AUTOMATED LOAD CONTROL DETECTION USING POWER QUALITY DATA AND MACHINE LEARNING

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ABSTRACT

Consumption flexibility, also known as demand response, allows balancing power systems in case of an electricity shortage or intermittent power generation. In the future, more distribution network customers are expected to participate in demand response through active control of their loads. If flexibility resources are controlled in large numbers, they may have an impact on distribution networks. Therefore, methods to automatically detect flexibility resources participating in reserve instruments are required to support distribution network operation and planning. In this study, machine learning is used to detect the commissioning of a flexibility resource load control and the days when the control has not been enabled. In the developed two-stage approach, first, feedforward neural networks are trained for feature engineering, and then, the load control detection is performed in two alternative scenarios – supervised and unsupervised learning, using random forest and isolation forest, respectively. The proposed methodology has been validated on the data collected from an office building in Finland that participates in FCR-N reserve of the transmission system operator with its ventilation and air cooling.

INTRODUCTION

Consumption is required to have more flexibility to balance power systems as the degree of intermittent solar and wind power generation increases. Additionally, consumption flexibility is needed to support power systems in case of an electricity shortage, which has become a higher risk during the current energy crisis in Europe. It can be expected that more customers in distribution networks will actively participate in demand response. Distribution network customer's resources can be aggregated for reserve markets of a transmission system operator (TSO). Suitable controlled loads can be, for example, ventilation and cooling systems. If the flexibility resources are controlled in large numbers in distribution networks, they may have an impact on network voltage control, reactive power compensation, and power quality.

Distribution system operators (DSOs) may not have knowledge about these actively controlled flexibility resources in their distribution networks like they have from distributed generation. Therefore, methods to detect flexibility resources participating in TSO reserve instruments are required to support network operation and planning. This study aims to detect the commissioning of a load control of a flexibility resource, and to detect the days when the load control has not been enabled. An office building, we focus on, participates in FCR-N reserve of TSO of Finland (Fingrid) with its ventilation and air cooling through a virtual power plant.

The load control detection is performed based on electrical measurement data of the ventilation feeder and the supply of the main distribution board of the building, the latter of which is close to a practical case where measurement data may be available in distribution networks. The data are used in machine learning model training, in addition to some knowledge about the flexibility resource control signal. We present two scenarios for the load control detection, in which random forest (supervised learning) and isolation forest (unsupervised learning) are trained. To improve the model performance, we propose an additional feature engineering step, in which more input variables are generated using artificial neural networks.

SITE AND DATA DESCRIPTION

Here, the site including the controlled loads and then the measurement data utilized in the detection are described.

Site

The site of the automated load control is an office building called Kampusareena located in Tampere University campus in Finland. The ventilation and air-cooling systems of the building are resources for a virtual power plant of Vibeco Oy that controls them according to the FCR-N reserve of Fingrid Oyj, that is the national TSO. FCR-N is operated in the frequency range of 49.9-50.1 Hz. In this paper, detection of the ventilation control is considered. Three-phase frequency converters of fans are controlled in continuous manner according to FCR-N starting from September 2020. Thus, it may be assumed that the control affects each of the phases similarly. The measurement data used for the load control detection have been collected at the ventilation feeder level and at the main distribution level that feeds several other loads. These two measurement points could be seen in Figure 1. In addition to the main distribution board, the ventilation is supplied by the solar power plant, however, its effect is at the lowest in winter periods analyzed in this study.

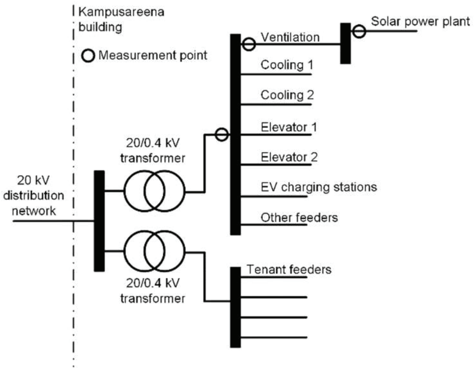

Figure 1. Main electricity distribution and measurement points in the building.

Data

The data were measured with eQL Laatuvahti3 meters at 1-second interval. The data are either averages or root mean square (rms) values of the interval depending on the measurement variable. The bandwidth of the meter is 0-2 kHz that is applied to measurement variables that do not consider a certain frequency. Total distortion in voltage and current include harmonics and interharmonics. The measurement system is further described in [1].

A set of electrical variables was selected from the measurement data collected at the ventilation feeder and the main distribution board supply (Table 1). All variables, except Freq, U2U1, and U0U1, were measured for three phases (denoted by L1, L2, and L3). Variables P_{act} and $Q1_{act}$ demonstrate the actual active power consumption when the production of the solar power plant is added to the active power measurement.

The measurement data utilized in this paper are from the winter periods November–February 2018–2019, 2019–2020, and 2020–2021. Also, control data of the flexibility resources are utilized to test the model outputs.

Table 1. Electrical variables used for the control detection.

Name	Unit	Description
Freq	Hz	Fundamental frequency
P	W	Active power
P_{act}	W	Actual active power consumed
S	VA	Apparent power
I	A	Current
U	V	Phase voltage
U2U1	%	Negative sequence component of voltage in percentage of positive sequence component
U0U1	%	Zero sequence component of voltage in percentage of positive sequence component
TDI	%	Total distortion of current in percentage of fundamental frequency component
TDU	%	Total distortion of voltage in percentage of fundamental frequency component
ITD	A	Total distortion of current in amperes
Qf	var	Fryze's reactive power, i.e., nonactive power
$Q1_{act}$	var	Actual fundamental frequency reactive power

METHODOLOGY

In this study, to detect the load control for FCR-N reserve, we implemented two scenarios using supervised and unsupervised learning. The first scenario is suitable for monitoring systems, where the load control has been commissioned and used for a while, whereas the second scenario could work for systems, where the load control has not been used at all (it is detected as an anomaly).

The same input variables were used in both scenarios. We compared several combinations of variables to find the one that leads to the highest model accuracy:

1. power measurements: P;
2. power quality measurements: TDU, ITD, $Q1_{act}$;
3. power and power quality measurements: P, TDU, ITD, $Q1_{act}$;
4. power quality measurements, estimates, and deviations: TDU, ITD, $Q1_{act}$, $\widehat{TDU}$, $\widehat{ITD}$, $\widehat{Q1}_{act}$, $TDU - \widehat{TDU}$, $ITD - \widehat{ITD}$, $Q1_{act} - \widehat{Q1}_{act}$.

For each variable, there were three phases, which were handled as separate inputs. All the inputs were aggregated and transformed in a similar way before using them for model training. In the last set of variables, the power quality estimates and their deviations from the measured values were produced in the additional feature engineering step. We assumed that these variables could increase the model accuracy in the load control detection.

The whole modeling pipeline implemented in this study [2] is presented in Figure 2. The following subsections describe its steps in more detail.

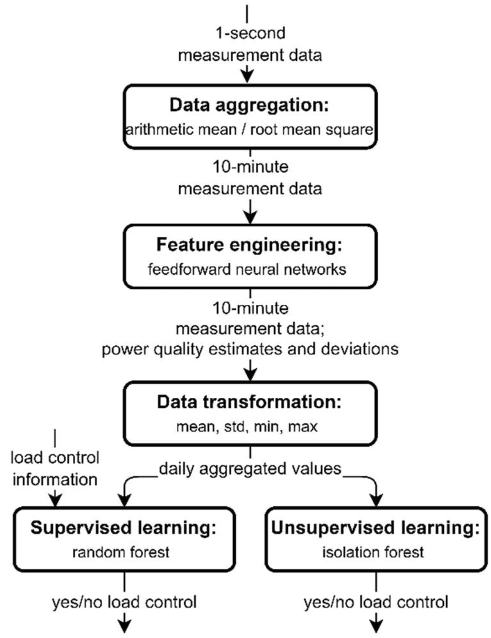

Figure 2. Modeling pipeline implemented for the load control detection in this study.

Data aggregation

The densely measured raw data were aggregated in the 10-minute data. Data aggregation was implemented by calculating either an arithmetic mean (Freq, P, P_{act}, S, Qf, Q1act) or an rms value (I, U, U2U1, U0U1, TDI, TDU, ITD) for 10-minute intervals. This preprocessing did not affect the results, but it allowed us to run the next steps in the modeling pipeline much faster.

Feature engineering

Feedforward neural networks (NNs) [3] were trained to estimate (i.e., nowcast) three power quality characteristics TDU, ITD, Q1act using electrical data presented in Table 1. Nine estimators (i.e., TDU, ITD, Q1act for three phases L1, L2, L3) were trained on the 10-minute aggregated data collected in November 2018 – February 2019, before the load control has been commissioned.

NNs were trained with the Adam algorithm implemented in Keras [4]. The model meta parameters and architecture were tuned using 5-fold cross-validation, the results were averaged over 10 runs.

Then, $\widehat{\mathrm{TDU}}$, $\widehat{\mathrm{ITD}}$, $\widehat{\mathrm{Q1act}}$ were estimated for November 2019 – February 2020 (with no load control) and November 2020 – February 2021 (with the load control) using the trained models. The performance of NNs in these two periods was compared based on several metrics such as root mean square error (RMSE), mean absolute error (MAE), index of agreement (IA), and bias. It was noticed that the NN-estimators were less accurate for the second period when the load control was used. Therefore, $\widehat{\mathrm{TDU}}$, $\widehat{\mathrm{ITD}}$, $\widehat{\mathrm{Q1act}}$ and their deviations from the measured values TDU, ITD, Q1act were assumed to be informative for the load control detection and tested in both supervised and unsupervised learning scenarios.

Data transformation

Power measurements, power quality measurements, along with their estimates and deviations generated in the feature engineering step, were selected from the 10-minute aggregated data to be used in the daily load control detection. For these input variables, daily samples were produced by calculating mean, maximum, minimum values, and standard deviations for three phases separately. These transformed data were later used in the daily load control detection.

Supervised learning approach for the load control detection

In the supervised learning scenario, the training and test data included days from both periods, i.e., with and without the load control. In our experiments, the data from November, January, and February in 2019–2020 and the same months in 2020–2021 were used to train the model, whereas the data from December 2019 and December 2020 were reserved to test the model.

A random forest model [5], implemented in scikit-learn [6], was trained to detect the load control. The maximum tree depth was optimized using the 5-fold cross-validation. For other model meta parameters, we used their default values in scikit-learn. The experiment was repeated 25 times to assess the average model accuracy on the test data. Finally, the variable importance was examined in the random forest model that achieved the highest accuracy. The scikit-learn documentation explains in detail, how the variable importance is calculated for random forests. In our experiments, the best model was trained 100 times and the variable importance was averaged over these independent runs.

Unsupervised learning approach for the load control detection

In the unsupervised learning scenario, the training data included days only from the period with no load control. Therefore, from the methodological point of view, it was seen as an anomaly in the system.

In this study, we applied an isolation forest model [7], implemented in the scikit-learn library, to estimate anomaly scores daily, so that we would detect the commissioning of the load control.

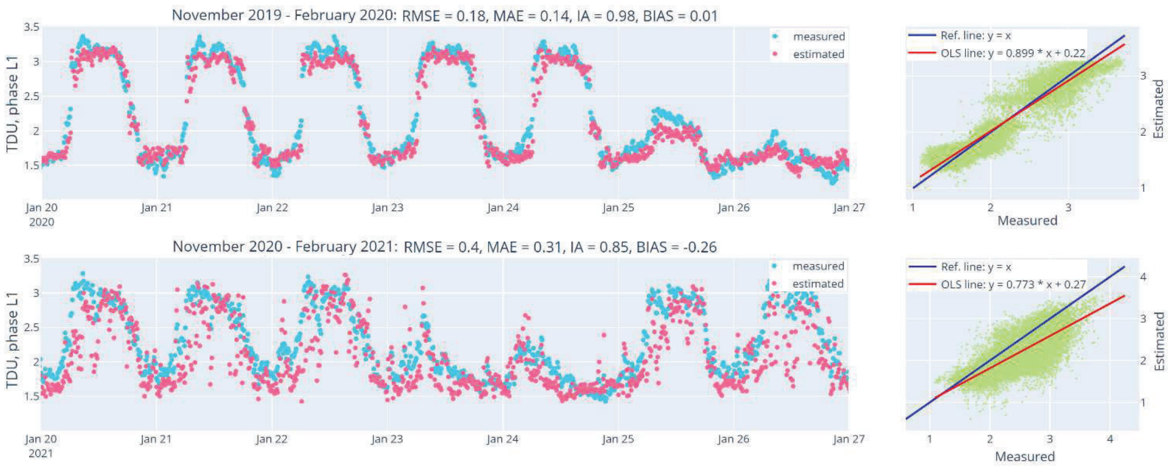

Figure 3. TDU, phase L1 measured at the ventilation feeder level and $\widehat{\mathrm{TDU}}$, phase L1 estimated with the NN model for November 2019 – February 2020 (with no load control) and November 2020 – February 2021 (with the load control). The left-hand side plots portray only seven days for the sake of better visibility (i.e., the plots are zoomed in), whereas the right-hand side scatter plots and the calculated metrics correspond to the whole specified periods.

The data from November, January, and February in 2019–2020 (no load control) were used to train the model, the data from December 2019 (no load control) were reserved to select a threshold needed to distinguish between normal and abnormal days based on their anomaly scores. The data from December 2020 (with the load control) were used to test the model. Thus, in this scenario, the model did not see the data with the load control when being trained.
The isolation forest model was trained with the default meta parameter values used in scikit-learn. The experiment was repeated 25 times to assess the average anomaly scores and model accuracy on the test data.

RESULTS

First, we illustrate the results of the feature engineering. The difference between measured and estimated values of power quality characteristics is exemplified with TDU, phase L1 of the ventilation system in Figure 3. It is seen that for the period with the load control, the NN model produces less accurate estimates, therefore, deviations $TDU - \widehat{TDU}$, $ITD - \widehat{ITD}$, $Q1act - \widehat{Q1act}$ could be informative in the load control detection.
Then, several combinations of electrical variables were tested as model inputs in the load control detection. The results obtained in the supervised learning scenario are presented in Figure 4. For both measurement points, i.e., the ventilation feeder and the main distribution board, the random forest models trained on power quality measurements, estimates and deviations (produced in the feature engineering step) demonstrated the highest accuracy, 99.87% and 99.03%, correspondingly. For the ventilation feeder, t-test run on the accuracy values obtained with the best model and the second-best model in 25 independent runs resulted in t-score = 1.613 and p-value = 0.113, which is a "borderline" value signaling that in this case the rather high accuracy could have been achieved even without feature engineering. However, for the main distribution board, the same analysis resulted in t-score = 5.840 and p-value = 4.391e-07, which indicates the significant improvement in the model accuracy due to the feature engineering.

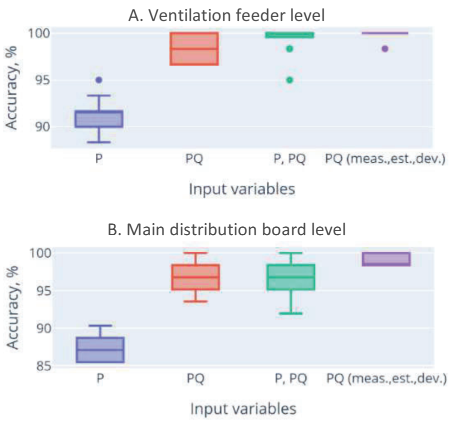

Figure 4. Test accuracy of the random forest model in the load control detection for different input variables.

When analyzing the variable importance (Tables 2 and 3), we found that power quality deviations were the most important in both cases (i.e., for the ventilation feeder and the main distribution board). Several power quality measurements and estimates also were found important in the load control detection for the main distribution board. Nevertheless, in the unsupervised learning scenario, we excluded power quality measurements and estimates from the fourth group of inputs and kept only deviations as they seemed the most important.

Table 2. Top 10 most informative variables in the load control detection for the ventilation feeder level.

Input variable	Importance
$\mathrm{mean}(ITD_{L1} - \widehat{ITD}_{L1})$	0.0963
$\mathrm{mean}(TDU_{L1} - \widehat{TDU}_{L1})$	0.0879
$\mathrm{mean}(TDU_{L2} - \widehat{TDU}_{L2})$	0.0753
$\mathrm{mean}(Q1act_{L1} - \widehat{Q1act}_{L1})$	0.0750
$\max(TDU_{L2} - \widehat{TDU}_{L2})$	0.0596
$\mathrm{mean}(Q1act_{L2} - \widehat{Q1act}_{L2})$	0.0522
$\min(Q1act_{L2} - \widehat{Q1act}_{L2})$	0.0509
$\mathrm{mean}(TDU_{L3} - \widehat{TDU}_{L3})$	0.0447
$\max(ITD_{L1} - \widehat{ITD}_{L1})$	0.0413
$\max(TDU_{L1} - \widehat{TDU}_{L1})$	0.0374

Table 3. Top 10 most informative variables in the load control detection for the main distribution board level.

Input variable	Importance
$\mathrm{mean}(TDU_{L1} - \widehat{TDU}_{L1})$	0.0928
$\max(ITD_{L1} - \widehat{ITD}_{L1})$	0.0529
$\mathrm{mean}(TDU_{L3} - \widehat{TDU}_{L3})$	0.0503
$\mathrm{mean}(TDU_{L2} - \widehat{TDU}_{L2})$	0.0456
$\max(TDU_{L1} - \widehat{TDU}_{L1})$	0.0448
$\min(TDU_{L3})$	0.0356
$\min(TDU_{L2})$	0.0333
$\mathrm{mean}(ITD_{L1} - \widehat{ITD}_{L1})$	0.0327
$\mathrm{std}(\widehat{ITD}_{L1})$	0.0315
$\min(TDU_{L1})$	0.0310

In the unsupervised learning scenario, a similar set of experiments with different input variables was conducted for both measurement points. The distributions of the averaged anomaly scores were approximated with histograms presented in Figure 5 (the smooth lines were built using kernel density estimations). In this scenario, more informative variables allow the better separation between the "test data" histogram (with the load control) and the "training data" histogram (with no load control). The vertical gray line in the figures indicates the "anomaly" threshold, which is defined as the largest k-th percentile of the "training data" anomaly scores that allows classifying all the validation days as normal (i.e., no load control). The threshold differs from the minimum "training data" anomaly score because the training data could contain anomalies caused by any other reasons.
First three sets of variables were the same as in the supervised learning scenario. Then, using Tables 2 and 3, we preselected inputs from the fourth group of variables,

(i.e., the power quality measurements, estimates, and deviations). For the ventilation system, we kept mean deviations, whereas for the main distribution board, we kept mean and maximum deviations.

Figure 5. Distributions of anomaly scores evaluated using different input variables on the training (no load control), validation (no load control), and test data (with the load control) for the ventilation feeder level (A) and for the main distribution board level (B).

As might be seen in Figure 5, these inputs led to the highest average accuracy: 96.67% and 64.52% of days with the load control were detected based on the data from the ventilation feeder and the main distribution board, correspondingly.

CONCLUSIONS

In this work, the load control detection of the FCR-N resource was performed using machine learning models trained on the electrical measurement data. We implemented two scenarios – supervised and unsupervised learning, which were preceded with the common feature engineering step. We selected ensemble-based models for the load control detection and NNs for the feature engineering as these models have demonstrated the highest performance in many different applications. As a result, we reached up to 99.87% and 96.67% accuracy for the ventilation feeder level, 99.03% and 64.52% for the main distribution board level in the supervised and unsupervised learning scenarios, correspondingly.

In the proposed approach, the load control detection was performed as post-analysis at the daily level, which could be considered as the main limitation. Nevertheless, using this approach, DSO may discover if their customers begin to have flexibility resources, when the flexibility has been in operation, or if there is a problem with the flexibility control. The methodology can be developed for other kind of demand response, markets, and flexibility resources (e.g., electric cars).

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