Classification of Fault Location and Prediction of Its Duration Using Machine Learning Models in Power Systems

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Introduction

- Detection of faults are critical for seamless operation of power systems. Utilities are working 24/7 to reduce outage rates that may arise due to contact with natural vegetation (e.g. a tree), animal, or weather event [1].
- According to [2], the cost experienced by an "average" consumer for an outage of one hour summer afternoon was estimated to be roughly $3 for a typical customer, $1200 for a small and medium organizations, and $82,000 for a large organization.
- In order to o protect and prevent the potential damages to people, equipment, and environment, advanced computational algorithms are needed to track, and locate and isolate the faults promptly [1].

Goal

- The purpose of this research is to evaluate a collection of Machine Learning models to detect three-phase fault's location and predicting its duration.

Methodology

- ***Data set***
  - Several fault scenarios have been simulated in GridPACK [3]. A 9-bus system with three generators has been considered and several three-phase faults have been simulated at various locations and with different durations.

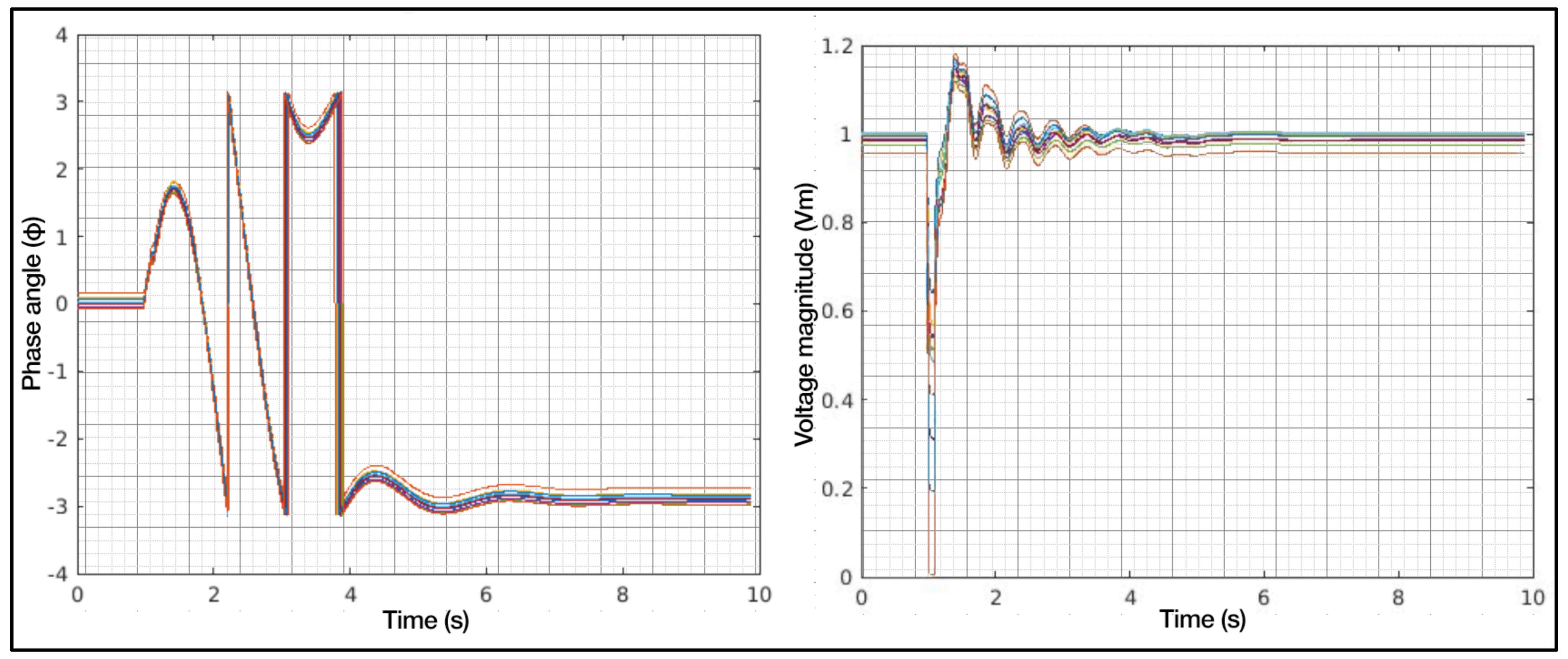

Fig. 1 a) Phase angle of 9 buses after applying fault, b) Voltage magnitude of 9 buses after applying fault

- ***Features***

To better capture the fault locations along with their respective durations, three features have been selected:
- The voltage magnitude (Vm) at each bus
- The phase angle (φ) at each bus,
- and the frequency (f) of the generators.

- ***Approach***

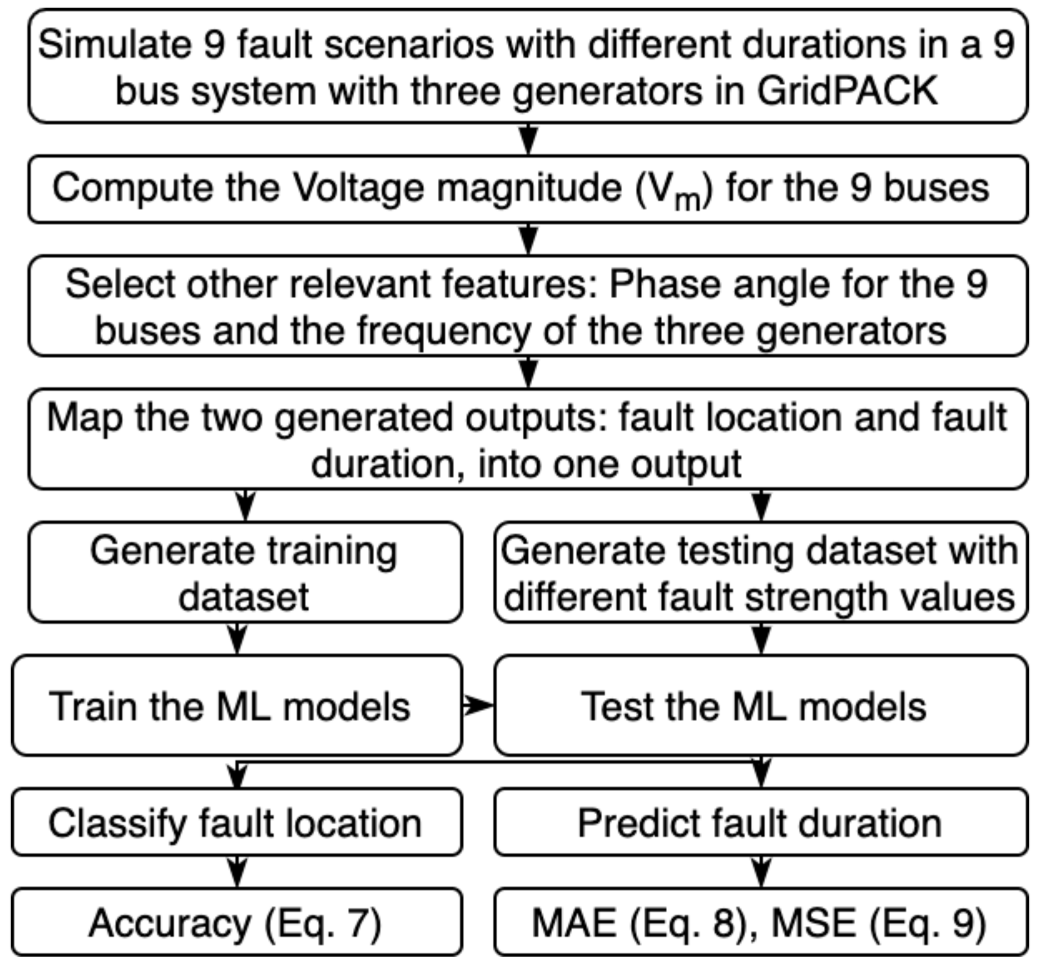

Fig. 2 Training/testing steps for Machine Learning models

Preliminary Results

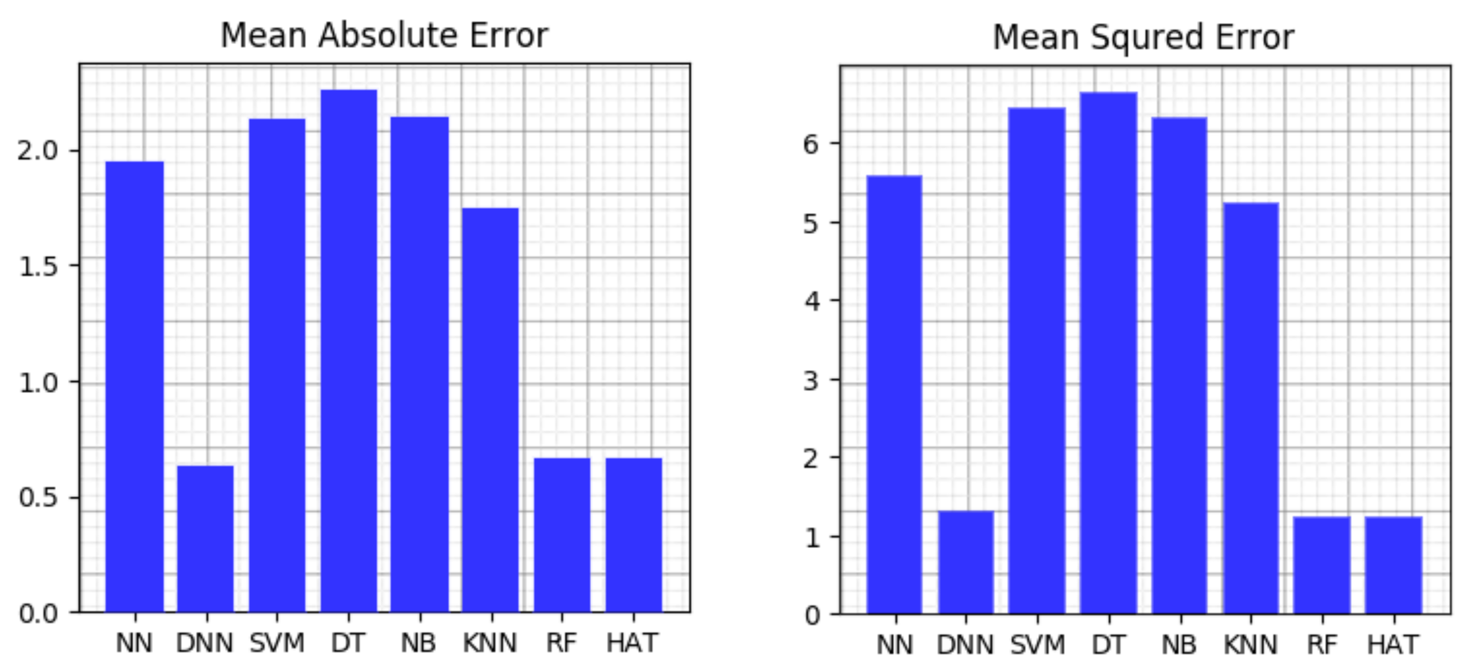

Fig. 3. Comparison between RFR and NN, DNN, SVM, NB, DT, HT in terms of MAE (a) and MSE (b)

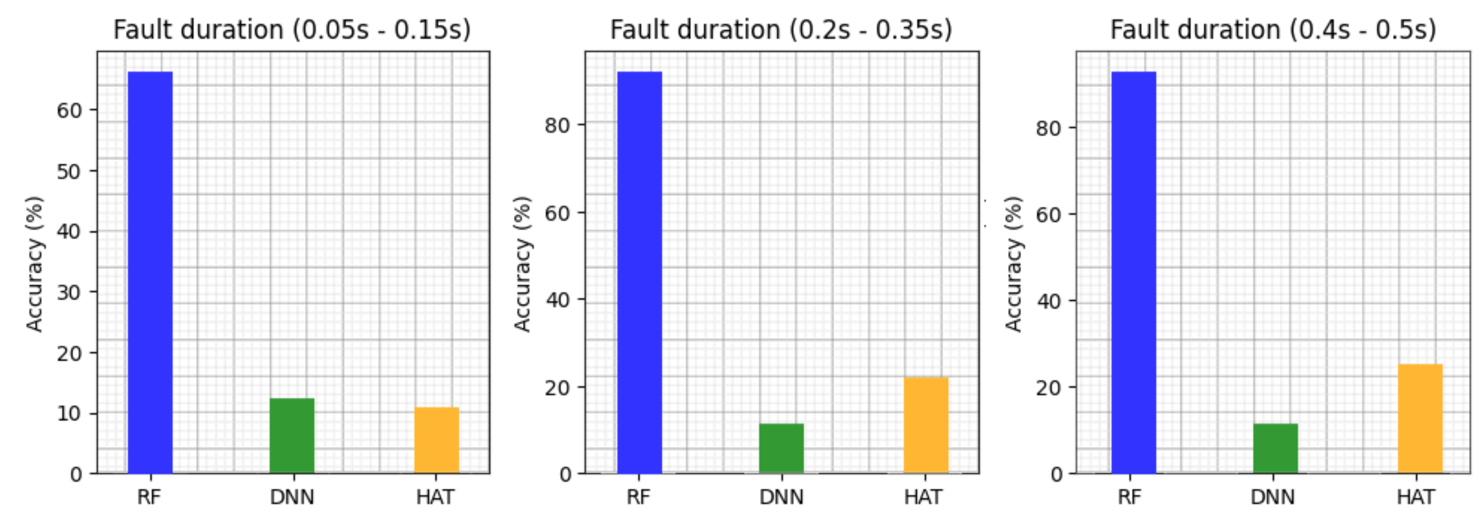

Fig. 4. Accuracy of RF, DNN, and HT in terms of predicting faults duration

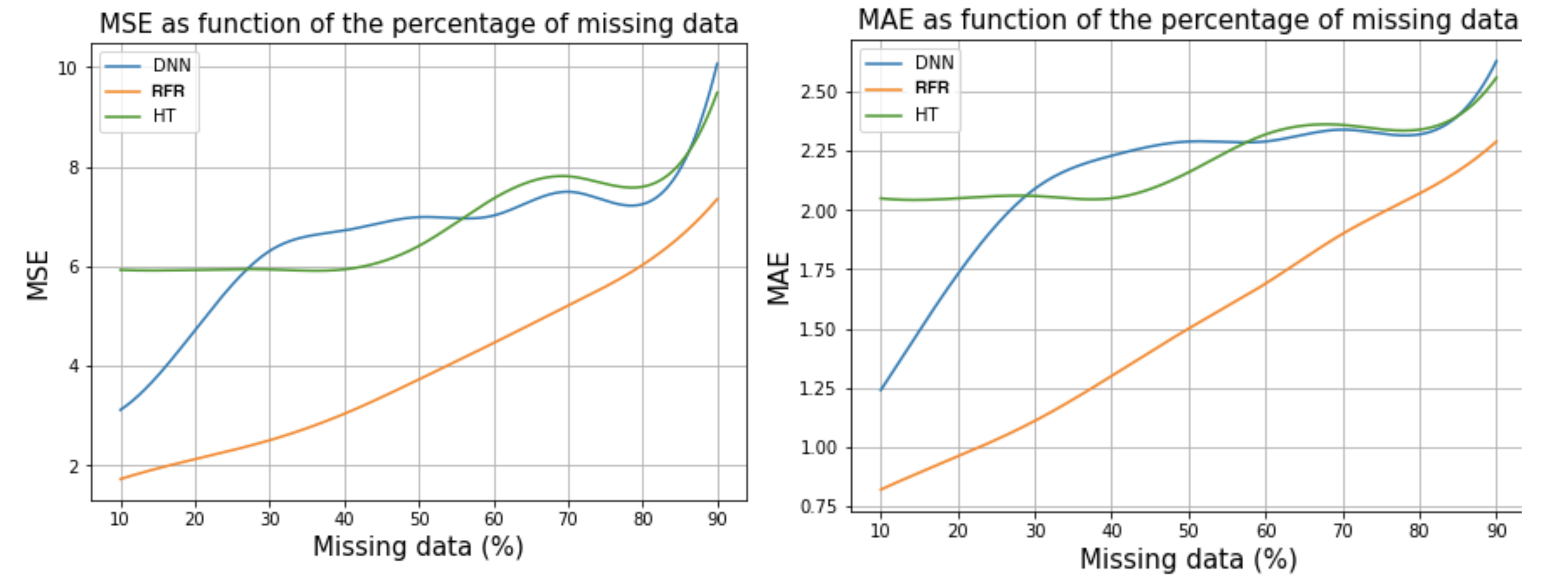

Fig. 5: MSE and MAE as a function of the percentage of missing data for the three models: DNN, HT, and RFR

Experiment	Performance metrics	RFR	DNN	HAT	NN	SVM	DT	NB	KNN
1. Fault location detection	Overall accuracy	65.2%	65%	14.77%	17%	16%	13.8 %	14.5 %	27.6 %
2. Fault duration prediction	MSE	1.1s	1.2s	1.1s	5.6s	6.5s	6.6s	6.2s	5.1s
	MAE	0.6s	0.6s	0.6s	1.9s	2.2s	2.5s	2.2s	1.8s
3. Fault duration prediction in streaming data	Processing time	0.0028 ms	0.0032 ms	0.7 ms	-	-	-	-	-
Overall ranking		High	Medium	Low	Low	Low	Low	Low	Low

Conclusion

- The results indicate that RFR outperforms DNN with an accuracy of 70% and it requires less processing time for detecting faults in streaming environment, hence, is suitable for real-time situational awareness environment to capture both fault location and its durations.

Acknowledgments

- This work is supported by the National Science Foundation (NSF) Award #1537565

References

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