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Uncertainty Management in Distribution Networks: A Comprehensive Review of Advanced Sampling Methods for Renewable Energy Integration

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Abstract

As renewable energy sources (RESs) continue to penetrate distribution networks worldwide, the need for robust uncertainty management has become increasingly vital. The efficiency and reliability of these networks heavily depend on properly designed control and protection systems that can handle the inherent uncertainties of RESs and demand patterns. With the focus on three main approaches -Markov Chain Monte Carlo (MCMC) methods, Monte Carlo (MC) methods, and sampling using the inverse Cumulative Distribution Function (CDF)- This study surveys various sampling techniques essential for uncertainty analysis in distribution networks. Each methodology is thoroughly explained along with its relevant subsections, detailing their mathematical foundations, implementation approaches, advantages, and limitations. The paper maps the evolution of these techniques from their inception to state-of- the-art implementations. Simulations are done to showcase the efficiency of HMC over MCMC at the end, which demonstrates a precision growth in the newest method.

Introduction

Survey sampling methods include Simple Random Sampling (SRS), bootstrapping, stratified sampling, multistage sampling, and snowball sampling. SRS ensures equal selection probability for all samples in a population. Bootstrapping evaluates accuracy measures like variance, bias, and confidence intervals using sampling with replacement. Stratified sampling divides populations into subgroups (strata), reducing sampling error by considering subpopulation proportions. Multistage sampling involves clustering a population, selecting a cluster randomly, and sampling within it. Snowball sampling relies on growing networks among participants, often introducing bias. This method is commonly used for hard-to-reach populations, such as drug users.

Probability distribution sampling occurs when phenomena are represented by distributions, and samples are drawn accordingly. Direct sampling from real-world probability distributions is often complex, leading researchers to sample from simpler distributions and extrapolate results using methods like the Monte Carlo approach. Monte Carlo sampling uses iterative, independent samples, akin to rejection sampling. Markov Chain Monte Carlo (MCMC) methods, such as the Metropolis algorithm, Metropolis-Hastings algorithm, and Gibbs sampling, retain memory of prior iterations, linking samples sequentially. To address speed limitations in the Metropolis algorithm, efficient methods like the Hamiltonian Monte Carlo (HMC) method have been developed. These approaches refine sampling processes for diverse applications.

Methods

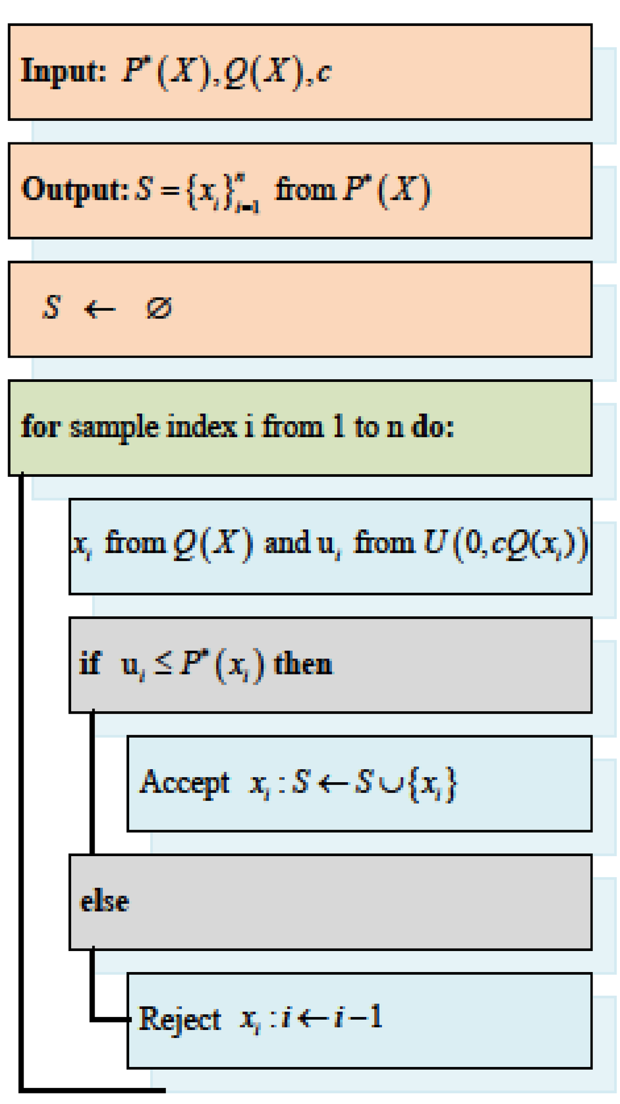

Fig.1. Rejection sampling algorithm

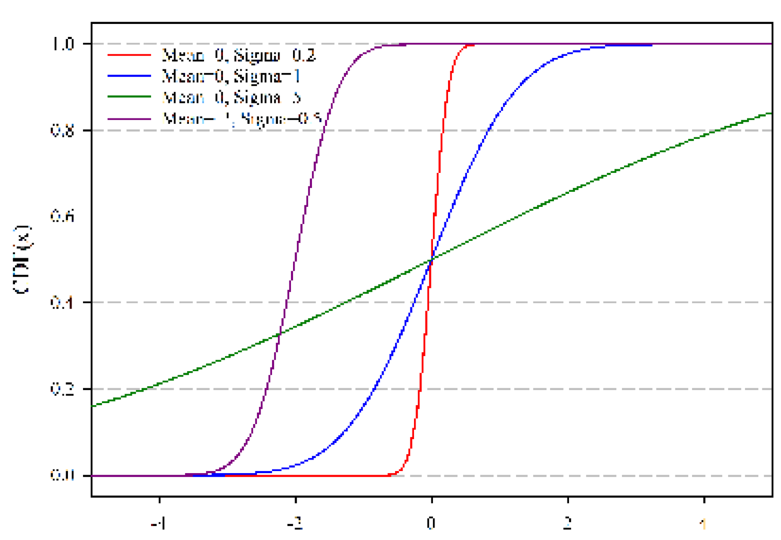

Fig.2. ICDF sampling

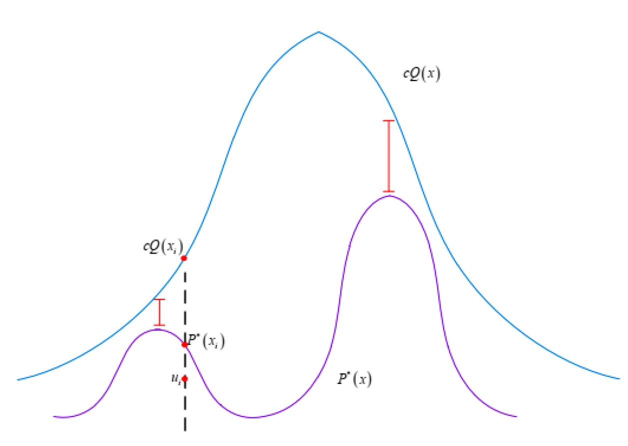

Fig.3. Process of Rejection sampling

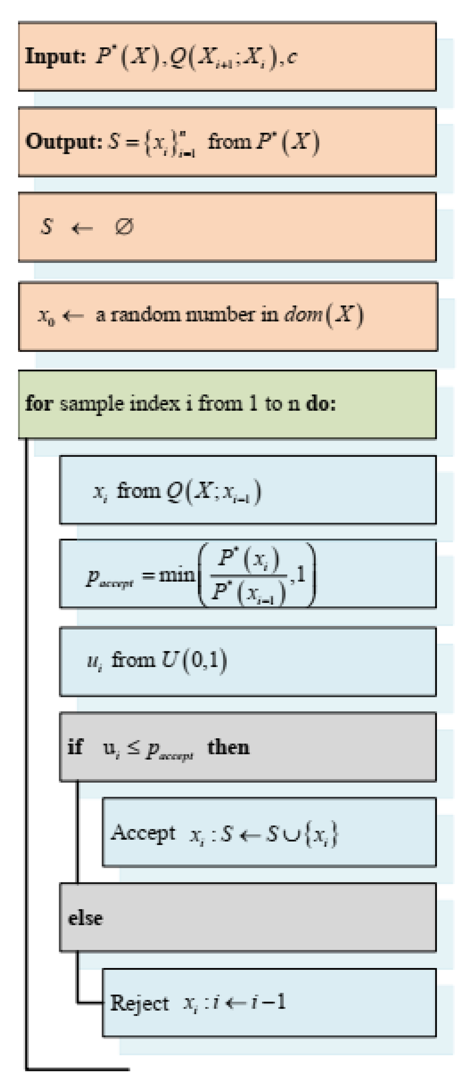

Fig.4. Metropolis Algorithm

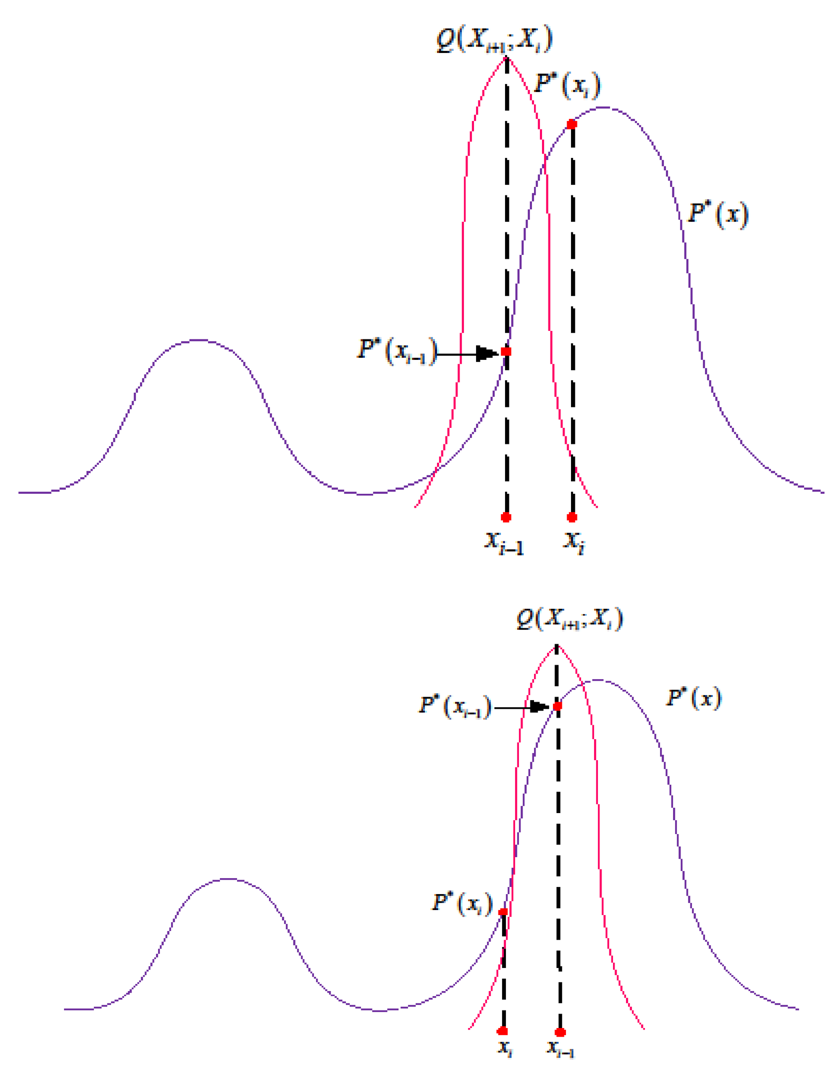

Fig.5. Process of Metropolis sampling

Results

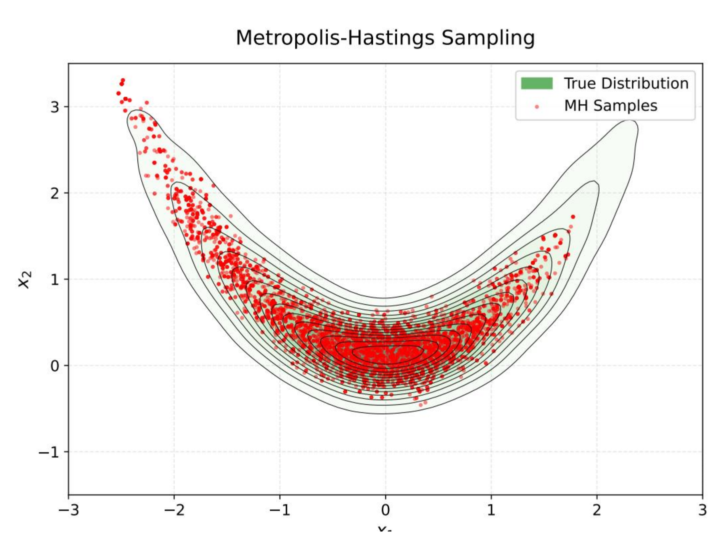

Fig.7 Metropolis-Hastings samples (red points) overlaid on the true banana-shaped distribution (green contours).

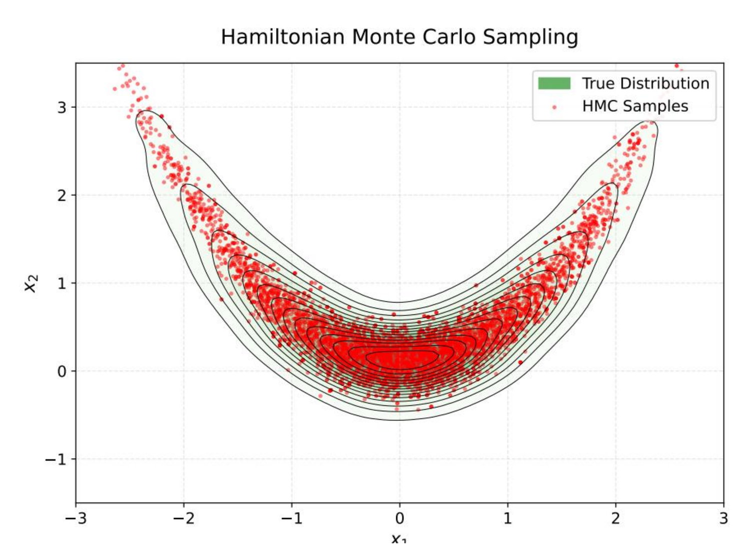

Fig. 8. Histogram of samples from the Hamiltonian Monte Carlo algorithm overlaid with the true Gaussian distribution.

Conclusions

We explored various statistical sampling techniques, including Monte Carlo and MCMC methods, analyzing their frameworks and applications for effective statistical inference and distribution approximation.

References

[1] Betancourt, M. (2017). A conceptual introduction to Hamiltonian Monte Carlo. arXiv preprint arXiv:1701.02434.
[2] Botev, Z., & Ridder, A. (2017). Variance reduction. Wiley statsRef: Statistics reference online, 1-6.