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Date: August 02, 2023

Acknowledgments

This doctoral thesis work has been possible because of many people, influences, and surroundings playing an intertwined and intricately helpful role. I would like to thank all those people who have contributed, supported, and inspired me in many ways.

I want to thank my parents, Mrs. A. Malathi Latha and Mr. A. Srinivasa Rao, for providing a joyful upbringing and patient nurturing. I am indebted to their constant support throughout my long academics. It is with their mental, moral, and financial support that I am able to reach this point in life and education. I would also like to sincerely thank my brother, Dr. A. Yeswanth, for his support and encouragement since childhood. Strangely, I cannot recollect any instance of us fighting or arguing about anything. The belief that I can turn to him for practical wisdom and helpful suggestions on any subject gives me strength. I express gratitude to my cousins and extended family for all the support. I am fortunate to be a part of this family.

I wish to express my sincere thanks to my love, my wife, A. Anusha, for the mental support and unconditional love. She gives me strength. She has seen my journey from my undergraduate days and patiently endured all my tantrums. She gives me responsibility. I can't fully express in words the intensity and gravity at which all the difficult times, memories, and experiences are hitting me right now; I find myself constantly wiping my teary eyes as I write this paragraph. She gives me joy. I can't thank her enough for taking care of our newborn, Vikram Krishna, all by herself while I stay away to finish thesis work and other collaborations. She completes me.

The major pillar of support and encouragement is my supervisor Prof. Abhijit. R. Abhyankar. This thesis is the result of his constant support and freedom. The first class I attended at the Indian Institute of Technology Delhi is of the course Power System Analysis, taught by Prof. Abhyankar. I was delighted to start the new journey under his supervision, and little did I know how I gradually got inspired by his teaching style and overall demeanor. I got to know that we share some hobbies like cricket and photography and have matching opinions about conducting research. The advice I received from Prof. Abhyankar at the beginning of my journey still resonates with me—that to excel in a

research topic, one must have a strong foundational understanding and be able to articulate it to anyone. I tried my best to foster the advice in my research, presentations, and talks. His compassion, faith, and treatment as an extended family have helped me to ride the strenuous waves of the Ph.D. calmly. His broad knowledge of power system analysis, optimization, and electricity markets has helped me and paved the way for the thesis contributions. I express my sincere thanks to Prof. Abhyankar for the guidance, technical discussions, and wisdom, without which this thesis work would not have been possible.

I sincerely thank my research committee members, Prof. B. K. Panigrahi, Prof. Senroy, and Dr. Ashu Verma, for constructive comments, detailed review, and helpful advice during the progress of this research work. The research committee has been patient with me all throughout and steered me in the right direction.

There have been many seniors and colleagues from the Power System Simulation Lab at the Indian Institute of Technology Delhi who have helped me through the Ph.D. journey. I want to thank Dr. A. P. Pratosh, Dr. Deep Kiran, Dr. Deepak Reddy, Dr. Kush Khanna, Dr. Shri Ram Vaishya, Dr. Ashok Jadav, and Dr. Tanuj Rawat for the technical support, generic advice, and inspiration. I also thank my lab mates and friends Megha Gupta, Shaziya Rasheed, Shruti Ranjan, Partik, Meenakshi Khandelwal, Shruti Kahaliya, Shilpa Bindal, Archita Vijayavargia, and others for the friendly discussions and the occasional technical brainstorming. I had a good time having long strolls and technical talks with Pankaj Achlekar, Abhishek Nayak, Parikshit Pareek, Diptak Pal, and others.

I finally thank my younger self for deciding to pursue higher education. The Master's and Ph.D. have taught me the importance of cultivating a sincere work ethic. The journey has not been easy at all; it was filled with self-doubt, a search for meaning, and the not-so-good consequences of thinking deeply about problems. But the same journey has opened a new perspective of life and thinking, which I will cherish all my life. With the support from all the mentioned people and the experience from the Ph.D. journey per se, I feel blessed to embark on the journey to the good, the bad, and the uncertain future.

August 02, 2023

Place: New Delhi

Attoti Bharath Krishna

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.

सार

महत्वाकांक्षी सरकारी नीतियों के साथ विद्युत ऊर्जा ग्रिड में नवीकरणीय ऊर्जा एकीकरण में वृद्धि का संकेत मिलता है, कई परिचालन चुनौतियों का खुलासा होने की उम्मीद है। नवीकरणीय और लोड पावर पूर्वानुमान बिजली प्रणाली सुरक्षा विश्लेषण और संचालन योजना के लिए महत्वपूर्ण हैं। हालांकि, नवीकरणीय ऊर्जा के बढ़ते प्रवेश और लोड मांग की उभरती भूमिका / प्रकृति के कारण, पूर्वानुमान अनिश्चितता एक महत्वपूर्ण मुद्दा बन गया है, जिससे सुरक्षित और लागत प्रभावी समाधानों से अवांछनीय विचलन होता है। इस प्रकार, विद्युत प्रवाह और इष्टतम विद्युत प्रवाह (ओपीएफ) जैसे पारंपरिक विद्युत प्रणाली उपकरणों में पूर्वानुमान त्रुटि अनिश्चितता को व्यवस्थित रूप से समायोजित करने की आवश्यकता बढ़ रही है। यह थीसिस डेटा-संचालित संभाव्य तरीकों को विकसित करने का प्रयास करता है जो बिजली प्रणाली विश्लेषण और अनुकूलन उपकरणों में पूर्वानुमान अनिश्चितताओं के लिए प्रभावी रूप से जिम्मेदार हो सकते हैं। प्रस्तावित तरीके बिजली प्रणाली ऑपरेटर्स और बिजली बाजार के खिलाड़ियों के लिए प्रभावी जोखिम विश्लेषण, सुरक्षा अध्ययन और पूर्वानुमान अनिश्चितताओं के तहत निर्णय लेने के लिए फायदेमंद हैं।

संभावित पावर सिस्टम विश्लेषण उपकरणों को हल करने के लिए मॉटे-कार्लो और अर्ध-मॉटे कार्लो (क्यूएमसी) विधियों को प्राथमिकता दी जाती है, जैसे संभावित बिजली प्रवाह (पीपीएफ) और संभावित ओपीएफ (पीओपीएफ), उनके गैर-हस्तक्षेप प्रकृति और पूर्ण निर्धारक मॉडल का उपयोग करने की क्षमता के कारण। हालांकि, असंगत सटीकता, परिवर्तनीय अभिसरण दर और गुणवत्ता उपाय की कमी की कमियां क्यूएमसी की व्यापक प्रयोज्यता में बाधा डालती हैं। इस उद्देश्य के लिए, थीसिस का पहला भाग गैर-गौसियन और निर्भर पूर्वानुमान अनिश्चितताओं के साथ पीपीएफ और पीओपीएफ को कुशलतापूर्वक और सटीक रूप से हल करने के लिए एक गैर-पैरामेट्रिक क्यूएमसी ढांचे का प्रस्ताव करता है। प्रस्तावित ढांचा समान प्रयोगात्मक डिजाइन (यूडी) नमूना पेश करता है, जो स्केलेबल है और आवेदन की सटीकता-दक्षता संतुलन में सुधार करता है। कॉपुला दृष्टिकोण पर लाभ उठाते हुए, प्रस्तावित विधि सीधे मानक गॉसियन अंतरिक्ष में वांछित सहसंबंध मैट्रिक्स का मूल्यांकन करती है, जो कम्प्यूटेशनल बोझ को काफी कम करती है। इसके अलावा, यह काम एक मजबूत नमूना गुणवत्ता उपाय के रूप में मिश्रण विसंगति (एमडी) का परिचय और वकालत करता है, जो सटीकता की तुलना के लिए किसी भी थकाऊ सिमुलेशन की आवश्यकता के बिना संभाव्य अनुप्रयोगों को हल करने के लिए सर्वश्रेष्ठ QMC नमूना सेट की पहचान करने में चिकित्सकों के लिए सहायक है। प्रस्तावित यूडी-आधारित क्यूएमसी पीपीएफ और पीओपीएफ को हल करने के लिए संशोधित परीक्षण प्रणालियों पर व्यापक मामले अध्ययन के माध्यम से मान्य है। पहले चार क्षणों का आकलन करने और आउटपुट के पूर्ण वितरण का अनुमान लगाने में

सटीकता मूल्यांकन से पता चलता है कि प्रस्तावित क्यूएमसी ढांचा किसी दिए गए नमूना आकार के लिए मौजूदा क्यूएमसी विधियों की तुलना में सटीक संभाव्य विश्लेषण प्रदान करता है। इसके अलावा, दोनों केस स्टडीज एमडी को पावर सिस्टम अनुप्रयोगों के लिए अपनी तरह का पहला नमूना गुणवत्ता उपाय के रूप में प्रमाणित करते हैं।

पूर्वानुमान अनिश्चितताओं के तहत विद्युत प्रणाली संचालन योजना को सुविधाजनक बनाने के लिए उन्नत स्टोकेस्टिक ओपीएफ फॉर्मूलेशन का प्रस्ताव किया जा रहा है। अधिकांश प्रस्तावित स्टोकेस्टिक ओपीएफ फॉर्मूलेशन के लिए परिदृश्यों के रूप में पूर्वानुमान त्रुटियों की आवश्यकता होती है, और अनिश्चितता के तहत किए गए निर्णयों की गुणवत्ता इनफीड परिदृश्यों की गुणवत्ता के प्रति संवेदनशील होती है। नतीजतन, परिदृश्य सृजन (एसजी) के सटीक और कुशल तरीकों की आवश्यकता है। मौजूदा संभावित पूर्वानुमान विधियों में से अधिकांश अविभाज्य हैं और पूर्वानुमान त्रुटियों के बीच निर्भरता संरचना को मॉडल नहीं करते हैं। प्रभावी मल्टीवेरिएट एसजी तकनीकों की अत्यधिक आवश्यकता के बावजूद, साहित्य इस संबंध में सीमित प्रस्ताव प्रदान करता है। इस उद्देश्य के लिए, थीसिस का दूसरा भाग मल्टीवेरिएट एसजी विधियों का प्रस्ताव करने का प्रयास करता है जो डाउनस्ट्रीम स्टोकेस्टिक ओपीएफ-आधारित पावर सिस्टम निर्णय लेने का लाभ उठाते हैं। कुल तीन दिन पहले मल्टीवेरिएट पवन ऊर्जा एसजी विधियों का प्रस्ताव है, जो मॉडल की गई निर्भरता संरचना की विधि और प्रकार में भिन्न होते हैं। हाल के साहित्य से पता चलता है कि कॉपुला-आधारित एसजी विधियां विशिष्ट संचालन योजना दिनचर्या के लिए उपयुक्त हैं। सभी पवन ऊर्जा एसजी प्रस्ताव डेटा-संचालित हैं, सशर्त सीमांत पूर्वानुमान के लिए quantile प्रतिगमन को रोजगार, और राज्य के अत्याधुनिक कोपुला कार्यों का उपयोग कर स्थानिक / अस्थायी निर्भरता मॉडल, निर्भरता संरचना से अलग सीमांत वितरण की भविष्यवाणी के एक मॉड्यूलर ढांचे को सक्षम करना। एसजी प्रस्तावों को मॉड्यूलर संरचनाओं से लाभ होता है और इसे सौर और लोड पावर परिदृश्यों की भविष्यवाणी करने के लिए बढ़ाया जा सकता है।

पहला एसजी प्रस्ताव दिन-अगले बिंदु पूर्वानुमानों पर वातानुकूलित, विचरण में कमी के साथ सशर्त संयुक्त पवन ऊर्जा परिदृश्य उत्पन्न करता है। प्रस्तावित ढांचा बेल कोपुला का उपयोग करके पवन खेतों के बीच निर्भरता को मॉडल करता है और एक उपन्यास विश्लेषणात्मक सशर्त नमूना एल्गोरिथ्म (सीएसए) प्रस्तुत करता है। मौजूदा काम के विपरीत, यह सीएसए स्वाभाविक रूप से सटीक है, थकाऊ मैनुअल सशर्त नमूना चयन से बचा जाता है, और उत्पन्न सशर्त परिदृश्यों की संख्या पर नियंत्रण सक्षम बनाता है। इसके अलावा, प्रस्तावित सीएसए में एक यूडी-आधारित अंतर में कमी को एकीकृत किया गया है, जो समाधान के बेहतर अभिसरण और सटीकता के साथ डाउनस्ट्रीम ओपी अनुप्रयोगों को लाभान्वित करता है। वास्तविक दुनिया के डेटासेट पर एक विस्तृत दो-चरण परिदृश्य मूल्यांकन प्रक्रिया की जाती है: पहले चरण में यूनिवेरिएट और मल्टीवेरिएट क्वालिटी मेट्रिक्स-आधारित सांख्यिकीय मूल्यांकन और दूसरे चरण में मौका-विहीन ओपीएफ आवेदन-आधारित

मूल्यांकन। परिणाम बताते हैं कि प्रस्तावित एसजी विधि पूर्वानुमानित पवन ऊर्जा परिदृश्यों की समग्र गुणवत्ता में काफी सुधार करती है और बेंचमार्क की तुलना में आवेदन में बेहतर लागत-जोखिम संतुलन प्रदान करती है।

दूसरा एसजी प्रस्ताव नियमित बेल कोपुला का उपयोग करके पूर्वानुमान क्षितिज के समय ब्लॉकों के बीच अस्थायी निर्भरता का मॉडल करता है और यूडी-आधारित पवन ऊर्जा परिदृश्य उत्पन्न करता है। चूंकि पवन ऊर्जा पूर्वानुमान त्रुटियां समय पर प्रचार करती हैं, इसलिए पूर्वानुमान क्षितिज पर अंतरिम निर्भरता (अस्थायी) को प्रतिबिंबित करने वाले पवन ऊर्जा परिदृश्य उत्पन्न करना डाउनस्ट्रीम बहु-अवधि संचालन नियोजन दिनचर्या के लिए सर्वोपरि है। नियमित बेल कोपुला को पवन ऊर्जा पूर्वानुमान त्रुटि की अस्थायी निर्भरता संरचना को मॉडल करने के लिए पेश किया जाता है, जो वास्तविक दुनिया के डेटा को मौजूदा कोपुला मॉडल से बेहतर फिट करने के लिए दिखाया जाता है। यूडी-आधारित नमूनाकरण सहित एक संशोधित नियमित बेल नमूनाकरण एल्गोरिदम, प्रस्तावित एसजी में एकीकृत है। एकाधिक मैट्रिक्स का उपयोग करके एक विस्तृत बहु-भिन्न परिदृश्य मूल्यांकन से पता चलता है कि प्रस्तावित एसजी मौजूदा बेंचमार्क की तुलना में अस्थायी परिदृश्यों की गुणवत्ता में सुधार करता है। डायबोल्ड-मारियानो सांख्यिकीय परीक्षण भी पवन ऊर्जा परिदृश्यों की गुणवत्ता में महत्वपूर्ण सुधार की पुष्टि करता है।

पहले दो एसजी प्रस्तावों से क्रमशः एकल-अवधि और बहु-अवधि स्टोकेस्टिक ओपीएफ-आधारित अनुप्रयोगों को लाभ होता है। हालांकि, कई पवन खेतों के साथ मल्टीपीरियड ओपीएफ अनुप्रयोग सटीक स्पैटिओ-अस्थायी एसजी विधियों से लाभ उठा सकते हैं जो मल्टीवेरिएट परिदृश्य उत्पन्न करते हैं जो स्थानिक और अस्थायी निर्भरता दोनों को एक साथ प्रतिबिंबित करते हैं। नतीजतन, तीसरा एसजी प्रस्ताव एक उपन्यास सशर्त स्पैटिओ-अस्थायी पवन ऊर्जा परिदृश्य उत्पादन (एसजी) ढांचा प्रस्तुत करता है जो स्थिर बेल कोपुला मॉडल का उपयोग करता है। प्रस्तावित पवन ऊर्जा एसजी मॉड्यूलर, स्केलेबल है, कुशल सशर्त नमूनाकरण की सुविधा प्रदान करता है, और स्पैटिओ-अस्थायी निर्भरता संरचना की सटीक भविष्यवाणी करता है। यह अत्याधुनिक बेंचमार्क के खिलाफ वास्तविक दुनिया के डेटासेट पर एक केस स्टडी प्रस्तावित एसजी की प्रभावकारिता की पुष्टि करती है।

संक्षेप में, यह थीसिस डेटा-संचालित संभाव्य तरीकों का प्रस्ताव करती है जो बिजली प्रणाली विश्लेषण और अनुकूलन उपकरणों में संयुक्त पूर्वानुमान अनिश्चितताओं के लिए प्रभावी रूप से जिम्मेदार हैं। इन तरीकों को पावर सिस्टम ऑपरेटर्स और बिजली बाजार के प्रतिभागियों को उनके जोखिम विश्लेषण और निर्णय लेने की प्रक्रियाओं में समर्थन करने के लिए डिज़ाइन किया गया है।

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List of Symbols

Sets:

\mathcal{I}	Set of N_b buses, indexed by i .
\mathcal{I}_G	Set of buses corresponding to N_g thermal generators, indexed by g .
\mathcal{I}_l	Set of N_l lines, indexed by l .
\mathcal{T}	Set of look-ahead time blocks in the day-ahead planning horizon, indexed by t .
$DS(n, C^s)$	Set of all possible candidate designs (n points) on $C^s = [0,1]^s$.
$\mathcal{U}(n, n^s)$	Set of all symmetrical U-type designs.

Random variables (bold), vectors (overbar), and related functions:

$\hat{\mathbf{P}}_j^t$	Random variable (bold) representing the forecasted power of wind farm j for time block t .
\mathbf{P}_j^t	Actual power of wind farm j for time block t , $j \in \{1, \dots, s\}$ and $t \in \mathcal{T}$.
\mathbf{E}_j^t	Forecast error of wind farm j for time block t , $j \in \{1, \dots, s\}$ and $t \in \mathcal{T}$.
$\bar{\mathbf{X}}$ or $\bar{\mathbf{X}}^t$	Random vector (overbar) consisting of \mathbf{P}_j^t and \mathbf{E}_j^t , $\forall j \in \{1, \dots, s\}$.
$\bar{\mathbf{U}}$	Random vector with independent standard uniform marginals.
$\bar{\mathbf{Z}}$	Random vector with independent standard Gaussian marginals.
$\bar{\mathbf{E}}$	Random vector of wind power forecast errors.

\mathcal{C}^{d_ξ}	Unit hypercube in d_ξ -dimensions, $[0,1]^{d_\xi}$.
F_i or F_{X_i}	Marginal cumulative distribution function (CDF) of \bar{X} , $i \in \{1, \dots, d = 2s\}$.
f_i or f_{X_i}	Marginal probability density function (PDF) of \bar{X} , $i \in \{1, \dots, d = 2s\}$.
$F_{i j}$	Conditional CDF of X_i , given some realization of $X_j = x_j$.
$F_{\bar{X}}$	Joint CDF of random vector \bar{X} .
$f_{\bar{X}}$	Joint PDF of random vector \bar{X} .
C	Copula, representing the dependence structure.

Decision Variables:

$P_{G,g}$	Power generation dispatch for generator g , $g \in \mathcal{J}_G$.
$R_{up,g}$	Up reserve allocation for generator g , $g \in \mathcal{J}_G$.
$R_{down,g}$	Down reserve allocation for generator g , $g \in \mathcal{J}_G$.
\bar{z}	Decision vector of the OPF formulation.

Parameters and other symbols:

p_i	Actual wind power at bus i , $i \in \mathcal{J}$.
\hat{p}_i	Forecasted wind power at bus i , $i \in \mathcal{J}$.
e_i	Wind power forecast error at bus i .
\bar{C}_1, \bar{C}_2	Cost vectors of thermal generation, of size $N_G \times 1$.
$\bar{\bar{C}}_2$	Diagonal matrix with \bar{C}_2 as diagonal elements.

$\bar{C}_{up}, \bar{C}_{dn}$	Cost vectors of UP reserve and DOWN reserve, of size $N_G \times 1$.
$P_{D,i}$	Forecasted power demand at bus $i, i \in \mathcal{J}$.
PTDF	Power transfer distribution factor matrix with N_l rows and N_b columns.
F_l^{max}	Maximum power flow in line l .
$P_{G,g}^{max}, P_{G,g}^{min}$	Maximum and minimum power limits of generator g .
β_g	Participation factor of generator g .
\wp	Design matrix or a sample matrix in unit hypercube.
$D_p^*(\wp)$	Star L_p -discrepancy D_p^* of a design matrix \wp .
CD or $D_{CD}(\wp)$	Centered L_2 -discrepancy of a design matrix \wp .
μ	Mean
σ or Std	Standard Deviation
T_{th}	Total number of test hours for evaluation.
$\epsilon^{set}, \epsilon^v$	Risk parameter of the joint chance-constraints, a-posteriori violation probability.
\bar{U}	A design (design matrix or pointset) with each column from the standard uniform space.
ρ	Pearson's correlation coefficient.
τ	Kendall's tau.
Ω	Integration domain
$Pr\{.\}$	Probability of

$var(.)$	Variance of
$cov(.)$	Covariance of
$E[.]$	Expectation of
$Q_{n,s}^{MC}$	Monte Carlo Integration estimate (quadrature rule) with n quadrature points in s dimensions
il	Index to represent the inner loop iteration number of ESE algorithm.
ol	Index to represent the outer loop iteration number of ESE algorithm.
J	Number of new neighborhood designs generated in each inner loop iteration of ESE algorithm.
M	Maximum number of inner loop iterations in ESE algorithm.
N	Maximum number of outer loop iterations in ESE algorithm.
T_{h0}	The initial threshold value used in the inner loop of the ESE algorithm, which is later updated in the outer loop iterations.
$\epsilon_{\bar{z}^*}^v$	Violation probability of the optimal solution \bar{z}^* of the CC-ERCO

List of Abbreviations

AIC	Akaike Information Criterion.
AKDE	Adaptive Kernel Density Estimation.
AT	Austria (country code, ENTSO-e).
CD	Centered L_2 -Discrepancy.
CDF	Cumulative Distribution Function.
CRPS	Continuous Ranked Probability Score.
CSA	Conditional Sampling Algorithm.
C-vine	Canonical vine copula.
CC-ERCO	Chance-Constrained Energy and Reserve Co-Optimization
DE	Germany (country code, used by ENTSO-e).
D-vine	Drawable vine copula.
DM-test	Diebold-Mariano test.
ENTSO-e	European Network of Transmission System Operators for electricity.
ES	Energy Score.
ESE	Enhanced Stochastic Evolutionary algorithm.
GAN	Generative Adversarial Networks
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity

GMM	Gaussian Mixture Model.
i.i.d	Independent and identically distributed.
KH-I	Koksma-Hlawka Inequality.
LHD	Latin Hypercube Design.
L_2D	Star L_2 -Discrepancy.
$L_\infty D$	Star L_∞ -Discrepancy.
LogS	Logarithmic Score.
MCS	Monte Carlo Simulation.
MD	Mixture Discrepancy.
OPF	Optimal Power Flow.
PCC	Pair-Copula Constructions.
PDF	Probability Density Function.
PEM	Point Estimate Method.
PIT	Probability Integral Transform
POPF	Probabilistic Optimal Power Flow.
PPF	Probabilistic Power Flow.
QMC	Quasi-Monte Carlo.
QR	Quantile Regression.
R-vine	Regular vine copula.
RV	Random Variable

SG	Scenario Generation.
UD	Uniform Design/Uniform experimental Design.
UK	United Kingdom (country code, used by ENTSO-e).
VAR	Vector AutoRegression
VC	Vine Copula.
VS	Variogram Score.
WD	Wrap-around L_2 -Discrepancy.
WF	Wind Farm.