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**Summary:**

Critical component identification holds paramount importance in ensuring the reliability, security, and resilience of power grids. While all components contribute to the stable operation of the grid and the consistent transmission of power, certain components are of greater significance due to their potential to initiate cascading events and substantial load shedding upon failure.

This study is focusing on the integration of feature selection techniques with machine learning algorithms to pinpoint these critical components. Existing methodologies rely on topological models, optimization techniques, and cascade failure analysis. However, these approaches have their limitations. Topological models often lack reliability, optimization techniques may fail to converge, and cascade failure analysis can be exceedingly time-consuming, often requiring a prior understanding of network characteristics.

In this research, a network-agnostic approach based on machine learning techniques is introduced. For this purpose, two distinct datasets are created, primarily differing in contingency generation and dataset size. These datasets incorporate load shedding data resulting from each contingency, calculated using an AC Cascading Failure Model, and classify them based on the magnitude of load shedding. The dataset features are only the network components and their status.

We employ feature selection techniques to identify the most critical components, subsequently training a machine learning model exclusively on these identified components. To validate our findings, we compare the results with a machine learning model trained on the entire dataset using Shapley Additive exPlanations (SHAP). In nearly all cases, SHAP corroborates the feature selection techniques.

Our machine learning classifier excels in predicting contingencies that lead to higher load shedding, boasting sensitivity ranging from 80.35% to 90.03% and specificity between 80.35% and 92.94%. Additionally, these predictions are made within a matter of nanoseconds, a crucial advantage when addressing fast cascading phenomena.