INTISARI

Penelitian ini mengembangkan kerangka klasifikasi tingkat keparahan kontingensi berbasis machine learning dengan integrasi penilaian dampak ekonomi pada Subsistem Tasikmalaya. Data simulasi N-1 dan N-2 pada 10 skenario menggunakan DIgSILENT PowerFactory menghasilkan 49.052 sampel dengan distribusi 35,8% Secure, 13,0% Insecure, dan 51,1% Highly Insecure. Model klasifikasi menggunakan tiga algoritma: K-Nearest Neighbors, Random Forest, dan Decision Tree. Random Forest mencapai akurasi 98,99% (F1-Macro 98,80%) pada evaluasi within-system. Model C memberikan indikasi kuat bahwa performa model tidak semata-mata berasal dari fitur agregat atau label (penurunan F1-Macro hanya 0,93 pp untuk Random Forest; Decision Tree 1,26 pp; KNN 5,31 pp). Validasi Leave-One-Scenario-Out menunjukkan penurunan F1-Macro ke 85,25%, sedangkan external cross-system stress test pada IEEE 14-bus dan IEEE 39-bus mengkonfirmasi domain shift nyata, memerlukan pelatihan ulang pada sistem dengan topologi berbeda.

Analisis fitur dominan mengidentifikasi tegangan bus Gardu Induk Tasikmalaya dan pembebanan saluran KSGHN-TSKBR, DEPOK-TSKBR, serta TASIK-BDSLN sebagai indikator paling berpengaruh. Penelitian mengintegrasikan dampak ekonomi melalui Economic Severity Index (ESI) yang menggabungkan Energy Not Supplied (ENS) dan Value of Lost Load (VoLL WTA = Rp 9.697/kWh) dengan faktor biaya total 1,40. Lima kontingensi paling parah secara ekonomi (#2653, #2128, #1282, #1083, #2662) berasal dari skenario malam dengan load lost $>$ 60 MW dan ESI Rp 3,270–3,629 miliar. Analisis sensitivitas menunjukkan ranking ekonomi stabil (Spearman $\rho = 1{,}00$) terhadap pilihan VoLL. Matriks risiko teknis-ekonomi mengidentifikasi 965 skenario pada kuadran HI-Rendah/E4-Catastrophic sebagai prioritas mitigasi.

Temuan utama menunjukkan klasifikasi ML mencapai akurasi tinggi pada sistem tertentu tetapi memerlukan transfer learning lintas sistem. Kontingensi paling parah secara teknis (OPI tinggi) tidak selalu paling mahal secara ekonomi (ESI tinggi), sehingga pendekatan dual-axis dalam matriks risiko teknis-ekonomi esensial untuk pengambilan keputusan operasional. Rekomendasi meliputi: (1) pengembangan VoLL residensial empiris untuk wilayah studi; (2) integrasi PMU real-time untuk framework RTCC penuh; (3) eksplorasi deep learning untuk meningkatkan generalisasi lintas sistem.

Kata kunci: klasifikasi kontingensi, machine learning, Overall Performance Index, Economic Severity Index, Value of Lost Load

ABSTRACT

This study develops a machine learning-based contingency severity classification framework integrated with economic impact assessment for the Tasikmalaya Power Subsystem. N-1 and N-2 simulation data across 10 operating scenarios, generated using DIgSILENT PowerFactory, yielded 49,052 samples distributed as 35.8% Secure, 13.0% Insecure, and 51.1% Highly Insecure. Three classification algorithms were evaluated: K-Nearest Neighbors, Random Forest, and Decision Tree. Random Forest achieved the highest within-system performance, with 98.99% accuracy (98.80% F1-Macro). An anti-leakage configuration (Model C) provided strong evidence that model performance does not rely solely on aggregate features or label artifacts, with F1-Macro decreasing by only 0.93 percentage points for Random Forest, 1.26 pp for Decision Tree, and 5.31 pp for KNN. Leave-One-Scenario-Out validation showed a decrease in F1-Macro to 85.25%, while an external cross-system stress test on the IEEE 14-bus and IEEE 39-bus systems confirmed substantial domain shift, indicating that retraining is required when the model is applied to systems with different topologies.

Feature importance analysis identified the Tasikmalaya substation bus voltage and the loading of the KSGHN-TSKBR, DEPOK-TSKBR, and TASIK-BDSLN transmission lines as the most influential indicators. The study further integrates economic impact through an Economic Severity Index (ESI), which combines Energy Not Supplied (ENS) and Value of Lost Load (VoLL, using the Willingness-to-Accept estimate of Rp 9,697/kWh) with a total cost factor of 1.40. The five economically most severe contingencies (#2653, #2128, #1282, #1083, #2662) originated from night-time scenarios with load loss exceeding 60 MW and ESI values of Rp 3.27–3.63 billion. Sensitivity analysis confirmed that the economic ranking remains stable (Spearman's $\rho = 1.00$) across different VoLL assumptions. The technical-economic risk matrix identified 965 scenarios in the Low-OPI/E4-Catastrophic quadrant as priority targets for mitigation.

The key finding is that ML-based classification achieves high accuracy within a specific system but requires cross-system transfer learning to generalize reliably. Contingencies that are technically severe (high OPI) are not always the most economically costly (high ESI), demonstrating that a dual-axis technical-economic risk matrix is essential for operational decision-making. Recommendations include: (1) developing empirical residential VoLL estimates for the study region; (2) integrating real-time PMU data toward a full RTCC framework; and (3) exploring deep learning approaches to improve cross-system generalization.

Keywords: contingency classification, machine learning, Overall Performance Index, Economic Severity Index, Value of Lost Load