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Detection of electric vehicle charging events in low voltage networks: enhancing load visibility for network planning

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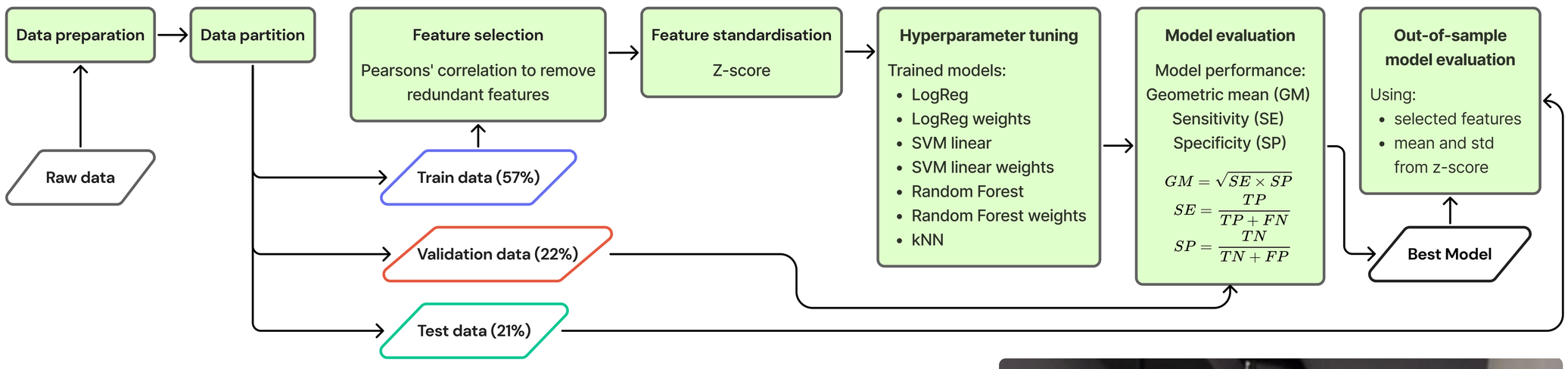
Background

//Electric vehicles (EVs) introduce non-linear loads in low-voltage (LV) networks increasing the risk of equipment overloading. //There is no visibility into EV mobility: how many EVs are charging in the grid at a given time at a particular transformer feeder?

Aims

//Use machine learning algorithms to identify patterns of EV-produced overload conditions on historical data. //Provide visibility of the peak load spikes produced by increasing EV adoption, allowing the Distributed System Operators to improve network planning.

Methodology



The dataset

- Two acquisition devices at the IST central building:
  - In the building transformer (Transformer data, one feeder);
  - In the EV charger switchboard (Charger data, two feeders);
- Two types of data were used to train the models:
  - Current and voltage data;
  - Network power quality (NPQ) data;
- Ground truth: active power from charger switchboard feeders 1 and 2.

F1. Transformer at Instituto Superior Técnico (office area)

Results

Model performance

Partition	Database	Best Model	GM (%)	SE (%)	SP (%)
Validation	Current, voltage and power	Random Forest	79.3	84.2	74.7
	NPQ	Linear SVM weights	81.3	86.5	76.4
	Current, voltage, power and NPQ	**Linear SVM**	**82.1**	**86.1**	**78.3**
Test	**Current, voltage, power and NPQ**	**Linear SVM**	**80.2**	**77.7**	**83.0**

Confusion matrix for the test dataset

		Predicted Value	
		Charging	**Not charging**
True Value	**Charging**	TP: 1503	FN: 432
	Not Charging	FP: 1192	TN: 5824

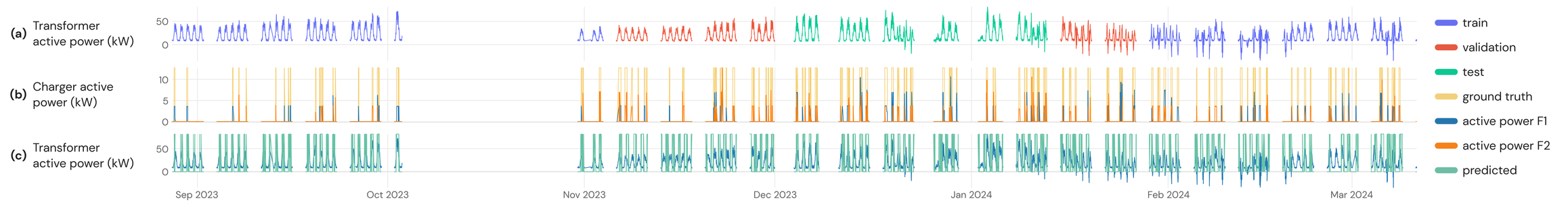


Figure 2: (a) Data partition shown for active power: data were divided into train, validation and out-of-sample test. (b) Ground truth (EV charging vs EV not charging) was obtained from both charger feeders using active power. EV charging events account for about 15% of all samples. PV activity can be seen in (b) when active power amplitude drops below zero. (c) Prediction results obtained for the best model (Linear SVM) on current, voltage and NPQ data.

Conclusions

//The results show that EV charging events can be detected with about 78% of sensitivity and 83% of specificity by training a linear SVM.//Despite its proficiency in identifying EV charging events, the models seem to detect load fluctuations other than EV charging (false positives), evidencing the problem of load decoupling. The presence of photovoltaic (PV) activity also seems to hinder model performance. //Future efforts will focus on reducing false positives and efficiently handle the presence of PV activity in the grid. //Also, models should be retrained with data from residential grids, in a context where one feeder provides for 10 to 12 houses in a neighbourhood.

Acknowledgements

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