Data-driven transient stability assessment focusing on location aspects and important system variables

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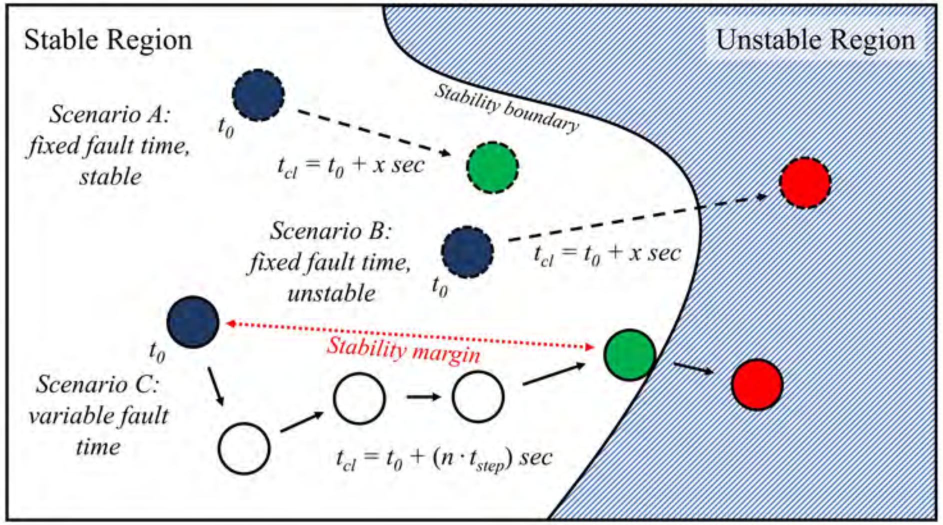
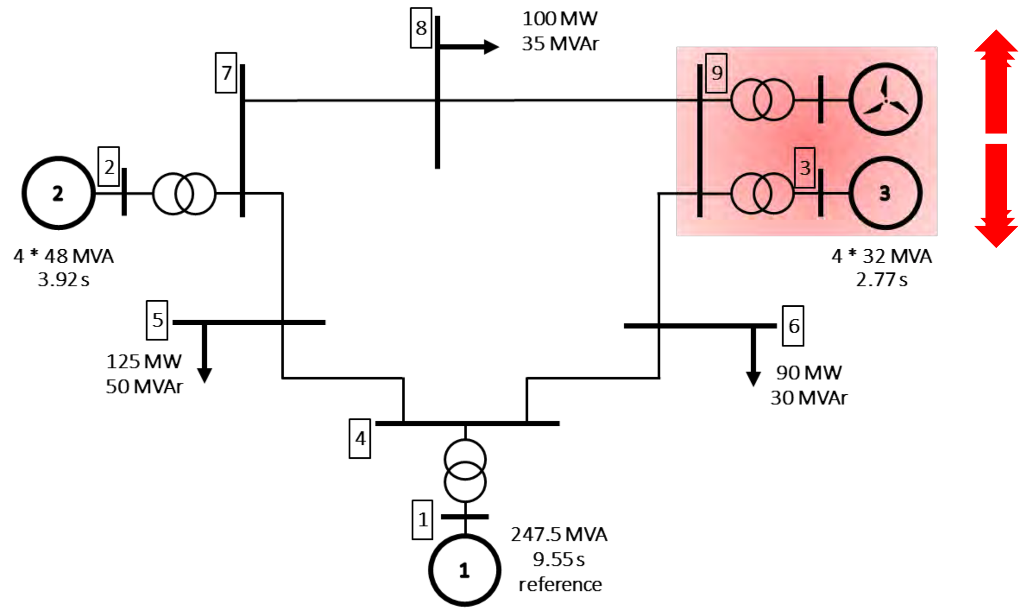
Transient Stability Assessment under increasing complexity and uncertainty

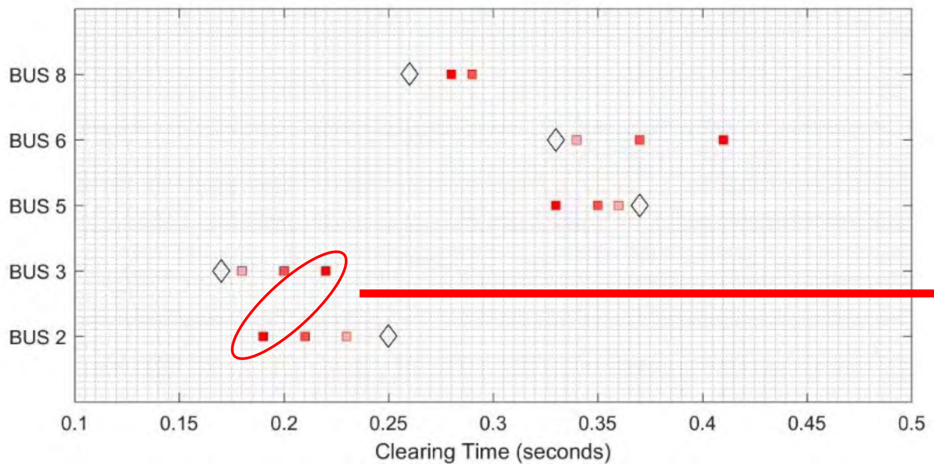
Complex phenomenon, not easy to identify clear trends

- Time-domain simulation
  - RMS: models the system dynamic components with differential-algebraic equations, solving iteratively in time
  - EMT: captures additional transient details
- Transient Energy Function
  - Less time consuming, very good insights but requires simplifications
- Machine Learning
  - Fast and accurate, but often 'black boxes'
- Locational aspects and margin offer important information



A simple example



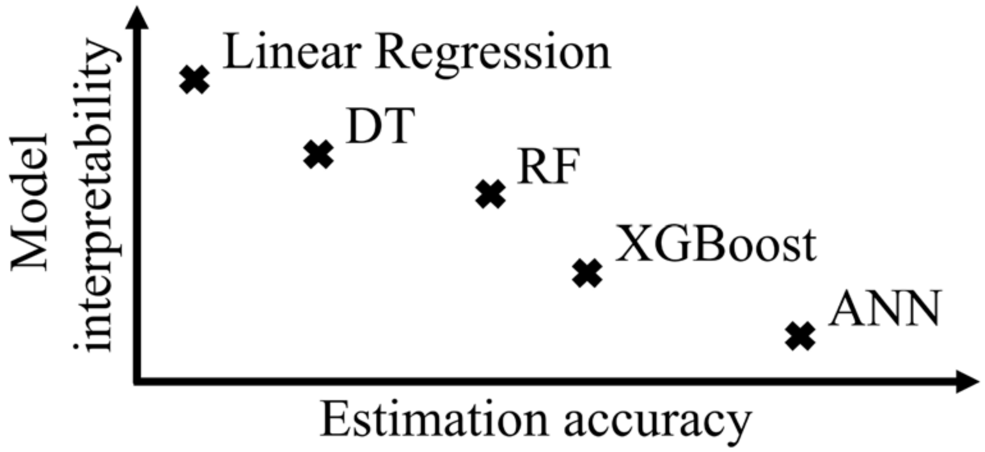


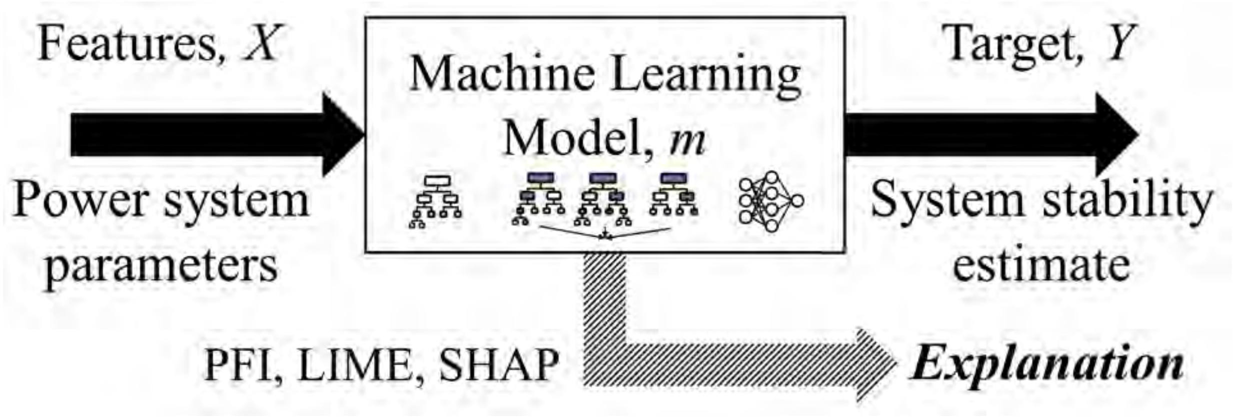
Change in critical bus

R. I. Hamilton, P. N. Papadopoulos, K. Bell, "An Investigation into Spatial and Temporal Aspects of Transient Stability in Power Systems with Increasing Renewable Generation", International Journal of Electrical Power and Energy Systems, vol. 115, February 2020.

Machine Learning for Transient Stability Assessment

- Several applications (DTs, SVM, ANN, LSTM, etc.)
  - Binary prediction (stable/unstable)
  - Unstable generator group prediction
  - Regression for stability margin
- Prediction of the stability margin – locational aspects
  - Changing dynamics can cause changes in critical locations
- Accuracy-interpretability tension exists in ML
- Why interpretability/explainability is important
  - enhance understanding of how the decision has been reached (enhancing confidence in the model) and
  - inform decision making process for design and development of stability improvement measures.

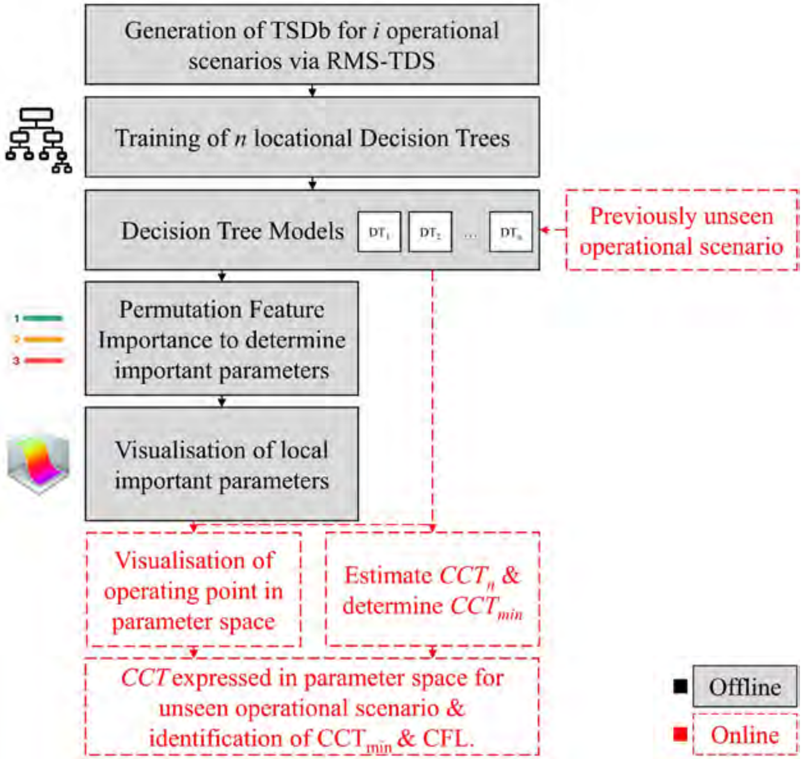


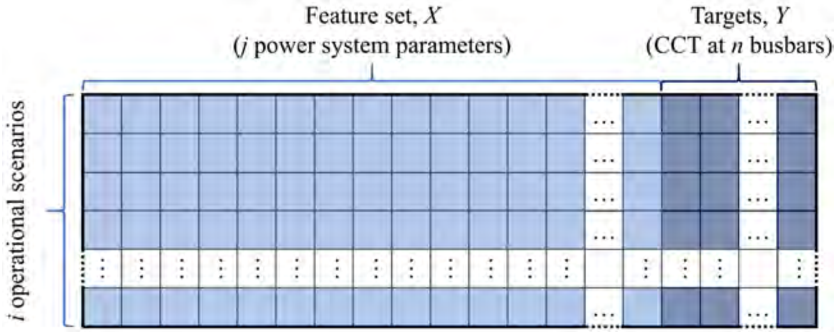


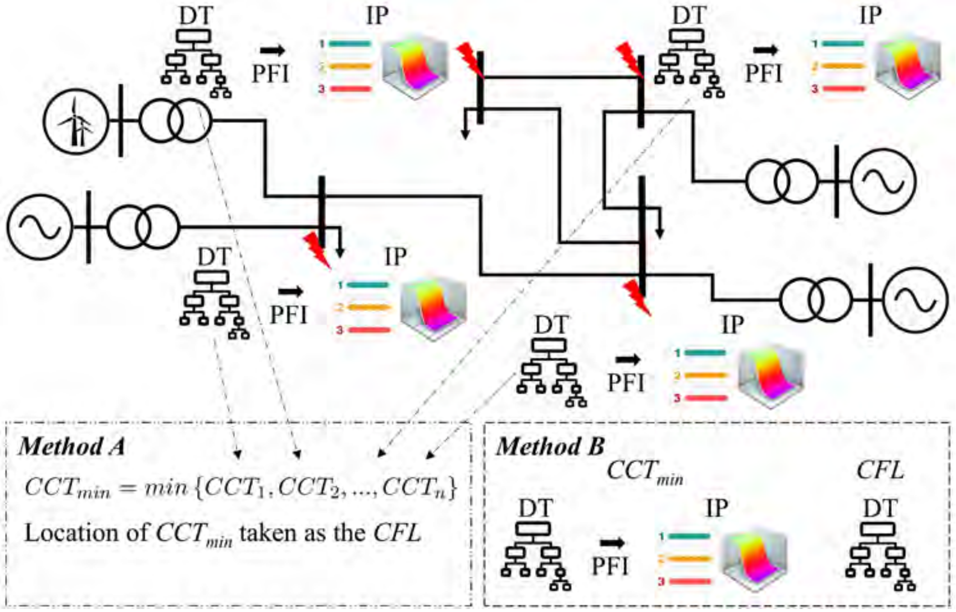
[1] L. Duchesne, E. Karangelos, and L. Wehenkel, "Recent Developments in Machine Learning for Energy Systems Reliability Management," Proceedings of the IEEE, vol. 108, no. 9, pp. 1656-1676, 2020.
[2] P. N. Papadopoulos, T. Guo and J. V. Milanović, "Probabilistic Framework for Online Identification of Dynamic Behavior of Power Systems With Renewable Generation," IEEE Trans. Power Syst., vol. 33, no. 1, pp. 45-54, Jan. 2018.

Locational Decision Trees and Permutation Feature Importance

- ML regression at each bus (CCT estimation)
  - *Up to 200-fold increase in computational time*
- Based on pre-fault data
  - Estimate CCT from incoming PMU measurements in operational time for improved situational awareness
  - Enables better situational awareness and fast screening of more cases to better understand risks







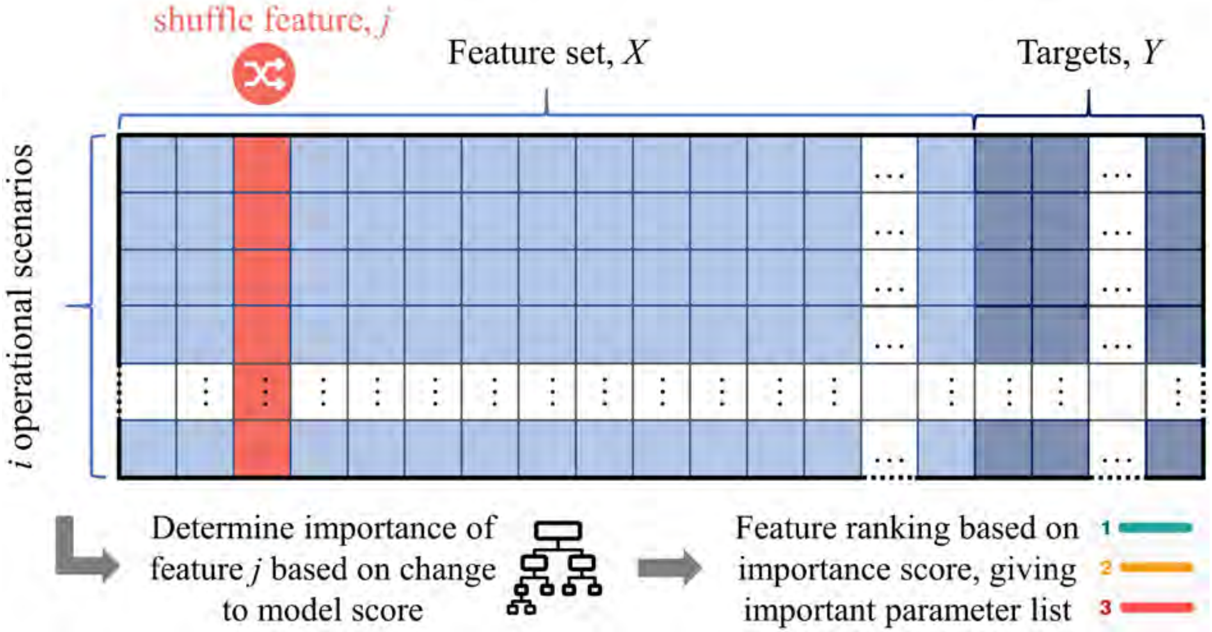
R. I. Hamilton, P. N. Papadopoulos, W. Bukhsh and K. Bell, "Identification of Important Locational, Physical and Economic Dimensions in Power System Transient Stability Margin Estimation," in IEEE Transactions on Sustainable Energy, vol. 13, no. 2, pp. 1135-1146, April 2022.

Permutation Feature Importance

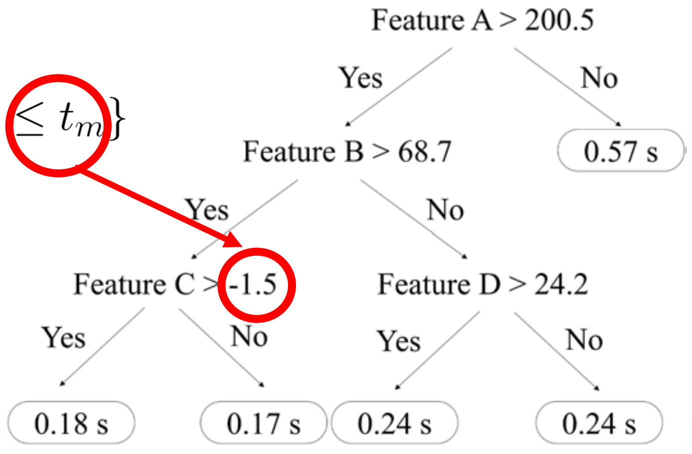
Rule extraction in combination with Decision Trees

- PFI is a model inspection technique
- Based on the decrease in a model score when a single feature value is randomly shuffled
- Determines feature importance of estimators in a given dataset
- Mean decrease in impurity-based importance method:
  - biased towards high cardinality features
  - computed on training set statistics and therefore do not reflect the ability of feature to be useful to make predictions that generalize to the test set (when the model has enough capacity).

$$importance_i = score - {}^{1}/_{k} \sum_{k=1}^{K} score_{k,i}$$



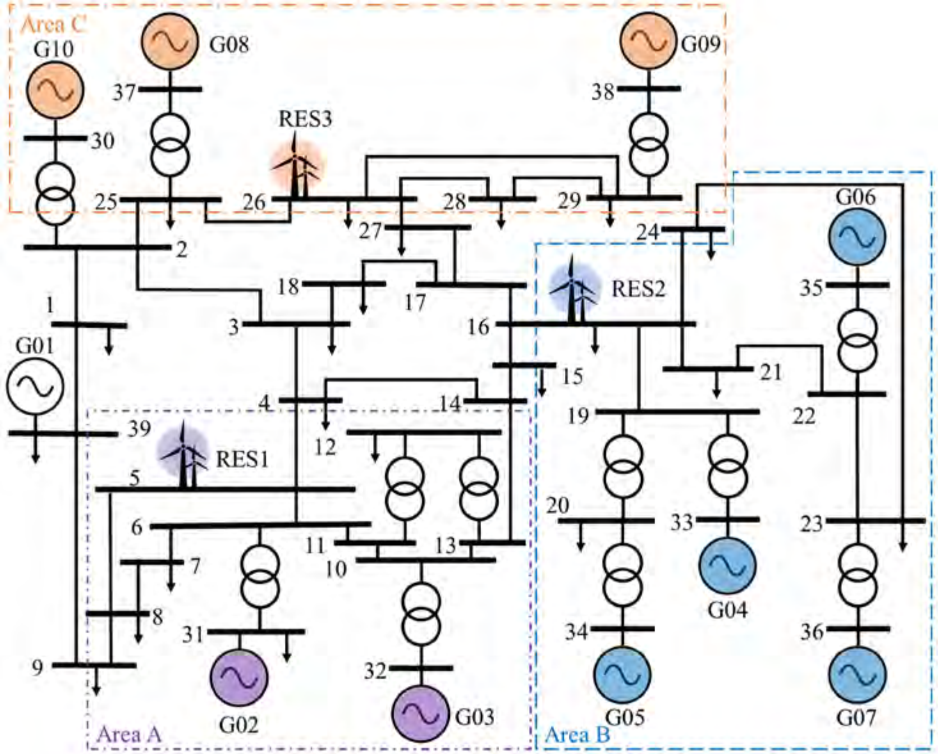
$$Q_m^{left}(\theta) = \{(x,y) | x_j \leq t_m\}$$

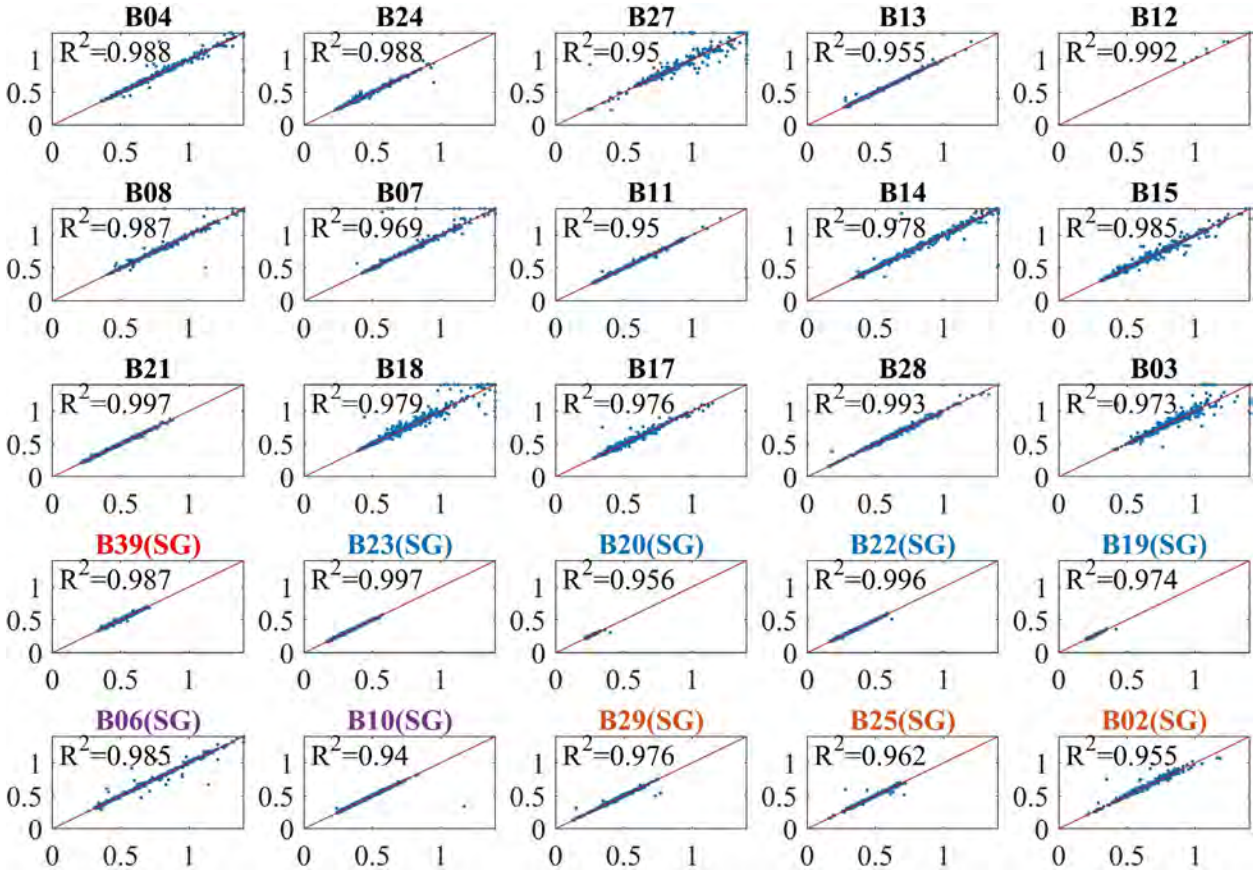


See: https://scikit-learn.org/stable/modules/tree.html

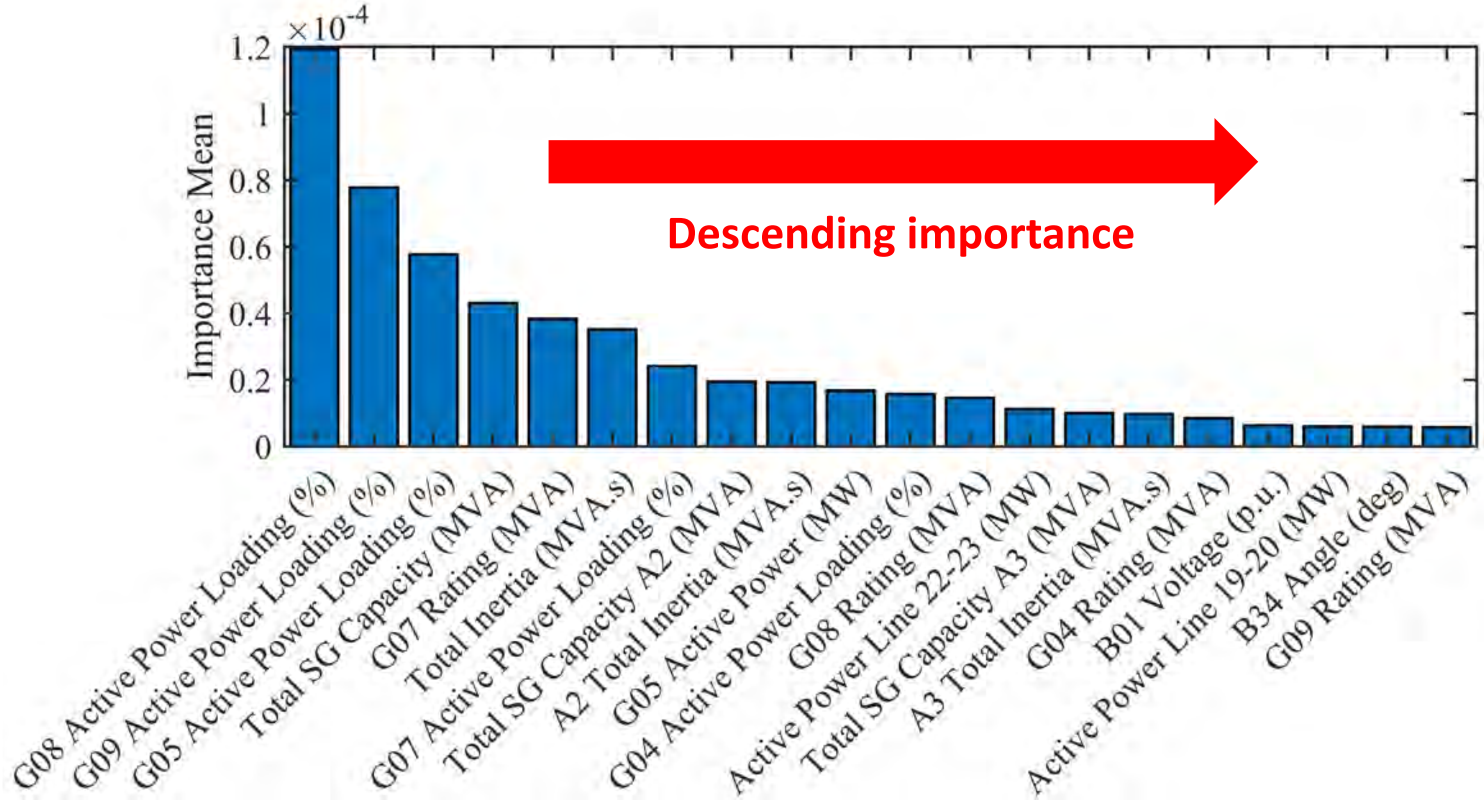
Locational estimation of CCT – Case study results

- Using DTs (CART)
  - Overall good performance
  - Outliers exist (MOE and MUE can be significant)



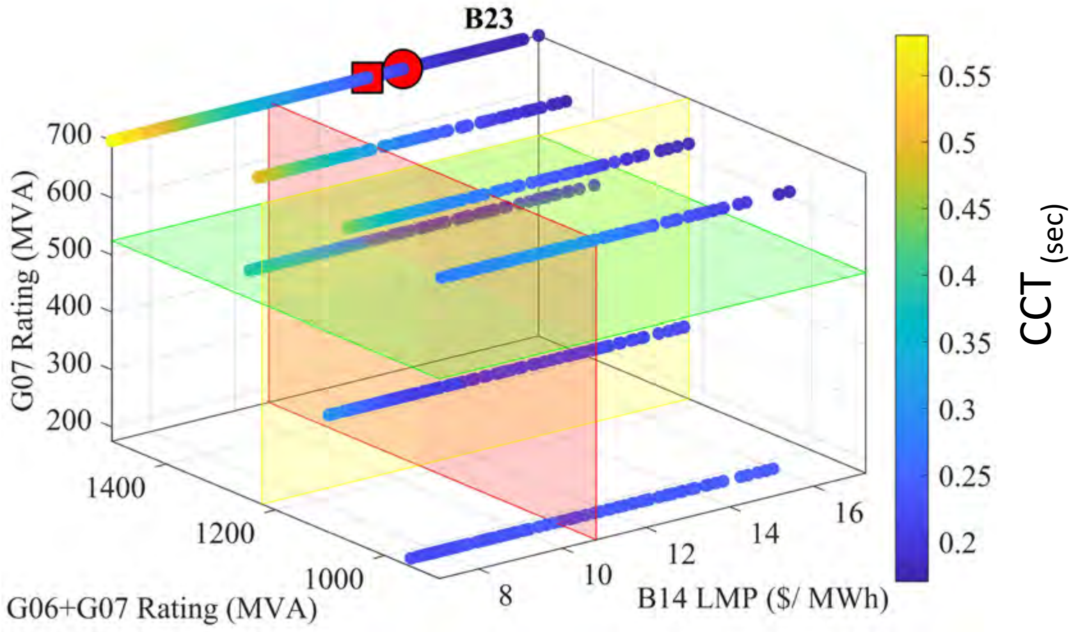


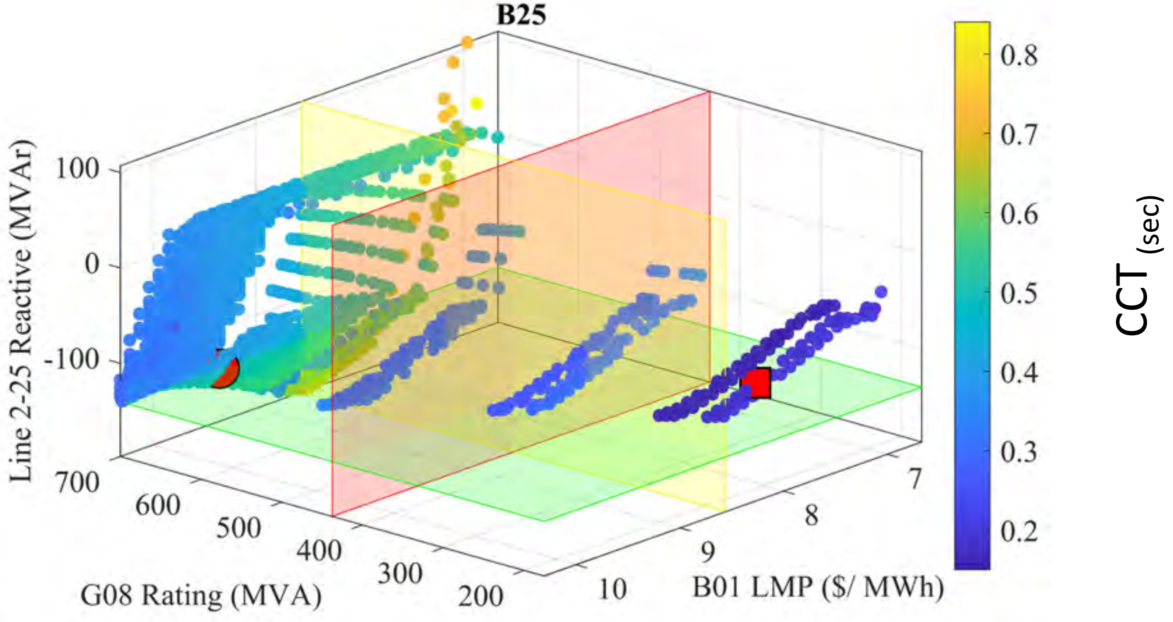
PFI interpretation – Case study results



PFI gives feature importance based on the mean importance and the decrease in model performance when a feature is permutated

PFI and DTs for rule extraction – Case study results





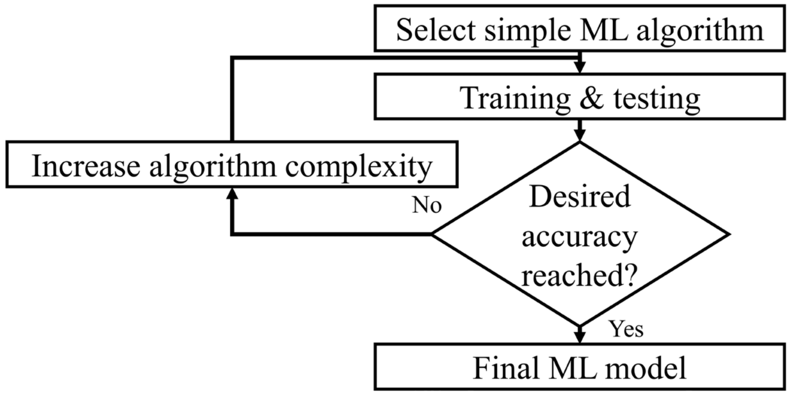
Operational Scenario details			Method A estimates				Method B estimates		Actual RMS TDS results			
Scenario	RES3	G08	CCT B23	CCT B25	CCT_{min}	CFL	CCT_{min}	CFL	CCT B23	CCT B25	CCT_{min}	CFL
A (red circle)	280	700	0.21	0.42	0.21	B23	0.21	B23	0.21	0.42	0.21	B23
B (red square)	932	175	0.24	0.19	0.19	B25	0.19	B23	0.24	0.19	0.19	B25

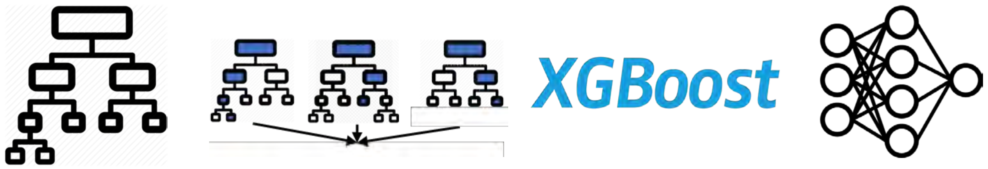
Locational Accuracy

- Mostly motivated by improvement in maximum errors

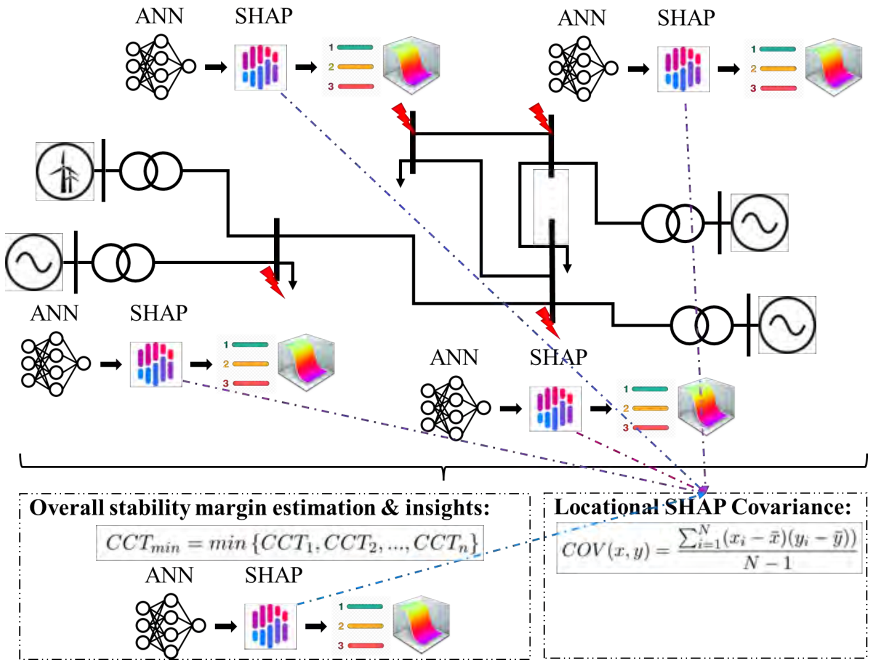
IMPACT OF ML ALGORITHM ON ACCURACY METRICS FOR ALL LOCATIONS

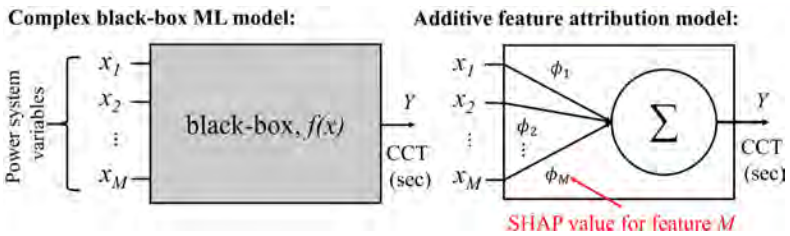
Performance Metric	DT	RF	XGBoost	ANN
Average RSQ				
Average MSE (sec^2)				
Average RMSE (sec)				
Max MOE (sec)				
Min MUE (sec)				
Max MOE < 0.3 (sec)				
Min MUE < 0.3 (sec)				



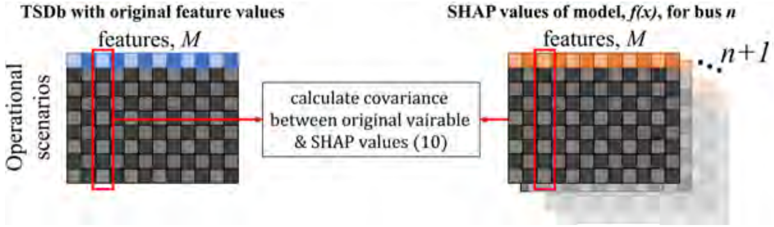


ML model interpretability using Shapley Additive Explanations





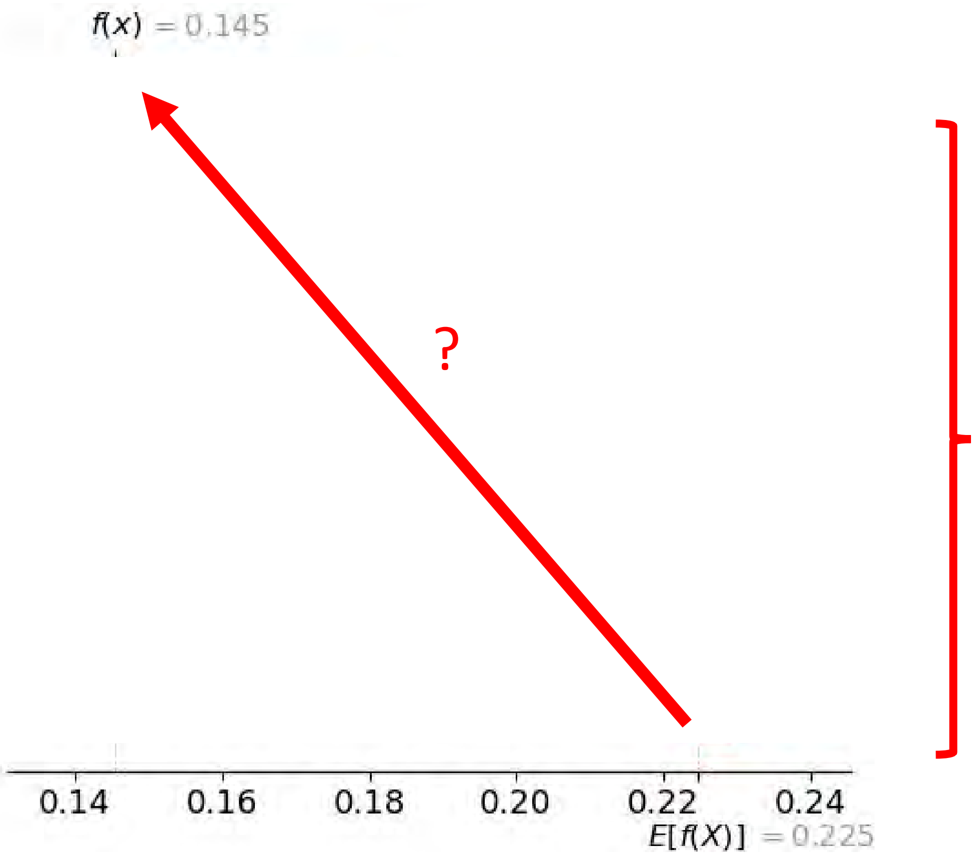
- Locational ML models for CCT estimation
- SHAP builds a simpler (linear) explanation model of the original (non-linear) black-box model
  - Uses approximate Shapley values defined as the average marginal contribution of a feature to all feature coalitions with that feature
  - *Provides feature effects*
  - *Local* (for one operating scenario) and *global* (for all operating scenarios) explanations
- Reveals tendencies (no guarantee of causal relations)
- Covariance between features and SHAP values can reveal locational aspects



R. I. Hamilton, P. N. Papadopoulos, "Using SHAP Values and Machine Learning to Understand Trends in the Transient Stability Margin", to be submitted.

SHAP – local interpretations

Prediction, $f(x)$ (sec)

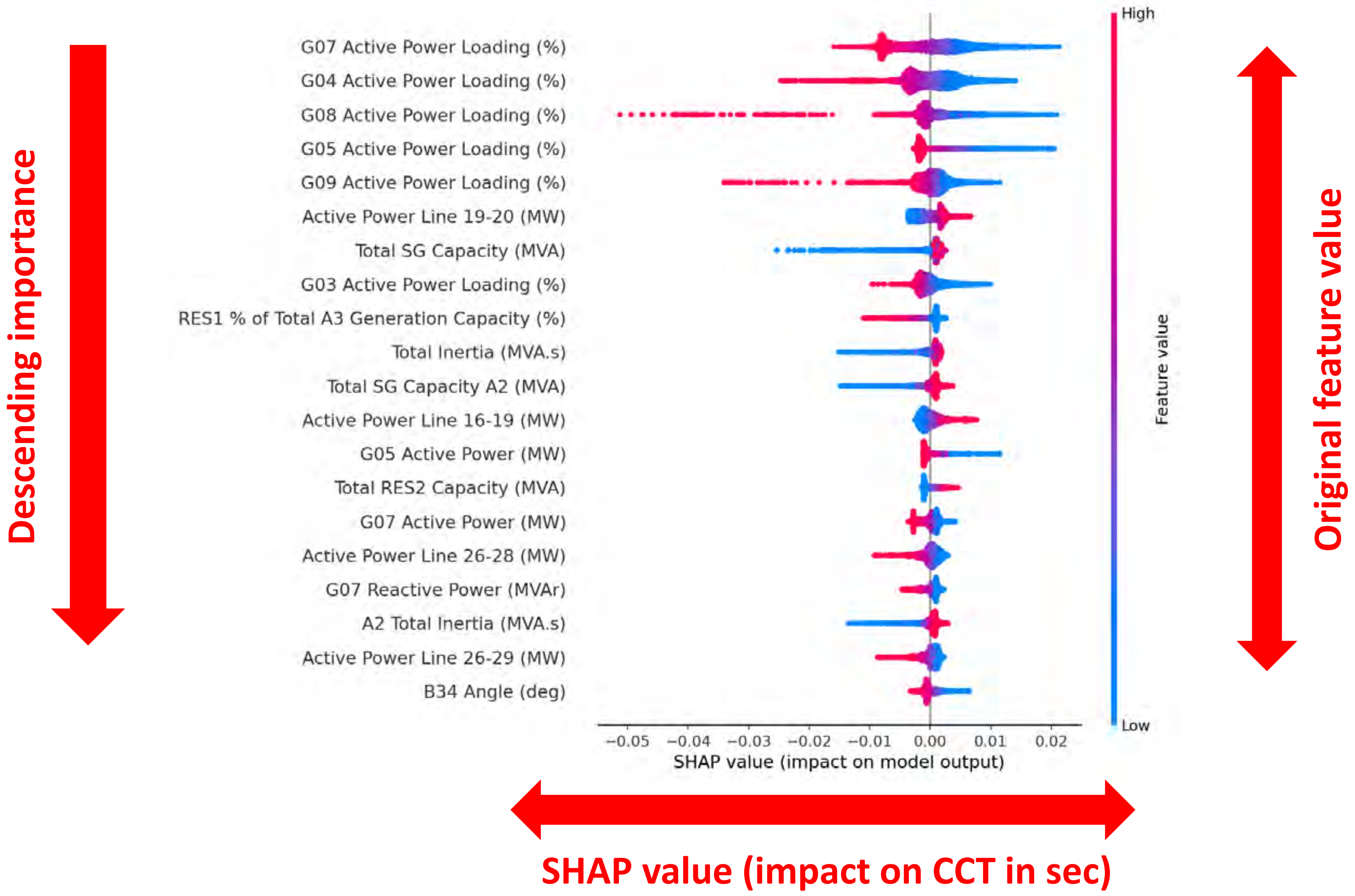


SHAP values, ϕ_i (sec)

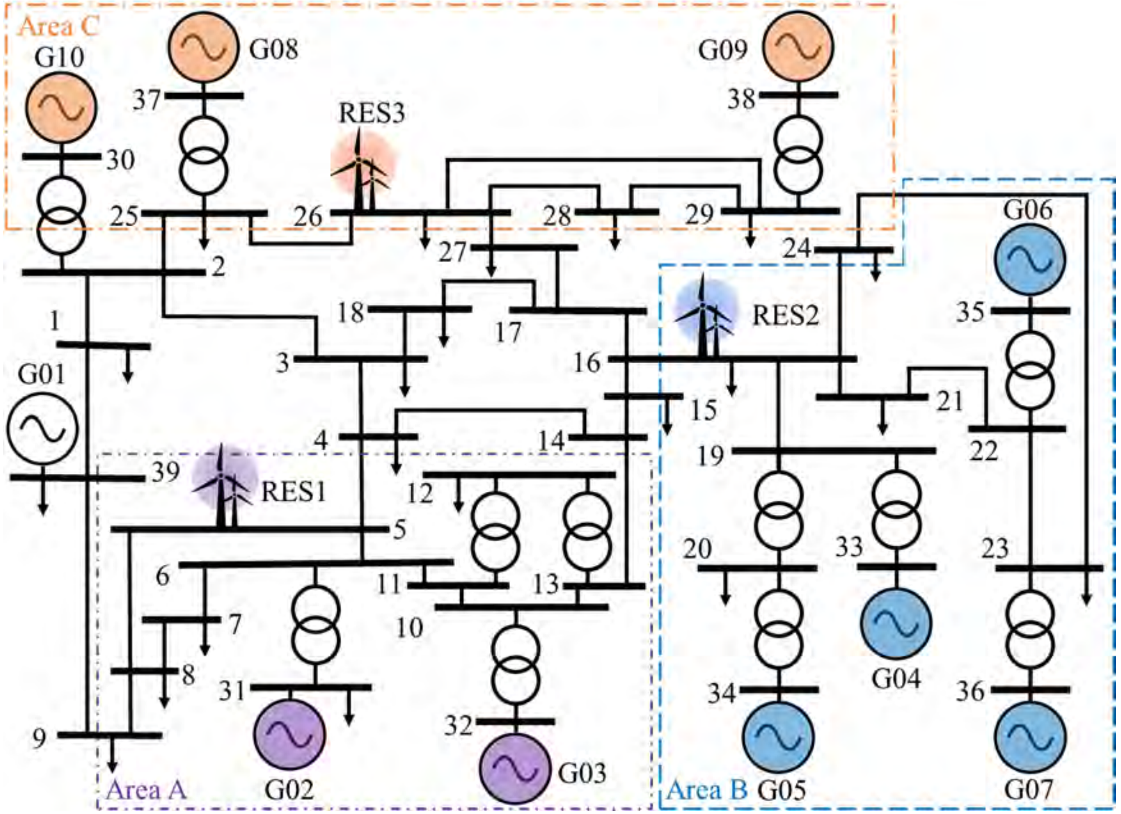
Expectation, $E[f(x)]$ (sec)

$$f(x) = E[f(x)] + \sum_{i=1}^{M} \phi_i$$

SHAP – global interpretations

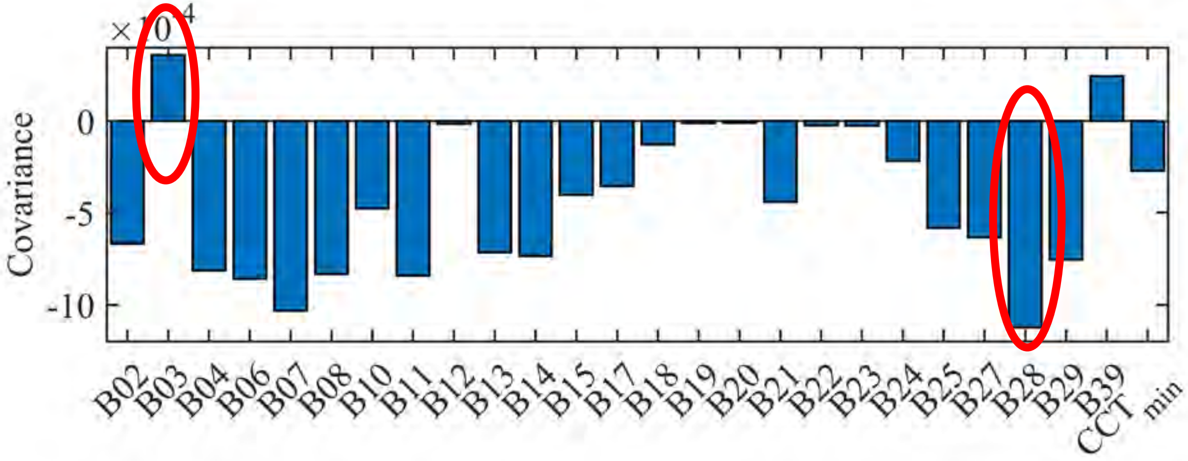


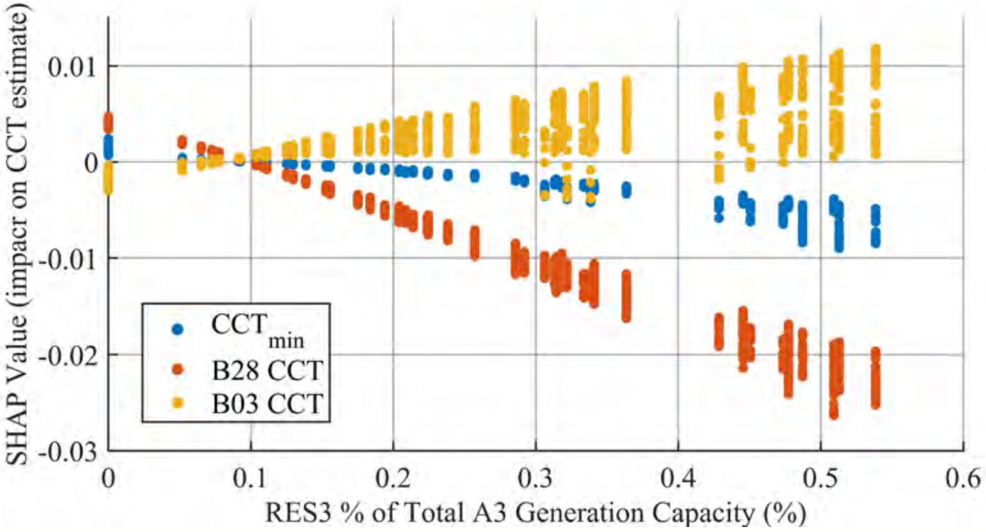
SHAP and locational aspects – Case study results

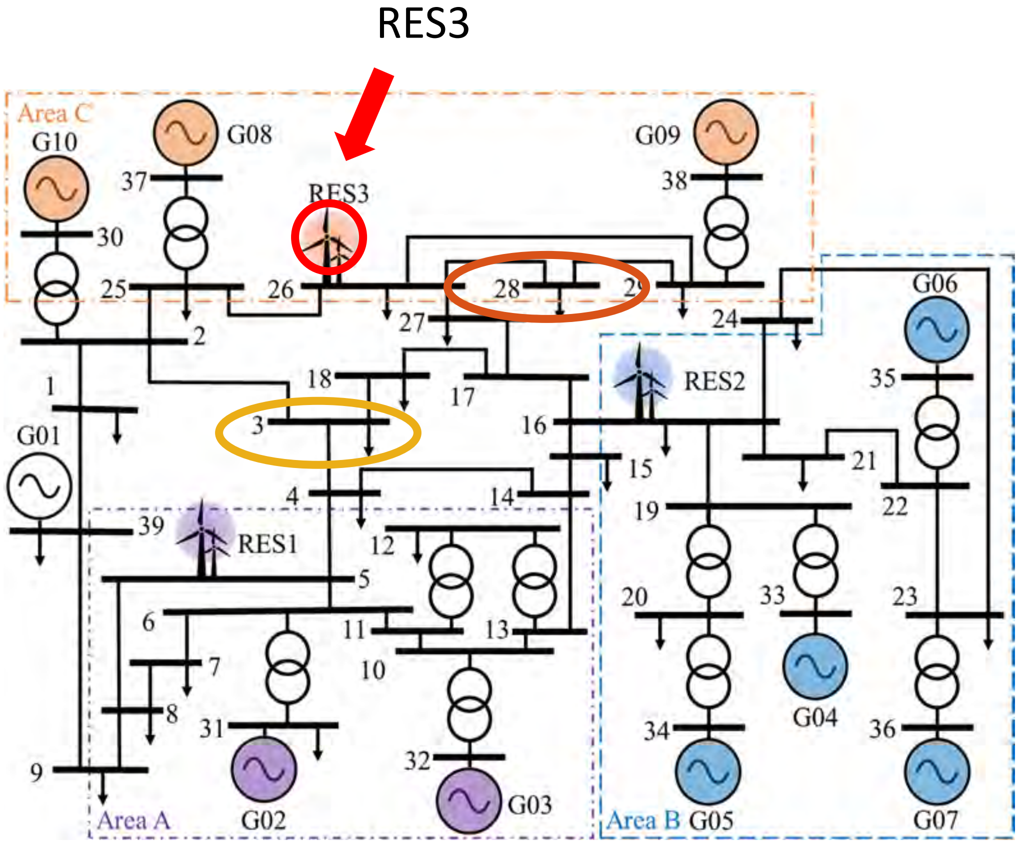


Example result of locational interpretability

- Increase in wind generation in area 3 (RES3) causes local reduction of CCT in Bus 3 but increase in Bus 28







Conclusions

- Locational Transient Stability Margin estimation using ML
  - Faster (up to 200-fold compared to time domain simulations)
  - Can be very accurate with powerful black-box models
  - Improved situational awareness and fast screening
- Interpretability techniques (SHAP and PFI)
  - Useful insights into complex dynamics
  - Suggest rules for operation/planning (what services are needed and where?)
  - Confidence in using ML models

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