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SC C2: Power system operation and control

PS2: Operational planning strategies, methodologies and supporting tools

10680 – Session 2022

Prediction of possible power system blackout risk with machine learning algorithms

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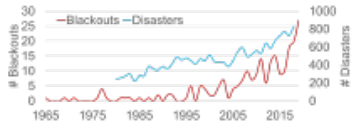
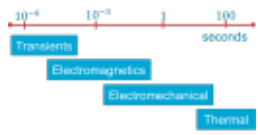
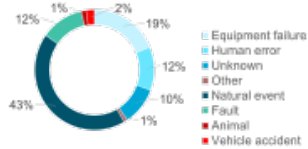
Motivation

- Blackouts are unpredictable, growing in numbers and costly.
- Faster power system dynamics require faster tools.
- Dynamic simulations are slow and complex.
- Machine learning can predict the blackout risk using only power flow results.



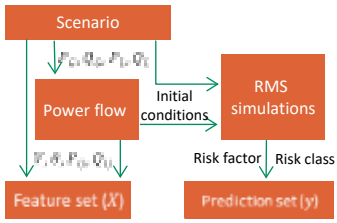


Location	Date	People affected	Duration	Cost
	14-28.08.2003	55 million	~14 days	$6 bil.
	28.09.2003	56 million	12 hours	€1.2 bil.
	30-31.06.2012	620 million	~2 days	NA



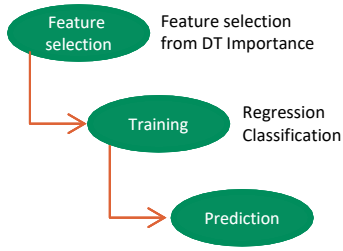
Risk Estimator Framework

- Scenario and data generation
- Power flow with the static model
- RMS simulations with the dynamic model
- Included controllers: Inverter (Type-IV), speed governor, AVR
- Wide range of operating conditions
- Change in system topology



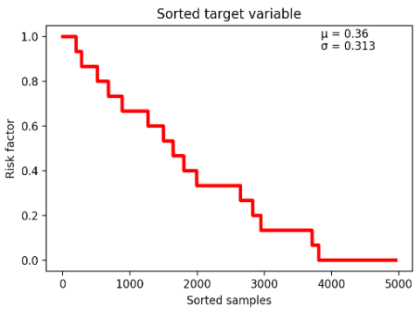
Risk factor – Regression
The normalized mean of simulation labels
Risk class - Classification
Clustered risk factor by thresholds

Decision Trees (DT), Support Vector Machine (SVM), Random Forest (RF), Artificial Neural Networks (ANN)

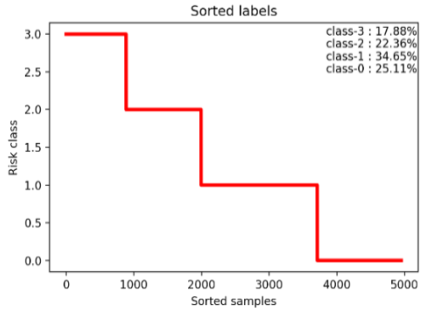


Experimental setup

4955 samples are generated with multiple RMS simulations by varying fault location and duration in IEEE 9 bus test system.

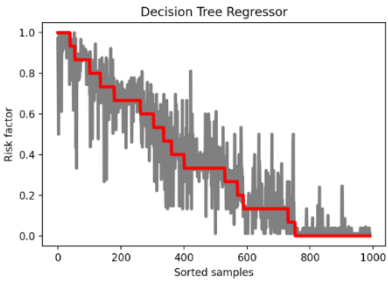


Class	If
C-0	Y<0.1
C-1	0.1<Y Y<0.35
C-2	0.35<Y Y<0.7
C-3	Y>0.7

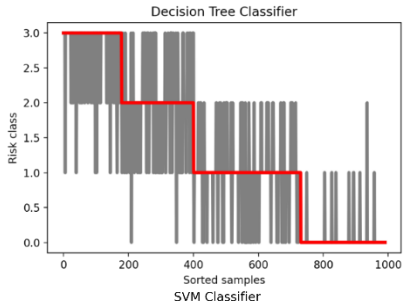


Results

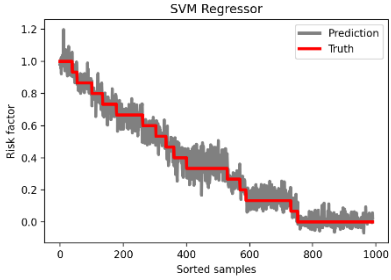
MSE 0.0094
R^2 score 0.9026
Max error 0.59



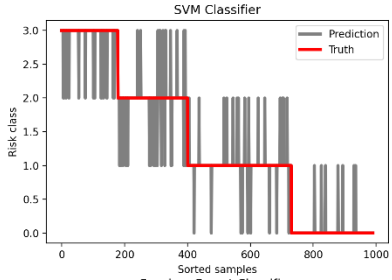
Accuracy 82.03%
F1 Score 0.8148
Recall 0.816



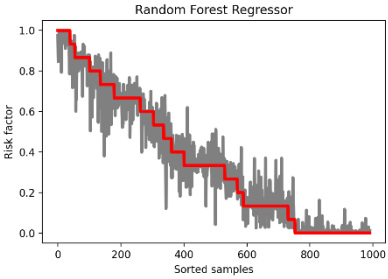
MSE 0.0027
R^2 score 0.9725
Max error 0.197



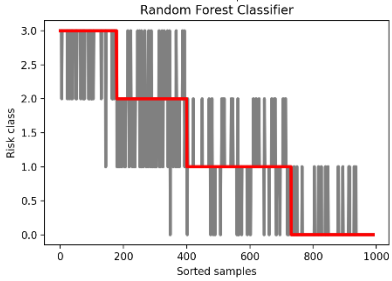
Accuracy 92.33%
F1 Score 0.9207
Recall 0.92



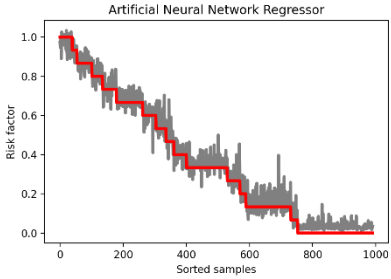
MSE 0.0045
R^2 score 0.9539
Max error 0.3526



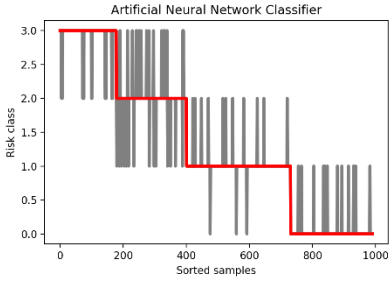
Accuracy 86.37%
F1 Score 0.8615
Recall 0.8591



MSE 0.0021
R^2 score 0.978
Max error 0.263



Accuracy 93.44%
F1 Score 0.9329
Recall 0.9304



Discussion & Conclusion

- Machine learning models enable us to predict the risk of the operational conditions fast, accurately, and robustly.
- Decision support tool for system operators to improve and monitor the security of the operation.
- Classification thresholds can be adjusted based on system operator needs.
- Tree-based models have lower prediction capabilities and are not suitable for our complex, nonlinear problem.
- SVM and ANN models outperformed other estimators in both regression and classification models.
- SVM and ANN classifiers' mismatches lie around the decision boundaries since operating conditions are similar.
- Performance is directly linked with the quality of the training data. Major changes in the system or multiple topological changes require system operators to generate new training data with simulations.
- Although machine learning models are easily scalable, running a large amount of RMS simulations is challenging and if the dynamic system model is not available then risk estimator cannot be implemented.