Study Committee C6

Active Distribution Systems and Distributed Energy Resources

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A STUDY ON THE EFFECT OF EVs' CHARGING STOCHASTICITY ON A ML-BASED FAULT DETECTION ALGORITHM

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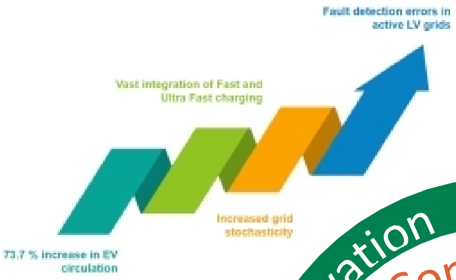
Motivation



Objective

The development of a robust ML-based fault location algorithm for LV grids, independent of the EVs' charging stochasticity.

Case study

The grid used for the generation of the training and test data is illustrated in Fig. 2. During the training phase the **load** and charging stations' **occupancy rate** were considered **static**. During the **testing** their values were simulated according to the **real expected values**, as found in the literature [1], [2].

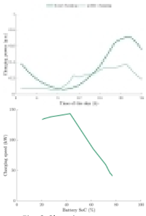


Fig. 3 Charging curves

FC → home charging
UFC → public charging

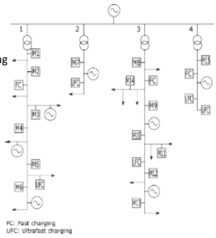


Fig. 2 Modified CIGRE European LV benchmark

Conclusions

1. Highly accurate fault detection algorithm unaffected by the EV FC & UFC.
2. ML model training with static data - no load predictions required.
3. Increased generalizability.
4. Instantaneous results.
5. Robustness against influencing parameters.

Method

The ML approach

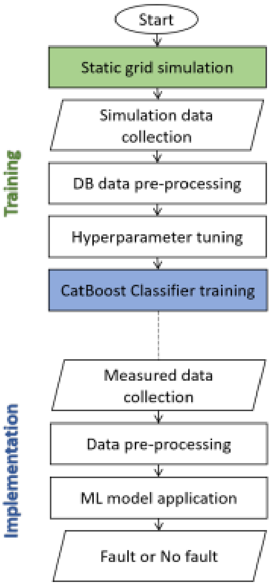


Fig. 1 Flowchart of the algorithm's training and implementation

Application
Static loads: Nominal values
EV charging: Nominal values or as zero
ML Model: *CatBoost* Classifier

Benefits
- ✓ **Independent** of the grid's stochasticity
- ✓ Increased **generalizability**
- ✓ Input **data minimization**
- ✓ Computational **speed**

Results

Fig. 5 and 6 indicate that the **algorithm's performance is better when the EV chargers are simulated as zero** during the generation of the training data. The difference between the two methods is primary located in the **computational times**. Fig. 7 presents a sample of the utilized data, providing an insight to the accuracy results.

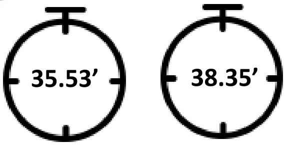


Fig. 5 The algorithm's training time without any EV charging and with full occupancy of the EV charging points.

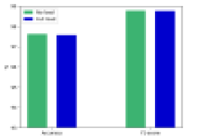


Fig. 6 Comparison of the algorithm's performance in the different EV simulation scenarios

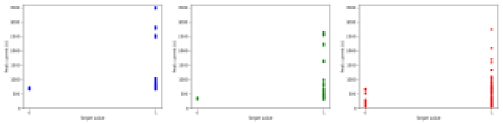


Fig. 7 Meter 1 current values when the EVs are simulated with full load, with no load and during the test cases

Finally, Fig. 8 illustrates the worst case results from the sensitivity analysis scenarios presented in Table 1. The algorithm is robust against the most important influencing parameters.

Table 1 The examined cases in the algorithm's sensitivity analysis.

Sensitivity analysis	
Parameters	Values
Fault resistance	0-100 Ohm
PV penetration	5 levels/ 0-13kW
Dataset size	1600-10000
No of meters	4-15

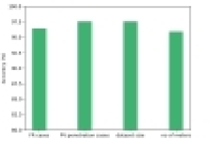


Fig. 8 Minimum accuracy in each of the performed sensitivity analyses

References

[1] J. Quirós-Tortós, A. N.- Espinosa, L. F. Ochoa, and T. Butler, "Statistical Representation of EV Charging: Real Data Analysis and Applications," in *2018 Power Systems Computation Conference (PSCC)*, Jun. 2018, pp. 1–7.

[2] S. Su *et al.*, "Research on an Electric Vehicle Owner-Friendly Charging Strategy Using Photovoltaic Generation at Office Sites in Major Chinese Cities," *Energies*, vol. 11, no. 2, p. 421, Feb. 2018

http://www.cigre.org