Impact of seasonal weather on forecasting of power quality disturbances in distribution grids

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***Abstract*—Power supply disruptions, including short-time disturbances, can lead to large direct and indirect financial losses. The ability to predict the risk of these disturbances allows for preventive actions and increases the reliability of the supply. This paper investigates the impact of using seasonal data of combined common weather conditions on the power quality prediction in distribution grids. Our main contribution consists of weather-based predictive models for three types of events that frequently occur in these grids, as well as an analysis of the influence of two training approaches: with either seasonal or all-year data, on their performance. All developed models score higher than arbitrary guessing; in several instances the improvement is considerable. It is demonstrated that in some cases the models improve when the training data is limited to a subset corresponding to a particular meteorological season. Examining variable importance values and distributions of the models' data, it is shown that this situation takes place particularly when weather conditions correlated with the occurrence of power grid events vary across seasons.**

***Index Terms*—power distribution faults, power system reliability, power system stability, smart grids, supervised learning.**

I. Introduction

The Norwegian power distribution grid, which this work is based on, is equipped with an event logging and analysis system [1], registering occurrences of operational disturbances. According to statistics from Statnett[1], difficult weather conditions can be attributed to 27% of these kinds of instabilities[2] [2], making them their most common underlying cause. Simultaneously, due to the interconnectivity of critical infrastructures, short-time disturbances in power supply can lead to disproportionately large socio-economic consequences, while their occurrence is significantly more frequent than that of severe faults. These reasons make weather-based forecasting of power quality disturbances an important research area for improving reliability of power grids.

Although several works on weather-related failures in power supply have been proposed, the effect of using explicit seasonal models remains poorly investigated. Furthermore, most of these works concern: i) extreme weather conditions, such as hurricanes or earthquakes [3]–[6] or ii) severe faults, such as power outages and interruptions [6], [7]. To date, there is no comprehensive body of research dedicated to the prediction of less severe, short-time disturbances utilizing the broad range of available data on common weather conditions.

In the following paper, it is demonstrated how weather forecasts and historical logs from power-quality-analyzer (PQA) instruments can be used to predict the risk level for a set of power quality disturbances in the power grid. Specifically, the disturbances considered are earth faults (EF), rapid voltage changes (RVC) and voltage dips (VD). It is investigated whether training the models on single-season as opposed to all-year data is of benefit to their performance. It is further analyzed in what situations this approach increases the predictive power. As the developed models are based on common, rather than extreme, weather conditions, they are suitable for risk assessment in daily grid operations.

II. Method

In this section, it is described what methods are used to develop, analyze and evaluate the performance of the models.

A. Models

Random forest models (a type of supervised machine learning algorithm; an ensemble of decision trees [8], [9]) were used to predict probability of occurrence of earth faults, rapid voltage changes, and voltage dips based on the weather forecast for a given day. The models are trained on preprocessed data (Table II, Section III), where their input consists of numerical values of daily weather forecast and the output is the probability of a particular event.

Two types of models are trained and evaluated for each disturbance type: *all-year models*, trained on data from the whole year and *seasonal models*, trained on data from a single meteorological season.[3]

The algorithm is chosen based on initial tests, where random forests presented higher performance than a set of other methods that can be analyzed for variable importance (e.g., linear regression, gradient boosting).

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[1]Statnett is the Norwegian transmission system operator (TSO).

[2]Statistics for the years 2009-2017. (23% in 2017, 28% in 2016).

[3]Seasons are spring (Mar. to May), summer (June to Aug.), autumn (Sept. to Nov.), and winter (Dec. to Feb.).

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TABLE I
CORRELATIONS IN THE METEOROLOGICAL DATA.

Correlated features	r
1: $\sum$ [LOW/MIDDLE/HIGH]_CLOUD_COVER 2: CLOUD_COVER	0.99
1: Δ PRECIPITATION_AMOUNT_ACCUMULATED 2: PRECIPITATION_AMOUNT	1.00
1: [LOW/MIDDLE/HIGH]_PRECIPITATION_ESTIMATE 2: PRECIPITATION_AMOUNT	> 0.82

r is the Pearson correlation coefficient. The retained variables are 4: [LOW/MIDDLE/HIGH]_CLOUD_COVER and PRECIPITATION_AMOUNT.

B. Variable importance

Trained random forest models can be analyzed to understand which variables they are most sensitive to. This is called variable (or feature) importance. In this work, the importance values are used to determine which meteorological variables contribute the most to predictions of the developed seasonal and all-year models. These values are also used to explain differences in the models' performance. The measure used is the decrease in Gini impurity of each variable (which is also a criterion used to build the trees), averaged over all trees of the random forest [10].

Correlated variables may have a negative effect on the interpretability of variable importance [11]. As such, within sets of correlated variables, only one was retained (see Table I), reducing their number from 17 to 12.

C. Model performance evaluation

Given a weather forecast, the output of the models is the probability for an event (earth fault, rapid voltage changes, or voltage dip, depending on the model) to occur within the next 24 hours. The probability is translated into a decision by selecting a threshold, which is a probability value above which the event is expected to occur.

By training the model on only a subset of the data, the remainder of the data (which is unknown to the model) can be used to evaluate the predictive performance of the model for a given threshold.[4] Performance is evaluated by computing the recall and precision. Intuitively, recall describes how many of all actual events are predicted as events, whereas precision indicates how many of the predicted events are actually true. If the threshold changes, recall and precision will also change. By varying the threshold, the relation between precision and recall can be constructed. This relation is represented by the precision-recall curve. Compared to other metrics (such as ROC curves), precision-recall curves are particularly suited for imbalanced datasets [12].

Since acceptable values of recall and precision require operational and financial considerations, threshold selection is out of scope for this work. Models will, therefore, be evaluated across all possible thresholds by summarizing the precision-recall curve through the (mean) average precision [13].

[4]In practice, this process is repeated five times with different splits to generate training and testing data (5-fold cross-validation). To avoid leakage, data is subset by year (or season) instead of at random.

TABLE II
DATA FORMAT USED TO TRAIN THE MODELS.

Date	x_1: AIR_PRESSURE	...	x_{12}: Y_WIND	y: EVENT
2015-01-01	101325 Pa	...	2 m/s	False
...	...	...	...	...
2019-12-31	101610 Pa	...	3 m/s	True

$x_1, ..., x_{12}$ are the meteorological variables used by the models to predict the y variable (event occurrence). y is either EF, RVC or VD.

TABLE III
NUMBER OF OBSERVATIONS OF AT LEAST ONE EVENT PER DAY BETWEEN 1 JAN. 2015 AND 31 DEC. 2019 (ALL 3 SITES ACCUMULATED).

Season	EF	RVC	VD	Total
Spring	70	80	94	244
Summer	174	139	163	476
Autumn	92	57	96	245
Winter	89	88	129	306
Total	425	364	482	1271

As a minimal bar, models need to outperform a baseline classifier, which is usually a variant of randomly choosing whether or not an event occurs. This work uses a stratified random baseline, which predicts events proportionately to their distribution in the training data. In the precision-recall curve, the stratified random baseline corresponds to a line of constant precision at a value representing the proportion of positive samples [12].

III. TRAINING DATA

The training data used to build the models combined event logs from PQA instruments in the Norwegian power grid and historical weather forecasts [14]. The data was preprocessed into daily averages (weather) and daily counts (events). The format of the data is shown in Table II. The period covered is 1 Jan. 2015 to 31 Dec. 2019.

Event logs were obtained from PQAs deployed in the Norwegian power grid. The data was examined using AHA [15], [16] to extract rapid voltage changes, voltage dips, and earth faults. The geographical locations of the measurement sites are known, but cannot be disclosed. The logs were transformed into a time-series of daily occurrences. Event counts are summarized in Table III.

Historical weather forecasts were obtained from the Norwegian Meteorological Institute[5]. The forecasts were produced by the METCOOP Ensemble Prediction System [17]. They cover the Nordics with grid resolution of $2.5 \times 2.5\,\mathrm{km}^2$ and time resolution of 1 hour. Available meteorological parameters include temperature, humidity, cloud cover, fog cover, wind speed and direction, and lightning indices (Table IV in the

[5]https://thredds.met.no/thredds/metno.html

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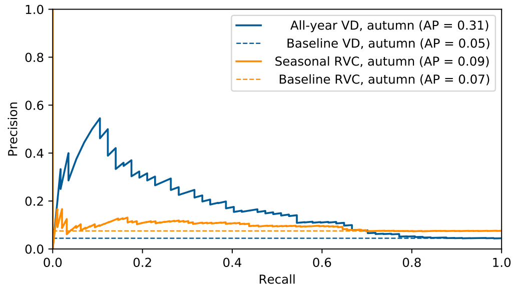

Fig. 1. Precision-recall curves of the best and worst performing model: the all-year VD model (blue) and the seasonal RVC model (orange) with their respective baselines (dashed). Better performing models have curves that tend towards the top right of the figure. PR curves are summarized into average precision (AP, see legend). Baseline models have constant precision.

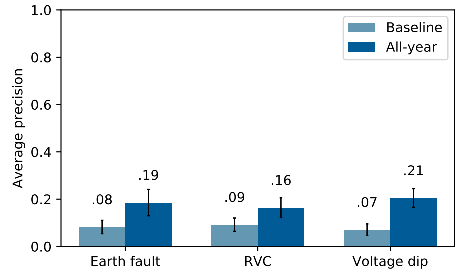

Fig. 2. Cross-validated average precision of the all-year models with respect to their baselines. Models are evaluated on all-year data. For each model type, the mean average precision (values) and its standard deviation (vertical bars) over the five folds is shown.

Appendix). For each site, forecast data is loaded from the grid cell the site is located in and transformed into a daily-averaged time-series.

The final time-series covers 1825 days of data. Out of these, 18% of days have at least one event occurring. Earth faults, rapid voltage changes and voltage dips occur on 8, 9, and 7% of days, respectively.

IV. Predictive power of the models

Fig. 1 shows the precision-recall (PR) curves for two of the models as well as their respective baselines. At a threshold of 0 (the bottom right of the curve), all instances are predicted as events. This results in maximal recall (equal to 1), as all actual events are predicted correctly. At the same time, precision is low (at the baseline), since all days without any disturbance are also predicted as event occurrences. As the threshold increases, fewer actual events are predicted as true, causing the recall to decrease. Precision may or may not increase, depending on the model's ability to correctly predict the actual events. At a threshold of 1, no cases are predicted as disturbances (recall equal to 0 and undefined precision).

The all-year model to detect voltage dips (VD) achieved the highest (0.31, 0.26 over the baseline) and the seasonal model for rapid voltage changes (RVC) the lowest (0.09, 0.02 over the baseline) mean average precision among all models. In the best model, a clear rise above the baseline is visible for recall values $\lesssim 0.7$ While the RVC model barely rises above the baseline across all thresholds, the VD model reaches precision values up to ~ 0.55. Hereafter, models are compared on the grounds of average precision instead of analyzing individual precision-recall curves.

All-year models are now evaluated on whole-year data before being compared to seasonal models.

A. All-year models

Fig. 2 shows the average precision for the three all-year models as well as their corresponding baselines. Models trained on the whole year data achieve better results than the baseline, which means they succeed in indicating an increased risk of instability. The absolute increase over the baseline in terms of average precision is 0.11 (2.4x improvement), 0.07 (1.8x), and 0.14 (3x) for earth faults, rapid voltage changes, and voltage dips, respectively. Overall, all-year models for voltage dips obtain both the highest absolute average precision and have the largest outperformance with respect to their baseline. Models for RVC prediction have the lowest performance, while earth fault models are in-between.

B. Seasonal models

Fig. 3 shows the predictive performance of seasonal models compared to both all-year models as well as their respective baselines. All models outperform their baseline models in every season. Averaged over four seasons, models for voltage dips perform best, followed by models for earth faults, and rapid voltage changes. Broken down by season, spring models are the weakest for all event types, while the season of the strongest model varies.

Averaged over the seasons, seasonal earth fault and voltage dip models perform at a similar level (0.22 and 0.21 in average precision) while rapid voltage change models perform worse (0.16). The average increase over their respective baselines follows the same order with earth fault and voltage dip models improving by 2.9x and 2.8x for an absolute increase in average precision of 0.13. The performance gain is the smallest for rapid voltage change models (1.6x relative, 0.07 absolute).

Seasonal models generally perform worse than all-year models, except in three cases. Earth faults in spring have the largest outperformance compared to all-year models with an increase in average precision of 0.09 (1.7x). Earth faults and rapid voltage changes in summer have much smaller outperformance of 0.01 (1.05x) and 0.01 (1.04x), respectively.

For earth faults, the seasonal models provide a more stable performance without compromising the predictive power (average precision of 0.19 – 0.26 in the seasonal models vs 0.13 – 0.26 in the all-year model). For rapid voltage changes, the all-year model is more stable (0.09 – 0.24 seasonal vs 0.14 – 0.23 all-year). The all-year voltage dip model always scores higher than the seasonal models (0.17 – 0.31 all-year).

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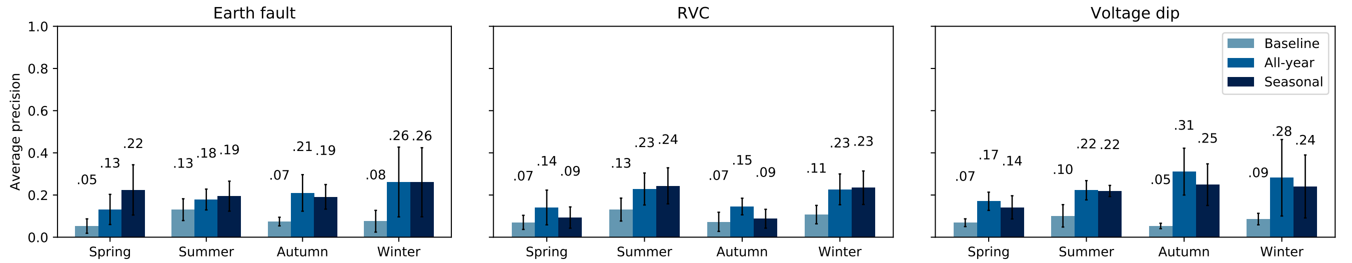

Fig. 3. Cross-validated average precision of the all-year and seasonal models with respect to their baselines. Models are evaluated on seasonal data. For each model type, the mean average precision (values) and its standard deviation (vertical bars) over the five folds is shown.

C. *Achievable performance of weather-based models*

It is known that in a significant number of cases the underlying cause of power system events (in particular the RVC) is not the weather, but rather phenomena such as production and consumption activities, component failures, and activities related to the operation of the grid [18]. The electric grid is also evidently robust enough to not suffer instabilities every time it is challenged by the weather. These factors limit the achievable predictive ability of models relying solely on meteorological data. Taking this into account, developed models should be considered to indicate only *weather-related* risk of system events.

V. Analysis of seasonal and all-year models

This section analyzes the contribution of weather variables to the prediction of power delivery disturbances in the models and the reasons behind the advantage in performance of different models in specific cases.

A. *Variable importance*

Fig. 4 shows the importance of each meteorological variable for predictions of each model. Distinct distributions of these values indicate that two models differ in what variables they rely on. For instance, in the earth fault models (left panel), the most important variable for all-year, spring, autumn and winter models is X_WIND (Gini impurity reduction of 0.15, 0.25, 0.31, and 0.16, respectively), while the summer model relies to a much higher degree on THUNDERSTORM_INDEX (0.26, as compared to 0.12 for X_WIND).

Overall, all-year models rely on multiple variables to a similar extent but seasonal models depend only on few dominant ones. For instance, in all-year EF models, the standard deviation over all variables is 0.03 (79% of the mean = 0.04). Spring, summer, autumn, and winter EF models have relative standard deviations of 157, 126, 193, and 104% of the mean, respectively. Models of RVC and VD follow the same pattern. This indicates that seasonal models tend to rely on fewer weather variables. In particular, the variables of wind strength and direction, thunderstorm indexes, air pressure and air temperature are most relevant.

When seasonal models outperform all-year models, the importance of meteorological variables is always and noticeably different in distribution than in all-year models. The largest deviation is found in spring and summer models for earth faults. Compared to the all-year model, the former relies strongly on meridional wind (Y_WIND) and the latter on the thunderstorm index. For RVC, the most important variables in the summer models are thunderstorm index and its daily change, while in the all-year model their contribution is not pronounced. When all-year and seasonal models score similarly (e.g., earth faults and rapid voltage changes in winter, voltage dips in summer), the variable importance is also distributed similarly.

Considering distinct disturbance types, wind-related variables are most important for earth faults and voltage dips, but not for rapid voltage changes. Air pressure is a factor that is significant only for rapid voltage changes. Finally, some factors are more significant in some seasons, e.g., thunderstorm-related variables in summer or wind-related variables in autumn.

B. *When does less data mean more?*

Machine learning models generally improve when trained on more data. Their performance depends on how well they are able to learn the structure of the input data and how representative this data is of its actual underlying distribution. Seeing more observations makes it more likely for the learner to generalize, derive important patterns and discard coincidental relationships. However, this assumes that training and operational data are drawn from the same distribution [19].

For meteorological data, distributions depend on the season of the year. As such, models trained on data from particular seasons should be more sensitive to conditions typical of the season which may make them achieve better performance. In contrast, if models are trained on more, but not seasonally representative data, they may become sensitive to conditions that are atypical for the seasons in which they are used (e.g., heavy snowfall in the summer) or succeed to capture only those relationships which are present across the whole year.

In this study, there are three cases in which the models perform better when trained on only seasonal, rather than the whole-year, data. Investigating the underlying variable distributions of these models can explain this advantage. Distributions are estimated using kernel density estimates (KDE) [20].

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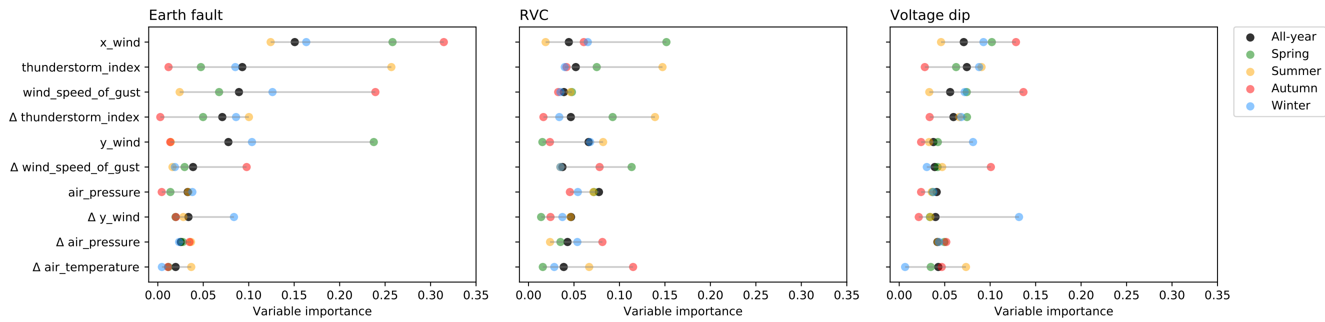

Fig. 4. Importance values of meteorological variables (see Table IV in the Appendix) for all developed models. The higher the value, the larger the contribution of a variable to the final prediction of a model. Variables preceded by Δ express a change with respect to the previous day. Each panel corresponds to all-year and seasonal models within one event category. Only variables that are among the two most important for at least one model are presented. For each model, importance values (including those not shown) sum to unity.

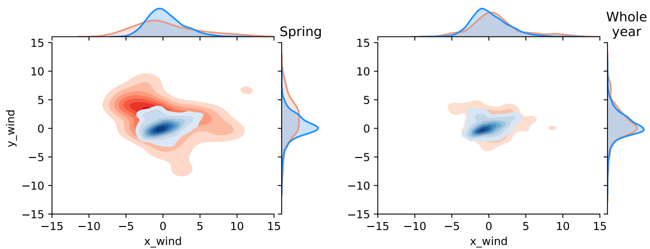

Fig. 5. Joint and marginal distributions of two most important variables in the spring earth fault model (X_WIND and Y_WIND; see Table IV in the Appendix). The distributions correspond to days with at least one earth fault occurrence (red) and without it (blue) in spring as compared to the whole year (left vs right panel).

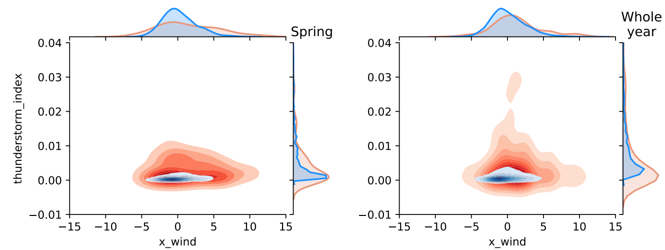

Fig. 6. Joint and marginal distributions of two most important variables in the spring voltage dip model (X_WIND and THUNDERSTORM_INDEX; see Table IV in the Appendix). The distributions correspond to days with at least one voltage dip occurrence (red) and without it (blue) in spring as compared to the whole year (left vs right panel).

Fig. 5 and 6 show distributions of the most important variables when higher performance is obtained by a seasonal (spring EF) or by the all-year model (spring VD), respectively.

Joint distributions of meridional and zonal wind (Y and X_WIND, Fig. 5) differ notably more between the days with and without earth faults in spring than across the whole year. In spring, higher absolute values of these variables correlate with earth fault occurrence, particularly when X_WIND < 0 and Y_WIND > 0 (as the distribution is centered at $x = -1.06$; $y = 1.87$). Since across the whole year this pattern is not pronounced, the relationship between meridional and zonal winds and earth fault occurrence is unlikely to be captured by the all-year model to the same extent. The focus of the models on these particular correlations is also represented by the importance values of corresponding variables. The same discrepancy between distributions is seen in the data used to train other outperforming seasonal models when considering their most important variables.

Contrarily, when all-year models succeed, it means that they capture correlations between an event and the weather that are present in a particular season. In cases when all-year and seasonal models share their dominant variables without seasonal models performing better, patterns learned by the models are likely consistent across the year.

All-year and seasonal models showed similar values for variable importance in four cases, whereas only the case of VD prediction in spring the all-year model obtained higher AP. In other cases (EF and RVC in winter, VD in summer) the performance was almost equal. Based on the aforementioned premises, the distributions of the most important variables of the all-year model should be similar. Indeed, while the THUNDERSTORM_INDEX distribution has a wider spread across the whole year, in both cases higher values of THUNDERSTORM_INDEX, as well as higher absolute values of X_WIND indicate an increased risk of an event (Fig. 6).

The above observations suggest that seasonal models outperform the all-year models in cases where weather conditions related to disturbances are specific for a particular season and uncommon during the rest of the year. This is observed regardless of whether more data is provided to the all-year models, as the additional data is not representative of the season in which the models are used. In these particular cases, only the seasonal models succeed in recognizing the importance of variables indicating an increased risk of a disturbance.

VI. Conclusion

The weather-based machine learning models for forecasting of power quality disturbances developed in this work have been shown to achieve better performance than random guessing (the baseline) in all cases. Given the limited achievable

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power of the models, in several instances this improvement was considerable: the average precision ranged from $+0.06$ to $+0.26$ higher than the baseline score for the best performing models for each season and event type.

With respect to training the models on seasonal, rather than all-year data, this approach was effective only for 3 in 12 models. Further analysis indicated that using a subset of data was of benefit to the models if the occurrence of events could be associated with seasonally-distinct distributions of meteorological variables. Since limiting the data increases model sensitivity to particular weather conditions, it can be assumed that seasonal training is of benefit when weather-related triggering causes are season-specific. Conversely, if weather-triggered events are caused by phenomena present across the whole year, training on all available data provides a better result.

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APPENDIX

TABLE IV
METEOROLOGICAL FORECAST VARIABLES.

Variable(s)	Description
AIR_PRESSURE	Air pressure at the mean sea level (MSLP) [21] (in Pa).
AIR_TEMPERATURE	Air temperature 2m above the ground (in K).
[LOW/MIDDLE/HIGH] _CLOUD_COVER	Horizontal area occupied by clouds: low, middle and high cloud type (3 variables; in %).
FOG_AREA	Horizontal area occupied by fog (in %).
PRECIPITATION_AMOUNT	Daily sum of precipitation [22] (in mm).
RELATIVE_HUMIDITY	Relative humidity 2 m above the ground.
THUNDERSTORM_INDEX	Combined thunderstorm indicator.
WIND_SPEED_OF_GUST	Maximal speed of gust at 10 m above the surface [17] (in m/s).
X_WIND	Zonal wind speed, i.e. speed of the wind blowing along the local parallel of latitude at 10 m above the surface (from the east $< 0 <$ from the west; in m/s).
Y_WIND	Meridional wind speed, i.e. speed of the wind blowing along the local meridian at 10 m above the surface (from the north $< 0 <$ from the south; in m/s).

TABLE V
LIST OF ABBREVIATIONS.

Abbreviation	Name
AHA	Automatisk Hendelsesanalyse (eng. automatic event analysis)
AP	Average precision
EF	Earth fault
PQA	Power quality analyzer
RVC	Rapid voltage changes
VD	Voltage dip

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