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Fast Classification of Static Voltage Stability Using Machine Learning with Generator Unit Commitment Status

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Abstract

Recent power systems with high penetration of renewable energy sources are increasingly facing challenges in satisfying voltage and reactive power constraints. This trend is mainly attributed to the reduced number of online synchronous generators, which can reduce system strength and reactive power availability. Consequently, operating conditions with small voltage stability margins tend to become more frequent, motivating the development of fast and reliable methods to assess static voltage stability under normal and contingency conditions for real-time operation.

Data-driven approaches based on machine learning, including neural network–based and ensemble learning methods, have been studied as promising methods for online static voltage stability assessment. However, in practical system operation, it is not always feasible to utilize all system state variables for learning. Therefore, the selection of compact and informative input features that capture overall system conditions remains a key challenge for practical deployment. In this context, this study focuses on generator unit commitment (UC) status as an input feature, motivated by the observation that online generator configurations affect system-wide voltage profiles, reactive power capability, and power flow distribution, and can serve as a compact, system-level representation for voltage stability assessment. Despite these characteristics, its explicit use as an input feature has not been sufficiently investigated in existing machine-learning-based voltage stability studies.

This study proposes a feature selection approach for static voltage stability classification incorporating UC status. Static voltage stability following assumed N−1 contingencies is evaluated using voltage stability margins and classified into three categories: stable, warning, and unstable. UC patterns and contingency-related information are treated as categorical features, while additional electrical variables are incrementally selected based on their contribution to classification performance. Additional electrical features include nodal and branch variables related to voltage, power flow, and voltage control. A gradient boosting–based ensemble learning algorithm, LightGBM, is employed for model training, and feature importance metrics are used to guide feature selection.

The proposed approach is evaluated using training data generated from the Nordic test system through iterative power flow calculations under varying load levels, UC patterns, and contingency scenarios. The results confirm that UC status exhibits relatively high feature importance among all input features. Furthermore, a feature set incorporating UC status achieves estimation accuracy comparable to a reference case assuming full availability of system-wide measurements, while requiring approximately 54% of the training time. These results suggest the potential of UC status as an effective input for fast static voltage stability classification.